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Stock Prediction by Deep Learning

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by

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University of Southampton

Abstract

Faculty of Engineering and Physical Sciences

Electronics and Computer Science

Doctor of Philosophy

STOCK PREDICTION BY DEEP LEARNING

by

Mehtabhorn Obthong

Stock market trading is an activity in which investors need fast and accurate information to make effective decisions. In this domain, fast denotes the capacity to acquire and analyse pertinent market data quickly enough for the results to remain actionable, as stock prices fluctuate within minutes or even seconds. Accurate denotes generating predictions with low forecasting error, ensuring that the expected price or return closely aligns with actual market movements. Effective decisions are those that enable investors or portfolio managers to choose appropriate buy, sell, or hold actions that improve returns or reduce risk. Since many stocks are traded on a stock exchange, numerous factors influence the decision-making process. Moreover, the behaviour of stock price is uncertain and hard to predict. For these reasons, stock price prediction is an important process and a challenging one. This leads to the research of finding the most effective prediction model that generates the most accurate prediction with the lowest error percentage. This research focuses on the prediction model for improving the performance of stock price prediction. The historical prices and financial news were be considered as inputs to this research and expect that they will improve the prediction efficiency of the models created.

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List of Additional Materials

Dataset A : Stock return of S&P 500 index (2016-2020) with sentiment score.

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Research Thesis: Declaration of Authorship

Print name: Mehtabhorn Obthong

Title of thesis: Stock Prediction by Deep Learning

I declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

I confirm that:

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 - Obthong, M. et al. (2020). A survey on machine learning for stock price prediction: Algorithms and techniques. *In proceedings of the 2nd International Conference on Finance, Economics, Management and IT Business (FEMIB2020)*.

Signature: Date:

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Chapter 1 Introduction

Artificial Intelligence (AI) has become increasingly prominent in financial markets as a tool for enhancing investment analysis, decision-making efficiency, and operational performance (Deloitte, 2019). Machine learning (ML), in particular, supports investors by processing large volumes of financial data and generating data-driven insights that inform investment and portfolio management decisions. The performance of ML models strongly depends on the availability of sufficient, high-quality data, as richer datasets generally improve predictive accuracy (Brynjolfsson and McAfee, 2017). Consequently, ML has attracted significant interest among investors seeking superior performance, particularly in the domain of securities trading. Securities enable investors to participate in firms either directly, through equity ownership, or indirectly, through debt instruments. These financial instruments serve as a mechanism through which firms raise capital from the public, thereby linking investors with institutions seeking funding. Financial securities encompass a wide range of instruments—including equities, bonds, and derivatives—each characterised by distinct risk–return profiles.

Equity securities represent one of the most actively traded instruments in global financial markets (Lin *et al.*, 2018). The advantages of stock investment are that:

1. Stocks offer potentially attractive returns through both capital gains and dividends.
2. Equity ownership confers participation rights, allowing investors to influence corporate governance through voting mechanisms.
3. Stocks are highly liquid assets due to the ease of trading on formal exchanges.

These attributes contribute to the widespread popularity of stocks among individual and institutional investors (He *et al.*, 2015; Chou and Nguyen, 2018). Accurate stock return forecasting plays a critical role in asset valuation, portfolio allocation, and risk management. Investors frequently establish a required rate of return to inform buy, hold, or sell decisions. Although return expectations guide investment strategies, predicting future returns is inherently challenging due to the complex and stochastic nature of financial markets (Dai, Zhu and Kang, 2021). Stock prices are influenced by a wide array of factors—including macroeconomic conditions, political developments, and investor sentiment—making their behaviour difficult to model (Hadavandi, Shavandi and Ghanbari, 2010; Nguyen, Shirai and Velcin, 2015; Göçken *et al.*, 2016; Chou and Nguyen, 2018). As a result, investors benefit from analytical tools that can synthesise multiple influencing factors to support more informed decision-making.

Considering only a limited set of explanatory variables often results in high prediction error, as omitted factors may substantially influence stock price dynamics. Achieving meaningful predictive accuracy therefore requires an analytical approach capable of incorporating numerous interacting variables.

Yet, the volume and complexity of relevant financial information make manual analysis infeasible, highlighting the need for computational tools such as statistical modelling and machine learning to support decision-making.

Machine learning (ML) has emerged as an essential analytical tool in finance, capable of processing large datasets and generating insights that support more informed investment decisions. ML models transform complex market information into structured features that can be used to produce predictive outputs, guiding investor decision-making. When effectively designed, ML-based decision-support systems can enhance investment performance by identifying patterns and relationships not visible through traditional analytical methods. However, the predictive performance of ML techniques—particularly for stock return forecasting—remains a significant challenge, and improving these capabilities is essential for gaining a competitive investment advantage.

The effectiveness of ML models depends not only on algorithmic design but also on the quality, structure, and diversity of the training datasets used. Deep learning (DL), a subfield of ML, represents a more advanced modelling approach capable of learning hierarchical representations from complex data. DL models use multi-layer neural networks that learn non-linear relationships directly from data, reducing the need for manual feature engineering. DL techniques have demonstrated strong potential in financial forecasting tasks and are increasingly applied in stock prediction due to their ability to capture temporal and structural dependencies in financial time-series data (Jiang, 2021).

The stock prediction is significant as stock return prediction directly impacts actual investing decisions, and even minor enhancements in predicting accuracy can provide substantial financial implications. The more accurate model matters in this domain because it is used by investors, portfolio managers, and automated trading systems to decide when to buy, sell, or hold assets. In a highly competitive and rapidly evolving market, a model that provides merely "good enough" performance may result in lost opportunities or heightened risk, whereas a model that reduces error rates—even marginally—can significantly improve decision-making outcomes and long-term returns (Huang & Vakharia, 2024; C. Wang, 2024). Therefore, investing effort in identifying the most effective prediction model is essential, as it provides users with more reliable and actionable information than simpler or less accurate approaches.

1.1 Research Aim

Despite advancements in financial forecasting, developing more accurate stock return prediction models remains an active research challenge (Nguyen, Shirai and Velcin, 2015; Sharma, Bhuriya and Singh, 2017; Jiang, 2021). Existing approaches often combine linear and non-linear modelling techniques that rely primarily on historical market data, such as price and volume. However, recent

literature suggests that investor sentiment—particularly as expressed through financial news—may provide additional predictive value for return forecasting. This study therefore hypothesises that integrating historical market data with sentiment features extracted from financial news can enhance the predictive capability of deep learning models.

The primary aim of this research is to identify strategies for improving stock return prediction performance using deep learning. Accordingly, the study addresses the following research question:

RQ “How can the performance of stock return prediction be improved using deep learning in order to support investor decision-making?”

To investigate this, it is divided into five objectives:

Objective 1: Review and analysis of price prediction techniques for financial news.

Objective 1 involved reviewing existing literature to identify the principal machine learning and deep learning techniques applied to stock price and return prediction. Although much prior research evaluates variations of individual models, relatively few studies conduct broad comparative analyses across multiple deep learning architectures. Through this review, three promising deep learning approaches were identified for further evaluation in this research.

Objective 2: Investigate how varying hyperparameters impact the predictive accuracy of the deep learning model.

Objective 2 involved empirically comparing the selected deep learning models to assess how different hyperparameters influence predictive accuracy. The experimental design systematically varied activation functions, window sizes, training epochs, and network architectures. Findings demonstrated that while index price prediction achieved relatively low error rates, return prediction based solely on historical data remained highly inaccurate highlighting the need for additional information sources.

Objective 3: Review and analyse sentiment techniques for financial news.

Objective 3 focused on reviewing sentiment analysis methodologies used in financial forecasting, assessing their strengths and limitations. From this review, three sentiment analysis approaches—particularly lexicon-based methods such as VADER—were identified as suitable for integration with deep learning models.

Objective 4: Examined how different lag periods of financial news sentiment influence the accuracy of return prediction.

Experiments were conducted using varying sentiment windows (e.g., 1-day, 3-day, 5-day aggregates) to determine the optimal lag structure for predictive performance.

Objective 5: Assessed the trade-off between computational runtime and predictive accuracy when incorporating sentiment features into deep learning models.

Comparative experiments quantified how the inclusion of sentiment analysis affected model training time and overall efficiency.

1.2 Report Outline

Chapter 2 establishes the theoretical and empirical foundation for this research. It is structured into two main sections to support the development of the experimental framework. The first section reviews key literature on machine learning and deep learning techniques for financial prediction, the characteristics of financial instruments, and the nature of financial time-series data. This review informs the selection of modelling approaches and guides the methodological decisions implemented in later chapters. The second section examines sentiment analysis methods and their use in stock market forecasting, with particular emphasis on investor sentiment derived from financial news. It outlines the theoretical role of investor sentiment in financial markets and evaluates the strengths and limitations of available sentiment analysis techniques. This section concludes by justifying the choice of sentiment extraction method used in the empirical phase of this study.

Chapter 3 outlines the two-phase experimental design developed to address the research question. It presents the modelling strategies used to forecast the S&P 500 index both with and without sentiment integration. Detailed descriptions of the preliminary and final experiments—including dataset preparation, feature construction, and modelling workflows—are provided. The chapter further specifies the deep learning architectures employed, the experimental settings, and the metrics used to evaluate model performance.

Chapter 4 reports the results of a comparative study evaluating three deep learning architectures—MLP, LSTM, and GRU—for S&P 500 index price and return prediction. The analysis draws on an extensive hyperparameter space, examining multiple activation functions, window sizes, epoch counts, and network configurations.

Chapter 5 presents the findings of the sentiment-enhanced forecasting experiments, in which financial news sentiment was integrated into return prediction models. Thirteen datasets combining various configurations of historical return data and sentiment features were evaluated using a deep MLP model to determine the predictive contribution of sentiment.

Chapter 6 synthesises the key findings from both experimental phases and discusses their theoretical, methodological, and practical implications.

Chapter 7 concludes the study by summarising its contributions, recognising its limitations, and proposing directions for future research.

1.3 Publication

The peer-reviewed conference paper based on the work of this research have been accepted for publication as below:

1. Obthong, M. *et al.* (2020). A survey on machine learning for stock price prediction: Algorithms and techniques. In *proceedings of the 2nd International Conference on Finance, Economics, Management and IT Business (FEMIB2020)*, April, pages 63–71.

Chapter 2 Machine Learning and Sentiment Analysis in Finance

Over the past few years, machine learning has been applied in many fields, such as bioinformatics (Min, Lee and Yoon, 2017), robotics (Polydoros and Nalpantidis, 2017), economics (Rui, IEEE and Donald, 2005), engineering (Lee, Shin and Realff, 2018; Ward *et al.*, 2018), and networks (Jiang *et al.*, 2017). Stock prices often reflect how well the economic sector is doing. Many people try and predict stock prices using economic data and ML is a common approach in predicting stock prices. Most ML in finance is based on historical financial data; therefore, businesses need to select their models and data carefully. The models will continuously automatically modify their parameters for more accurate results. The success rates of ML, however, depends on efficient infrastructure, gathering relevant information, and using the appropriate algorithms (Alpaydin, 2014). The better the quality of data, the more accurate the ML result. In terms of financial investments, ML has changed the way investors use information and it offers optimal analytic opportunities for of all types. Thus, ML is a significant tool to help financial investment.

This chapter aims to present a background relating to the issue introduced in Chapter 1. The content studied is divided into two parts: machine learning and various techniques used for stock prediction, and sentiment analysis techniques that will be used to enhance the performance of the prediction model. The chapter starts with an overview of ML that is illustrated in section 2.1. Section 2.2 and 2.3 describe the characteristics of machine learning methods and the advantages and disadvantages of each machine learning technique. Section 2.4 provides the general information of the financial instruments that include stocks and other financial instruments after that ML techniques for financial instruments are presented in Section 2.5. Section 2.6 explains the component of time series data that is the feature of stock data. In section 2.7 focus on Machine learning for stock prediction and 3 well-known stock prediction techniques. Sections 2.8 to 2.12 investigate the impact of investors' sentiment on stock price movement; in other words, sentiment analysis techniques are used to predict stock prices. Sections 2.8 and 2.9 describe the role of investor sentiment in the stock market, and principles of sentiment analysis, respectively. Section 2.10 reviews each of the sentiment classification techniques. Section 2.11 discusses the benefits and drawbacks of the Lexicon-based, machine learning-based, and deep learning-based approaches. Section 2.12 reviews how sentiment analysis has been applied previously to stock returns prediction, before Section 2.13 summarises the chapter and mentions the prediction technique and sentiment analysis method chosen

2.1 Machine Learning

Machine Learning is a branch of AI that enables the computer program to learn from existing datasets and improve its performance automatically. The goal of ML is to improve the quality of prediction by using the experience embedded in the past data (Mohri, Rostamizadeh and Talwalkar, 2012). ML combines statistical tools for predictions; this is one of the most exciting advantages of machine learning (Dingli and Fournier, 2017). Examples of ML applications are fraud detection, predictive maintenance, and portfolio optimisation. ML techniques fall into four techniques (Ayodele, 2012), listed below.

2.1.1 Supervised Learning

This technique uses learning from labelled training data sets in order to train a computer program to understand the pattern of data and create a hypothesis to work with future data. Supervised learning methods of classification and regression are well-known (Alpaydin, 2010). The target of the supervised learning is to provide accurate output (Ghahramani, 2003). Supervised learning is an underlying technique used to train the computer program (the learner) by using past information; hence, its success depends on the quality and size of information received (Mohri, Rostamizadeh and Talwalkar, 2012).

2.1.1.1 Classification

This technique tries to predict the category of data based on training with a set of labelled data. The objective is to correctly select the class of a new instance. Classification is applied in many research fields; for instance, it can be used to identify students that will be performing well (Devasia, Vinushree and Hegde, 2016; Senthil and Lin, 2018), to classify marketing sentiments (Cho and Kang, 2012; Cambria, 2016), and to solve engineering problems (Chou and Pham, 2015). Sample classification algorithms are support vector machine (SVM), k-nearest neighbour (KNN), and random forest (RF) (see Table 2-1).

2.1.1.2 Regression

This technique is used to predict numerical results. The aim of this technique is to predict output for new input. The regression model uses both linear and non-linear approaches, but linear regression is used the most because its computation is easy. Regression algorithms that are widely used include linear regression, decision trees, support vector regression (SVR), logistic regression (LR), and artificial neural network (ANNs) (see Table 2-1).

2.1.2 Unsupervised Learning

Unsupervised learning is a learning method using unlabelled input datasets, but this learning will cluster data based on similarities (and differences) between input patterns. One well-known unsupervised learning approach is clustering. The target of the unsupervised learning is to find an interesting structure (patterns) in the data sets (Chapelle, Schölkopf and Zien, 2006).

Clustering is different from supervised classification learning. This technique will cluster data based on their similarity without knowing the categories of groups (class labels) and the number of groups. The cluster analysis process is an attempt to categorise the data into the same groups based on some similarity measure (Dy and Brodley, 2004). Clustering techniques have been applied in various fields to analyse data that is so large and complex that it cannot be analysed manually (Rui, IEEE and Donald, 2005). Examples include marketing (You et al., 2015; Bi et al., 2016), economics (Giannakis and Bruggeman, 2015; Wang et al., 2017), and bioinformatics (Kashyap et al., 2015; Sedlar, Kupkova and Provaznik, 2017). Many clustering algorithms have been developed and widely used, such as k-means, k-medoids, fuzzy c-means, and hierarchical clustering, as can be seen in Table 2-1.

2.1.3 Semi-Supervised Learning

Semi-Supervised learning is a special technique that uses both labelled and unlabelled data sets for training. This learning is midway of supervised and unsupervised learning (Chapelle, Schölkopf and Zien, 2006). In fact, traditional classification uses labelled data for training (Zhu, 2008), but semi-supervised learning uses only a sample of the labelled training data. This learning, therefore, resembles supervised learning, but use additional unlabelled data to achieve better learning.

2.1.4 Reinforcement Learning

This is a pattern learning that defines the system actions from the things observed. The concept is learning from the surroundings that cause stimulation, to create the model which responds with what should be done next. “Reinforcement learning is closely related to the fields of decision theory (in statistics and management science), and control theory (in engineering).” (Ghahramani, 2003).

2.2 Characteristics of Machine Learning Methods

Because of the availability of high computing power, ML techniques play an important role in many aspects of systems applied in financial management, such as approving loans, managing assets, assessing risks, and predicting stock prices. Financial data analysis research has used a variety of ML techniques. These can be divided into: model and algorithm.

2.2.1 Model

A model is a simplified description of a system or thing, consisting of a set of relationships between its components (e.g. variables), used for explaining how something works or calculating what might happen and assisting calculations and prediction, especially, in mathematics and algorithms. For example, multilayer perceptron (MLP) long short-term memory (LSTM), hidden markov model (HMM), and artificial neural networks (ANNs), etc. See Table 2-1 for more information.

In the model, some variables may be changed or optimized during the calculation or prediction process as to acquire the best result or indicator, also known as an accuracy. However, to get the best result or accuracy, some models need to be trained prior to the testing and later deployment. With this process, the models can be improved through Long Short Term Memory (Zheng et al., 2016).

2.2.2 Algorithm

An algorithm is a process that uses mathematics techniques (Narin'yani, 2001). It is represented by a set of rules, procedures, and flows that need to be followed step-by-step (e.g. pseudocodes) in order to solve a problem. The algorithms are constructed based on models built for solving the problem.

Some examples of ML algorithms are: fuzzy c-means (FCM), genetic algorithms (GAs), support vector machine (SVM), random forest (RF) (see Table 2-1).

2.3 The Advantage and Disadvantage of Machine Learning Techniques

Many ML techniques have been developed to analyse the huge quantity of data already generated and increasing every minute. A technique might work properly when applied to one type of dataset, but does not for others. The purposes for which ML techniques are developed are different, such as data classification, forecasting, and data clustering; the techniques are composed of algorithm, model, and estimation. Each of these techniques have different strengths and weaknesses. A comparison of the individual techniques is given in Table 2-2.

Machine learning can be a tool that increases return rates to investors, but the investors must accept the risk from financial market volatility. To increase the returns and lower the risk, investors have to make better decisions, by analysing the financial information, and diversifying their portfolios. Although this research focuses on a stock investment, there are the other investments using other financial instruments.

Table 2-1: Characteristics of machine learning techniques

Method	Type of machine learning		Characteristics of method	
	Supervised	Unsupervised	Model	Algorithm
Machine learning				
ANNs	✓		✓	
BNN	✓		✓	
BPNN	✓		✓	
BSM	✓		✓	
CART	✓		✓	
FCM		✓		✓
GAs	✓	✓		✓
GMDH	✓			✓
GP	✓		✓	
GRNN	✓		✓	
Hierarchical Clustering		✓		✓
HMM	✓	✓	✓	
K-Means		✓		✓
k-medoids (PAM)		✓		✓
KNN	✓			✓
LR	✓		✓	
LSTM	✓		✓	
MCS	✓		✓	
MLP	✓		✓	
PSO	✓		✓	✓
QRNN	✓		✓	
RBF	✓		✓	
RF	✓			✓
RNN	✓		✓	
SOM	✓	✓		✓
SVM	✓			✓
SVR	✓		✓	

2.4 Financial Instruments

A financial asset is a claim to the income produced by real assets (selling cocoa beans, letting a building, providing a service). Two examples of financial assets are stocks and bonds. An investment involves giving wealth up now in the expectation of future gain and includes a contractual arrangement through the buying of securities. Profit, interest and dividends are the forms of gains from an investment, and depends on the type of securities invested in. More information about the instrument, securities, stock, and bond will be described later in Section 2.4.1 – 2.4.5.

Table 2-2: Advantage and disadvantage of each ML technique

Methods	Data	Purpose	Method	Advantages	Disadvantages	References
ANNs: Artificial Neural network	Non-time series, Time-series and Financial time series	Classification and Forecasting	Model	– High ability to tackle complex nonlinear patterns (Khashei and Bijari, 2010) – High accuracy for modelling the relationship in data groups (Zhang and Qi, 2005; Khashei and Bijari, 2010) – Can model both linear and non-linear processes (Zhang and Qi, 2005) – Robust model that can handle noisy and missing data (Versace <i>et al.</i>, 2004; Göçken <i>et al.</i>, 2016) – High predictive power (Sharma and Kaushik, 2018)	– Over fitting (Han and Lee, 2008; Zhou and Fan, 2019) – Sensitive to parameter selection (Wang <i>et al.</i>, 2011) – ANNs just give predicted target values for some unknown data without any variance information to assess the prediction (Han and Lee, 2008) – Black box (Sharma and Kaushik, 2018) – Takes a long time processing for large Neural networks (Sharma and Kaushik, 2018)	- Han and Lee (2008) - Khashei and Bijari (2010) - Zhang and Qi (2005) - Versace <i>et al.</i> (2004) - Göçken <i>et al.</i> (2016) - Zhou and Fan (2019) - Wang <i>et al.</i> (2011) - Sharma and Kaushik (2018)
ARIMA: Autoregressive integrated moving average model	Time-series, Financial time-series	Forecasting and Clustering	Model	– Works well for linear time series (Liang, 2005) – It is the most effective forecasting technique in social science (Adebiyi, Adewumi and Ayo, 2014) – For short-run forecasting, it provides more robust and efficient than the relative models with more complex structural (Adebiyi, Adewumi and Ayo, 2014) – Robust to missing data (Nickerson and Madsen, 2005) – Works well for computing the continuous sets of data (Nickerson and Madsen, 2005)	– Does not work well for nonlinear time series (Liang, 2005; Aslanargun <i>et al.</i>, 2007) – The model determined for one series will not be suitable for another (Selvin <i>et al.</i>, 2017) – Requires more data (Hyndman and Athanasopoulos, 2018) – Takes a long time processing for a large dataset (Andreopoulos <i>et al.</i>, 2009; Aghabozorgi, Seyed and Wah, 2015) – Requires set parameters and is based on user assumptions that may be false, the resulting clusters being inaccurate (Andreopoulos <i>et al.</i>, 2009; Aghabozorgi, Seyed and Wah, 2015) – The forecast results are based on past values of the series and previous error terms (Adebiyi, Adewumi and Ayo, 2014)	- Selvin <i>et al.</i> (2017) - Adebiyi, Adewumi and Ayo (2014) - Liang (2005) - Aslanargun <i>et al.</i> (2007) - Selvin <i>et al.</i> (2017) - Hyndman and Athanasopoulos (2018) - Andreopoulos <i>et al.</i> (2009) - Aghabozorgi, Seyed and Wah (2015) - Nickerson and Madsen (2005)
BPNN: Back propagation neural network	Non-time series, Time-series and	Forecasting	Model	– Flexible nonlinear modelling capability (Zhao <i>et al.</i>, 2010; Wang, Zeng and Chen, 2015; Singh and Tripathi, 2017)	– Sensitive to noise – Actual performance based on initial values (Zhao <i>et al.</i>, 2010)	- Zhao <i>et al.</i> (2010) - Wang, Zeng and Chen (2015) - Aslanargun <i>et al.</i> (2007) - Singh and Tripathi (2017)

Methods	Data	Purpose	Method	Advantages	Disadvantages	References
	Financial time series			– Strong adaptability (Wang, Zeng and Chen, 2015; Singh and Tripathi, 2017) – Capable of learning and massively parallel computing (Wang, Zeng and Chen, 2015; Singh and Tripathi, 2017) – Popular for predicting complex nonlinear systems (Aslanargun et al., 2007; Wang, Zeng and Chen, 2015; Singh and Tripathi, 2017) – Fast response (Chen <i>et al.</i>, 2008) – High learning accuracy (Chen <i>et al.</i>, 2008)	– Slow convergent speed (Zhao et al., 2010) – Easily converging to a local minimum (Zhao et al., 2010)	- Chen <i>et al.</i> (2008)
CART: Classification and Regression Trees	Non-time series, Financial time-series	Classification and Forecasting	Model	– Can model nonlinearity very well (Pradeepkumar and Ravi, 2017) – Results are easily interpretable (Pradeepkumar and Ravi, 2017)	– Unstable even when the training data are small changed (Pradeepkumar and Ravi, 2017)	- Pradeepkumar and Ravi (2017) - Breiman, et al. (1984)
FCM: Fuzzy c means	Non-time series, Time-series and Financial time series	Clustering	Algorithm	– Works well for searching spherical-shaped clusters (Liao, 2005) – Work effectively for small to medium datasets (Liao, 2005)	– Sensitive to noise (Suganya and Shanthi, 2012). – Has problems with handling high dimensional datasets (Grover, 2014). – The membership of the data point depends directly on the membership values of other cluster centres which may lead to undesirable results (Grover, 2014).	- Liao (2005) - Suganya and Shanthi (2012) - Grover (2014)
GAs: Genetic Algorithms	Non-time series, Time-series and	Clustering, Classification and Forecasting	Algorithm	– Can search the clusters with different shapes by using different criteria (Pattarin, Paterlini and Minerva, 2004)	– Sensitive to parameter selection (Wang et al., 2011)	- Pattarin, Paterlini and Minerva (2004) - Haviluddin and Alfred (2015) - Wang <i>et al.</i> (2011)

Methods	Data	Purpose	Method	Advantages	Disadvantages	References
	Financial time series			– One of the best-suited algorithms for learning the time-series datasets (Haviluddin and Alfred, 2015) – Works well for the noisy data (Bose and Mahapatra, 2001) – Suitable for peculiarly hard problems when little or no knowledge of the optimal function is given and the search space is very large (Versace et al., 2004) – Suitable for solving the issue of defining proper parameters for ANNs (Versace et al., 2004)		- Bose and Mahapatra (2001) - Versace <i>et al.</i> (2004)
GMDH: Group Method of Data Handling	Financial time-series	Forecasting	Algorithm	– Best ANN for handling the incorrect, noisy, or small datasets (Pradeepkumar and Ravi, 2017) – Provides higher accuracy and is an easier structure than traditional ANN models (Katabchi et al., 2010)	– Can generate a complicated polynomial even for a simple system (Oh et al., 2001; Pradeepkumar and Ravi, 2017) – Does not consider the input-output relationship well because of its limited architecture (Oh et al., 2001; Pradeepkumar and Ravi, 2017) – Inefficient for modelling nonlinear systems that have different characteristics in different environments (Oh et al., 2001; Pradeepkumar and Ravi, 2017)	- Pradeepkumar and Ravi (2017) - Katabchi <i>et al.</i> (2010) - Oh <i>et al.</i> (2001)
GP: Gaussian Processes	Time-series and Financial time-series	Classification and Forecasting	Model	– Flexible and easy computational implementation (Rizvi et al., 2017) – Sufficiently robust to generate the automatic model (Obrezanova, Gola and Segall, 2007)	– Generates "black box" models which are difficult to interpret (Obrezanova, Gola and Segall, 2007) – Can be computationally expensive (Obrezanova, Gola and Segall, 2007)	- Rizvi <i>et al.</i> (2017) - Obrezanova, Gola and Segall (2007).
GRNN: Generalized Regression Neural Network	Non-time series, Time-series and Financial time series	Classification and Forecasting	Model	– Easy to implement because of a much faster training procedure than other ANNs (Chen and Wang, 2018) – Useful for performing predictions in real-time (Pradeepkumar and Ravi, 2017) – Does not require an iterative training process (Moreno, Pol and Gracia, 2011) – Can estimate any arbitrary function by adapting the function exactly from the	– Requires more memory space to store the model (Pradeepkumar and Ravi, 2017) – Can be computationally expensive because of its huge size	- Pradeepkumar and Ravi (2017) - Moreno, Pol and Gracia, (2011) - Al-Mahasneh, Anavatti and Garratt (2018) - Chen and Wang (2018)

Methods	Data	Purpose	Method	Advantages	Disadvantages	References
				training data (Moreno, Pol and Gracia, 2011) – Quick training approach (Al-Mahasneh, Anavatti and Garratt, 2018) – Provides the high accuracy of both linear and nonlinear functional regressions, based on the kernel estimation theory (Al-Mahasneh, Anavatti and Garratt, 2018; Chen and Wang, 2018)		
GRU: Gated Recurrent Units	Non-time series, Time-series and Financial Time Series	Classification, Forecasting, Speech recognition, and language modelling	Model	– High performance for multiclass classification tasks (Singh <i>et al.</i> , 2021) – High prediction efficiency (Zeng <i>et al.</i> , 2022) – The model structure is more concise (Wang <i>et al.</i> , 2019) – Each recurrent unit adaptively captures dependencies of different time scales (Wang <i>et al.</i> , 2019) – Able to deal with the time sequence problem of RNNs (Gao <i>et al.</i> , 2020)	– Lack of attribute of attention on important moments (Wang <i>et al.</i> , 2019)	- Wang et al. (2019) - Gao et al. (2020) - Singh et al. (2021) - Zeng et al. (2022)
Hierarchical Clustering	Non-time series, Time-series	Clustering	Algorithm	– Does not need to set any parameters, e.g. the number of clusters (Keogh and Lin, 2005)	– The length of each time series is the same because of the Euclidean distance calculation requirement (Wang, Smith and Hyndman, 2006) – Unable to handle long time series effectively because of poor scalability (Wang, Smith and Hyndman, 2006) – Useful only for small datasets because of its quadratic computational complexity (Keogh and Lin, 2005)	- Keogh and Lin (2005) - Wang, Smith and Hyndman (2006)
HMM: Hidden Markov Model	Non-time series, Time-series and Financial time series	Clustering, Classification and Forecasting	Model	– Strong statistical foundation (Belgacem, Chatelain and Paquet, 2017) – Able to model high level information (language model, or syntactical rules) (Belgacem, Chatelain and Paquet, 2017)	– Requires parameters to be set and is based on user assumptions that may be false with the result that clusters would be inaccurate (Andreopoulos et al., 2009; Aghabozorgi, Seyed and Wah, 2015) – Takes a long time processing for a large dataset (Andreopoulos et al., 2009; Aghabozorgi, Seyed and Wah, 2015)	- Aghabozorgi, Seyed and Wah (2015) - Andreopoulos <i>et al.</i> (2009) - Mohamed & Hinton (2010) - Belgacem, Chatelain and Paquet (2017)

Methods	Data	Purpose	Method	Advantages	Disadvantages	References
k-Means	Non-time series, Time-series and Financial time series	Clustering	Algorithm	– Works well for searching spherical-shaped clusters (Liao, 2005) – Works effectively for small to medium datasets (Liao, 2005) – Faster than hierarchical clustering (Wang, Smith and Hyndman, 2006)	– The number of clusters must be specified in advance (Bradley and Fayyad, 1998; Wang, Smith and Hyndman, 2006; Boomija, 2008) – Sensitive to noise (Vlachos et al., 2003) – Only spherical shapes can be determined as clusters (Boomija, 2008) – The quality of clustering is highly dependent on the selection of initial centres (Vlachos et al., 2003) – The length of each time series is the same because of the Euclidean distance calculation requirement (Wang, Smith and Hyndman, 2006) – Unable to handle long time series effectively because of poor scalability (Wang, Smith and Hyndman, 2006)	- Bradley and Fayyad (1998) - Wang, Smith and Hyndman (2006) - Liao (2005) - Boomija (2008) - Vlachos <i>et al.</i> (2003)
k-Medoids (PAM)	Non-time series and Time-series	Clustering	Algorithm	– Works well for searching spherical-shaped clusters (Liao, 2005) – Works effectively for small to medium datasets (Liao, 2005; Boomija, 2008) – More robust to noisy data and outliers than k-means (Boomija, 2008).	– The number of clusters must be specified in advance (Aghabozorgi, Seyed and Wah, 2015) – Only spherical shapes can be determined as clusters (Boomija, 2008) – Does not scale well for large datasets (Boomija, 2008)	- Liao (2005) - Boomija (2008) - Aghabozorgi, Seyed and Wah (2015)
KNN: K Nearest Neighbour	Non-time series, Time-series and Financial time series	Classification and Forecasting	Algorithm	– Robust to noisy training data (Jadhav and Channe, 2016) – Very efficient if the training datasets are large (Archana and Elangovan, 2014) – Simple to implement (Alkhatib <i>et al.</i>, 2013)	– The number of nearest neighbours must first be determined (Archana and Elangovan, 2014). – Can be computationally expensive (Jadhav and Channe, 2016) – Memory limitation (Jadhav and Channe, 2016) – Sensitive to the local structure of the data (Jadhav and Channe, 2016)	- Jadhav and Channe (2016) - Archana and Elangovan (2014) - Alkhatib <i>et al.</i> (2013)
LR: Logistic Regression	Financial time-series	Classification and Forecasting	Model	– High ability to tackle complex nonlinear patterns (Khashei and Bijari, 2010)	– Sensitive to outliers (Wu and Li, 2018) – Strong assumptions (Khashei and Bijari, 2010)	- Khashei and Bijari (2010) - Wu and Li (2018)
LSTM: Long Short-Term Memory	Non-time series, Time-series	Classification and Forecasting	Model	– It is easy to detect and capture important features over a long distance (Wang <i>et al.</i>, 2019)	– Lacks a mechanism to index the memory while writing and reading the data (Daniehelka et al., 2016)	- Selvin <i>et al.</i> (2017) - Kumar, Goomer and Singh

Methods	Data	Purpose	Method	Advantages	Disadvantages	References
	and Financial Time Series			– It is the most effective model for sequence learning (Nunes <i>et al.</i>, 2019) – Well-suited to classify, process, and predict financial time series (Nunes <i>et al.</i>, 2019) – Capable of dealing with multivariate problems (Nunes <i>et al.</i>, 2019) – Able to deal with the time sequence problem of RNNs (Gao <i>et al.</i>, 2020) – Capable of analysing and exploiting the interactions and patterns existing in data through a self-learning process (Selvin <i>et al.</i>, 2017). – Makes good predictions because it analyses the interactions and hidden patterns within the data (Selvin <i>et al.</i>, 2017) – Good in remembering information for long time (Kumar, Goomer and Singh, 2018) – Long and short term information is retained (Wang <i>et al.</i>, 2019)	– The number of memory cells is linked to the size of the recurrent weight matrices (Daniehelka <i>et al.</i>, 2016) – More complex model structure than RNN (Wang <i>et al.</i>, 2019) – High computational complexity in model training (Wang <i>et al.</i>, 2019)	(2018) - Daniehelka <i>et al.</i> (2016) - Wang <i>et al.</i> (2019)
MCS: Monte Carlo Simulation	Financial time-series	Forecasting	Model	– Very flexible and virtually no limit for analysis (Kantas <i>et al.</i>, 2009) – Easily understood by non-mathematicians (Kantas <i>et al.</i>, 2009) – Easy to see which inputs had the biggest effect on the results (Kantas <i>et al.</i>, 2009) – Can model complex systems (Smid <i>et al.</i>, 2010) – All kinds of probability distributions can be modeled (Smid <i>et al.</i>, 2010) – Time to results quite short (Smid <i>et al.</i>, 2010)	– No interactive link between data and parameters (Smid <i>et al.</i>, 2010) – Unidirectional (Smid <i>et al.</i>, 2010) – Does not allow “backward reasoning” (Smid <i>et al.</i>, 2010)	- Smid <i>et al.</i> (2010) - Kantas <i>et al.</i> (2009)
MLP: Multilayer Perceptron	Non-time series, Time-series, Financial time series	Forecasting, Classification	Mode	– Robust to noise (Brownlee, 2018) – Flexible for function mapping (Brownlee, 2018) – Easy to learn linear and nonlinear relationships (Brownlee, 2018)	– Convergence is quite slow (Wankhede, 2014; Pradeepkumar and Ravi, 2017) – Local minima can affect the training process (Pradeepkumar and Ravi, 2017) – Hard to scale (Pradeepkumar and Ravi, 2017)	- Pradeepkumar and Ravi (2017) - Strader <i>et al.</i> (2020) - Brownlee (2018)

Methods	Data	Purpose	Method	Advantages	Disadvantages	References
				– Easy to adapt the coefficients by backpropagation algorithm (Elliott, 2001) – Providing the strong support for multi-step and multivariate forecasting (Brownlee, 2018) – Can yield accurate predictions for challenging problems (Pradeepkumar and Ravi, 2017) – It is the best and most practical ANN architecture (Strader <i>et al.</i>, 2020) – High ability to computation (Wankhede, 2014) – High adaptive learning when have to learn how to do tasks from the training data given (Wankhede, 2014)		
PSO: Particle Swarm Optimization	Non-time series, Time-series and Financial time series	Forecasting	Algorithm	– Easy to implement (Pradeepkumar and Ravi, 2017) – Very few parameters to tweak (Pradeepkumar and Ravi, 2017)	– Lacks a solid mathematical foundation for analysing future development of relevant theories (Lee and Park, 2006)	- Pradeepkumar and Ravi (2017) - Lee and Park (2006)
RBF: Radial Basis Function Neural Networks	Non-time series, Time-series and Financial time series	Classification and Forecasting	Model	– Robust to noisy input (Yu et al., 2011) – The training is faster than perceptron since there is no back propagation learning involved (Markopoulos, Georgiopoulos and Manolakos, 2016) – Very stable, and a generalization capability (Markopoulos, Georgiopoulos and Manolakos, 2016) – Good comprehensive adaptive and learning abilities (Liu et al., 2007) – Powerful technique for improvement in multi-dimensional space (Liu et al., 2007) – Quicker in convergence and more accurate in the model than the Back Propagation Neural Network (Liu et al., 2007)	– Classification process is slower than MLP (Markopoulos, Georgiopoulos and Manolakos, 2016)	- Aslanargun <i>et al.</i> (2007) - Liu <i>et al.</i> (2007) - Yu <i>et al.</i> (2011) - Markopoulos, Georgiopoulos and Manolakos (2016)

Methods	Data	Purpose	Method	Advantages	Disadvantages	References
				– Does not suffer from local minima in the same way as the multilayer perceptron (Liu et al., 2007) – Only has one hidden layer making faster learning than MLP (Aslanargun et al., 2007)		
RF: Random Forest	Non-time series, Time-series and Financial time series	Classification and Forecasting	Algorithm	– Robust method for forecasting and classification problems since its design that is filled with various decision trees, and the feature space is modelled randomly (Pradeepkumar and Ravi, 2017) – Automatically handles missing values (Kubosova et al., 2010) – Works well with both discrete and continuous variables (Kubosova et al., 2010) – Powerful for complex classification tasks (Sharma and Kaushik, 2018)	– Requires more computational power and resources because it creates a lot of trees (Pradeepkumar and Ravi, 2017) – Requires more time to train than decision trees (Kubosova et al., 2010) – Might be high processing time if the number of trees is large (Sharma and Kaushik, 2018)	- Pradeepkumar and Ravi (2017) - Kubosova et al. (2010) - Sharma and Kaushik (2018)
RNN: Recurrent neural networks	Non-time series, Time-series and Financial Time series	Classification and Forecasting	Model	– Very useful where for showing the time relationships that occur between the inputs and outputs in the neural network (Elman, 1990; Moreno, Pol and Gracia, 2011) – Capable of handling a variable-length sequence input (Wang <i>et al.</i>, 2019) – Short-Term information is retained (Wang <i>et al.</i>, 2019)	– Difficult to train (Bengio et al., 1994; Pascanu, Mikolov and Bengio, 2013; Bai, Kolter and Koltun, 2018) – The problem of vanishing or divergence of gradients (Souma, Vodenska and Aoyama, 2019) – Difficult to capture long term dependencies (Wang <i>et al.</i>, 2019) – The problem of gradients vanishing or explosion makes gradient-based optimization method struggle (Wang <i>et al.</i>, 2019)	- Montañó Moreno, Palmer Pol and Muñoz Gracia (2011) - Elman (1990) - Bengio <i>et al.</i> (1994) - Pascanu, Mikolov and Bengio (2013) - Bai, Kolter and Koltun (2018) - Wang <i>et al.</i> (2019)
SOM: Self organizing maps	Non-time series, Time-series and Financial time series	Clustering and Classification	Algorithm	– Robust to parameter selection (Wang, Smith and Hyndman, 2006) – Yields a good clustering result (Wang, Smith and Hyndman, 2006) – Excellent data-exploring tool (Shieh and Liao, 2012; Chaudhary, Bhatia and Ahlawat, 2014)	– Does not work well for time series of unequal length because of the difficulty involved in determining the scale of weight vectors (Liao, 2005; Aghabozorgi, Seyed and Wah, 2015) – Sensitive to outliers (Andreopoulos et al., 2009)	- Wang, Smith and Hyndman (2006) - Shieh and Liao (2012) - Chaudhary, Bhatia and Ahlawat (2014) - Liao (2005) - Aghabozorgi, Seyed and Wah (2015) - Andreopoulos <i>et al.</i> (2009)

Methods	Data	Purpose	Method	Advantages	Disadvantages	References
SVM: Support Vector Machine	Non-time series, Time-series and Financial time series	Classification and Forecasting	Algorithm	– Can provide the optimal global solution and has excellent predictive accuracy capability (Karamizadeh et al., 2014; Niu et al., 2017) – Works well on a range of classification problems, such as those with high dimensions (Karamizadeh et al., 2014) – High accuracy (Sharma and Kaushik, 2018)	– Sensitive to outliers (Andreopoulos et al., 2009) – Sensitive to parameter selection (Wang et al., 2011) – Takes a long time processing for non-linear data (Sharma and Kaushik, 2018) – Hard to interpret (Sharma and Kaushik, 2018)	- Andreopoulos <i>et al.</i> (2009) - Wang <i>et al.</i> (2011) - Niu <i>et al.</i> (2017) - Karamizadeh <i>et al.</i> (2014) - Sharma and Kaushik (2018)
SVR: Support Vector Regression	Time-series and Financial Time Series	Forecasting	Model	– Powerful for financial time series prediction (Nava, Matteo and Aste, 2018) – Particularly suited to handle multiple inputs (Nava, Matteo and Aste, 2018) – Provides high prediction accuracy (Awad and Khanna, 2015) – Ability to tackle the overfitting problem (Basak, Pal and Patranabis, 2007)	– Sensitive to users' defined free parameters (Basak, Pal and Patranabis, 2007)	- Nava, Matteo and Aste (2018) - Awad and Khanna (2015) - Basak, Pal and Patranabis (2007)

Securities are tradable-financial assets; two main types of securities are equity and debt (Chen, 2019). Equity securities are shares in a company that entitles the owner to claim on assets of that company. Equity securities will be sold to investors whenever the publicly-traded companies want to raise new capital for their operations. This instrument often provides consistent income as dividends, but its market value might be affected by the fluctuation of the business cycle or the performance of a company. In contrast, debt securities (fixed-income securities) represent money that is borrowed with a promise to repay the whole of the borrowed amount, as well as interest, on a specific date. Debt securities are often issued for a set time period and must be repaid by the end of that time period. Some examples of debt securities are government bonds, corporate bonds, notes, and debentures. A security in a financial context is thus a financial instrument that has monetary value and can be traded (Kenton, 2019).

Staszkiwicz and Staszkiwicz (2015) define the meaning of financial instrument as a contract that gives the right to part- or wholly-own an entity or to claim the assets of the entity. Financial instruments are tradable assets; the financial market is the centre where the financial instruments such as stocks, bonds, bills, currencies, swaps, futures, and options, are traded (Lehmann, 2008). A financial transaction will be recorded as “asset” for the holder and as “liability” for the issuer (Blake, 2000; Lehmann, 2008).

For this research, the focus will be exclusively on stocks for two reasons. First, the stock market price is one of the primary indicators of the growth of the economy in a country (Perwej and Perwej, 2012; Göçken *et al.*, 2016; Selvin *et al.*, 2017). Therefore, the prediction of the movement of the stock market price is an important process for forecasting economic conditions (Khan, Alin and Hussain, 2011). Secondly, predicting the trends of stock markets is one of the most important tasks for investors (Kim and Kang, 2019), because stock market volatility can lead to a considerable loss of investment. These predictions are thus useful for investors, and also useful for analysing the direction of stock market indexes (Kim and Kang, 2019). The process of decision-making in stock trading is an important process because it must be taken exactly at the right time (Gamil *et al.*, 2007; Ijegwa *et al.*, 2014). This is why research into stock price prediction gets more attention and is studied continuously (Nguyen *et al.*, 2015; Attigeri *et al.*, 2016; Kim and Kang, 2019). However, other instruments are also outlined in Section 2.4.6.

2.4.1 Stocks

A stock, also known as a share, is an equity instrument issued by a public company to represent partial ownership of that company that is held by an individual or group (also known as the stockholders or shareholders). The stockholders will have the status of company owner. When the company wishes to expand its business, more capital may be needed to finance this plan. To raise this capital, the company

can issue new shares, after approval by the shareholders (because it dilutes their investment), and sell them to investors. The quoted value of the stock will increase if the company is successful. Therefore, the performance of the stock investment relates to both the success and to the real assets of the company (Bodie, Kane and Marcus, 2018). Stocks come in many types, but most shares traded in the market are in forms discussed below (Ganti, 2019).

Common Stock

Common stock, also known as ordinary shares, is the right to ownership of a company. The stockholders will receive one vote for each share owned, and receive the right to nominate the Board of Directors. Stockholders also gain the right to priority subscription for newly-issued ordinary shares. The returns are in the form of dividends (dependent on the proportion of shares held) paid from the profit, after tax and interest payments on the debt of the company.

Preferred stock

Preferred stock, also known as preference shares, represents ownership of a company. Holders of preferred stocks do not have voting rights over the company's management. However, where the company is dissolved, the preferred stockholders will get their shares before the holders of common stock. For normal returns, the preferred stockholder will receive a fixed payment, which might be higher or lower than the common stockholder. Preferred stock normally does not have a fixed maturity date, but the issuer may recall the preferred stock. Dividend payments can be accumulated, but must be paid to the preferred stockholders before the holders of common stock. It is at the discretion of the company to pay those dividends (Bodie, Kane and Marcus, 2011).

2.4.2 Stock Market

A stock market, also known as equity market or share market, is a public market where traders (investors in the financial markets) buy and sell the company's stock and derivatives by exchanging or processing in electronic or in physical form (Perwej and Perwej, 2012; Preethi and Santhi, 2012; Göçken *et al.*, 2016). Generally, financial instruments are traded in the capital market comprising a primary market and a secondary market (LSE, 2009). The primary market is the place where securities are distributed for the first time. The initial public offering (IPO) occurs here. The secondary market refers to the market for trading among the investors. Examples of a stock market are New York Stock Exchange (NYSE), London Stock Exchange (LSE), Japan Exchange Group (JPX), Shanghai Stock Exchange (SSE), and NASDAQ.

2.4.3 Stock price and stock return

A stock price denotes the prevailing value at which a share of a corporation is traded in the market. It is the aggregate assessment of investors of a company's value, determined by aspects such as financial performance, growth prospects, market conditions, and investor sentiment. Stock prices are constantly changing due to the dynamic nature of supply and demand. When demand for a stock increase, its price generally rises. When the supply increases due to a greater number of sellers, the price often declines. Comprehending stock prices is essential for investors, traders, corporations, policymakers, and researchers. Predicting stock price fluctuations has been a long-standing challenge due to the market's integration of extensive information, both rational and emotional, into price changes. Modern techniques such as machine learning, deep learning, and sentiment analysis are progressively employed to enhance the comprehension and forecasting of stock price fluctuations, with the objective of uncovering concealed patterns and behavioural insights that conventional models might overlook.

A stock return quantifies the profit or loss generated by holding a stock over a certain period. It signifies the earnings generated by an investment in a stock in relation to its initial cost and serves as a crucial measure of the stock's financial performance. Greater returns are typically correlated with increased risks. Returns enable investors to evaluate the performance of various stocks, funds, or entire markets. Stock return prediction constitutes a significant domain within financial research, frequently employing historical data, machine learning techniques, and sentiment analysis to model and predict future returns.

In summary, the stock price denotes the current market value at which a company's shares are exchanged, reflecting real-time supply and demand and serving as a measure of perceived value at a given moment. Conversely, stock return quantifies the percentage variation in stock price over a specified duration, reflecting the extent to which an investment has appreciated or depreciated in value. Stock price represents a definitive monetary value, but stock return is a comparative metric of performance, essential for evaluating profitability, studying historical trends, assessing investment risks, and informing future investment decisions.

2.4.4 Stock Index

Stock index is a representative of a group of stocks' prices. This index is computed from the prices of defined stocks and its change can reflect the overall performance of the stocks listed in the index. In particular, a stock index is a weighted average market value of a number of firms compared with the value on the base trading day (Bodie, Kane and Marcus, 2018).

For example, the Financial Times Stock Exchange 100 Index (FTSE 100) and FTSE SmallCap Index (FTSC) are stock indexes in the UK. The FTSE 100 is an index of the top 100 public companies with the highest value. The FTSC is a stock index of a group of companies with small market capitalisation, covering 281 companies. Both FTSE100 and FTSC indexes are listed on the London Stock Exchange Group.

Examples from the United States are the Dow Jones Industrial Average (DJIA) and Standard & Poor's Composite 500 Index (S&P 500). The DJIA is the best-known measure of the performance of its stock market (Bodie, Kane and Marcus, 2018) and is an index of 30 large public companies, which are also included the S&P 500 Index. The S&P 500 is a stock index of 500 large US public companies listed on Chicago Board Options Exchange (CBOE)¹. S&P 500 is one of the leading indicators and the important benchmark for the 500 top-traded companies (Althelaya, El-Alfy and Mohammed, 2018).

2.4.5 Stock Trading

Stock market trading is an important challenge for investors because trading decision and stock prices can be affected by the variety and complexity of information including economic conditions, local politics, international politics, and social factors (Hadavandi, Shavandi and Ghanbari, 2010; Chourmouziadis and Chatzoglou, 2016; Naranjo, Arroyo and Santos, 2018). Stock trading involves buying and selling shares in companies. Many different trading methods are used by traders, such as day trading, position trading, swing trading, and scalping (Mann and Kutz, 2016).

Stock Trading strategies

- Day Trading (also known as intra-day trading) is the most well-known trading style. Shares are bought and sold within the same day or multiple times over a day without holding them overnight. Before the market closes, the day traders will close all their trades. Therefore, most day traders use their ability to amplify the returns produced from small movements in price. This trading strategy is used by the professional trader, e.g. specialists, and market makers.
- Position Trading is to trade for weeks to months. Traders try to forecast whether the current trend will continue in the future. The aim of this trading is to make a profit from the movement of the market as it both rises and falls.
- Swing Trading is a short-term strategy that tries to make profits from stock trading with a period of 2-3 days or weeks. Swing traders mostly use technical analysis to identify the stocks that have short-term price momentum.

¹ CBOE is one of the world's largest options market operator.

- Scalping or micro-trading involves buying and selling within seconds or minutes. This trading strategy tries to make any profits from small price changes. This method is not suitable for beginners.

2.4.6 Other financial instruments

Bonds, also known as debt securities, are issued by an obligated borrower to make the specified coupon payments to the holder, also known as a bondholder, over a specified period. Debt instruments include treasury notes and bonds, municipal bonds, corporate bonds, federal agency debt, and mortgage securities (Bodie, Kane and Marcus, 2011). Most of these instruments promise either fixed income streams or income streams that are defined from a specific formula. That is the reason why they are sometimes called fixed-income securities.

Derivatives are securities whose payoffs are based on the value of other assets, so-called underlying assets, for example, stocks, currencies, bonds, commodities, etc. (Cuthbertson and Nitzsche, 2008; Bodie, Kane and Marcus, 2018). Financial derivatives play an important role in the financial markets because they are used to hedge² risks occurring from the operational, financing and investment activities of companies (Cuthbertson and Nitzsche, 2008; Lehmann, 2008; Bodie, Kane and Marcus, 2011). Four popular types of derivatives are **futures**, **options**, **forwards**, and **swaps**.

The **foreign exchange** market trades currencies. The foreign exchange rate is the price of one currency against the value of another. The foreign exchange market is a formal network in which the group of banks and brokers can exchange currencies immediately or enter a contract to exchange currencies in the future at the determined rate (Bodie, Kane and Marcus, 2018). The contracts traded in the exchange markets divided into three types: **spot**, **outright forward**, and **swap** (Brown, 2017).

Some **commodities** can be underlying assets of derivatives. Commodities are interchangeable with the same type and same grade of commodities, usually used as a raw material (cocoa, tea, silver) to produce goods or services. Commodities can be traded based on current prices either in the spot market, also known as the cash market, or in the futures market (Roncoroni, Fusai and Cummins, 2014). Commodities trading in the spot market are used for immediate delivery, but the futures market is used for trading for delivery at an agreed date in the future. The commodities that are traded in the derivatives market include agricultural products, precious metals, and energy (e.g. wheat, barley, soybeans, sugar, maize, crude oil, gold, and metals) (Whalley, 2016).

Returns on financial investments vary with the risk of financial instruments. The riskier an investment is, the higher yield it returns (Kase, 2015).

² Hedging is other form of investment in assets or derivatives security to offset a specific source of risk.

2.5 Machine Learning Techniques for Financial Instruments

In recent years, many unexpected factors affected the financial markets. Volatility in financial markets has been high and there are volumes of financial data (Chou and Nguyen, 2018). Investors try to find the best return on investment. Many researchers have used ML algorithms to create tools for supporting decision-making in investment. For example, Jeong, Kim and Yoon (2018) used ML algorithms to support decision-making of stock investment by using financial news data and social media data.

Chou and Nguyen (2018) forecast the stock prices of construction companies in Taiwan by presenting a promising prediction model for nonlinear time series by using the regression model. Table 2-2 summarises ML techniques applied to forecasting asset returns or finding the pattern or distribution of asset returns. These techniques include clustering, prediction, classification, and others, e.g. portfolio optimisation. Many researchers have used these techniques to analyse data on various types of financial instrument. Definitions of the techniques are provided in Appendix A.

2.6 Time Series Data

Time series data are groups of continuous data that were collected given a period of time (T), such as yearly, monthly, weekly, daily or every hour, minute, or few seconds. The collected data is denoted x_t where t represents time step ($t \in 1, \dots, T$). For examples, the daily exchange rate of pounds sterling (GBP) against the US dollar (USD) between 1 January 2019 and the 31 December 2019, the monthly UK unemployment rate each year, the daily closing price of stocks, and so on.

Time series data is comprised of four components (Yaffee and McGee, 2000): Trend, cycle, seasonality, and irregularity.

2.6.1 Trend

A trend or secular trend shows movement or variation of data in the long term. The tendencies may be stable, increasing, or decreasing, during different time intervals. Figure 2-1(a) shows an example of an upward trend of retail sales between 2014 and 2019.

2.6.2 Cycle

A cycle is data movement patterns over periods longer than one year also known as a cyclical variation or cyclic fluctuation. These fluctuations are usually affected by conditions associated with an economic or business cycle (Hyndman and Athanasopoulos, 2018). Cycle is similar to season, but with longer duration of fluctuations, at least two years. The nature of cyclical variation is periodic and will repeat

itself; for example, the rise and fall of the number of batteries sold by National Battery Sales, Inc. from 1984 to 2003.

Table 2-3: Existing ML techniques applied to financial instruments

Type of machine learning	Method	Type of financial instrument				
		Stocks	Bonds	Derivatives	Foreign Exchange	Commodities
Clustering	K-Means	✓				
	SOM	✓				
	Hierarchical Clustering	✓				
Prediction	RF	✓	✓			✓
	SVM	✓	✓			
	ARIMA	✓	✓		✓	✓
	GARCH	✓			✓	✓
	MLP	✓		✓	✓	✓
	LSTM	✓				
	RNN	✓	✓	✓	✓	✓
	GAs	✓		✓		✓
	KNN	✓	✓	✓	✓	
	SVR	✓	✓	✓	✓	
	MCS	✓	✓	✓	✓	
	ANNs	✓	✓	✓		
	CART	✓	✓			
	GP	✓		✓		
	BSM	✓		✓		
	QR	✓			✓	
	GRNN	✓				✓
	RBF			✓		
	BPNN	✓	✓	✓		
	LR	✓		✓		
	HMM	✓	✓	✓		
Classification	SVM	✓	✓			✓
	KNN	✓	✓		✓	✓
	LR		✓			
	ANNs		✓			

2.6.3 Seasonality

Seasonality, also known as seasonal variation, seasonal fluctuation or seasonal effect, is movement data caused by the influence of an annual season or specific period that will be repeated at the same time of the year such as month effects and quarter effects. The factors that might influence these changes are natural conditions, business procedures, social and cultural behaviour. Figure 2-1(b) shows the seasonal time series of retail sales that rises in the fourth quarter and decreases in every first quarter of the year. Note that retail sales have tended to increase over long periods of time. For example, some retail sales climb to a peak in the Christmas season after which it will fall off. The

seasonality of the time series in this picture displays the season peak at roughly the same size and direction every year. It shows that this change might be influenced by social and cultural behaviour (Christmas).



Figure 2-1(a)



Figure 2-1(b)

Figure 2-1: Example of the variations of typical retail sales

2.6.4 Irregularity

Irregularity or irregular variation is a random variable that represents short-period irregular movements in the time series data, for example because of disasters, wars, or strikes. This variation usually affects business activity pattern, for example, the rise in the price of steel due to earthquakes.

In conclusion, time series analysis has been applied to economics and to finance (Chatfield, 2003; Shumway and Stoffer, 2016) such as in economic forecasting, sales forecasting, stock market analysis, and yield projection (Montgomery, Jennings and Kulahci, 2015). As a matter of fact, many ML applications have both been proposed and been created to swiftly cope with, and solve, problems in time series analysis (Siame-Namin and Siame-Namin, 2018).

2.7 Machine Learning for Stock Prediction

Machine learning is used as a tool to solve various problems of financial time series. The challenge of financial data analysis is to predict stock prices to obtain high profits and high returns. For forecasting, ML is applied to improve the accuracy of prediction (Bao, Lu and Zhang, 2010; Attigeri *et al.*, 2016; Nelson, Pereira and De Oliveira, 2017; Selvin *et al.*, 2017; Chou and Nguyen, 2018). The stock price prediction based on ML methods has proven popular and successful (Atsalakis and Valavanis, 2009; Cavalcante *et al.*, 2016; Beyaz *et al.*, 2018). The problems of stock price prediction fall into three patterns (Selvin *et al.*, 2017) as follows:

- Short-term is used to predict by the second, minute, hour, day, week or months
- Medium-term will predict between 1 and 2 years
- Long-term prediction is used for more than 2 years ahead

Two analysis methodologies are generally used for stock price prediction: technical analysis and fundamental analysis (Patel *et al.*, 2015; Beyaz *et al.*, 2018). These analytical models are used as tools to make decision in the stock market (Isidore and Christie, 2017). Market analysts use technical analysis to read historical prices and interpret price movements. In contrast, fundamental analysis is used for analysing factors such as economic data, and social and political behaviour.

Technical analysis is a technique mostly used for short-term prediction using the historical price of stocks to predict the future price (Selvin *et al.*, 2017). This method focuses on an analysis of securities' prices and trading volume, forecasting trends of the securities. Many tools (or indicators) are used for technical analysis, for example, volume, relative strength index (RSI), accumulation/distribution line (A/D line), average directional index (ADX), etc. To get better results, the technical analysis tools to be used should be appropriately selected. Much research (Hegazy, Soliman and Salam, 2013; Adebisi, Adewumi and Ayo, 2014a; Patel *et al.*, 2015; Khare *et al.*, 2017; Roondiwala, Patel and Varma, 2017; Selvin *et al.*, 2017) predict the trend of stock prices using historical prices. Some features are:

- *Opening Price* is the first price of any listed stock at the beginning of an exchange on a trading day.
- *High and Low Prices* are the highest and lowest price of stock on that day. Generally, these data are used by traders to measure volatility of stock.
- *Closing Price* is a price of the stock at the close of the trading day.
- *Volume* is the number of stocks or contracts traded in a security in all the markets during a given time period. Whenever buyers and sellers agree to make a transaction for a certain price, it will be counted as one transaction and a volume of one.
- *Adjusted Closed Prices* is considered as the true price of that stock and shows the stock's value after distributing dividends.

Fundamental analysis is a technique mostly used for long term predictions (Selvin *et al.*, 2017). This method calculates the stock price based on a detailed study of the basic business drivers that relate to the company and to the general economy (Beyaz *et al.*, 2018), such as operational efficiencies, profitability, and managerial expertise.

According to the literature, many techniques have been proposed for stock price prediction, as shown in Section 2.5. Table 2-3 compares ML techniques with type of datasets and performance.

These studies used one or more ML techniques to predict the future of stock market index values. Each technique had the strengths and weaknesses, as shown in Table 2-2. One of the main tasks of this research is finding the model that provides the best basis, in terms of prediction, for development in future work of this study. The next section focuses on three popular prediction techniques and their details: Multilayer Perceptron, Long Short-Term Memory, and Gated Recurrent Units.

Table 2-4: Comparison of ML techniques in financial stock price prediction

Paper	Prediction Techniques	Stocks/Index	Input Data	Accuracy Percentage	Error Percentage
(Hegazy, Soliman and Salam, 2013)	- PSO - LS-SVM - ANNs	S&P 500	historical daily stock prices	N/A	- LS-SVM: 0.1147 - PSO: 0.7417 - ANN: 1.7212 <u>Note</u> : average of 13 companies which cover all stock sectors in S&P 500 stock market
(Adebiyi, Adewumi and Ayo, 2014)	- ARIMA - ANN	Dell index	historical daily stock prices (open price, low price, high price, close price, and volume trading)	N/A	- ARIMA: 0.608 - ANN: 0.8614 <u>Note</u> : average of one-month prediction
(Attigeri <i>et al.</i> , 2015)	- LR	Stock market price of two companies	historical daily stock prices (open price, low price, high price, close price, and Adj. Close) news articles social media data (twitter)	- LR: 70	N/A
(Nguyen, Shirai and Velcin, 2015)	- SVM	AAPL, AMZN, BA, BAC, CSCO, DELL, EBAY, ETFC, GOOG, IBM, INTC, KO, MSFT, NVDA, ORCL, T, XOM, YHOO	historical daily stock prices (open price, low price, high price, and close price) mood information	- 54.41 (average) - 60 (few stocks)	N/A
(Patel <i>et al.</i> , 2015)	- ANN - SVM - RF - naïve-Bayes (Gaussian process)	CNX nifty index S&P Bombay Stock Exchange (BSE) Sensex index Infosys Ltd. Reliance Industries (*India stock market)	historical daily stock prices (open price, low price, high price, and close price)	- naïve-Bayes: 90.19 - RF: 89.98 - SVM: 89.33 - ANN: 86.69	N/A
(Dang and Duong, 2016)	- SVM	VN30 Index: EIB, MSN, STB, VIC, VNM	the news relating to companies in the VN30 Index	- SVM: 73	N/A

Paper	Prediction Techniques	Stocks/Index	Input Data	Accuracy Percentage	Error Percentage
(Selvin, <i>et al.</i> , 2017)	- LSTM - RNN - CNN - ARIMA	NIFTY-IT index (Infosys, TCS) NIFTY-Pharma index (Cipla)	minute by minute stock prices (day stamp, time stamp, transaction id, stock price, and volume traded)	N/A	Infosys: - CNN: 2.36 - RNN: 3.9 - LSTM: 4.18 - ARIMA: 31.91 TCS: - CNN: 8.96 - RNN: 7.65 - LSTM: 7.82 - ARIMA: 21.16 Cipla: - CNN: 3.63 - RNN: 3.83 - LSTM: 3.94 - ARIMA: 36.53
(Roondiwala, Patel and Varma, 2017)	- LSTM	NIFTY 50	historical daily stock prices (open price, low price, high price, and close price)	N/A	0.00859
(Khare <i>et al.</i> , 2017)	- LSTM - MLP	10 unique stocks on New York Stock Exchange	minute by minute stock prices	N/A	- MLP: 0.0025 (average) - LSTM: 0.048 (average)
(Althelaya, El-Alfy and Mohammed, 2018a)	- MLP - LSTM - SLSTM - BLSTM	S&P 500	historical daily closing price	N/A	Short-term - BLSTM: 0.00947 - SLSTM: 0.01248 - LSTM: 0.01582 - MLP: 0.03875 Long-term - MLP: 0.09369 - LSTM: 0.08371 - SLSTM: 0.06637 - BLSTM: 0.06055
(Hossain <i>et al.</i> , 2018)	- LSTM - GRU - GRU+LSTM - Proposed model	S&P 500	historical daily stock prices (open price, close price, and volume)	N/A	LSTM * - MAE: 0.055 - MSE: 0.007 - MAPE: 8.558 GRU * - MAE: 0.036 - MSE: 0.002 - MAPE: 6.016 GRU+LSTM - MAE: 0.063 - MSE: 0.008 - MAPE: 9.36 Proposed model - MAE: 0.023 - MSE: 0.00098 - MAPE: 4.13 * average of three-layer architecture (single, two, and three layers)

2.7.1 Multilayer Perceptron (MLP)

The Multilayer perceptron (MLP), also known as a feed-forward network, is a simple neural network of the most well-known type (Elliott, 2001). A typical structure includes three layers: input, hidden, and output (Hiransha *et al.*, 2018). If an MLP architecture has more than one hidden layer, it can be already considered as deep (Weissbart, 2020), as illustrated in Figure 2-2. A common approach for training a neural network is to use the backpropagation algorithm. Backpropagation is a generalisation of the least mean squares algorithm for the linear perceptron.

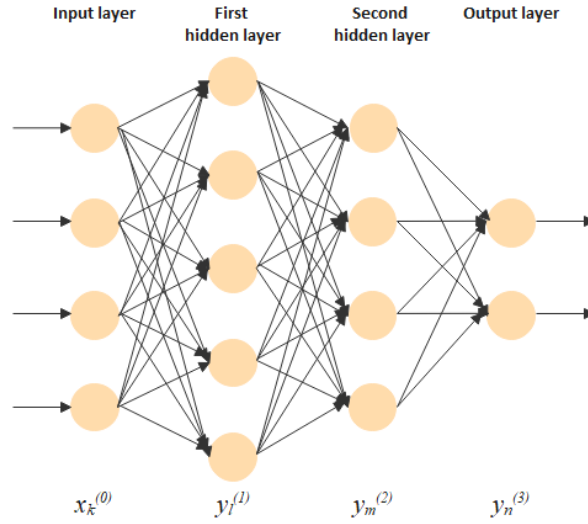


Figure 2-2: Multilayer perceptron architecture

Figure 2-2 shows multiple layers of nodes, with each layer fully connected to the next layer. The model of each neuron in the network includes a nonlinear activation function that is differentiable. The performance of the MLP comes precisely from these non-linear activation functions. Some of the most used activation functions are: rectified linear unit (ReLU), hyperbolic tangent (TanH), and Sigmoid. The equations defining these three activation functions are:

$$\tanh(z) = \frac{2}{1+e^{-2z}} - 1 \quad (2.1)$$

$$\text{sigmoid}(z) = \frac{1}{1+e^{-z}} \quad (2.2)$$

$$\text{relu}(z) = \begin{cases} 0 & \text{for } z < 0 \\ z & \text{for } z \geq 0 \end{cases} \quad (2.3)$$

The output is a weighted sum of m inputs x_i evaluated through a non-linear activation function A :

$$\text{Output} = A(\sum_{i=0}^m w_i \cdot x_i) \quad (2.4)$$

The advantages of MLP are that it is robust to noise, has easy to learn linear and nonlinear relationships, and is flexible for function mapping. Moreover, MLP showed very good prediction results with many financial examples (Huynh, Dang and Duong, 2017). However, one weakness of MLP is that the architecture of networks must be chosen so as to avoid overtraining (Tsai *et al.*, 2011).

2.7.2 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) network (Hochreiter, 1997) is a type of recurrent neural network (RNN). It was proposed for solving the problems of vanishing and of exploding gradients of RNN by incorporating memory units (Gao *et al.*, 2020). This capability helps the network learn when to forget the previous hidden states, and when to update the hidden states with new information (Huynh, Dang and Duong, 2017). This is why LSTM is well-known for its excellent performance in memorising long short-term dependencies. Moreover, LSTM is also accepted as an efficient model for forecasting financial time series (Hwang, 2020; Qiu, Wang and Zhou, 2020). LSTM networks are composed of an input layer, one or more hidden layers, and an output layer. The basic architecture of the LSTM cell is shown in Figure 2-3.

where

x_t denotes the input vector

h_t and h_{t-1} denote the hidden state (h_t) at time step t and $t-1$

C_t and C_{t-1} denote the cell state (C_t) at time step t and $t-1$

$\tanh$ is the TanH activation function used to update the hidden state

σ is the sigmoid activation function that helps form the output value in the range of [0,1]

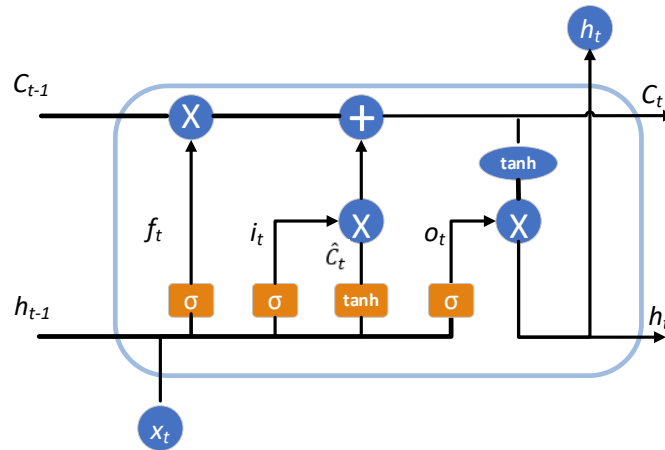


Figure 2-3: LSTM architecture

The structure also shows that both hidden state and cell state will be transferred to the next time step. The LSTM cell consists of three gates to maintain and adjust its cell state (C_t) and hidden state (h_t): a forget gate (f_t), an input gate (i_t), and an output gate (o_t). These gates are the filters and serve different purposes as follows:

- 1) The forget gate (f_t) defines which information will be removed from cell state (C_t).
- 2) The input gate (i_t) assigns which information is going to be added to cell state (C_t).
- 3) The output gate (o_t) assigns which information from cell state (C_t) is used as output.

These three gates allow LSTM cells to capture complex correlations in both short and long-term time series that are a key improvement over traditional RNN (Gao *et al.*, 2020). The cell state and hidden state of LSTM cell are calculated as follows.

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \quad (2.5)$$

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \quad (2.6)$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \quad (2.7)$$

$$\hat{C}_t = \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \quad (2.8)$$

$$C_t = f_t \otimes C_{t-1} + i_t \otimes \hat{C}_t \quad (2.9)$$

$$h_t = o_t \tanh C_t \quad (2.10)$$

where

W_{xf} , W_{hf} , W_{xi} , W_{hi} , W_{xo} , W_{ho} , W_{xc} , and W_{hc} are weight matrices

b_f , b_i , b_c , and b_o , are bias vectors

f_t , i_t , and o_t are vectors for the activation function values of the forget, input and output gates

$\otimes$ is element-wise multiplication

The LSTM networks will be proposed to solve the RNN problem, but their structure is complex so the training process of LSTM often takes a long time. To reduce the complexity of the training process, GRU is proposed with a simpler structure (Gao *et al.*, 2020).

2.7.3 Gated Recurrent Units (GRU)

Gated Recurrent Unit (GRU) networks were proposed by Cho *et al.* (2014) to solve the RNN problems. GRUs run faster than LSTM because they are less complex. However, both GRU and LSTM use a gating mechanism to control the memorisation process. The key difference is that GRU merges the hidden state and cell state into one. Therefore, there are only two control gates in GRU, the update gate (z_t) and the reset gate (r_t), as shown in Figure 2-4. The update gate (z_t) is used to determine the amount of previous information (at the time step $t-1$) that needs to be passed to the next state. The reset gate (r_t) controls how much the previous information is written into the current candidate set $\hat{h}_t$.

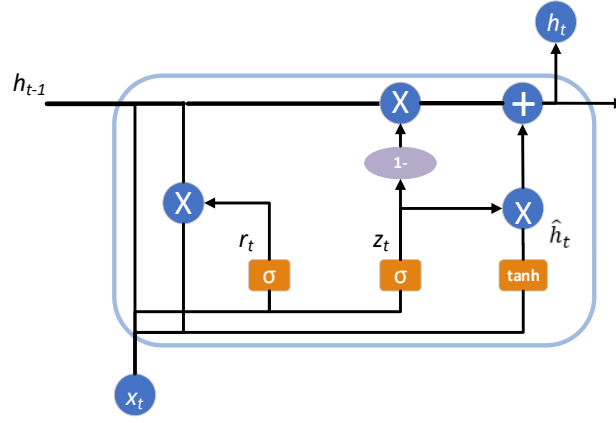


Figure 2-4: GRU architecture

The updated equation of GRU cell in Figure 2-4, are calculated as follows:

$$r_t = \sigma(W_{xr}x_t + W_{hr}h_{t-1} + b_r) \quad (2.11)$$

$$z_t = \sigma(W_{xz}x_t + W_{hz}h_{t-1} + b_z) \quad (2.12)$$

$$\hat{h}_t = \tanh(W_{xh}x_t + W_{hh}(r_t \otimes h_{t-1}) + b_h) \quad (2.13)$$

$$h_t = (1 - z_t) \otimes h_{t-1} + z_t \otimes \hat{h}_t \quad (2.14)$$

where

W_{xr} , W_{hr} , W_{xz} , W_{hz} , W_{xh} and W_{hh} are weight matrices

b_r , b_z , and b_h , are bias vectors

r_t and z_t are vectors for the activation function values of the update and reset gates

$\otimes$ is element-wise multiplication

Sections 2.1 to 2.7 examined machine learning and deep learning methodologies employed for stock forecasting utilising historical stock price data. Nonetheless, financial markets are significantly affected by human emotions, perceptions, and responses to news—factors that are not necessarily reflected in numerical data alone. This is the domain of sentiment analysis. In stock prediction, sentiment analysis evaluates the positivity, negativity, or neutrality of public sentiments towards specific stocks, sectors, or the overall market. By combining sentiment data with traditional stock indicators, researchers and investors aim to build more accurate predictive models. For instance, a sudden surge in positive tweets about a company could signal a potential stock price rise. Conversely, negative news sentiment might predict a decline. Therefore, the subsequent part will provide an overview of sentiment analysis and the methodologies frequently employed nowadays.

2.8 Sentiment Analysis

Sentiment analysis (SA), also known as opinion mining, is the application of natural language processing to the analysis of people's opinions, sentiments, appraisals, attitudes, evaluations, and

emotions towards subjects such as organisations, products, services, issues, topics, individuals, events, and their attributes (Liu, 2012; Medhat et al., 2014; Vinodhini & Chandrasekaran, 2012). SA has played an important role in many applications, e.g. product reviews, restaurant reviews (Liu & Zhang, 2012; Nguyen et al., 2015; Pang & Lee, 2008), and movie reviews (Pang et al., 2002). In the financial context, many studies have documented how tweets by Donald Trump affected the stock market (Imbert, 2019; Ossinger & Patterson, 2019).

One instance is the tweet by President Trump on 16 July 2019 that the U.S.A. might impose a boycott on an additional \$325 billion worth of imported Chinese goods. CNBC News reported the following day that the stock market experienced slight losses after Trump's comments about a US-China trade war (DiChristopher, 2019; Imbert, 2019). *The Wall Street Journal* also reported the progress of the trade deal with China in the same way. Both CNBC News and *The Wall Street Journal* commented on affected stocks, which closed at their lows for the day. For example, the Dow Jones Industrial Average index (DJIA)³ dropped 0.42%, while the S&P 500 dropped 0.65%. These examples show that social media and news about the markets and the economy can have a direct effect on the stock market.

In addition to the comments of prominent people, often many investors voice their opinions and discuss the share prices or performance of various companies in the public media. These opinions can have a significant influence on other investors' decision-making. For this reason, discussions on social media platforms about the stock market and stock news have attracted the attention of researchers (G. Wang et al., 2020). The cumulative feeling of individual investors, both positive or negative, towards a particular company can be an indicator of the future value of that stock (Derakhshan & Beigy, 2019; Jin et al., 2020; Nguyen & Shirai, 2015). Furthermore, behavioural finance researchers point out that the propensity to speculate is driven by the fluctuation of investor sentiment (see, for example, Baker and Wurgler, 2006). Many researchers have attempted to apply SA to stock price prediction (Nguyen and Shirai, 2015; Minh et al., 2018; Derakhshan and Beigy, 2019; Jin, Yang and Liu, 2020; Li, Jin and Quan, 2020; Nti, Adekoya and Weyori, 2020), and stock returns prediction (Li, Huang, et al., 2014; Li, Xie, et al., 2014; Kee Sul, Dennis and Yuan, 2017; Renault, 2017; Ma, Xiao and Ma, 2018). Also to increase prediction performance, by using financial news (X. Li et al., 2014; Minh et al., 2018; Nti et al., 2021), and social media (Jin et al., 2020; Nti et al., 2021; Renault, 2017). They generally found that the investor sentiment extracted from financial news and social media significantly improved the accuracy of both stock predictions. Financial news and social media exhibit different features: news is relatively objective due to its reliance on facts, while social data is quite subjective as it may be based on opinion and rumours created by investors (Jeong et al., 2018).

³ Dow Jones Industrial Average index (DJIA), also simply known as Dow, is a stock market index consisting of 30 prominent companies on the US stock market (Liu and Strid, 2020).

This all implies that information (especially qualitative data such as tweets or investors' sentiment) from the famous, from the top 10 largest shareholders, or from general investors, has an impact on stock prices. Therefore, using investor sentiment – together with historical prices – generates a piece of useful information for prediction, and is a key focus of current research.

2.9 Sentiment Analysis Process

In the SA process, the analysis of opinions about the stock market from online resources such as news and social media, is illustrated in Figure 2-5. The process is to obtain the opinions, then identify the sentiments they express, and to classify their polarity into either positive or negative sentiments (Khedr et al., 2017; Medhat et al., 2014). The three main processes required to analyse the opinion from the data source, are described below.

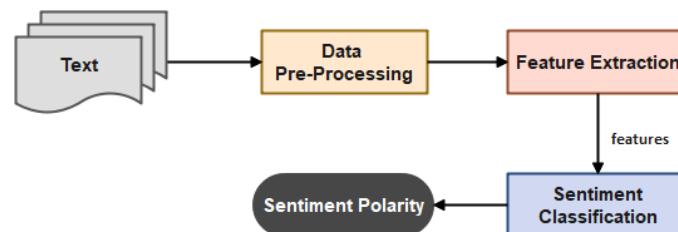


Figure 2-5: Sentiment analysis process (Zad *et al.*, 2021)

2.9.1 Data Pre-processing

The raw data is unstructured text. This cannot be used directly as an input and therefore needs to be pre-processed. In this section, the steps used in pre-processing are presented.

Tokenisation

Tokenisation is the process of breaking the text into smaller words, called tokens, and is considered part of lexical analysis. The main objective of tokenisation is to identify meaningful keywords (Khedr et al., 2017). For example, from a newscast:

“The price of Brent crude is today expected to rise beyond \$58 a barrel.”

The tokens, separated by /, are:

"/The/ /price/ /of/ /Brent/ /crude/ /is/ /today/ /expected/ /to/ /rise/ /beyond/ /\$/58/ /a/ /barrel/."/

Stop Words Removal

Removing stop words can reduce the dimensionality of the data sets and extract only keywords into the review corpus for identifying the words more easily (Asghar et al., 2014). Examples of stop words

to be removed are “a”, “and”, “of”, “not”, “by”, and so on, which are taken from a widely available list of stop words.

Social Media Symbols

Social media data frequently contains symbols #, @, \$, URLs, extra spaces, specialised abbreviations (IMHO), emojis (☺), and punctuation for feelings (emoticons). All these symbols except \$ (and currency symbols such as £ ¥) will be removed because they have no value in sentiment analysis. A tweet word that starts with \$ is a ticker of the company name that may contain useful information for sentiment analysis.

2.9.2 Feature Extraction

The next process is the extraction of features from the tokenised text. This process is used for removing words that are not relevant to the keywords, which can reduce computing complexity and deal with overfitting problems. Feature extraction techniques commonly used in SA are:

Parts of Speech Tagging (POS), also known as word-category disambiguation, is useful for classification tasks (Mejova & Srinivasan, 2011). POS software has been widely used in Natural Language Processing (NLP) tasks that require only some information about the categories of words. POS reads the text and specifies words such as adjectives, nouns, verbs, adverbs, and so on. Finding adjectives is important for POS as they are major indicators of opinions (Medhat et al., 2014).

Bag of Words (BOWs) is a commonly used technique to extract features from the messages or news articles because of its simplicity for the classification process. This method measures the number of occurrences of each word. The text information will then be converted into vector spaces by using these occurrences.

N-Gram Feature is a series of words or tokens of length n . This method is commonly used in text mining and NLP tasks. For the stock prediction task, an N-Gram is created to extract keyword features from the news or message corpus. Assume that $n = 2$, N-Gram will generate the sequence of adjacent word-pairs for each document. The features identified from two sequences of word combinations can improve the accuracy of the classifier. There are three main advantages of N-Gram: it automatically captures the most frequent roots in the messages, it does not require the use of a specific dictionary, and it is robust to deformation and spelling errors (Khedr et al., 2017).

Term frequency-inverse document frequency (TF-IDF) is a technique used to discover the importance of the words in a document or corpus. TF-IDF can consider the value of individual words by the ratio of IDF in the specified document to all the other documents in the corpus. The words with a high TF-IDF value suggest that they have a strong relationship with the specified document (Medhat et al., 2014).

2.9.3 Sentiment Classification

Traditional sentiment classification techniques are divided into: lexicon-based, machine learning-based (ML-based), and hybrid (Hasan et al., 2018; Medhat et al., 2014; Sharma et al., 2019). The lexicon-based and ML-based methods are detailed below, while the hybrid method is a combination of the lexicon-based and ML-based. Besides these traditional sentiment classification techniques, the deep learning-based (DL-based) approach has become popular in sentiment analysis research over the past few years. Therefore, the DL-based approach for SA will also be covered here.

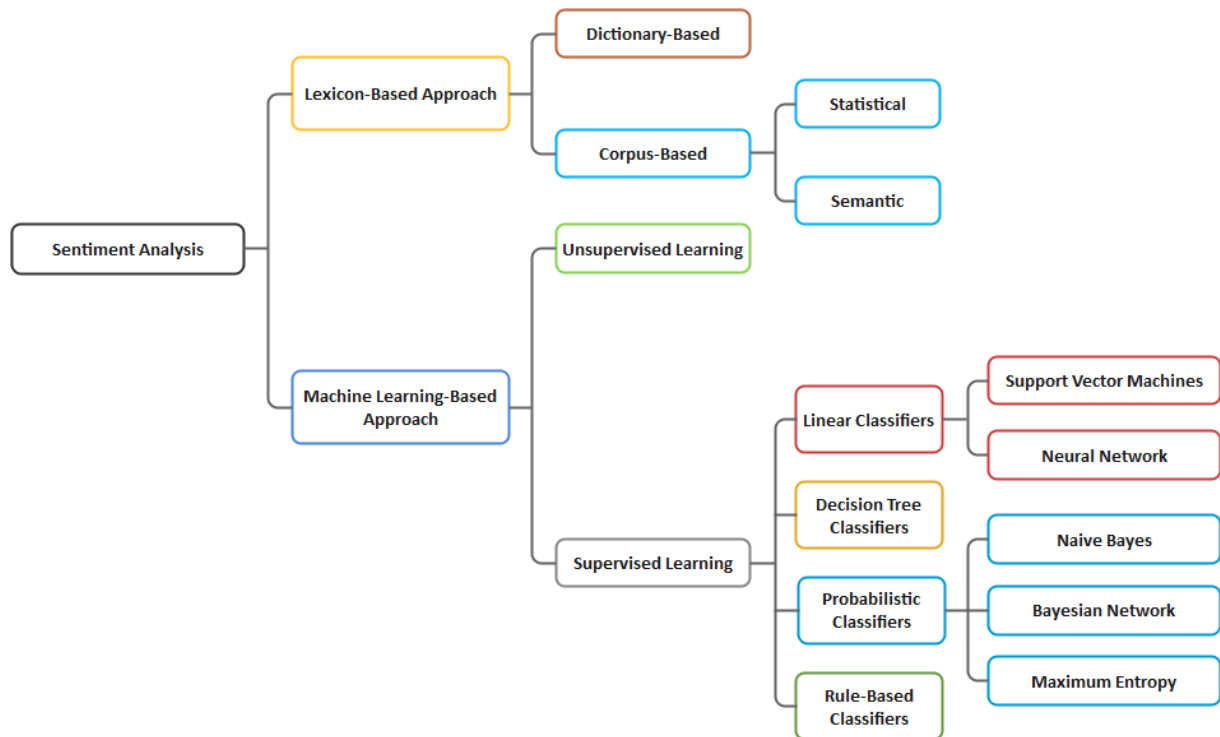


Figure 2-6: Sentiment classification techniques (Medhat, Hassan and Korashy, 2014)

2.9.3.1 Lexicon-Based Approach

The lexicon-based approach is a technique based on an opinion dictionary, which is used to analyse the text. A lexicon or a dictionary will be created and used to classify the polarity of a sentence, document, or feature. There are two main methods in this approach.

1. **The dictionary-based approach** is a technique that uses a dictionary that contains synonyms and antonyms of a word. The main idea is to use a few seed sentiment words to commence the process, based on the synonym and antonym structure of the dictionary. In the first step, a small set of sentiment words (seeds) with known positive or negative orientations will be collected manually. The algorithm then expands this set by searching for their synonyms and antonyms in any dictionary available online. The list of seeds will be increased with the new-found words and this process is repeated until no more new words are found.

2. The corpus-based approach is a technique that helps to solve the problem of finding opinion words with context specifications and orientations, by using an underlying corpus as an inventory of language data. The corpus-based approach can be divided into two categories:

- 1) Statistical Approach is the technique for finding co-occurrence patterns of the opinion words by using statistical techniques. For example, if there is a word that is often found in positive or negative texts, then the polarity of the word is positive or negative, respectively. In cases where the word occurs in both positive and negative texts equally, or the frequency is not significantly different, then it is a neutral word (Carvalho et al., 2014).
- 2) Semantic Approach is the technique used to find meaning from texts. It enables the system to interpret and understand sentences, paragraphs, or documents by analysing their grammatical structure and discovering the relationships between each word in a specific context. The approach directly provides sentiment value by computing the similarity among words. For example, it could be used by expanding the initial text with antonyms and synonyms, then considering the polarity of unknown words by the relative count of negative and positive synonyms (Medhat et al., 2014).

The lexicon-based SA tools popularly used are TextBlob and Valence Aware Dictionary and Sentiment Reasoner (VADER) (Nemes & Kiss, 2021) as explained below.

TextBlob is a Python library that provides an interface to perform various NLP tasks, which is built on Natural Language Toolkit (NLTK) (Das et al., 2021; Nemes & Kiss, 2021). Subjectivity and polarity are two properties of the sentiment analysis function in Text Blob. These two properties will be given measured numeric values. The polarity indicates whether the sentence is negative or positive, and is in the range $[-1, +1]$.

where -1 indicates negative sentiment

and $+1$ indicates positive sentiment

The data will be labelled with the correct sentiment value: positive, negative, and neutral. Subjectivity, meanwhile, shows how objective a text is: opinion, emotion, or judgment. The subjective value will be a decimal in the range $[0.0, 1.0]$ that measures the number of personal opinions and facts contained in the text. A higher subjectiveness means that the statement contains more personal opinions than factual information.

VADER has a relatively simple process for sentiment classification that can deal with words, abbreviations, slang, emoticons, and emojis commonly found on social media (Nemes & Kiss, 2021; Pano & Kashef, 2020). VADER is also a NLTK toolkit found in Python libraries, which is lexicon- and rule-based. Each text's body generates a polarity vector that is negative, neutral, positive, and compound polarities of sentiment scores. The negative, neutral, and positive polarities are given a normalised

score between 0 and 1, depending on the sentiment within the article. The compound polarity calculates a score based on the amount of positive, negative, and neutral sentiment in the article and the compound polarity score is between -1 and $+1$. The compound polarity score can be interpreted in three ways:

- a score in the range $[+0.1, +1]$ means that it is positive
- a score in the range $[-0.1, +0.1]$ is taken as neutral
- a score in the range $[-1, -0.1]$ means that it is negative

In summary, with TextBlob and VADER, sentiment is determined by the semantic orientation and intensity of each word in a sentence. This process has to use a pre-defined dictionary to classify negative and positive words. TextBlob and VADER sentiment analyses produce a similar polarity score between -1 and $+1$ that shows positive, neutral, and negative sentiment values. Besides the polarity, TextBlob returns the subjectivity of the sentence, which helps with the fine-grained analysis; that is, how much personal opinion and factual information is contained in the text. On the other hand, VADER returns a compound score that reflects the sum of all the lexicon ratings. The rating does not measure only one word, but measures the average of the ratings for each word (Rao *et al.*, 2020). In addition, VADER also concentrates on emoticons, punctuation, and capitalisation seen in the text, and is thus more sensitive to sentiment expressions in the context of social media than TextBlob (Hutto and Gilbert, 2014; Rao *et al.*, 2020).

2.9.3.2 Machine Learning-Based Approach

An ML-based approach to sentiment classification applies ML techniques with syntactic and linguistic features to solve the text classification problem. There are two approaches: supervised learning and unsupervised learning. Supervised ML is conducted by entering the set of features with labels – that is their polarity – which then predicts the polarity of unseen text. Unsupervised ML is used when the features have no labels. Supervised ML come in four main categories: linear classifiers, decision tree classifiers, probabilistic classifiers, and rule-based classifiers. The common ML classifiers used in sentiment classification are shown below.

Support Vector Machines (SVM) is an efficient algorithm for both regression and classification tasks. The performance of SVM increases as the dimensional space increases, and it still performs well even when the dimension number is larger than the sample number (Ahuja *et al.*, 2019). Each training data set is labelled as belonging to one of the classes. To increase the computational efficiency of SVM, cross-validation is usually used to protect a model from overfitting problems.

The key principle of SVM is to define linear separators in the search area where the different classes can be best separated. Figure 2-7 shows two classes, and three possible hyperplanes A, B, and C.

Hyperplane B provides the best separation between the classes because it presents the maximum margin of separation.

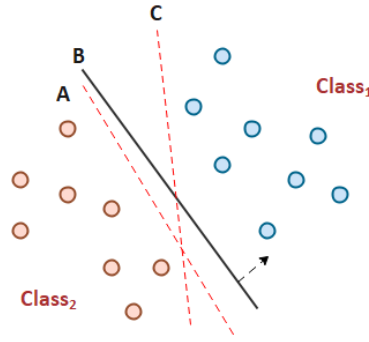


Figure 2-7: Support vector machine for classification problem

Decision Tree (DT) is the classification that uses the condition to divide the data (Kaur et al., 2017). DT consists of nodes, branches, and leaves. A node is where the testing of the given feature's value takes place, a branch corresponds to the testing result and links to other nodes depending on the result, and a leaf is the last node of each branch which is the classifying result or target. DT is very fast when applied to unknown records, and easy to interpret as a tree when it is small. However, it can easily lead to overfitting, where a small change of training data can wildly change the classification result, and it is difficult to interpret when the tree is large. Decision tree classifiers have been applied to many areas such as engineering, biomedical engineering, civil planning, and financial analysis.

Naïve Bayes (NB) is the simplest, most commonly used, classification algorithm, and efficient in solving classification problems: high-dimensional, sparse, and short texts (Y. Li et al., 2020; Medhat et al., 2014). The NB model calculates the posterior probability of a class, based on the word distribution in the text. The model works in conjunction with BOWs feature extraction, which ignores word position in the text. This model uses Bayes' Theorem to predict the probability that a given attribute set belongs to a specific label.

$$P(\text{label}|\text{features}) = \frac{P(\text{label}) * P(\text{features}|\text{label})}{P(\text{features})} \quad (2.15)$$

where

$P(\text{label})$ is the prior probability of a label

$P(\text{features}|\text{label})$ is the prior probability that a given feature set is being classified as a label

$P(\text{features})$ is the prior probability that a given feature set has occurred

From Bayes' assumption, which states that all features are independent, the equation could be rewritten (Medhat et al., 2014) as Equation 2.16:

$$P(\text{label}|\text{features}) = \frac{P(\text{label}) * P(f_1|\text{label}) * ... * P(f_n|\text{label})}{P(\text{features})} \quad (2.16)$$

Bayesian network (BN) is a type of probabilistic graphical model that is made up of nodes (features or variables) and edges (links or relationships) between them, called a Directed Acyclic Graph (DAG). Directed links between nodes indicate that one node directly influences another. For example, it can be used to compute the probabilities of diseases from the symptoms. BN provides a complete model of the features and their links. BN is not often used in text mining because the computational complexity is very expensive (Medhat et al., 2014).

Maximum Entropy Classifier (ME) is one of the probabilistic classifiers. Unlike the Naïve Bayes classifier, ME does not make any assumption about probability distribution, but learns from the data. ME is also known as a conditional exponential classifier because it belongs to the class of exponential models, and this classifier is often used for large text classification such as sentiment analysis. ME has displayed an outstanding ability to solve the optimisation problem to estimate the parameters of the models, but ME requires more time to train than Naïve Bayes (Gupte et al., 2014).

Rule-Based classifier constructs the decisions by using a collection of “if-then” rules for classification. The condition part of the rules (if) is called a *rule antecedent*, which can consist of one or more conditions (Asghar et al., 2017). The predicted or labelled class of each rule (then) is called the *consequent*. This classifier is easy to understand, and cause-and-effect is very clear so the domain expert or user can verify the rules if necessary. On the other hand, it cannot detect unknown classes such as new malware and new kinds of disease, as a set of new rules must be added to the system for unforeseen events.

2.9.3.3 Deep learning-based approach

The outstanding performance of deep learning has become popular in recent NLP research areas (Basiri et al., 2021; Wankhade et al., 2022). Deep learning has replaced the various classical ML-based SA approaches, e.g. SVM, Naïve Bayes, rule-based classifier, and Bayesian network (Minaee et al., 2019). The traditional methods for SA tasks are mainly lexicon- or ML-based, and use classification, regression, and other methods to derive feature extraction and classification, but these two traditional methods also suffer data-sparse and word order problems (Lin et al., 2020). The DL-based approach can avoid some feature selection processes, automatically abstract the features, learn the corresponding parameters, and capture the sophisticated features. Moreover, deep learning mechanisms can effectively learn deeper information from high-dimensional data because there are hidden layers between the input and output of DL-based methods to simulate intermediate representations of data that cannot be learned by other algorithms (Lin et al., 2020). The architecture of deep learning, therefore, can be adapted to many types of task, including text sentiment analysis. Deep learning is a kind of representation learning technique (Tang et al., 2015), so in the SA tasks, DL-based approaches learn multi-level representation with non-linear neural networks. Each of these transforms the representation at one level into a representation at a higher and more abstract level

(Tang et al., 2015). Therefore, these learned representations can be used as features for classification tasks.

The focus below is on two deep learning models widely adopted for sentiment analysis: LSTM and convolutional neural networks (CNNs).

LSTM is an improved network structure designed based on the RNN. The architecture of RNN helps the the persistence of information by using previous information to connect to the current task and guessing the current text using past texts (Lin et al., 2020). When a historical text is too long, the effective information in the text cannot be saved (long-term dependency problem). LSTM can solve this problem well and yield good results in the sequential analysis of a long text (Behera et al., 2021), but it cannot predict the information following and also cannot judge the emotion polarity transfer (Lin et al., 2020).

CNNs are very successful for several NLP tasks because of their speciality in exploiting the local correlation and pattern of the data learned by their feature maps. CNNs are aimed at exploiting local features within the text. Many researchers have used CNNs for sentiment analysis and their results showed great performance (Doğru et al., 2021; Yayla et al., 2021). CNNs have been highly effective in local feature selection. However, CNN's disadvantages are that CNNs abandon the relationship between context during the training process, and therefore cannot solve the timing problem and cannot accurately analyse the data in transitional sentence format (Lin et al., 2020). Moreover, although CNNs give excellent accuracy in structured data classification, they do not work for unstructured data, especially text (Zagabathuni, 2021).

2.10 Review of Sentiment Classification research

This section reviews recent research, developments, and solutions that cover the three types of sentiment classification.

Doğru et al. (2021) investigated the efficiency of the ML-based and DL-based approaches, i.e. Gauss Naïve Bayes (GNB), RF, NB, SVM, and CNNs, by using the Turkish Text Classification (TTC-3600) dataset. They also tested the effect of text pre-processing steps on the success rate, where Doc2Vec was used for the text pre-processing. Their dataset (TTC-3600) consists of 3600 documents containing 6 categories. To explore the effect of text pre-processing, the dataset was divided into 4 parts: the original dataset, the cleaned dataset, and the dataset prepared by reducing words to their roots using Zemberek (Zemb-DS), and both cleaned and Zemb-DS datasets. Each dataset was sectioned into 90% training with the Doc2Vec model, and 10% for testing. After the Doc2Vec text pre-processing process, the classifying process by the selected classification model was conducted. Using Doc2Vec with the

cleaned and the Zemb-DS dataset with CNNs gave the highest accuracy of 94%, performing better than all the comparable ML-based approaches, such as GNB (89%), SVM (86%), NB (85%), and RF (84%).

Yayla, Diyar Demirkol and Alqaraleh (2021) proved the performance of two DL-based classification techniques including CNNs and LSTM with the same dataset (TTC-3600). In the first of three experiments, there were four feature extractions, i.e. Word level TF-IDF, N-gram level TF-IDF, Characters level TF-IDF, and the Word2vec. The most suitable technique for the Turkish language was found to be Word2vec. In the second experiment, the effect of pre-processing on the accuracy of the classification process was measured. The accuracy was calculated for classifiers: with pre-processing, without pre-processing, and with pre-processing but no stemming. This found that pre-processing without stemming had the highest accuracy. In the last experiment, to find the best approach, CNNs and LSTM with pre-processing without stemming, and the word2vec method, were tested in five iterations. The result showed that the two methods were not significantly different (CNNs was 92.78% and LSTM was 92.94%), but LSTM took three times longer than CNNs' to execute.

To classify the movie reviews, Bonta, Kumaresh and Janardhan (2019) focused on the lexicon-based approaches: VADER, TextBlob, and NLTK sentiment analysis tools. The data were downloaded from a Cornell University website. The methodology was divided into four steps: data collection, pre-processing, sentiment extraction, and sentiment classification (positive and negative). VADER outperformed TextBlob and NLTK, with VADER having the highest accuracy at 77%, with TextBlob at 74% and NLTK 62%. Focusing on the texts from social media and other Web sources, VADER performed better than TextBlob because the sentiment often appeared with emoticons. They claimed that VADER is very suited for analysing social media sentences containing slang, conjunctions, punctuation, capitalisation, and the way the words are written along with their context. Moreover, VADER is suitable for tasks requiring fast processing.

Hutto and Gilbert (2014) compared 12 sentiment classification techniques, both lexicon-based and ML-based. Eight of these were lexicon-based: VADER, Linguistic Inquiry and Word Count (LIWC), Affective Norms for English Words (ANEW), General Inquirer (GI), SentiWordNet (SWN), SenticNet (SCN), Word-Sense Disambiguation (WSD) using WordNet, and the Hu-Liu04 opinion lexicon. The four ML-based approaches used were: Naïve Baye, ME, SVM-classification (SVM-C), and SVM-regression (SVM-R). The four groups of data used for their experiments were 4,000 tweets; 10,605 sentences from movie reviews; 3,708 sentences from technical product reviews; and 5,190 sentences of opinion news articles. The experiments classified these into Negative, Neutral, and Positive. The selected classification techniques were then used to validate valence scores that indicated the sentiment polarity. The VADER technique was compared with the seven other lexicon-based techniques, and performed exceptionally well in the social media domain. When VADER was compared with the four ML-based models, in the same domain as the training one, it was found that VADER performed better

across all domains. The results also showed that VADER's simplicity makes it computationally efficient. It was noted that the SVM models could not fully process movie reviews and opinion news articles data that are very intensive, even running on multicore systems with large RAM.

2.11 Benefits and Disadvantages

Table 4.1 presents the analysis of the strength and weakness of each sentiment classification approach and shows the main characteristics of each.

1. The main aim of a lexicon-based SA approach is to create a sentiment lexicon containing as many words expressing an opinion or sentiment as possible (Li et al., 2020). The proposed sentiment lexicons are then applied to classify the textual items. The main benefit of the lexical-based approach is that it does not require any training data, while the main drawbacks are that it is highly domain-oriented and that words from one domain cannot be used in another domain (Wankhade et al., 2022). The dictionary lexicon-based approaches give good outcomes for domains with fewer bands and quick access to the vocabulary of word meanings, while the corpus lexicon-based approaches can provide superior results if domains are explicit and can identify expressions of opinion with a particular content orientation (Wankhade et al., 2022). Another drawback of both dictionary lexicon-based and corpus lexicon-based approaches is that the finding of opinion words specific to each domain (polarity) may vary (Wankhade et al., 2022).
2. The ML-based approach focuses on training a powerful model to classify textual items. However, the existing ML-based approaches cannot completely solve the embedding problem for SA. There are many drawbacks to ML-based approaches that should be considered before using them to solve SA tasks (Hutto and Gilbert, 2014), detailed below.
 - a. The ML-based approach requires (often large) training data, which is like a validated sentiment vocabulary that is sometimes is difficult to obtain.
 - b. The ML-based approach relies on the training set to display as many features as possible, but this usually is not the case, especially in the case of short messages on social media.
 - c. The ML-based approach tends to be computationally more expensive in terms of CPU processing, memory requirements, and training or classification time.
 - d. The ML-based approach often registers the features within a "black box" that cannot be (easily) interpreted by humans, so it is difficult to summarise, modify, or expand to other domains.
3. The existing DL-based approach for sentiment classification commonly comprises two steps (Tang et al., 2015). First, they learn the word embedding from the text corpus, and the word embedding will then be applied to create the representation of sentences with their semantic composition. DL uses a cascade of multiple layers of nonlinear processing units for feature extraction and

transformation. The main disadvantage of deep learning-based approach is thus that the training of deep neural networks is complicated, and that the computation is very expensive (L. Zhang et al., 2018). The DL-based approach is still not perfect when compared with lexicon-based and ML-based approaches, but also has some advantages and disadvantages for different types of text (W. Li, Jin, et al., 2020), detailed below.

- a. The DL-based approach can automatically learn multi-level features that can solve the manual feature extraction of machine learning. So the robust learning of deep neural networks produces results that are often more accurate than traditionally-based approaches. Nevertheless, many useless parameters will be created at runtime that need a large amount of data for network training. It seems that the DL-based method is more suitable for sentiment analysis with large amounts of data, but traditional methods are better for small volumes of data.
- b. The focus of the DL-based approach is to design a more efficient network structure and to train more accurate parameters, while the ML-based and dictionary-based approaches focus on how to build a mathematical model and what features to extract.
- c. The DL-based approach can be applied to many fields and has obtained good results because deep-learning networks can automatically modify the weights of parameters to reach the desired efficiency as closely as possible. The same training method and model may be applied to different problems, but the network structure and parameter weights will be different, so the input and output must correspond one-to-one. However, in the sentiment tasks, language text usually has complexity and variety, which may make the sentiment valuation vary.

In summary, the Lexicon-based approach takes less time than ML- and DL-based approaches because it does not need training data. ML- and DL-based approaches need a large amount of training data, so these techniques require costly CPU processing, memory, and training or classification time. Although the DL-based approach produces more accurate results in classification tasks than the traditionally-based methods (lexicon- and ML-based approach), the sentiment analysis tasks on social media and online news are quite complex and varied, which is hard to evaluate when using a DL-based approach. Many techniques in the Lexicon-based approach were popularly used for sentiment analysis obtained from online resources because they can handle words, emotions, slang, emojis, and punctuation marks, commonly found in social media and online news. Although much research has compared the performance of Lexicon-, ML-, and DL-based approaches (Hutto and Gilbert, 2014; Dhaoui, Webster and Tan, 2017; Abainia, Kara and Hamouni, 2022), and claim they have similar performance, the processing time is very different.

Table 2-5: Publications that applied sentiment analysis to stock price prediction and stock return prediction

Authors	Year	Input data source	Stock Data	SA techniques	Polarity	Language	Prediction techniques	Objective	Results
Nti, Adekoya and Weyori	2021	HSR GTI EI SM ON MB	The stock of two companies on Ghana Stock Exchange (GSE)	NLTK	Pos/Neg	English	IKN-ConvLSTM*	Stock price movement prediction	98 % prediction accuracy
Jin, Yang and Liu	2020	HSP MB	AAPL	Word2vec CNN Word2Vec	Bullish/Bearish	English	S_EMDAM_LSTM*	Closing price Prediction	71% prediction accuracy
Li, et al.	2020	HSR MB	CSI 300 index	BoW Corpus-based NB	Pos/Neu/Neg	Chinese	LSTM	Closing price Prediction	64% prediction accuracy
Derakhshan and Beigy	2019	HSP MB	18 stocks of the U.S. market 5 stocks of Iranian markets	LDA-POS* SVM	Feature vector (up/down)	English Persian	ANN	Stock price movement prediction	56 % (English) 55% (Persian) prediction accuracy
Minh et al.	2018	HSP TI ON	S&P 500 index	HVD Stock2Vec*	Pos/Neg	English	TGRU*	Stock price movement prediction	66% prediction accuracy
Nguyen and Shirai	2015	HSP MB	XOM DELL EBAY IBM KO	TSLDA*	Pos/Neu/Neg	English	SVM	Stock price movement prediction	56% prediction accuracy
Renault	2017	SM	S&P 500 index ETF	BoW N-Gram LMD	Pos/Neg	English	Predictive regressions	Explores the relationship between online investor sentiment	The online investor sentiment helps forecast the intra-

Authors	Year	Input data source	Stock Data	SA techniques	Polarity	Language	Prediction techniques	Objective	Results
				HVD ME				and intraday stock return	day stock index returns The first half-hour change in investor sentiment predicts the last half-hour S&P 500 index ETF return.
Li, Huang, et al.	2014	NA HSP	HKEx	TF-IDF	Weighting	Chinese	MKSVR	Intra-day stock return prediction	MKSVR was a better predictor when using stock prices and news articles than when using only news articles
Li, Xie, et al.	2014	NA HSP	50 stocks in Hang Seng Index	HVD LMD SN BoW	Pos/Neu/Neg	English	SVM	Proof that financial news impacts stock returns	Sentiment analysis can improve the prediction accuracy The models which use sentiment polarity do not perform well in all the tests

Note: *ON* = Online news, *HSP* = Historical stock prices, *HSR* = Historical stock returns, *SM* = social media, *MB* = Message Board, *TI* = Technical indicator, *EI* = Economic indicator, *GTI* = Google trends index, *NA* = News articles

*Denotes a new technique.

2.12 Summary

This chapter has provided an in-depth review of the literature on machine learning (ML) and sentiment analysis (SA) techniques in the context of stock market prediction. The review was structured in two main parts: (1) ML techniques for time-series stock forecasting, and (2) SA approaches used to extract investor sentiment from textual data to enhance prediction performance.

In the first part, a range of machine learning methods were introduced, with attention to their categorization (supervised, unsupervised, semi-supervised, and reinforcement learning), characteristics, and suitability for financial applications. Particular emphasis was placed on the advantages of using deep learning models over traditional statistical and shallow ML methods. Among the many techniques reviewed, three deep learning architectures—Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU)—stood out in the literature for their strong predictive performance in modelling complex, nonlinear, and sequential financial time-series data. These models are widely applied in financial prediction tasks due to their ability to capture temporal dependencies, adapt to changing market patterns, and handle noisy or incomplete datasets. Their computational efficiency and proven success in real-world financial environments make them particularly suitable for the objectives of this research. Therefore, these three models are selected as the core forecasting models for experimental evaluation in Chapter 3.

The literature also highlighted the limitations of using only quantitative data—such as historical prices, trading volume, or financial ratios—for stock prediction. Especially in emerging markets, where information asymmetry is more pronounced, purely numerical models may fail to capture the full context behind price movements. This observation has led to increased interest in integrating qualitative data sources—particularly those capturing public sentiment and investor psychology—into prediction models.

The second part of the chapter focused on sentiment analysis, an area of growing importance in financial forecasting. SA refers to the process of extracting subjective information from textual data, such as financial news articles, social media posts, and investor forums. This type of data reflects real-time market sentiment, behavioural cues, and emotional reactions, all of which can influence investor decision-making and stock price fluctuations. The review discussed the standard SA pipeline, including data collection, preprocessing, feature extraction, and sentiment classification. It also examined the three dominant SA approaches: lexicon-based, machine learning-based, and deep learning-based methods.

Among these, the lexicon-based method known as VADER (Valence Aware Dictionary and sEntiment Reasoner) was identified as particularly effective for financial sentiment analysis. VADER offers several

advantages: it does not require training data, it performs well on social media-style text, and it is computationally lightweight—making it ideal for real-time processing in large-scale financial applications. When compared with other lexicon-based tools (e.g., TextBlob, LIWC, SentiWordNet) and ML-based classifiers (e.g., SVM, Naïve Bayes, Random Forest), VADER consistently achieved higher accuracy in capturing sentiment from informal, context-rich financial content. As a result, this research adopts VADER as the SA tool for processing qualitative data from financial news sources.

Additionally, the chapter reviewed hybrid models that combine quantitative and qualitative data for stock prediction. Numerous studies indicate that integrating sentiment features with historical stock data improves the robustness and accuracy of forecasting models. This multimodal approach is especially useful in volatile or sentiment-sensitive markets, where news and investor mood can trigger rapid price changes. A particularly novel aspect of this study is the exploration of optimal sentiment windows—testing how the timing of sentiment (e.g., immediate vs. lagged impact) influences prediction performance, a dimension not widely explored in previous research.

In conclusion, the literature reviewed in this chapter provides strong theoretical and empirical support for a hybrid predictive framework that integrates deep learning with sentiment analysis. MLP, LSTM, and GRU will be employed for their strengths in modelling financial time series, while VADER will be used to quantify sentiment from financial news. Together, these tools will form the methodological backbone of this research. The next chapter will detail the design of the experimental framework that empirically evaluates these models, with a focus on improving the accuracy and reliability of stock return predictions.

Chapter 3 The Experiment Design

The preceding chapters outlined the research objectives, research question, and foundational theoretical background relevant to this study. Before presenting the empirical findings, it is necessary to specify the experimental procedures that underpin the study. This chapter therefore details the experimental design and procedures used to ensure that the results are robust, transparent, and reproducible. The primary objective is to describe the two-phase experimental framework: a preliminary phase that compares deep learning models for price and return prediction, and a final phase that augments return prediction with sentiment features. This section also clarifies how the experimental setup is structured to explore why some models work better than others under the specific constraints of stock price and return forecasting.

In the preliminary phase, deep learning models are used to forecast both the S&P 500 index price and index return. The purpose of this phase is to determine which target variable—price or return—is more difficult to predict, and therefore most in need of methodological enhancement in the final phase. The dataset associated with the lowest predictive performance is subsequently selected as the focus of improvement in the final experiment. Three deep learning architectures—Multi-Layer Perceptron (MLP), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU)—are evaluated in this phase. Across the experiments, 10,800 model configurations are generated by systematically varying key hyperparameters:

- Three activation functions (ReLU, TanH, Sigmoid);
- Four window sizes corresponding to 1, 3, 6, and 12 months of trading days;
- Six epoch settings (10, 20, 50, 100, 150, 200);
- Five architectural depths (1, 2, 4, 8, 16 hidden layers).

This exhaustive grid enables a structured comparison of which model families and hyperparameter choices are compatible with the characteristics of the S&P 500 data, and which configurations are inefficient or ineffective in this problem setting.

In the final phase, the target variable with the poorest predictive performance—index return—is modelled using the best-performing deep learning architecture from the preliminary phase. This phase integrates sentiment analysis features, based on financial news, and systematically varies sentiment lag periods to assess whether external qualitative information can reduce forecasting error. Section 3.1 presents an overview of the experimental framework, while Sections 3.2 and 3.3 describe in detail the preliminary and final experiment designs, respectively. Together, these phases are designed not merely to train many models, but to reveal how different architectures behave under the constraints of noisy financial data, walk-forward evaluation, and realistic training-time limits

3.1 Overview of the experimental design

The stock price reflects the current market valuation of a security, whereas the stock return—typically defined as the percentage change in price—captures the gain or loss experienced over a specific period. Index returns are widely used as a measure of trading performance and portfolio profitability (Marquering and Verbeek, 2004; Joseph, Larrain and Turner, 2017; Zhong and Enke, 2019; Bhowmik and Wang, 2020) and investors are particularly interested in whether daily returns are positive or negative. Importantly, a model that performs well in predicting index prices does not necessarily achieve comparable accuracy when predicting returns. For example, predicting prices of 990 or 1,010 when the actual price is 1,000 corresponds to a high level of price accuracy, yet these small deviations can still translate into substantial uncertainty about the sign and magnitude of returns. Thus, return prediction is a more demanding and practically relevant forecasting task. This distinction foreshadows why return prediction, as evaluated in later chapters, exhibits much higher error rates than price prediction, despite using the same underlying models and features.

Given the practical relevance of both price and return, the preliminary experiment evaluates deep learning models on both datasets to compare their relative predictability and identify systematic weaknesses. The target variable associated with the lowest prediction efficacy—index return—is then selected as the focus of enhancement in the sentiment-augmented final phase.

Figure 3-1 summarises the overall research workflow across the two experimental phases. In the preliminary experiment (Figure 3-1a), historical index prices and returns are used as inputs to evaluate the three deep learning models and identify the most suitable architecture. These experiments examine differences in prediction performance between price and return, and the least predictable target (return) becomes the focus of refinement in the final experiment. The best-performing model from the preliminary phase is then used in the final phase (Figure 3-1b) to assess whether incorporating news sentiment can improve predictive performance for index returns.

The preliminary experiment focuses on one-step-ahead prediction of the S&P 500 daily index price and return using the three selected deep learning models, as illustrated in Figure 3-2. The experimental pipeline begins with data collection via the Yahoo Finance API. The API provides daily closing prices, from which daily index returns are calculated. The precise computation of daily index return is described in Subsection 3.2.1.2.

In the final experiment, the index return series is prepared using the same procedure as in the preliminary phase, while financial news articles related to S&P 500 companies are collected from the Finnhub Stock API. These articles are then processed using the VADER sentiment analysis tool to derive sentiment scores. The resulting sentiment scores are combined with historical returns to construct

hybrid feature sets that integrate quantitative market data with qualitative sentiment information. This design explicitly tests whether augmenting noisy return data with sentiment features can mitigate the high error rates observed when models are trained on historical numerical data alone.

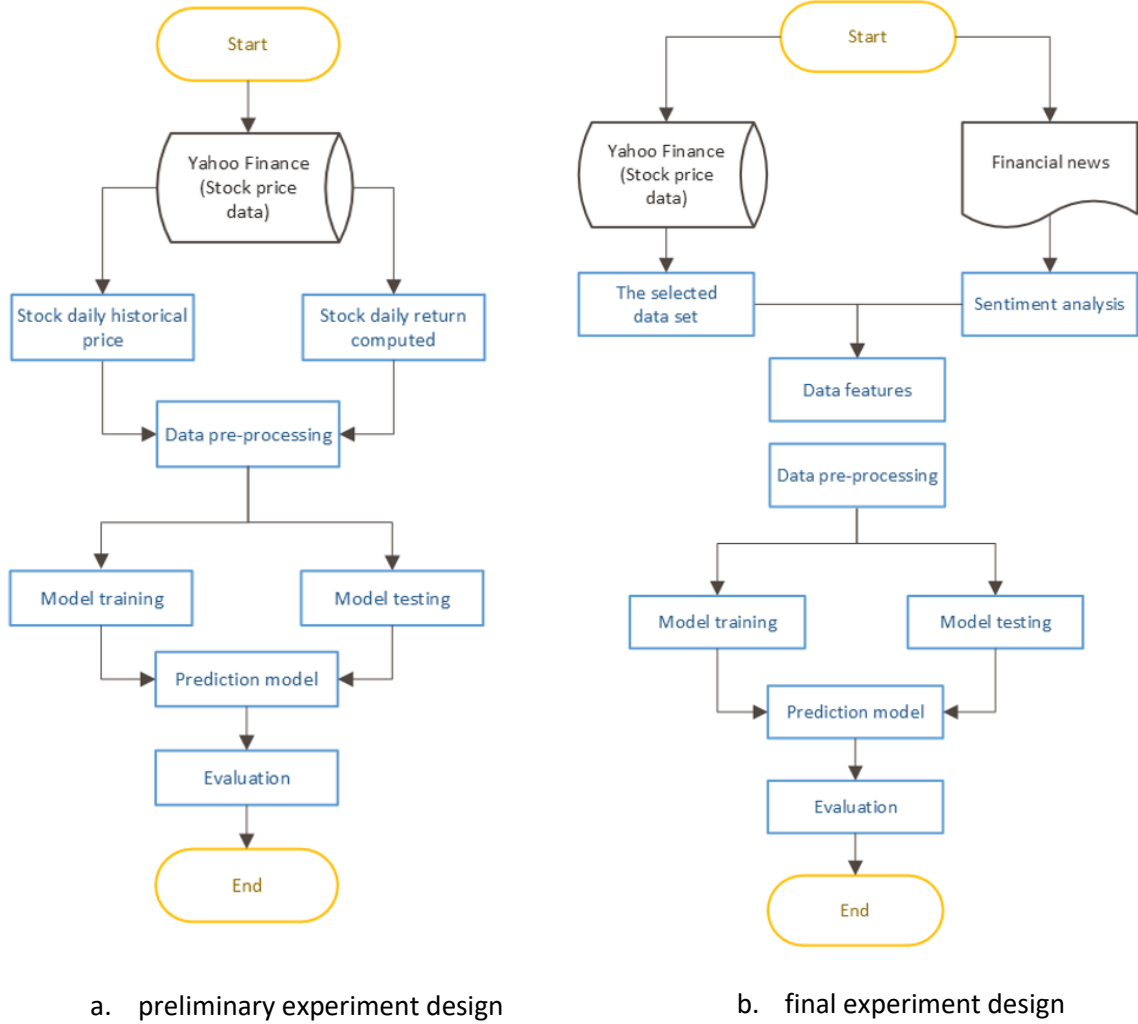


Figure 3-1: Proposed system for S&P 500 index experiment design

Following data collection, pre-processing is applied to transform the raw datasets into a format suitable for deep learning models. Four main pre-processing stages are implemented:

- (a) Data cleansing to handle missing or erroneous values;
- (b) Feature extraction to construct the input variables for each experiment;
- (c) Data normalisation to rescale variables to comparable ranges;
- (d) Data splitting into training and testing sets for model evaluation.

In the model training step, stock price and return are predicted using different time-window lengths and hyperparameter settings, as detailed in Section 3.2.2. Model performance is evaluated and compared using forecasting error metrics and training runtime (Qian and Chen, 2019; Zhou, Zhou and Wang, 2022), enabling an analysis of both predictive accuracy and computational efficiency. By jointly

considering error metrics and runtime, the design allows later chapters to explain not only how large the errors are, but also why certain configurations are impractical or unsuitable for this forecasting task.

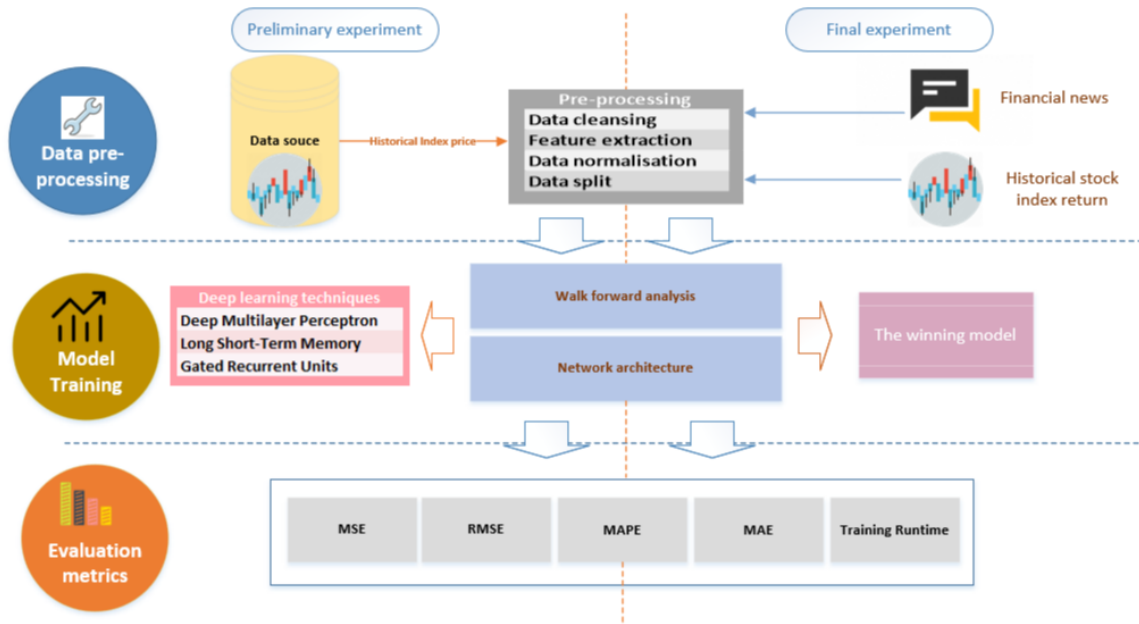


Figure 3-2: The overall procedure of the experimental design

The high-level procedures are summarised in the figures above. Sections 3.2 to 3.4 provide a detailed description of each step for both the preliminary and final experiments. These sections describe the data sources, feature construction, training and testing procedures, and evaluation methods used in the study.

3.2 The preliminary experiment set up

In the first phase of the experiment, both the S&P 500 index price and index return are used as input variables to evaluate the performance of the deep learning models. Daily closing prices are selected because they reflect market consensus at the end of each trading day and offer high liquidity and computational tractability (Krauss, Do and Huck, 2017). The S&P 500, comprising 500 large-cap U.S. companies across multiple sectors, serves as a widely used benchmark for overall market performance (Althelaya, El-Alfy and Mohammed, 2018a). Daily closing prices are obtained via the Yahoo Finance API, and all computational procedures are implemented in Python. The detailed specifications of the data collection process and the calculation of daily index returns are provided in Subsection 3.2.1.2.

3.2.1 Dataset and data pre-processing

The historical daily stock prices and returns will be the dataset input for the models during this phase. These datasets obtained from the Yahoo Finance API contain the opening price, closing price, greatest price, lowest price, and volume of stock traded, as shown in Table 3-1.

Table 3-1: The sample of S&P 500 index from Yahoo API

Date	Open	High	Low	Close	Volume
2000-01-03	1469.25	1478.00	1438.36	1455.22	931800000
2000-01-04	1455.22	1455.22	1397.43	1399.42	1009000000
2000-01-05	1399.42	1413.27	1377.68	1402.11	1085500000
2000-01-06	1402.11	1411.90	1392.10	1403.45	1092300000
2000-01-07	1403.45	1441.47	1400.73	1441.47	1225200000

A total of 5,032 trading days were observed between January 1999 and December 2019 (20 years). Table 3-1 shows the sample of S&P 500 index price that receive from Yahoo API. The input data get from 2000 to 2019 that is used for the preliminary experiment. The data collected from Yahoo finance API had some missing values. Data cleansing in section 3.2.1, therefore, was an important process to improve data quality. The daily index closing prices were then used to compute the daily index return, by Equation 3.1 in Section 3.2.1. The data preprocessing is illustrated in the subsequent sub-section.

3.2.1.1 Data cleansing

Missing values affect the quality of the deep learning model. To avoid this problem, a data cleansing step was used to enhance the data integrity. The U.S. stock exchange holidays include New Year's Day, Martin Luther King Jr. Day, President's Day, Good Friday, Memorial Day, Independence Day, Labor Day, Thanksgiving Day, and Christmas Day. Except for these holidays, missing values were filled by averaging the values of the previous and next days of trading (Zhong and Enke, 2019).

3.2.1.2 Feature extraction

There were two experiments. In the first, the input data were the daily closing price (Althelaya, El-Alfy and Mohammed, 2018a; Hiransha *et al.*, 2018; Basak *et al.*, 2019), shown in the form $(date, S_t)$. In the second experiment, the input data were the daily index return (Zhong and Enke, 2019), shown in the form $(date, stock\ index\ return)$. The stock index return was computed from the closing price series S_t from the following equation:

$$stock\ index\ return = \left(\frac{S_t}{S_{t-1}} \right) - 1 \quad (3.1)$$

Table 3-2 shows a sample the input data used for the prediction process. These data have to be normalised before deploying a machine learning technique (Hiransha *et al.*, 2018), described in the next section.

Table 3-2: The sample of input data for the experiment

Index Price		Index Return	
Date	Close	Date	Return
2000-01-03	1455.22	2000-01-03	0
2000-01-04	1399.42	2000-01-04	-0.038345
2000-01-05	1402.11	2000-01-05	0.001922
2000-01-06	1403.45	2000-01-06	0.000956
2000-01-07	1441.47	2000-01-07	0.027090

3.2.1.3 Data normalisation

Data normalisation is used to guarantee data quality before feeding the data into any learning algorithm. It is a requisite data pre-processing task for improving the prediction accuracy (Nayak, Misra and Behera, 2014). The dataset received from the normalisation process can enhance the learning ability of the network with minimum error. To avoid the effect of the different measurement units, the normalisation will scale the data to values between 0 and 1. This study used the *MinMaxScaler* function provided by the Python library scikit-learn framework. The normalisation function is:

$$x' = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad (3.2)$$

3.2.1.4 Data split

Each dataset was divided into a training set and a testing set. Following Althelaya, El-Alfy and Mohammed (2018a), the first 80% of the whole data was employed for the training, while the remaining 20% was used for the testing. After the data cleansing process was completed, the dataset consists of 5,155 trading days: 4,124 observations for the training stage and 1,031 observations for the testing stage respectively, as shown in Figure 3-3.

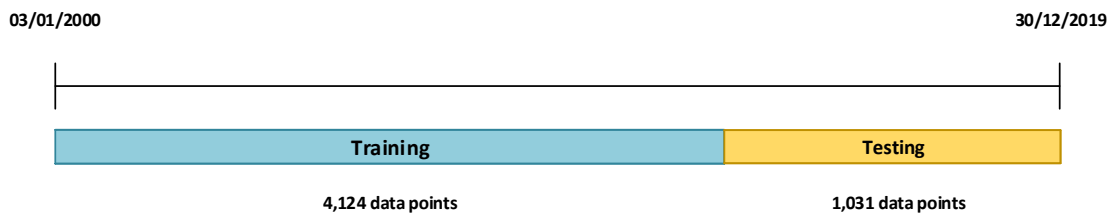


Figure 3-3: The division example of training and testing sets of the preliminary experiment

3.2.2 The model training

In this stage, the model was trained with the quantitative data (stock market index data). The data generated from the stock market is huge and highly non-linear, so the data was analysed for any existing hidden patterns. The approaches selected for training were: Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU). These are all deep learning algorithms capable of mapping non-linear functions (Selvin *et al.*, 2017). Moreover, these algorithms can identify hidden patterns in the data through the self-learning process. In summary, these approaches can effectively model stock market data and give a good prediction by analysing the interactions and hidden patterns within the data.

Apart from the capabilities mentioned, each approach has additional strengths, listed below.

Multilayer Perceptron: MLP provides very good prediction results on many financial examples because it is robust to noise (Brownlee, 2018), high-efficient in computation (Wankhede, 2014), highly-adaptive learning (Wankhede, 2014), and highly-accurate for challenging problems (Pradeepkumar and Ravi, 2017).

Long Short-Term Memory: LSTM is a powerful model that performs better and faster than others in forecasting using financial time series (Hossain *et al.*, 2018; Nunes *et al.*, 2019). LSTM has gating mechanisms to control the flow of information (Gu *et al.*, 2020). The intermediate output will be systematically retained at each time step, which allows LSTM to memorise temporal patterns over a longer period (Wang *et al.*, 2019).

Gated Recurrent Units: GRU has comparable performance to LSTM, but uses fewer parameters (Gao *et al.*, 2020). While LSTM has three gates (input, output, and forget), GRU has only two gates (reset and update), which generally reduces the training time (Gao *et al.*, 2020).

From an implementation perspective, the experiments in this chapter were designed and executed using the deep learning software and hardware platforms available around 2019, namely contemporary Python-based libraries with GPU support. These platforms mainly affect the *computational* layer of the study: they determine how quickly and conveniently the 10,800 model configurations (spanning three architectures, multiple window sizes, activation functions, epochs, and depths) can be trained and evaluated, but they do not alter the underlying research questions, the structure of the models, or the choice of evaluation metrics described in Sections 3.2–3.3. In other words, newer releases of deep learning platforms (such as modern versions of TensorFlow, PyTorch or comparable frameworks) would primarily reduce wall-clock training time and simplify hyperparameter management, while the core experimental design—comparing MLP, LSTM and GRU under controlled hyperparameter grids for price and return prediction—remains valid and directly transferable to current software stacks.

Given the characteristics of the S&P 500 data used in this research—daily observations, approximately 4,124 training points in the preliminary phase and 1,040 in the final phase, combined with a very low signal-to-noise ratio—the most appropriate use of deep learning platforms is to support relatively compact models that can be retrained frequently and deployed efficiently. Very deep or heavily parameterised recurrent architectures (for example, multi-layer LSTM and GRU networks with large numbers of units) are computationally much more demanding and, as later shown in Chapters 4 and 5, do not deliver forecasting errors that justify their substantially longer training times. By contrast, deep MLPs with ReLU activation and moderate depth provide a better trade-off between accuracy and runtime in this setting, especially when models must be re-estimated regularly as new data arrive. Consequently, within the problem set-up of this thesis, deep learning platforms or services that encourage extremely large sequential models or very broad automated architecture searches are unlikely to yield practical benefits, whereas platforms that offer fast, stable training of MLP-type models and straightforward deployment pipelines align well with the empirical findings and intended use of the proposed system.

3.2.2.1 Walk forward analysis for training and testing data

Using the 80% allocated as training data, a rolling window approach was used to train the algorithms, as shown in Figure 3-4. The training window size w was set to the time interval of 21, 63, 125, and 250 days, to predict the following 1 day's result. These time intervals correspond to the number of stock trading days in one month, three months, six months, and one year respectively. This experiment will therefore take $(4,124 - w)/1$ training sessions. For example, if the window size is 63, the experiment will produce $(4,124 - 63)/1 = 4,061$ training sessions, which create 4,061 prediction outputs. This walk-forward design intentionally mimics real-world forecasting but also contributes to the difficulty of the task: each training window contains limited historical information, and returns are dominated by noise, which later helps explain the large error rates observed in return prediction.

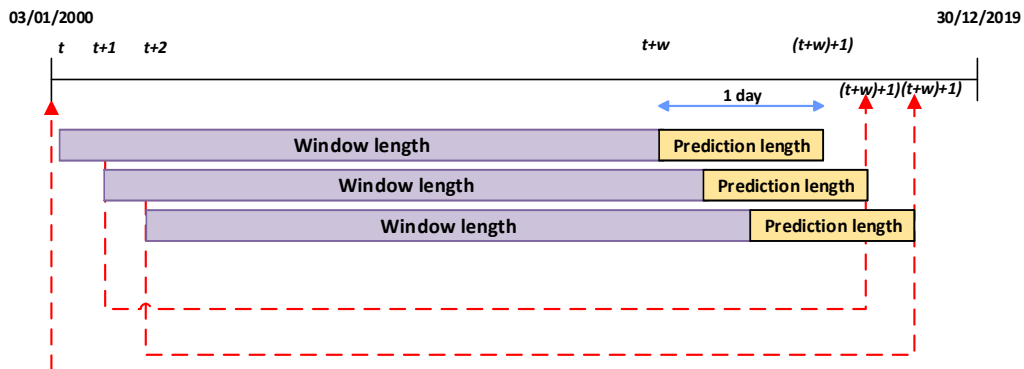


Figure 3-4: The window size w , prediction length, and rolling window for the whole data

3.2.2.2 Network architecture

To determine which ML technique produced the best results, all models were trained using a different number of hidden layers and each hidden layer had a different number of neurons. For all training, both the number of hidden layers (h) and the number of neurons (*nodes* or n) per hidden layer were chosen from the set $\{1,2,4,8,16\}$. The reason for using a variable number of hidden layers and neurons was to study the relation between accuracy and the number of hidden layers. However, if the number of neurons in the hidden layer is too large, it will require very long training and recalling time (Vujičić and Matijević, 2016). The detail of the network setting is shown in Table 3-3. Later empirical results (Chapters 4 and 5) show that simpler architectures provide a better balance between accuracy and computational cost, whereas deeper settings with many layers and nodes increase runtime without materially reducing error, making them less suitable for this problem context.

Input layer has only one neuron, which is the input closing price or index return.

Hidden layers consist of n neurons and have an activation function, but the most suitable activation function for individual dataset has yet to be determined. Maguolo, Nanni and Ghidoni (2020) proposed an ensemble of Convolutional Neural Networks model using several different activation functions on 10 different datasets. Their results revealed no activation consistently better than others, when applied to different datasets. Therefore, this experiment investigated the most suitable function from three activation functions often used in stock prediction research: rectified linear unit (ReLU), hyperbolic tangent (TanH), and Sigmoid. The result might be useful for improving the training behaviour of layered neural networks in future work.

Output layer has one neuron that produces the prediction. A linear activation function is used in this layer, and a linear regression approach was adopted.

In the context of daily S&P 500 returns, this scalar-output setup is deliberately kept simple so that any systematic structure in the data can be detected; however, as later chapters show, the combination of low signal-to-noise ratio and one-step-ahead targets means that even expressive architectures struggle to reduce error substantially, particularly for returns.

The activation functions used for model training are shown in Table 3-4. These activation functions were applied to all models. Each model used the same activation function in each hidden layer, although the output layer used the Linear activation function. As an example, Figure 3-5 shows the model architecture for an MLP network structure with $h = 2$, $n = 4$, with the ReLU activation function.

Table 3-3: Setting the network architectures

Techniques	Number of hidden layers (h)	Nodes per layer (n)	Model structure (Input-Hidden(node)-Output)
MLP, LSTM, GRU	1	1	1-1(1)-1
	1	2	1-1(2)-1
	1	4	1-1(3)-1
	1	8	1-1(4)-1
	1	16	1-1(16)-1
	2	1	1-2(1)-1
	2	2	1-2(2)-1
	2	4	1-2(3)-1
	2	8	1-2(4)-1
	2	16	1-2(16)-1
	4	1	1-4(1)-1
	4	2	1-4(2)-1
	4	4	1-4(3)-1
	4	8	1-4(4)-1
	4	16	1-4(16)-1
	8	1	1-8(1)-1
	8	2	1-8(2)-1
	8	4	1-8(3)-1
	8	8	1-8(4)-1
	8	16	1-8(16)-1
	16	1	1-16(1)-1
	16	2	1-16(2)-1
	16	4	1-16(3)-1
	16	8	1-16(4)-1
	16	16	1-16(16)-1

Table 3-4: Activation function for each layer

Hidden layer	Output Layer
ReLU	Linear
TanH	Linear
Sigmoid	Linear

Loss function and optimiser

Each model was optimised using the mean square error (MSE) loss function (Hossain *et al.*, 2018), suitable for regression problems, and the efficient Adam optimiser of gradient descent. MSE is formally defined in Equation 3.3.

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (3.3)$$

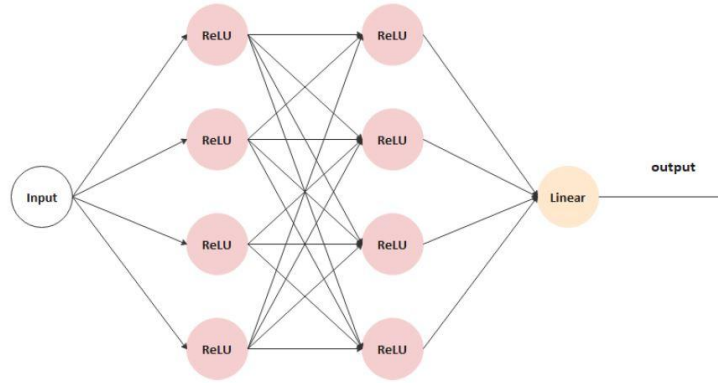


Figure 3-5: MLP architecture for $h = 2$, $n = 4$ using *ReLU* activation function

Adam optimiser is an algorithm used to minimise the error of all selected models (Hossain *et al.*, 2018). Adam algorithm is computationally efficient, requires little memory, works well for problems that have large amounts of data or parameters (Kingma and Ba, 2015), and has the great advantage for solving the non-convex optimisation problem (Ding and Qin, 2019). The learning rate for all experiments was initialised to 0.001. By holding the optimisation scheme constant across architectures, any observed differences in error rates can be attributed primarily to model structure, input representation, and data characteristics rather than to changes in the training algorithm itself.

Dropout training

Dropout is a technique for addressing the overfitting problem by eliminating units in a neural network, both hidden and visible (temporarily removing units from the network). For the hidden layer, a good value of dropout is between 0.5 and 0.8 (Hinton, 2014). To avoid the overfitting problem, the dropout layer was used following each of the hidden layer networks in all experiments, with dropout probability 0.5 (Huynh, Dang and Duong, 2017; Hossain *et al.*, 2018) as shown in Figure 3.6.

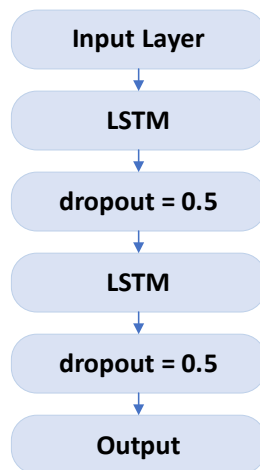


Figure 3-6: LSTM with dropout architecture for $h = 2$

All parameter values for the experiments are shown in Table 3-5. All techniques were trained with the same parameter values, with the number of epochs set to 10,20,50,100,150, and 200. This systematic

grid search over epochs, depths, activation functions, and window sizes allows the later analysis (Chapters 4 and 5) to distinguish between error driven by suboptimal hyperparameter choices and error that stems from more fundamental properties of the data, such as the noise structure of returns and the constraints imposed by rolling-window forecasting.

Table 3-5: Parameter settings for models

Parameter	values
learning rate	0.001
number epoch	10,20,50,100,150,200
batch size	32
dropout	0.5

After the training process, the models were used to predict stock index price and index return using the test dataset. To measure the performance of all the techniques for this regression problem, evaluation metrics include the error rate and the training runtime of each model.

3.2.2.3 Evaluation Metrics

Two metrics were used to evaluate the performance of the selected model: forecasting error and training runtime. The evaluations of forecasting error used in the experiment are MSE (the formula has been shown in Equation 3.3) (used by Chou and Nguyen, 2018; Hossain *et al.*, 2019), root mean square error (RMSE) (used by Althelaya, El-Alfy and Mohammed, 2018a; Chou and Nguyen, 2018), mean absolute error (MAE) (employed in Althelaya, El-Alfy and Mohammed, 2018a; Chou and Nguyen, 2018; Hossain *et al.*, 2019), and mean absolute percentage error (MAPE) (used in Chou and Nguyen, 2018; Hiransha *et al.*, 2018; Hossain *et al.*, 2019). These were used to measure whether the model-predicted values were close to the actual values. The computation of each method is defined as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (3.4)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (3.5)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left(\left| \frac{y_i - \hat{y}_i}{y_i} \right| \right) \quad (3.6)$$

Where y is the actual value
 $\hat{y}$ is the predicted value
 n is the number of data samples

The better the prediction, the lower the values of MSE, RMSE, MAE, and MAPE. The performance of the model training in Section 3.3 was compared using these goodness-of-fit measurements to indicate the best fit model for S&P 500.

In later chapters, particular attention is paid to persistently large MAPE values in return prediction; these are not treated as isolated numbers but are analysed in relation to the underlying data properties (e.g. very small denominators in percentage errors, low signal-to-noise ratios, and the impact of rolling-window segmentation), in order to explain why certain configurations fail to reduce error and to motivate the move toward sentiment-augmented models.

The design of the preliminary experiment was tested in Chapter 4. The test results indicated that predicting stock returns had a very high error rate. Among the deep learning models, MLP performed best in predicting stock returns, but still had a high prediction error of 90.64%, which is significantly higher than the error in stock price prediction. Therefore, the focus of improving prediction performance in this research is on forecasting stock returns using the MLP model. To enhance prediction accuracy, financial news data will be integrated with historical stock return data. The design of the final experiment is described in Section 3.3. This shift of emphasis—from merely reporting large error rates to systematically probing their causes and testing error-reduction strategies via sentiment features—directly addresses the unexpectedly high return-prediction errors observed in the preliminary phase and forms the basis for the investigations in Chapters 5 and 6.

3.3 The final experiment set up

Phase 2 experiment inputs included the daily stock return, and the sentiment score derived from the financial news articles. This section describes the source of the data, how the data serves the model, and how the model is trained and tested. The historical daily closing prices for the S&P 500 companies were collected from Yahoo! Finance, while news articles were collected from *Finnhub* Stock API. Next, the historical daily price was computed to find the daily return, while the collected news articles were processed by VADER to calculate the sentiment scores. Both sets of data were then grouped to create the data feature which is a mix of daily stock return and sentiment scores. Pre-processing prepared the datasets in the right format for input to the model, for training and testing. Finally, the architecture of the deep learning model predicted the next day's return and computed the error percentage. Each component of the data collection is described in detail in the sub-section that follows.

3.3.1 Data collection

There are two data collections in the research, including the historical daily price of the S&P 500 index (at close of trading) and news articles about the companies in the S&P 500 index. The historical return

and news sentiment data were observed over a five-year period between January 2016 and December 2020, a total of 1,300 trading days. The utilisation of a 5-year data span is necessitated by the constraint that news items obtained from the *Finnhub* Stock API for educational purposes are restricted to this duration. Therefore, this data consists of 1,300 historical stock index closing prices and 1,252,879 news articles, with an average of 686 articles per day.

In addition, it is important to note that the data request to the *Finnhub* Stock API was initiated prior to the onset of the COVID-19 pandemic, during a period in which the platform's terms of use for educational access imposed a strict limitation on the retrievable historical horizon. Specifically, *Finnhub* permits academic users to obtain no more than five years of historical data, which directly constrained the temporal scope of this study. Consequently, the dataset is restricted to the five-year window from January 2016 to December 2020. This limitation is not a methodological choice but a technical boundary set by the data provider, thereby determining the maximum feasible period for collecting both historical market prices and news sentiment information.

3.3.1.1 Stock historical daily return

The stock daily return collection used in this phase required 1,300 stock closing prices to be cleaned, by checking for missing values, which were then calculated by averaging the values of the previous and next days of trading. The cleaned daily index closing prices were then used to compute the daily index return, by using Equation 3.1.

3.3.1.2 News articles

The five-year collected news articles contain news about the companies in the S&P 500 index. Note the companies that constitute the S&P 500 did change over this time (see Appendix F). For this stage of the experiment, if a company was, or is currently, in the S&P 500, all news articles related to that company were pulled from the news feeds from *Finnhub*. The list of companies that constitute the S&P 500 on a particular day was taken from *Wikipedia*⁴. One data example from *Finnhub* is shown in Figure 3-7.

news_id	category	datetime	headline	summary	source	image	url	related
31791077	company	2016-01-01T00:44:40	Sentio: a better way to perform...	Since January 2015, I have been using a	https://glenn	https://glen	https://finnhub.i	['DIS', 'GOOGL', 'MAT']
7883941	company	2016-01-01T06:12:51	Algorithms Need Managers, Too	Know how to get the most out of your	https://hbr.or	https://hbr.	https://finnhub.i	['GOOGL']
55083488	company	2016-01-01T07:00:00	The Innovative Power of Criticism...	Judgment, not ideation, is the key to...	https://hbr.or	https://hbr.	https://finnhub.i	['MSFT']
62021416	company	2016-01-01T07:00:00	The Golden Parachute: 5 Shocking...	Photo: U.S. Army , via Flickr There are	Nasdaq	https://ww	https://finnhub.i	['F']
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
62060755	company	2020-12-30T23:56:00	DuPont de Nemours Inc. stock...	Shares of DuPont de Nemours Inc. ...	MarketWatch	https://imag	https://finnhub.i	['APD', 'DD', 'DOW',
62060799	company	2020-12-30T23:56:00	Fortinet Inc. stock rises Wednesday,	Shares of Fortinet Inc. inched 0.33%..	MarketWatch	https://imag	https://finnhub.i	['CS CO', 'HPQ', 'FTNT']
62064364	company	2020-12-30T23:56:28	Tech report card 2020: From Apple..	Technology overtook the world as...	https://www.f	https://imag	https://finnhub.i	['FB']
62064383	company	2020-12-31T00:00:00	3 Stocks Poised for Huge Growth...	Newer ways of doing business,...	https://www.f	https://g.fo	https://finnhub.i	['NFLX']

Figure 3-7: Example of a news dataset from Finnhub

⁴ Wikipedia periodically displays changes to the List of S&P 500 companies and keeps the index up to date.

3.3.1.3 Polarity score

The polarity score process uses a sentiment analysis model called VADER, contained in the NLTK package (Khemani & Adgaonkar, 2021), which was reviewed in Chapter 2. VADER was principally used because its process does not require additional training data, so it performs much faster than ML-based and DL-based sentiment analysis (Hutto & Gilbert, 2014b; Pano & Kashef, 2020). VADER does not need data pre-processing, which is generally seen as a fundamental part of sentiment analysis. Palomino and Aider (2022) claimed that VADER achieved its best performance without pre-processing. Pre-processing also damages its accuracy because VADER performs its own text pre-processing (Palomino & Aider, 2022). For each body of texts, VADER generates a compound polarity score between -1 and $+1$ that can be interpreted to be positive (0.1 , $+1.0$), neutral (-0.1 , $+0.1$), and negative (-1.0 , -0.1).

3.3.1.4 Sentiment analysis

To calculate the sentiment analysis per day, for all the companies that constitute the S&P 500 on that particular day, a transformation approach was used. Only the polarity scores for an article pertaining to the companies that were part of the S&P 500 on that particular day were used.

The first transformation approach was a simple sentiment compound score:

$$\text{Compound score} = \frac{\sum \text{Compound Polarity Scores}}{\text{number of Articles}} \quad (3.7)$$

The news's headline and summary from *Finnhub* generated a polarity vector of negative, neutral, positive, and compound polarities of sentiment scores, as shown in Figure 3-8.

news_id	category	date	time	headline	summary	related	neg	neu	pos	compound
38194341	company	12/02/2020	00:00:31	T-Mobile's Takeover of Sprint A...	Attorneys general from 13 sta...	['TMUS']	0.083	0.825	0.092	0.0772
15809752	company	12/02/2020	00:00:43	Marriott Bonvoy Brilliant Amex...	CNBC Select reviews all the...	['AXP', 'MAR']	0	0.696	0.304	0.9485
15807881	company	12/02/2020	00:00:59	Pentagon Keeps Focus on Mode...	The Pentagon's FY 2021 budge...	['HII']	0	1	0	0
55179521	company	12/02/2020	00:01:58	Mythic Quest is the best Apple...	Mythic Quest is a must-watch...	['AAPL']	0	0.707	0.293	0.8519
67095	company	12/02/2020	00:02:00	Kraft Heinz Earnings Are Coming...	Kraft Heinz reports fourth-quar...	['KHC']	0	0.945	0.055	0.2023
341135	company	12/02/2020	00:08:38	Mid-Day Market Update: Amkor...	Midway through trading Tuesday	['HAS', 'S', 'SBAC']	0	0.891	0.109	0.6124
67012	company	12/02/2020	00:10:07	Will Broadcom Inc. (AVGO) Beat...	Broadcom Inc. (AVGO) has an...	['AVGO']	0	0.876	0.124	0.6597
17962084	company	12/02/2020	00:11:50	Microsoft Shares More Details...	Microsoft reveals new Win32...	['MSFT']	0	0.919	0.081	0.296
681698	company	12/02/2020	00:12:10	Judge approves T-Mobile and ...	Federal judge rejected argum...	['DISH', 'T', 'TMUS', 'VZ', 'S']	0.178	0.742	0.08	-0.5106
681692	company	12/02/2020	00:13:00	New Hampshire primary: Stock...	As New Hampshire Democrats ...	['SPGI']	0.064	0.936	0	-0.34

Figure 3-8: Dataset showing the polarity and compound scores calculated by VADER

All the negative, neutral, and positive polarities were given a normalised score between 0 and 1, depending on how much the sentiment is within the news's headline and summary. The compound polarity score is between -1 and $+1$, divided into three cases: (0.1 , $+1$) is positive, (-0.1 , -1) is negative, and neutral is between (-0.1 , $+0.1$). The closer the compound score is to $+1$, the higher the positivity of the text. Otherwise, the compound score will show the difference in the text, as in Figure 3-9.

<pre>print(sentiment.polarity_scores("S&P 500 rebounds as investors hope " "for easier Fed, cooling China tensions")) {'neg': 0.155, 'neu': 0.517, 'pos': 0.328, 'compound': 0.4588}</pre>
a. The positive compound score
<pre>print(sentiment.polarity_scores("Stock fall for a second day as investors weigh " "U.S. tensions, new batch of earnings")) {'neg': 0.172, 'neu': 0.828, 'pos': 0.0, 'compound': -0.4019}</pre>
b. The negative compound score
<pre>print(sentiment.polarity_scores("The athletic-apparel maker reported a 2% decline " "in sales in North America, its biggest market")) {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}</pre>
c. The neutral compound score

Figure 3-9: Compound scores calculated for sample sentences

The polarity score for all 1,252,879 collected articles was calculated. These gave a baseline score. The positive, negative, neutral, and compound scores were used as input to the experiments.

3.3.2 Data Features

The data has five features: historical index return, compound scores, negative scores, neutral scores, and positive scores. The individual data features are explained below.

- **Historical index return** are the daily past rate of return and performance of the S&P 500 index between January 2016 and December 2020.
- The **positive**, **negative**, and **neutral scores** are the corresponding sentiments the texts hold, obtained from the VADER calculated processes in sentiment analysis for that trading day.
- The **compound score** is calculated by the summation of the ratings from the positive, negative, and neutral score for that trading day, and takes values from -1 to $+1$.

Table 3-6 shows the four groups of experiments, the number of features used for each, with the relevant period of the sentiment scores.

where **current-day** is the sentiment score for the trading day

1-day is the previous trading day's sentiment score

3-days represents the mean of three days of sentiment scores, starting from the previous trading day

5-days represents the mean of five days of sentiment scores, starting from the previous trading day

Financial-news sentiment released at time t_0 typically influences asset returns over a short but variable reaction horizon. Prior empirical studies show that markets incorporate new information within approximately 1–5 trading days, depending on news type, investor attention, and information diffusion speed (Tetlock, 2007; Engelberg & Parsons, 2011).

Table 3-6: Grouping of features for testing the model

Input Data		
Dataset Group	Features	Sentiment scores period
Group 1	1 feature: - historical return	none
Group 2	2 features: - historical return - compound score	<i>current-day</i> <i>1-day</i> <i>3-days</i> <i>5-days</i>
Group 3	3 features: - historical return - negative score - positive score	<i>current-day</i> <i>1-day</i> <i>3-days</i> <i>5-days</i>
Group 4	4 features: - historical return - negative score - neutral score - positive score	<i>current-day</i> <i>1-day</i> <i>3-days</i> <i>5-days</i>

Anchored in this behavioural evidence, this experiment evaluates four sentiment windows: (1) current-day sentiment (t_0), capturing immediate market expectations; (2) 1-day lagged sentiment (t_{-1}), reflecting the first full day of market assimilation; (3) 3-day aggregated sentiment, representing short-run adjustment and delayed trading activity; and (4) 5-day aggregated sentiment, capturing weekly sentiment diffusion. This design explicitly examines how sentiment at time t_0 relates to returns at t_i by comparing multiple empirically grounded reaction windows rather than assuming an arbitrary one-day link. By systematically testing these temporal structures, the experiment evaluates whether news affects returns immediately, with delay, or cumulatively—thereby grounding the sentiment-return linkage in established market-reaction dynamics.

The current-day sentiment score for the trading day indicates how the sentiment score shows before the market closed. The 5-days sentiment score indicates how the sentiment score shows in a trading week. The 1-day and 3-days previous to the trading day's sentiment scores were used to investigate which period score produces the higher performance in the model.

Group 1 dataset is the baseline (only historical return), as used in Chapter 3, to compare the results with the other groups. Group 2, Group 3, and Group 4 datasets were used to test the performance of the prediction when using the difference sentiment scores. This resulted in 13 datasets for testing, as shown in Figure 3-10.

date returns	
2016-01-06	-0.01312
2016-01-07	-0.02370
2016-01-08	-0.01084
2016-01-11	0.00085
2016-01-12	0.00780

a. one feature

date	returns	compound
2016-01-06	-0.01312	0.06891
2016-01-07	-0.02370	0.07634
2016-01-08	-0.01084	0.08182
2016-01-11	0.00085	0.11937
2016-01-12	0.00780	0.08113

date	returns	neg	pos
2016-01-06	-0.01312	0.06434	0.09462
2016-01-07	-0.02370	0.04729	0.08980
2016-01-08	-0.01084	0.04566	0.08390
2016-01-11	0.00085	0.04552	0.10499
2016-01-12	0.00780	0.05495	0.09532

date	returns	neg	neu	pos
2016-01-06	-0.01312	0.06434	0.84103	0.09462
2016-01-07	-0.02370	0.04729	0.86290	0.08980
2016-01-08	-0.01084	0.04566	0.87044	0.08390
2016-01-11	0.00085	0.04552	0.84949	0.10499
2016-01-12	0.00780	0.05495	0.84972	0.09532

b. current-day two features

c. current-day three features

d. current-day four features

date	returns	compound
2016-01-06	-0.01312	0.07664
2016-01-07	-0.02370	0.06891
2016-01-08	-0.01084	0.07634
2016-01-11	0.00085	0.20466
2016-01-12	0.00780	0.11937

date	returns	negative	positive
2016-01-06	-0.01312	0.03886	0.07887
2016-01-07	-0.02370	0.06434	0.09462
2016-01-08	-0.01084	0.04729	0.08980
2016-01-11	0.00085	0.03312	0.14042
2016-01-12	0.00780	0.04552	0.10499

date	returns	negative	neutral	positive
2016-01-06	-0.01312	0.03886	0.88228	0.07887
2016-01-07	-0.02370	0.06434	0.84103	0.09462
2016-01-08	-0.01084	0.04729	0.86290	0.08980
2016-01-11	0.00085	0.03312	0.82638	0.14042
2016-01-12	0.00780	0.04552	0.84949	0.10499

e. 1-day two features

f. 1-day three features

g. 1-day four features

date	returns	compound
2016-01-06	-0.01312	0.09106
2016-01-07	-0.02370	0.09110
2016-01-08	-0.01084	0.07396
2016-01-11	0.00085	0.17505
2016-01-12	0.00780	0.18756

date	returns	neg	pos
2016-01-06	-0.01312	0.03582	0.09299
2016-01-07	-0.02370	0.04907	0.09286
2016-01-08	-0.01084	0.05016	0.08776
2016-01-11	0.00085	0.04819	0.12033
2016-01-12	0.00780	0.04815	0.12736

date	returns	neg	neu	pos
2016-01-06	-0.01312	0.03582	0.87120	0.09299
2016-01-07	-0.02370	0.04907	0.85807	0.09286
2016-01-08	-0.01084	0.05016	0.86207	0.08776
2016-01-11	0.00085	0.04819	0.83147	0.12033
2016-01-12	0.00780	0.04815	0.82449	0.12736

h. 3-days two features

i. 3-days three features

j. 3-days four features

date	returns	compound
06/01/2016	-0.01312	0.16628
07/01/2016	-0.02370	0.13418
08/01/2016	-0.01084	0.08369
11/01/2016	0.00085	0.13408
12/01/2016	0.00780	0.14417

date	returns	neg	pos
2016-01-06	-0.01312	0.03291	0.12320
2016-01-07	-0.02370	0.03534	0.10863
2016-01-08	-0.01084	0.04382	0.09268
2016-01-11	0.00085	0.05124	0.10908
2016-01-12	0.00780	0.04748	0.11116

date	returns	neg	neu	pos
2016-01-06	-0.01312	0.03291	0.84391	0.12320
2016-01-07	-0.02370	0.03534	0.85603	0.10863
2016-01-08	-0.01084	0.04382	0.86351	0.09268
2016-01-11	0.00085	0.05124	0.83967	0.10908
2016-01-12	0.00780	0.04748	0.84136	0.11116

k. 5-days two features

l. 5-days three features

m. 5-days four features

Figure 3-10: Features of the input datasets for the experiments

3.3.3 The experiment

This section describes the experimental workflow: data pre-processing, prediction model, and model evaluation. These three steps will be discussed in separate sections below.

3.3.3.1 Source data pre-processing

To prepare all 13 datasets, they were adapted by normalisation into a form acceptable for the deployment of a machine learning technique, to improve the prediction efficiency. The *MinMaxScaler* function was used for this work, Equation 3.2. After that, the datasets were arbitrarily split so that 80% of the data was for training, while the remaining 20% was used for testing. The data for all 1,300 trading days were divided into 1,040 observations for the training stage and 260 observations for the testing stage.

3.3.3.2 Prediction model

The experimental results of the preliminary phase from Chapter 4 showed that, for stock return prediction, deep MLP demonstrated the best average prediction performance with the ReLU activation function when the window size was 63, and the epoch was 50. Deep MLP also gave the best training time, which was 30 times faster than LSTM and 150 times faster than GRU. This justified selecting the deep MLP model for handling the prediction task, with a sentiment score to predict the next day's return. All three activation functions were still investigated because the results of the mean percentage error between them was not much different (97.20 to 101.87). However, the results of the stock return prediction in Chapter 3 cannot represent the best method, unlike the price prediction which showed that $h = 1$ and $n = 16$ were the best parameters. Therefore, to determine whether using the sentiment score would improve the performance of stock return prediction, and which architecture would produce the best results, the deep MLP model was trained using the same set $\{1, 2, 4, 8, 16\}$ of hidden and node layers. Furthermore, each hidden layer would use the same activation function, but a Linear activation function would be used for the output layer (see details in Tables 3-3 and 3-4). To address the overfitting problem, the dropout layer was used in all experiments following each of the hidden layer networks, with a dropout probability of 0.5.

The *MSE loss function* and *Adam optimizer with 0.001 learning rate* were used in model training because their performance is suitable for regression problems and is computationally efficient (Ding & Qin, 2020; Hossain et al., 2018; Kingma & Ba, 2015). *Walk-forward analysis* was used for the training and testing window size with time intervals of 21, 63, 125, and 250 days (1, 3, 6, and 12 months). All techniques used and the hyperparameter values in this experiment are summarised in Table 3-7.

Table 3-7: Hyperparameters, loss function, and optimiser used in the S&P 500 index return prediction

Title	Value
loss function	MSE
optimiser	Adam
learning rate	0.001
batch size	32
dropout	0.5
number of hidden layers	$\{1, 2, 4, 8, 16\}$
number of nodes	$\{1, 2, 4, 8, 16\}$
window size	21, 63, 125, 250
number epoch	10, 20, 50, 100, 150, 200

To evaluate the hyperparameter used for the training and testing process in this experiment, thirteen different datasets were processed by deep MLP, using the following algorithm.

- For each dataset, the experiment looked at three different activation functions (ReLU, sigmoid, TanH).
- For each activation function, 5 different architecture layers {1, 2, 4, 8, 16} were adopted to find the layers giving the best result.
- For each layer the window size of the data was varied to find the length of the period giving the best prediction (1, 3, 6, and 12 months).
- For each window, the prediction was conducted, and the performance evaluated for 6 different epochs (10, 20, 50, 100, 150, 200).

The performance of the deep MLP approach with different parameters was measured in terms of time taken and forecasting error. The results from the Group 1 dataset were used as a baseline to compare the performance with other datasets.

3.3.4 Model evaluation

The techniques used for error evaluation of the model in training and testing mode were MSE, RMSE, MAE, and MAPE. MAPE was used for calculating the percentage error between the actual and predicted values because it is easy to understand and popularly used (Henrique et al., 2018; Hiransha et al., 2018; Jin et al., 2020). Table 3-8 summarises the techniques used in the experiment.

Table 3-8: The evaluation techniques used in the experiment

Training and testing mode	Predicted output
MSE	MAPE
RMSE	
MAE	
MAPE	

A key methodological contribution of this chapter is that it does not merely enumerate model configurations, but establishes a domain-specific rationale explaining *why* certain architectures are expected to succeed or fail in the context of daily financial forecasting. The experimental design recognises that stock returns exhibit low signal-to-noise ratios and limited temporal dependence, meaning that complex recurrent architectures such as LSTM and GRU—although theoretically capable of modelling long-term dependencies—may amplify noise, overfit small windows, and incur excessive computational cost when applied in walk-forward training regimes. Conversely, simpler feed-forward architectures such as MLPs are better aligned with the characteristics of this domain: they converge quickly, remain stable across a wide range of hyperparameters, and are less sensitive to the weak

dependency structures present in daily return series. By systematically varying window lengths, epoch counts, activation functions and architectural depths, the experimental design explicitly tests which modelling choices suppress prediction error and which consistently degrade performance. This allows the research to evaluate not only the numerical outcomes but also the *practical appropriateness* of each technique for real-world financial decision-making, where frequent model retraining, low latency, and robustness to noise are essential. In doing so, the chapter directly addresses the question of how deep learning methods can and cannot be effectively deployed in this domain, demonstrating that model suitability—not algorithmic novelty—is the central determinant of predictive viability in noisy financial environments.

3.4 Summary

This research adopts a two-phase experimental framework designed to systematically evaluate and enhance the performance of deep learning models for stock prediction tasks. The framework builds upon the hypothesis that prediction difficulty differs between stock index price and return, and that additional contextual information, such as sentiment from financial news, may improve prediction accuracy, particularly for volatile and noisy financial indicators like returns.

The first phase, known as the preliminary experiment, investigates the comparative predictability of stock price and return using three deep learning models: Multi-Layer Perceptron (MLP), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). These models are trained and tested on historical S&P 500 data collected over a twenty-year period (2000–2019), sourced from Yahoo Finance. The models are evaluated using a comprehensive grid of hyperparameter settings that include three widely used activation functions (ReLU, TanH, Sigmoid), four different window sizes (21, 63, 125, and 250 days), six epoch counts (10, 20, 50, 100, 150, 200), and a range of architecture depths from one to sixteen hidden layers with varying node sizes. The training is conducted using a walk-forward validation method, where each time window predicts the next trading day. This rolling approach mirrors real-world financial forecasting and helps prevent data leakage.

During this phase, performance is assessed based on standard error metrics—Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE)—as well as training time, to understand the trade-off between computational efficiency and accuracy. This extensive experimental setup results in over 10,000 model configurations being tested. The output of this phase identifies the combination of data type and model structure with the lowest prediction performance, which then becomes the target for enhancement in the final phase. Notably, preliminary results indicate that index return prediction is significantly less accurate than price prediction, and that MLP with ReLU activation function offers the best performance-speed trade-off in return prediction.

The second phase of the experiment, the final experiment, is designed to improve prediction accuracy for the more challenging task—index return forecasting—by integrating external, non-numerical data in the form of sentiment extracted from financial news. Sentiment data is collected using the *Finnhub* API, comprising over 1.2 million news articles related to S&P 500 companies from 2016 to 2020. These are processed using the VADER sentiment analysis tool, which computes polarity scores (positive, neutral, negative, and compound). The hybrid dataset is then formed by combining historical return data with these sentiment scores over multiple time frames: same-day, 1-day lag, 3-day average, and 5-day average.

The final experiment evaluates thirteen different feature combinations grouped by sentiment type and time frame. Each dataset is pre-processed using standard normalization and split into 80% training and 20% testing subsets. The MLP model is retrained using these expanded inputs across the same activation functions and architectural setups as in the preliminary phase. Dropout layers (with a rate of 0.5) are applied after each hidden layer to reduce overfitting. Model optimization is performed using the MSE loss function and Adam optimizer with a learning rate of 0.001, ensuring computational efficiency while preserving performance.

Ultimately, the final experiment assesses whether integrating sentiment-based features can reduce forecasting errors in return prediction. The model performance is again evaluated using MSE, RMSE, MAE, and MAPE, while training time is also recorded to evaluate real-world feasibility. The experimental pipeline is designed to be rigorous and reproducible, with results that contribute to understanding the practical benefits of hybrid financial models that merge quantitative and qualitative data.

Although the historical data used in this study spans 2000–2019, the deep learning experiments conducted in Chapter 3 are not limited by the age of the dataset because the purpose of this work is to evaluate the suitability of modern deep learning architectures—MLP, LSTM, and GRU—under the specific structural and computational conditions of stock-return forecasting. The chapter systematically analyses how these architectures respond to variations in window size, epoch count, activation function, and network depth across more than 10,000 model configurations, revealing clear differences in training stability and predictive performance.

The experimental setup shows that recurrent architectures such as LSTM and GRU struggle with long training times and unstable error profiles under walk-forward evaluation, making them less suitable for this problem where thousands of sequential windows must be retrained. In contrast, deep MLP architectures exhibit faster convergence, greater robustness to hyperparameter variation, and significantly lower computational cost, making them better aligned with real-world forecasting workflows that require frequent retraining. Recent studies (Zhou et al., 2022; Kalfa et al., 2024; Li & Chen, 2024) similarly report that simpler architectures often outperform complex recurrent models in

noisy, low-signal financial settings. Therefore, this chapter's contribution is not tied to the age of the raw data, but to demonstrating which modern DL architectures remain operationally viable and which do not under the specific constraints of high-frequency, walk-forward financial prediction.

By following this dual-phase methodology, the research aims not only to select the most robust model and configuration for stock forecasting but also to demonstrate the predictive potential of incorporating sentiment analysis into financial deep learning systems. The design of both experimental phases will be conducted, and the prediction results will be presented in Chapter 4, with the discussion of the results provided in Chapter 5.

Chapter 4 The S&P 500 experiment in deep learning

This chapter presents the experimental results for S&P 500 price and return prediction using three deep learning architectures—MLP, LSTM, and GRU—while also interpreting the results in relation to the financial-domain characteristics that influence their performance. Each of these models was evaluated under a comprehensive range of hyperparameters—including different activation functions, window sizes, training epochs, and architectural depths—to identify which configurations yield favourable results and to examine whether these techniques are appropriate for financial time-series prediction. These hyperparameters were selected because they directly influence model capacity, temporal sensitivity, and generalisation behaviour—factors that are particularly important when dealing with noisy and weakly autocorrelated financial data.

The performance of each configuration was evaluated using four commonly accepted error metrics: Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), as endorsed in the literature output (Hiransha *et al.*, 2018; Hiransha *et al.*, 2018). Training runtime was also measured to evaluate the efficiency of each model. Prior research suggests that deep learning techniques such as LSTM and GRU are effective for capturing temporal dependencies in financial time series data (Marquering & Verbeek, 2004; Hiransha *et al.*, 2018), though recent works also emphasise that stock returns behave as a random walk (Malafeyev *et al.*, 2019), complicating prediction tasks. To validate the findings statistically, MANOVA and independent t-tests were applied to explore the significance of each model parameter.

The structure of this chapter is organised as follows. Section 4.1 presents results for index price prediction, identifying the top-performing model configurations. Section 4.2 details the more challenging task of index return prediction and interprets why accuracy remains low despite architectural tuning. Section 4.3 provides statistical support to validate the influence of key hyperparameters. Section 4.4 closes the chapter by synthesising all findings and justifying the model chosen for further development.

4.1 Index price prediction results

This section presents the results of the index price prediction. The out-of-sample performance of the three different approaches was evaluated using the 20% of the dataset identified for this purpose. The results of two evaluation metrics, error evaluation (error of testing mode, and the predicted error), and training runtime, are shown in the subsections below.

4.1.1 Error evaluation of testing mode

Table 4-1 shows that, in the testing mode, all three models displayed an error less than 45%, for all activation functions, architecture layers, window sizes, and epochs. Moreover, all three models using the TanH activation function show the smallest error across the four measures. GRU with all activation functions provided the smallest error, while MLP model with Sigmoid yielded a much larger size of error (measured by RMSE, MAE, and MAPE).

Table 4-1: Error rate of different models and activation functions on index price prediction

Activation Function	Technique	Average measure in testing data			
		MSE	RMSE	MAE	MAPE
ReLU	MLP	1.28E+06	1090.18	1051.78	40.50%
	LSTM	1.20E+06	1056.48	1002.1	38.53%
	GRU	1.14E+06	999.26	958.57	36.89%
TanH	MLP	8.81E+05	866.13	822.98	31.48%
	LSTM	7.67E+05	786.84	742.58	28.33%
	GRU	4.01E+05	561.61	516.99	19.54%
Sigmoid	MLP	1.38E+06	1160.69	1112.11	42.68%
	LSTM	1.40E+06	1163.66	1115.45	42.82%
	GRU	1.39E+06	1159.16	1111.49	42.68%

4.1.2 Error evaluation of index price predicted output

Figure 4-1 compares the average error rate of three activation functions for all architecture layers, window sizes, and epochs. The results clearly show that all three models yielded the smallest error rate with the TanH activation function. The GRU model with the TanH function exhibited the best error percentage (31.13%). The Sigmoid function displayed almost no difference across the three models, with an error rate of more than 50% for all three models.

Now focussing on GRU with the TanH activation function, Figure 4-3(a) shows that the GRU with the TanH activation function showed the smallest error (26.56%) when it had 10-epochs training. The graph also shows that the error rate increases as the training epoch increases.

Figure 4-3(b) shows that the lowest error percentage was produced by the 50-training epoch of MLP with window size 21. However, the chart also shows that little difference between epochs. For LSTM, the result is not so clear-cut, as shown in Figure 4-3(c). The training epoch comparison is shown for the average of all window sizes, and reveal that the lowest error as 38.91% for the 20-epoch training. The specifics of the prediction chart for error evaluation for each of the three models are detailed in Appendix C.1.

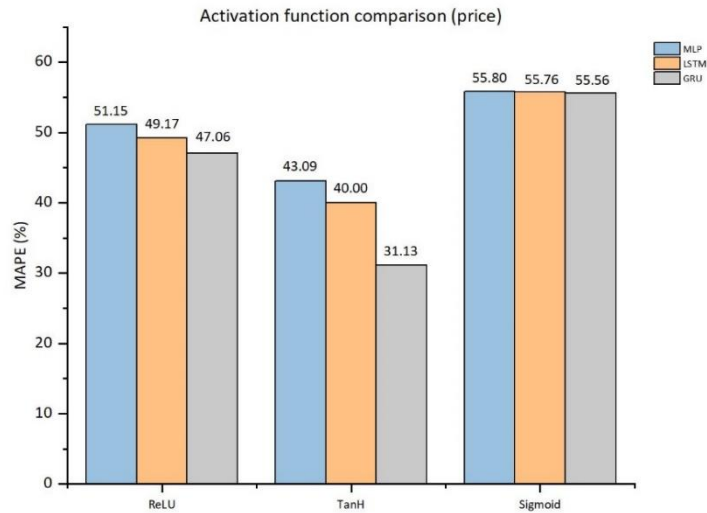


Figure 4-1: Average error rate of all window size, epochs, and architecture across three models on index price prediction

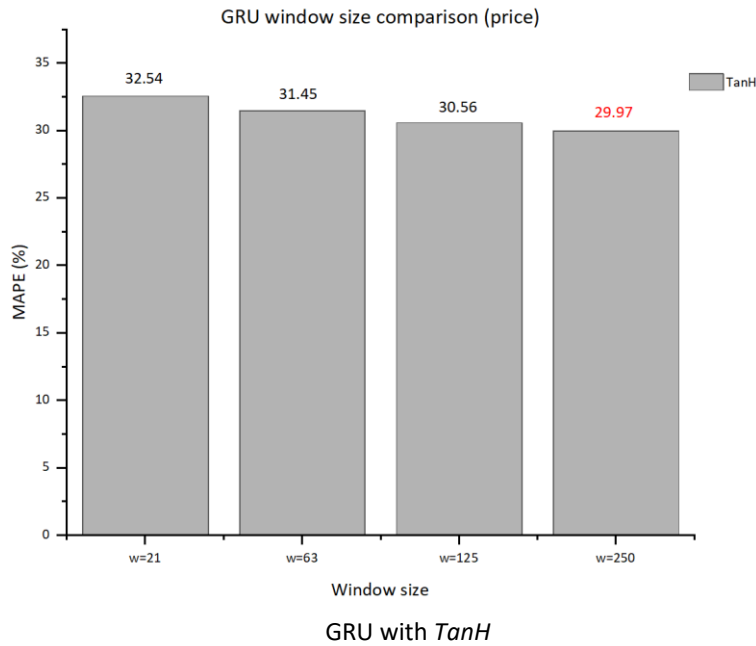


Figure 4-2: Window sizes compared for all epochs when activation function is TanH for GRU

Figure 4-4(a) compares the architecture of the three models with the TanH activation function, using the best GRU window size ($w = 250$) and epoch ($e = 10$). For GRU the best architecture resulted when the number of hidden layers was 1 and the number of nodes was 16. Moreover, it is evident that as n increased, the error rate reduced, but there was little to no trend in h . Figures 4-4(b) and (c) plotted the result for MLP and LSTM, where it is clear that the error rate increases with h but decreases with n , with the exception of $h = 16$, where there is essentially insignificant change in the error rate when n increases. See more details in Appendix C.1.

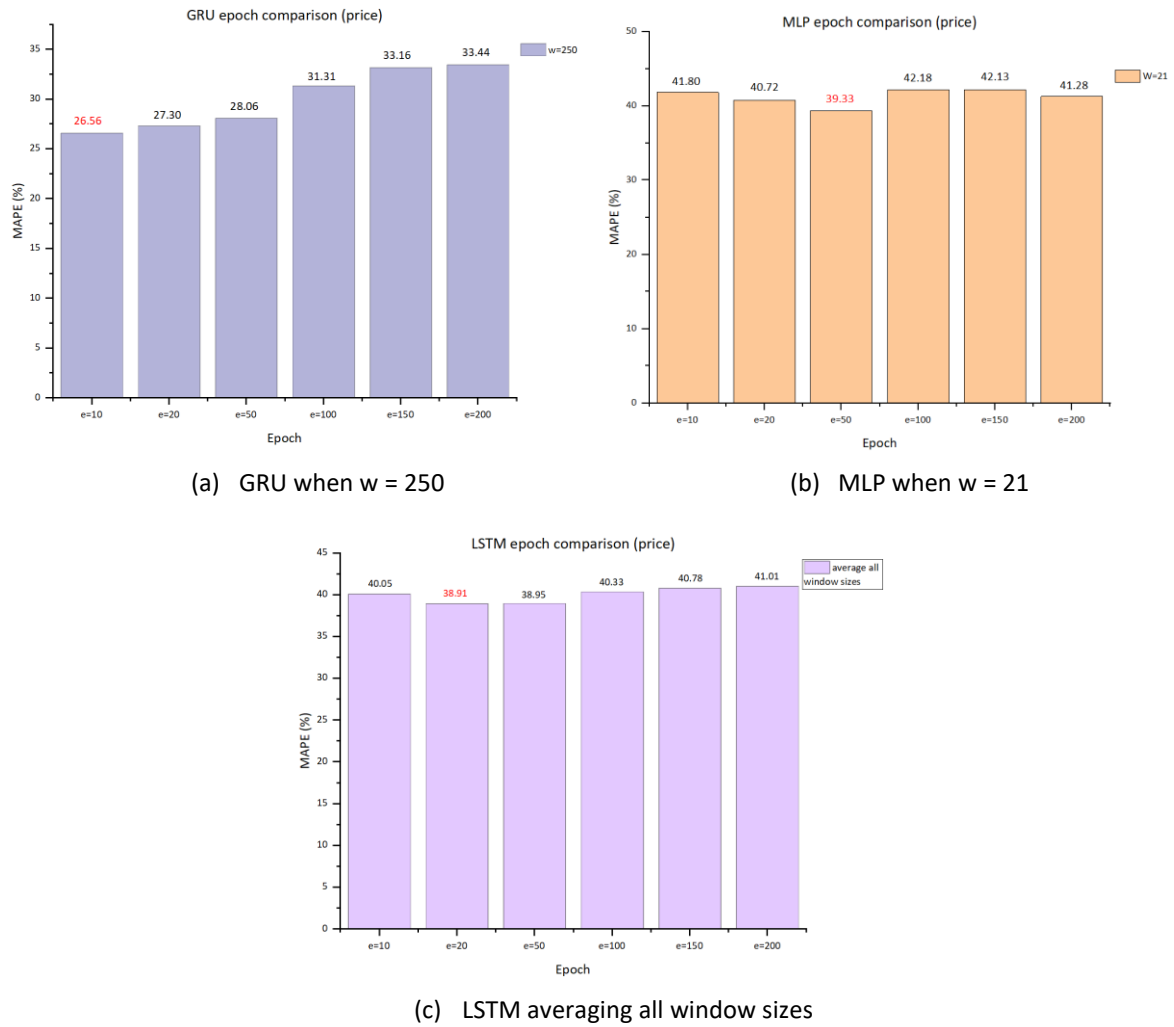
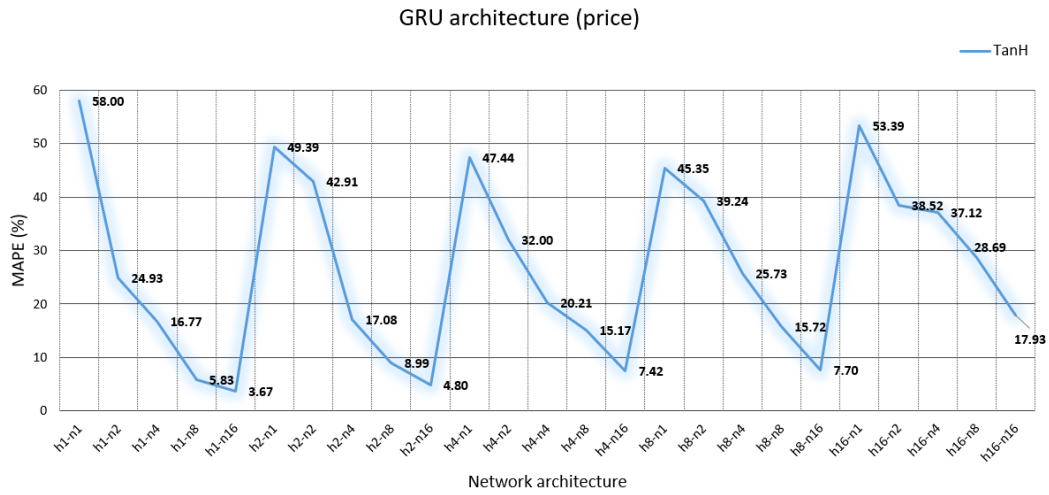


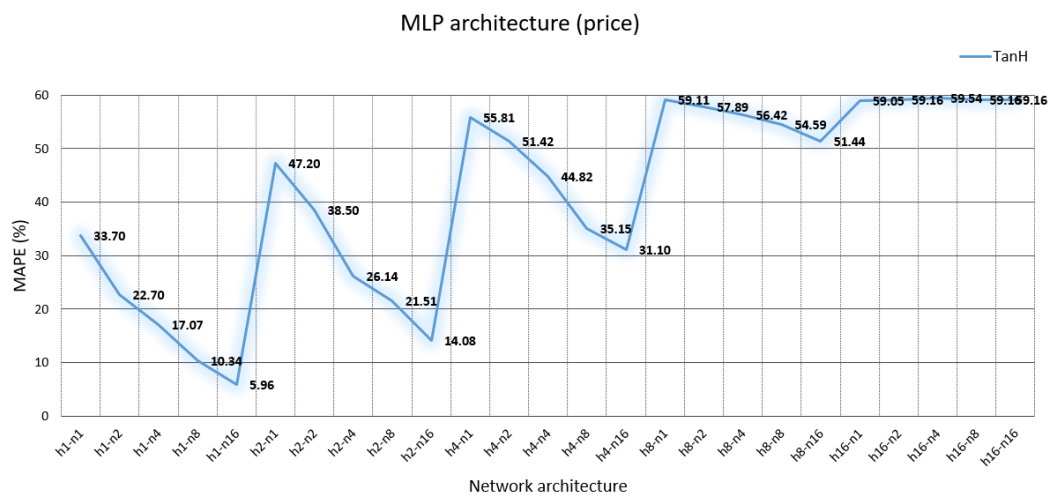
Figure 4-3: Epoch comparison on index price prediction of three models with the TanH activation function

4.1.3 Training runtime for index price

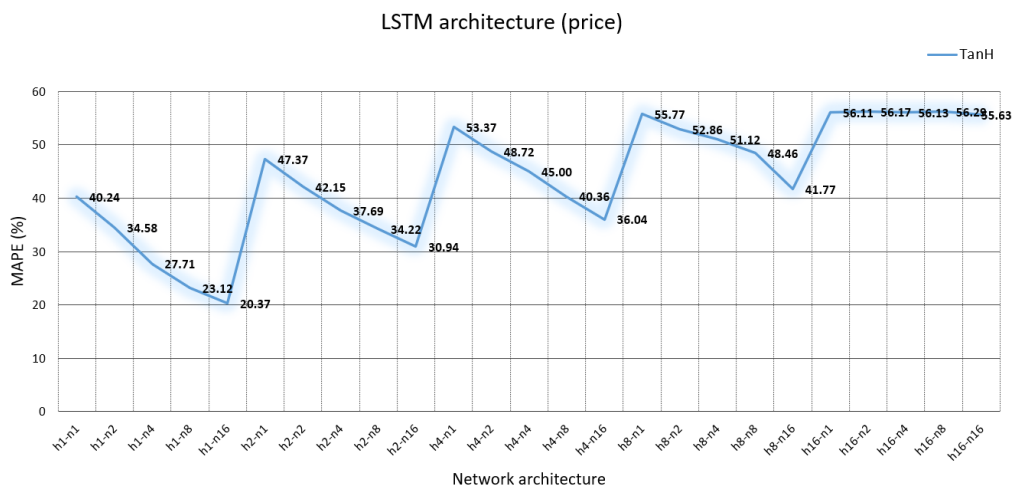
The average training runtime of the model is shown in Table 4-2 and Figure 4-5. The GRU model yielded the slowest training time for all activation functions, while the MLP model was the fastest. The training time of the LSTM and GRU models varied with w , increasing as w became larger, whereas MLP produced a relatively stable training time of 13.79 on average, regardless of w .



(a) GRU when window size = 250 and epoch = 10



(b) MLP when window size = 21 with average all epochs



(c) LSTM with average all window sizes and all epochs

Figure 4-4: Comparison of architectures for all three models with the TanH activation function on index price prediction

Table 4-3 shows the validation loss by activation function of the models. It shows that the validation loss declines as training time increases. However, there is a slight fluctuation in all models with ReLU, and in the MLP model with TanH. For the same training times, the GRU average validation loss is lower than the other two models, especially the TanH activation function. This result corresponds to the accuracy of the test phase, where GRU yielded the highest average prediction accuracy.

Table 4-2: Training runtime in seconds for the techniques and activation

Activation Function	Technique	Average of all epoch sets*				
		w = 21	w = 63	w = 125	w = 250	Average
ReLU	MLP	13.99	14.06	13.95	13.97	13.99
	LSTM	76.93	198.89	399.88	866.14	385.46
	GRU	261.81	758.11	1611.84	3626.31	1564.52
TanH	MLP	12.92	13.73	13.84	13.84	13.58
	LSTM	76.68	197.81	397.45	855.03	381.74
	GRU	260.55	762.81	1616.55	3570.02	1552.48
Sigmoid	MLP	13.86	13.76	13.78	13.82	13.81
	LSTM	77.22	199.88	401.52	862.07	385.17
	GRU	262.32	764.08	1611.51	3574.13	1553.01

*epoch sets = 10, 20, 50, 100, 150, 200

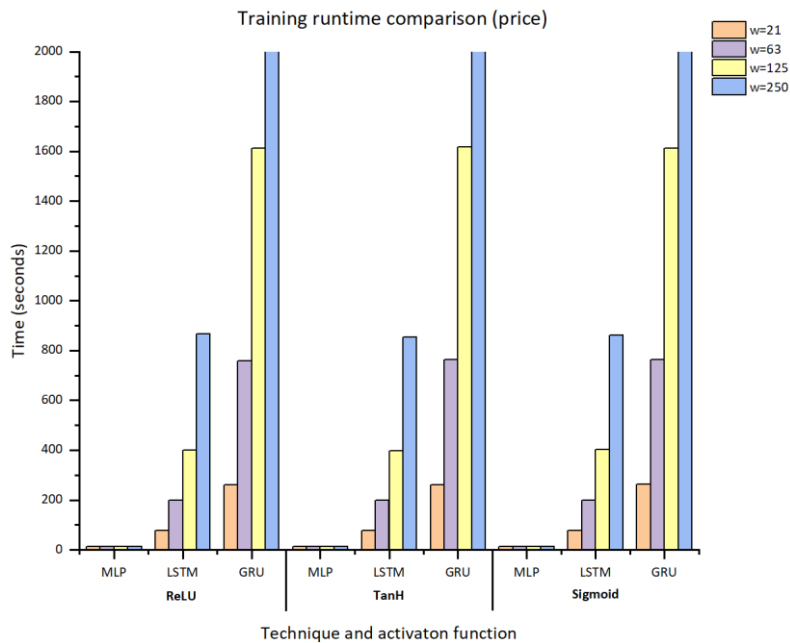


Figure 4-5: Average of training time in seconds for all window sizes on index price

Table 4-3: Average validation loss of three models across different training times
on index price prediction

Training Times (epochs)	Technique								
	ReLU			TanH			Sigmoid		
	MLP	LSTM	GRU	MLP	LSTM	GRU	MLP	LSTM	GRU
10	0.0212	0.0181	0.0629	0.0233	0.0205	0.0131	0.1189	0.1321	0.1312
20	0.0622	0.0152	0.0135	0.0172	0.0145	0.0093	0.0805	0.0690	0.0706
50	0.0152	0.0162	0.0120	0.0199	0.0115	0.0064	0.0399	0.0354	0.0376
100	0.0140	0.0129	0.0114	0.0146	0.0099	0.0055	0.0266	0.0254	0.0250
150	0.0143	0.0124	0.0107	0.0174	0.0093	0.0052	0.0221	0.0209	0.0212
200	0.0140	0.0126	0.0115	0.0138	0.0089	0.0051	0.0195	0.0191	0.0187

4.2 Index return prediction results

This section presents the results of the index return prediction. The experiment was conducted similarly to that for the index price prediction. The results are summarised in the tables and charts in Appendix C.2 and are presented below. Table 4-4 shows the average error rate for the different models and activation functions on index return prediction across all epochs and all window sizes.

Table 4-4: Average error rate of different models and activation functions
on index return prediction

Activation Function	Technique	Average measure in testing data			
		MSE	RMSE	MAE	MAPE
ReLU	MLP	6.59E-05	8.11E-03	5.49E-03	168.85%
	LSTM	6.49E-05	8.06E-03	5.45E-03	158.24%
	GRU	6.43E-05	8.02E-03	5.40E-03	130.64%
TanH	MLP	6.55E-05	8.09E-03	5.50E-03	163.00%
	LSTM	6.54E-05	8.09E-03	5.49E-03	184.82%
	GRU	6.46E-05	8.04E-03	5.43E-03	146.57%
Sigmoid	MLP	6.72E-05	8.12E-03	5.53E-03	160.98%
	LSTM	6.51E-05	8.06E-03	5.46E-03	164.01%
	GRU	7.13E-05	8.33E-03	5.79E-03	215.20%

4.2.1 Error evaluation of testing mode

Table 4-4 shows that the error rate was almost the same value for all measurement techniques. However, GRU with Sigmoid provided the highest error rate across the four measures (0.33), but GRU gave the lowest error when the activation function was ReLU or TanH. Meanwhile, MLP with ReLU and TanH gave a higher error than the other two models, but MLP gave a lower error than the others when the activation function was Sigmoid.

4.2.2 Error evaluation of predicted output

Figure 4-6 shows that MLP and LSTM with ReLU, and LSTM with TanH, provided the lowest average error rate at 97.20%, 97.28%, and 96.91% respectively, but the results did not differ significantly. The chart shows that the result of GRU with ReLU and with TanH have lower error rates than the result of GRU with sigmoid.

LSTM and GRU were unable to clearly identify the best activation function. Therefore, to identify the window size that generates the lowest error, both ReLU and TanH activation functions results of the three models were examined, and are shown in Figure 4-5 (the number on the graph shows the lowest error rate of each model). It is apparent that MLP with ReLU ranked first (93.53%) when $w = 63$, followed by LSTM with TanH when $w = 125$ (95.62%). For GRU, the chart shows the smallest error when paired with ReLU at $w = 21$ (99.52%), but the result is hardly different from its TanH activation function. These experimental results suggest that none of the models was outstanding across all four window sizes.

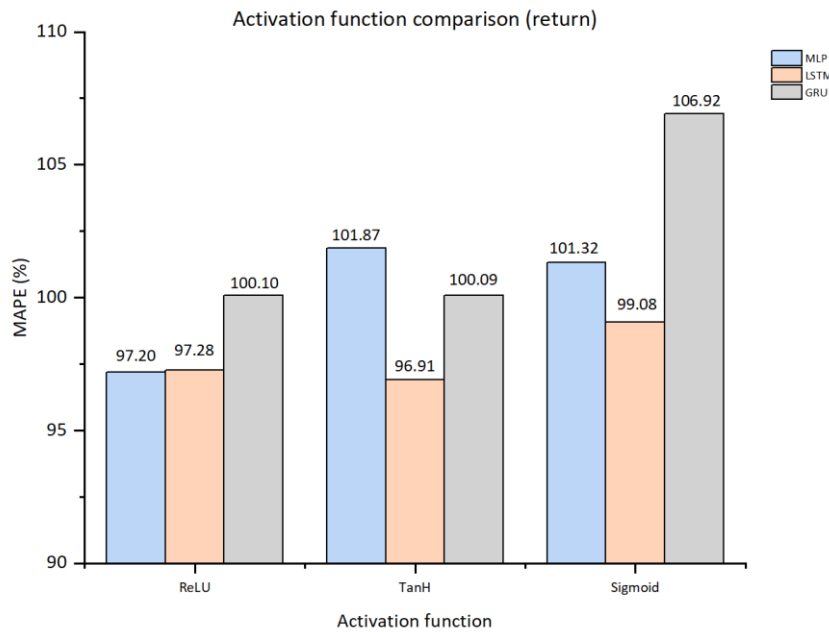


Figure 4-6: Average error rate of all parameters across three models on index return prediction

For MLP with ReLU, Figure 4-8 (a) compares all the epochs and $w = 63$. The lowest error rate occurs at $e = 50$ (90.64%). Figure 4-8 (b), for LSTM with TanH and $w = 125$, the training epoch of 10 gave the lowest error (92.62%), while Figure 4-8 (c), for GRU with ReLU and $w = 21$, the smallest error occurred when $e = 100$ (96.93%). Indeed, the result for GRU was nearly the same for all training epochs beyond 10. Error evaluation information for all models is given in Appendix C2.1.

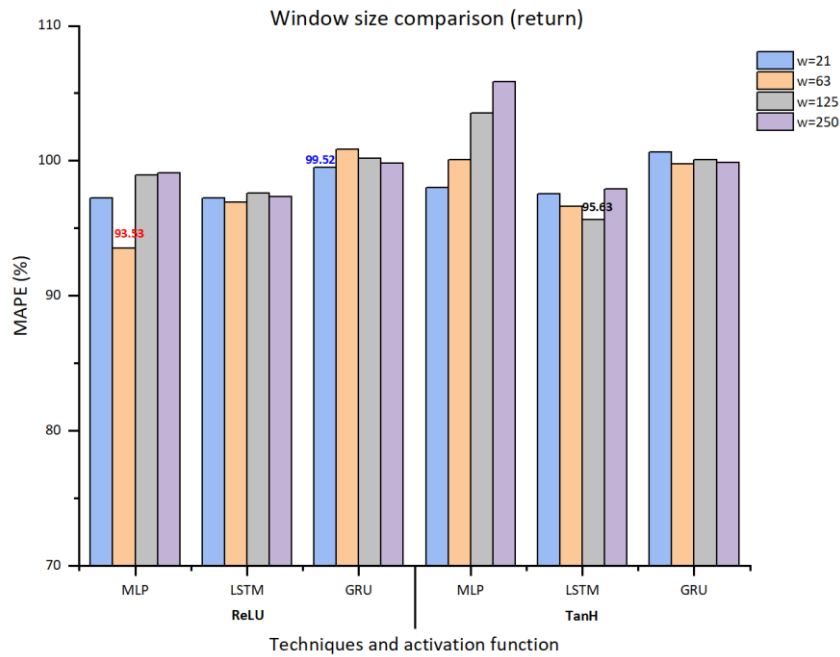


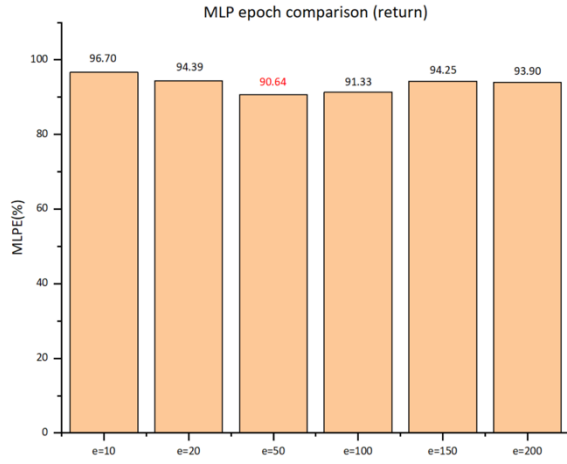
Figure 4-7: Average error rate for all epochs of three models when activation function is ReLU and TanH for index return prediction

When compared by architecture, none of the models showed a trend in the error rate, as shown in Figures 4-8 (a-c). There are fluctuations in all the architectures across all three models. When considering the average of all window sizes and all epochs (see Figure C.9-17 in Appendix C2.1), TanH and ReLU activation functions with all three models provided an average error (all window sizes and all epochs) between 70% and 120%. At the same time, Sigmoid was more volatile, with a mean between 90% and 160%.

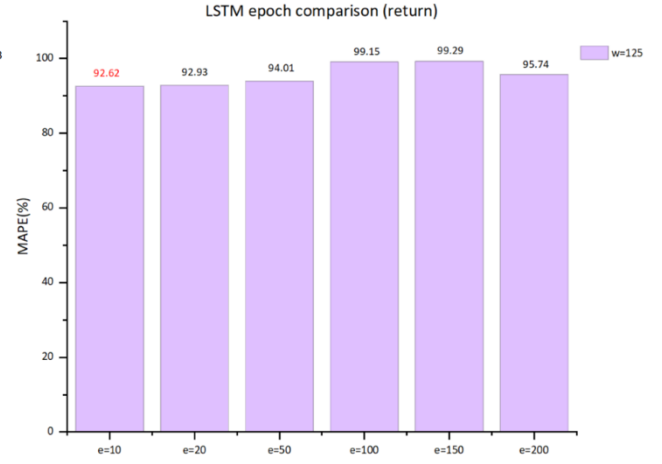
4.2.3 Training runtime

The average training runtime of the model is shown in Table 4-5 and Figure 4-10, for all epoch sets. The larger the w , the greater the training time taken by LSTM and GRU, but it did not affect MLP. MLP provided a stable training time of 10.78 seconds on average. MLP showed the fastest training time, while GRU showed the slowest time, for all window sizes.

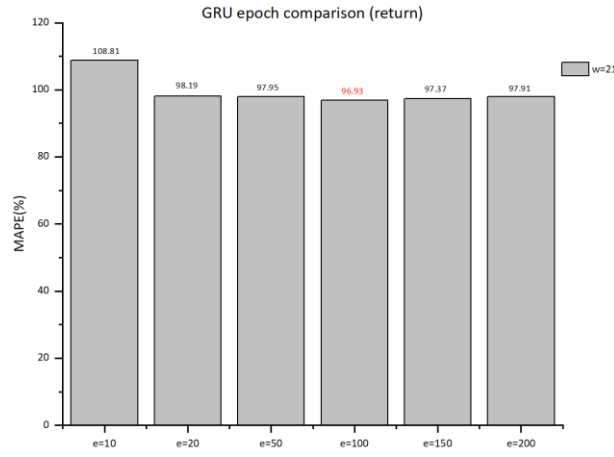
Table 4-6 shows the validation loss mostly continuously declined as training epochs increased, except LSTM with ReLU and TanH, and MLP with Sigmoid, which had a slight fluctuation. At the same training points, the average validation loss of MLP was lower than the other two models, ReLU and TanH.



(a) MLP with ReLU when $w=63$



(b) LSTM with TanH when $w=125$

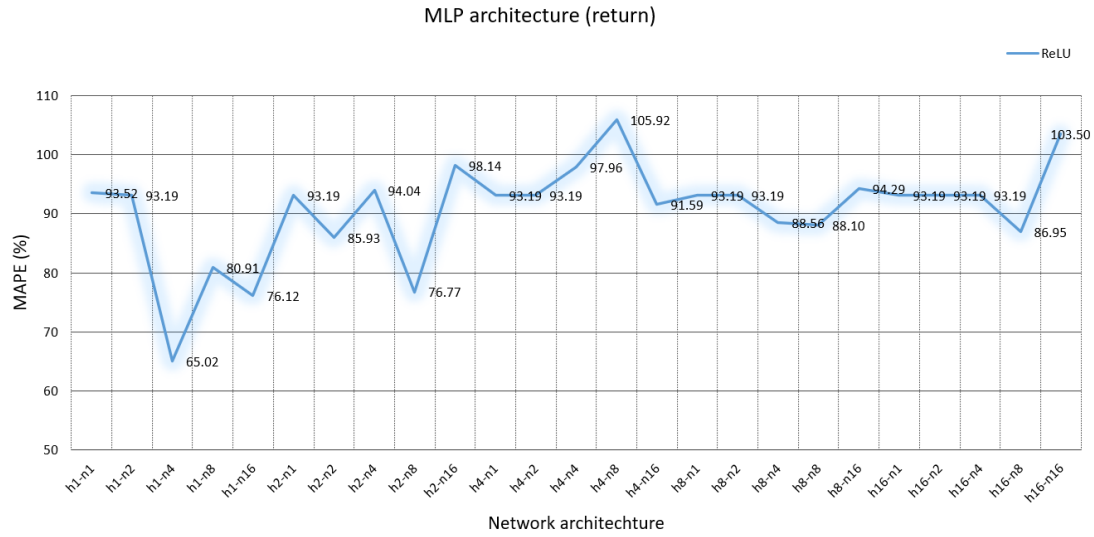


(c) GRU with ReLU when $w=21$

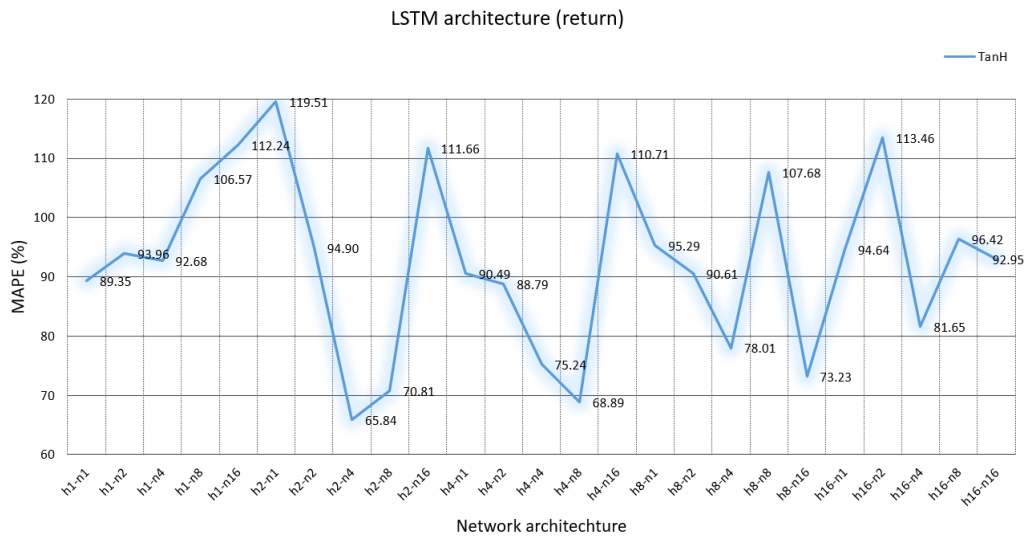
Figure 4-8: Epoch comparison of three models on index return prediction

4.3 Statistical analysis of the results

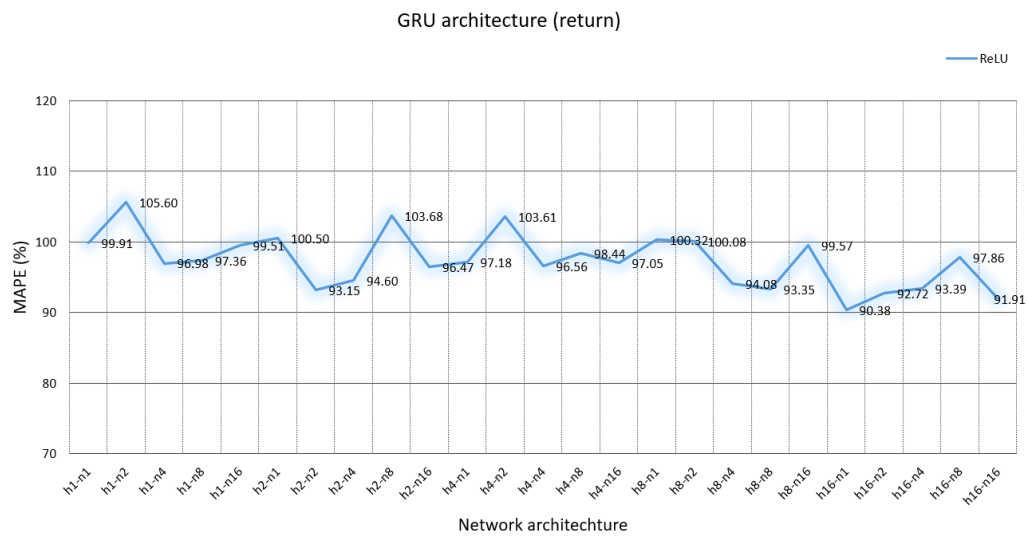
Both price and return prediction results were tested once with Python, and then by multivariate analysis of variance (MANOVA). The analysis compared whether both results were consistent. MANOVA analysis was suitable for identifying statistical differences among the means of several dependent variables. The MANOVA analysis was used to compare the three models (MLP, LSTM, and GRU) to find the mean differences between the groups across activation functions, hidden layers, nodes, window sizes, and epochs. All the MANOVA of index price and index return prediction results and discussion are shown in Appendix D. *Wilks' Lambda distribution* was used to detect statistically significant differences.



(a) MLP with ReLU when $w = 63$ and $e = 50$



(b) LSTM with TanH when $w = 125$ and $e = 10$



(c) GRU with ReLU when $w = 21$ and $e = 100$

Figure 4-9: Comparison of architectures for all three models on index return prediction

Table 4-5: Average training runtime in seconds of different techniques and activation functions across each window size on index return prediction

Activation Function	Technique	Average of all epoch sets*				
		w = 21	w = 63	w = 125	w = 250	Average
ReLU	MLP	11.02	10.79	10.72	10.71	10.81
	LSTM	73.06	192.9	373.41	841.97	370.33
	GRU	273.27	775.98	1623.26	3622.9	1573.85
TanH	MLP	10.84	10.76	10.69	10.84	10.78
	LSTM	72.65	192.77	397.09	858.82	380.33
	GRU	264.23	778.89	1644.83	3623.82	1577.94
Sigmoid	MLP	10.84	10.76	10.73	10.75	10.77
	LSTM	72.49	193.59	396.67	850.28	378.26
	GRU	261.22	784.5	1633.53	3648.63	1581.97

*epoch sets = 10, 20, 50, 100, 150, 200

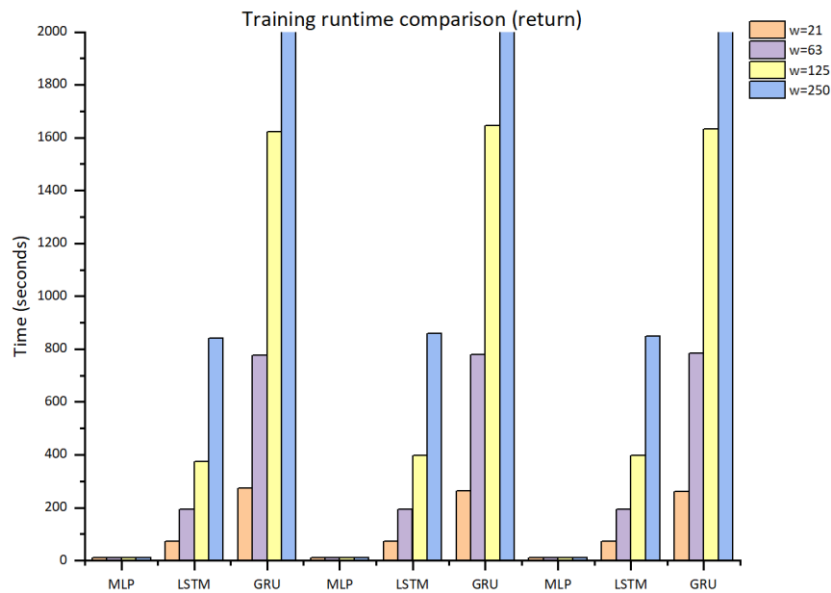


Figure 4-10: Average of training time for all epochs on index return prediction

The statistical analysis rigorously evaluates the influence of key hyperparameters—activation function, window size, training epochs, number of hidden layers, and number of nodes—on the predictive performance of deep learning models (MLP, LSTM, GRU) for both S&P 500 index price and return forecasting.

Using Multivariate Analysis of Variance (MANOVA) and independent samples t-tests, the analysis reveals that:

Table 4-6: Average validation loss of three models across different training time
on index return prediction

Training Times (epochs)	<i>Technique</i>								
	<i>ReLU</i>			<i>TanH</i>			<i>Sigmoid</i>		
	<i>MLP</i>	<i>LSTM</i>	<i>GRU</i>	<i>MLP</i>	<i>LSTM</i>	<i>GRU</i>	<i>MLP</i>	<i>LSTM</i>	<i>GRU</i>
10	0.0089	0.0111	0.0109	0.0020	0.0026	0.0047	0.0285	0.0163	0.0453
20	0.0054	0.0065	0.0067	0.0019	0.0021	0.0040	0.0074	0.0129	0.0106
50	0.0030	0.0032	0.0035	0.0016	0.0017	0.0022	0.0068	0.0048	0.0065
100	0.0022	0.0024	0.0025	0.0016	0.0018	0.0021	0.0027	0.0037	0.0042
150	0.0020	0.0027	0.0021	0.0016	0.0016	0.0018	0.0036	0.0031	0.0042
200	0.0019	0.0020	0.0019	0.0016	0.0016	0.0017	0.0023	0.0025	0.0031

For index price prediction, the activation function and architectural depth (hidden layers and nodes) have a statistically significant effect on model performance across all error metrics. Notably, the TanH activation function consistently yields the lowest prediction errors for GRU and LSTM models. Simpler architectures (fewer layers and nodes) also tend to result in lower error and faster training times, with GRU emerging as the most effective but computationally intensive model.

For index return prediction, however, none of the hyperparameters—including model type, activation function, or network configuration—show a statistically significant impact on improving prediction accuracy. Errors remain consistently high (>90%) regardless of configuration, confirming that historical data alone is insufficient for effective return forecasting.

Overall, the statistical tests confirm the earlier empirical findings: hyperparameter tuning can meaningfully enhance price prediction, but not return prediction. These insights provide empirical justification for the transition to sentiment-enhanced models in the next chapter.

4.4 Discussion of the results

The results of index price prediction (4.1) and index return prediction (4.2) indicated that there was no clear best technique, since no one technique outperforms all the others across the three metrics. However, the experiments in this chapter have led to the following findings, which help answer the first research question.

4.4.1 Prediction performance

GRU was the best technique and yielded the lowest error rate for index price prediction. The findings pointed to the TanH activation function as the one that offered the lowest error in all three models. LSTM ranked second, followed by MLP. The statistical analysis showed that the activation function had a significant effect on the prediction performance of the three models.

In the case of index return prediction, no activation function provided the lowest or the highest error across the three models. Based on the average of all parameters, it was determined that LSTM with TanH performed the best, followed by MLP (with *ReLU*) and LSTM (with *ReLU*). When window sizes and epochs were also considered, however, MLP demonstrated a lower mean prediction error than LSTM when MLP was trained with ReLU, $w=21$, and $e=50$. According to the results of the multivariate test, the activation function had a significant impact on the performance of the three models in terms of prediction. However, the comparison of activation functions between groups revealed that there is a significant difference between the three activation functions in GRU and LSTM but not in MLP.

4.4.2 Training Time

MLP yielded the fastest training time prediction for both index price and index return, which was quite stable even when changing w . LSTM ranked second for training time models, but took considerably more time than GRU. Moreover, the training time for LSTM and GRU varied with the size of w . The different activation functions did not affect the training time. In summary, both index price and index return yielded the same, see Table 4-7. The addition of more complexity did not decrease the prediction error for index price prediction. Moreover, the complex architecture increased not only the training time but also the validation loss. Therefore, a slimmer architecture with small h and n would perform well on this dataset. On the other hand, it was not clear which architecture was suitable for index return prediction.

Table 4-7: Average training time of all epochs and window sizes compared

Activation function	Average Training Time (sec)					
	Index Price			Index Return		
	MLP	LSTM	GRU	MLP	LSTM	GRU
ReLU	13.99	381.74	1563.53	10.81	370.33	1573.85
TanH	13.58	380.16	1552.48	10.78	380.33	1577.94
Sigmoid	13.81	385.17	1553.01	10.77	378.26	1581.97

4.4.3 Parameter Analysis

The network configuration $h = 1$, $n = 16$ was the best architecture, which provided the lowest error for index price prediction, and the results in section 4.1.3 support this finding (see Appendix Tables C.1 to C.3). These results suggest that the performance of predictions may improve as n increases. MLP produced the best average prediction error across all activation functions when $w = 21$, while GRU with TanH showed the best average prediction error prediction when $w = 250$, but LSTM could not clearly identify the best window size. However, statistical testing did reveal that window size had no effect on the predictive performance of any of the three models, but only on training time.

Neither window size nor epoch provided the lowest error for index return prediction (see Appendix Tables C.4 to C.6). These findings are consistent with the tests of between-group effects, which determined that neither window size nor epoch had an impact on the predictive performance. MLP with ReLU and Sigmoid, $h = 1$ and $n = 4$ provided the best prediction error, while $h = 1$ and $n = 1$ was best for the TanH activation function. GRU and LSTM did not clearly identify a network architecture. A summary of the parameters for all three techniques is shown in Table 4-8.

Table 4-8: Parameter summary of different techniques and activation functions
on the index price and index return predictions

	Parameter	ReLU			TanH			Sigmoid		
		MLP	LSTM	GRU	MLP	LSTM	GRU	MLP	LSTM	GRU
Index Price Prediction	w	N/E	N/E	N/E	N/E	N/E	N/E	N/E	N/E	N/E
	e	N/E	N/E	N/E	N/E	N/E	N/E	N/E	N/E	N/E
	h, n	1, 16	1, 16	1, 16	1, 16	1, 16	1, 16	1, 16	1, 16	1, 16
Index Return Prediction	w	63	N/E	N/E	21	N/E	N/E	63	N/E	N/E
	e	N/E	N/E	N/E	N/E	N/E	N/E	N/E	N/E	N/E
	h, n	1, 4	N/A	N/A	1, 1	N/A	N/A	1, 4	N/A	N/A

N/E = No Effect N/A = Not Applicable

The substantial error rates observed in this research—particularly for index return prediction—are not incidental but reflect inherent structural limitations within both the dataset and the experimental design. As demonstrated throughout this Chapter, the S&P 500 return series displays an exceptionally low signal-to-noise ratio, a characteristic consistent with the random-walk behaviour widely reported in financial economics (Malafeyev et al., 2019; Marquering & Verbeek, 2004). Consequently, daily returns contain minimal deterministic information for deep learning models to learn, resulting in persistently high error rates (exceeding 90%) across all architectures, activation functions, window sizes, and training epochs, as evidenced in Tables 4-4 and Figures 4-6 to 4-9. A further contributing factor concerns the segmentation of historical data into fixed window sizes (21–250 days). While such windows capture price dynamics and short-term temporal dependencies, they offer limited predictive value for future returns, which are largely dominated by noise and weak serial correlation (Bodie et al., 2018). This distinction explains why hyperparameter optimisation produced measurable improvements in index price prediction but yielded negligible gains for return forecasting. Additionally, the exclusive use of closing prices—without supplementary information such as technical indicators, market microstructure variables, macroeconomic indicators, or sentiment data—reduces the informational richness of the input features available to the models, a limitation also noted in previous empirical research (Hiransha et al., 2018). The MANOVA results reported in Section 4.3 further corroborate this interpretation, showing that none of the hyperparameters exerted a statistically

significant effect on return prediction accuracy. Accordingly, the observed prediction boundary is attributable to data constraints rather than model configuration. Future work may therefore investigate alternative modelling strategies, such as predicting directional movement rather than continuous returns, adopting volatility-normalised transformations, experimenting with alternative windowing procedures, or incorporating exogenous predictors such as investor sentiment (Jiang, 2021). These extensions, introduced in Chapter 5, have the potential to enhance the structural sophistication of the modelling process and may contribute to reducing the magnitude of forecasting errors reported in this chapter.

The findings of this chapter demonstrate that model performance in financial forecasting cannot be understood merely by comparing raw error rates; rather, the key insight lies in understanding *why* certain architectures outperform others under the constraints of noisy, weakly autocorrelated financial data. The consistently high error rates in return prediction are not an indication of model failure but evidence of structural market properties—specifically, the near-random-walk behaviour of daily returns and the limited predictive value of past return sequences. Techniques that successfully suppress error in this domain are therefore those that minimise overfitting to noise, stabilise training across rolling windows, and maintain computational feasibility for frequent retraining. The results indicate that MLP achieves this balance most effectively: its shallow architecture avoids the error amplification observed in deeper or recurrent networks, its ReLU activation supports stable gradient flow, and its low computational cost enables practical deployment in environments where models must be re-estimated daily. In contrast, LSTM and GRU, while theoretically suited for sequential data, offer negligible gains in accuracy and disproportionately high training times, making them inappropriate for real-time financial applications that demand both efficiency and robustness. Thus, this chapter not only compares models but identifies the architectural principles—parsimony, stability, and computational efficiency—that are essential to achieving the lowest error levels possible within the constraints of stock-return forecasting.

4.5 Summary

This experiment has conducted a comparative analysis of prediction methods for the S&P 500 index performance. The study utilised end-of-day stock index values (historical index prices) and their corresponding percentage changes (historical index returns).

A stock index price is an aggregate measure representing the performance of a selected group of stocks, calculated from their individual prices. Changes in the index provide an indication of the collective performance of the underlying listed stocks (Bodie, Kane, & Marcus, 2018). On trading days, the index price data comprises four distinct types: opening price, closing price, lowest price, and highest price. For the purpose of this experiment, only the closing prices were used, as these serve as

critical indicators for investors to evaluate the performance of the index over specified periods (Hiransha et al., 2018).

However, the existing literature on stock market predictability highlights that stock prices generally follow a random walk, implying no economically exploitable predictable pattern exists (Marquering & Verbeek, 2004; Malafeyev et al., 2019). Although stock prices may exhibit trends, these are not indicative of consistent patterns or predictable movements. Consequently, price changes are typically independent of historical price fluctuations (Malafeyev et al., 2019). Therefore, most existing research integrates additional factors such as technical indicators, financial news, and exchange rates alongside historical prices to improve future price prediction accuracy.

A notable limitation identified in prior studies is their reliance on a single deep learning approach with specific activation functions and architectures. To address this gap, the current research explored three prominent deep learning methods: Multi-Layer Perceptron (MLP), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). Each method was systematically evaluated across:

- Three activation functions (ReLU, Sigmoid, TanH).
- Four different data window sizes (1, 3, 6, and 12 months) to ascertain optimal prediction intervals.
- Six different training epochs (10, 20, 50, 100, 150, 200) to evaluate model convergence.
- Five distinct architectural configurations (1, 2, 4, 8, and 16 layers) to determine optimal structural complexity.

This chapter detailed the experimental design, methodological decisions, and sequential stages implemented to select the most effective prediction technique and address the first sub-research question. The findings demonstrated that GRU delivered the highest accuracy in predicting index prices; however, it required significantly longer training times—five times longer than LSTM and ten times longer than MLP. Furthermore, the experimental results indicated sensitivity to minor changes in model parameters, notably affecting prediction accuracy. In contrast, when predicting returns, variations in parameters did not substantially influence prediction outcomes.

Among the tested models, MLP produced the lowest error in return prediction; however, the error rate remained notably high, suggesting inherent unpredictability in return data using these techniques. Although MLP demonstrated marginally superior average forecasting accuracy compared to LSTM and GRU, the differences were statistically insignificant. Given the faster training speed of MLP relative to other methods, it was selected for subsequent experiments. Moreover, the absence of clear trends in index returns underscores the limitations of solely using historical data for return predictions,

highlighting the potential value of incorporating external information, such as investor sentiment, to enhance predictive performance.

Chapter 5 S&P 500 index return prediction using news sentiment

Chapter 4 revealed that stock return prediction exhibited a significantly high error rate, exceeding 90%, whereas stock price prediction demonstrated comparatively lower error rates ranging from 30% to 60%. These findings indicated that relying solely on historical price or return data was inadequate for achieving accurate predictions—particularly in the case of stock return, where all three deep learning models produced errors above 90%. As a result, the research focus was directed toward improving the accuracy of stock return prediction. This chapter specifically addresses the remaining research question: whether incorporating investor sentiment can enhance predictive performance. The central aim is to determine if sentiment information, derived from financial news related to companies within the S&P 500 index, can meaningfully improve the accuracy of stock return forecasts.

This chapter presents the results of forecasting S&P 500 index returns using sentiment derived from financial news. A total of 13 datasets—both with and without sentiment features—were employed to assess the predictive performance of the deep MLP model. Section 5.1 outlines the experimental results, including evaluation of prediction error in the testing phase, next day return forecasts, and training runtime. Section 5.2 analyses the correlation and mean differences between dataset groups across various hyperparameter configurations. Section 5.3 provides a detailed discussion of the experimental findings, while Section 5.4 concludes the chapter with a summary of key insights.

5.1 Experimental Results

This section reports all outcomes of the experiment. These results were conducted using a deep MLP model with 13 datasets to determine which one would enable the model to provide the best performance. Each dataset utilised unique data characteristics and sentiment score periods that were compared to the baseline dataset (daily stock index return only). In addition, the deep MLP was tested with different hyperparameters, activation functions, the numbers of hidden and node layers, window sizes, and training epochs. The output consisted of three subsections: the error evaluation of testing mode, prediction outcomes, and training runtime.

5.1.1 Error evaluation of testing mode

Table 5-1 displays the error measurement of the model in testing mode for each of the 13 datasets. The findings display the average error of all activation functions, window sizes, architecture layers, and epochs and reveal that dataset *a* (using historical return only) achieved less error across four error measurements and three activation functions than the remaining 12 datasets. For all 12 datasets (using

historical return and including various sentiment scores), dataset *i* exhibited the smallest error across four error measures when the activation function was *ReLU* and *TanH*, whereas dataset *j* exhibited the smallest error when the activation function was *Sigmoid*.

5.1.2 Prediction outcomes

The percentage error of MAPE was used to calculate the error rate in the predicted output (Hiransha *et al.*, 2018). The prediction results of data feature *a* (using historical return only) were compared to those of the remaining 12 data features (historical return with sentiment scores).

Figure G.1-1 in Appendix G shows that *TanH* was the best activation function (with the smallest average error) for ten of the thirteen datasets. However, the best average activation functions for datasets *d*, *f*, and *g* (current-day with four features, 1-day with 3 features, and 1-day with four features) were *ReLU*, *Sigmoid*, and *ReLU*, respectively. If only the data features with sentiment ratings are considered, dataset *i* achieved the lowest average prediction error (1139%) with *TanH*.

Figure 5-1 depicts the results of a comparison of the window size (*w*) across all three activation functions. *w*21 had the lowest average prediction error rate across all 13 datasets. *TanH* was the best activation function for dataset *a* across all four window sizes, with the lowest average prediction error at window size *w*21, and an increasing tendency for error as *w* increased. With the *Sigmoid* activation function, dataset *i* (3 days with 3 features) showed the lowest average rate of prediction error (75%) among the 12 datasets. The results for dataset *a* suggested that the average proportion of incorrect predictions was 613%, which looked to be the greatest among sentiment datasets (see more results in Figure F.1 to F.2 in Appendix F).

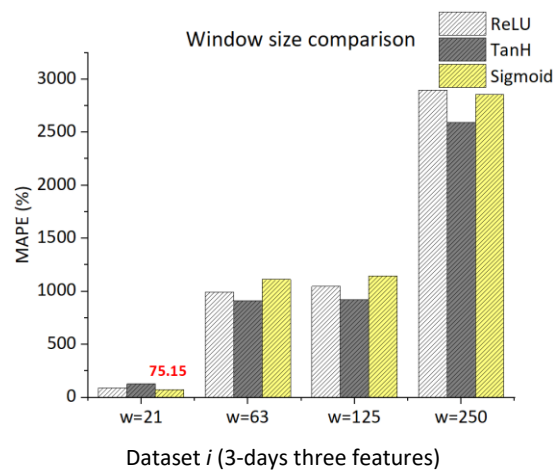


Figure 5-1: Window size comparison for all epoch across three activation functions

Table 5-1: Error rate for different activation functions on 13 datasets in testing mode

Activation function	Data feature	Average measure in testing data			
		MSE	RMSE	MAE	MAPE
ReLU	<i>a</i>	0.0012	0.0301	0.0232	519.18
	<i>b</i>	0.0045	0.0665	0.0636	2053.75
	<i>c</i>	0.0030	0.0539	0.0506	1611.30
	<i>d</i>	0.0031	0.0541	0.0508	1618.12
	<i>e</i>	0.0024	0.0470	0.0433	1350.67
	<i>f</i>	0.0034	0.0573	0.0542	1733.42
	<i>g</i>	0.0034	0.0573	0.0542	1734.67
	<i>h</i>	0.0039	0.0614	0.0584	1872.84
	<i>i</i>	0.0020	0.0431	0.0392	1207.66
	<i>j</i>	0.0021	0.0437	0.0398	1229.92
	<i>k</i>	0.0051	0.0708	0.0679	2191.68
	<i>l</i>	0.0025	0.0481	0.0444	1394.76
	<i>m</i>	0.0025	0.0481	0.0444	1394.76
TanH	<i>a</i>	0.0008	0.0273	0.0195	392.80
	<i>b</i>	0.0039	0.0614	0.0578	1844.30
	<i>c</i>	0.0028	0.0513	0.0472	1498.03
	<i>d</i>	0.0028	0.0513	0.0473	1500.70
	<i>e</i>	0.0019	0.0426	0.0380	1154.55
	<i>f</i>	0.0031	0.0554	0.0518	1651.30
	<i>g</i>	0.0032	0.0554	0.0520	1657.53
	<i>h</i>	0.0034	0.0571	0.0531	1673.44
	<i>i</i>	0.0017	0.0399	0.0351	1075.16
	<i>j</i>	0.0019	0.0408	0.0362	1114.83
	<i>k</i>	0.0044	0.0652	0.0613	1950.89
	<i>l</i>	0.0022	0.0458	0.0410	1280.44
	<i>m</i>	0.0022	0.0458	0.0410	1280.44
Sigmoid	<i>a</i>	0.0019	0.0324	0.0257	598.32
	<i>b</i>	0.0054	0.0702	0.0675	2183.65
	<i>c</i>	0.0034	0.0554	0.0522	1661.04
	<i>d</i>	0.0038	0.0567	0.0535	1704.25
	<i>e</i>	0.0032	0.0503	0.0467	1466.00
	<i>f</i>	0.0037	0.0583	0.0552	1767.91
	<i>g</i>	0.0040	0.0596	0.0565	1810.55
	<i>h</i>	0.0047	0.0656	0.0628	2021.59
	<i>i</i>	0.0025	0.0450	0.0411	1271.44
	<i>j</i>	0.0024	0.0441	0.0403	1244.60
	<i>k</i>	0.0059	0.0746	0.0720	2330.95
	<i>l</i>	0.0028	0.0496	0.046	1448.44
	<i>m</i>	0.0028	0.0496	0.046	1448.44

a is one feature data (historical return)

b is current-day two features (historical return and compound scores)

c is current-day three features (historical return, negative, and positive)

d is current-day four features (historical return, negative, neutral, and positive)

e is 1-day two features (historical return and compound scores)

f is 1-day three features (historical return, negative, and positive)

g is 1-day four features (historical return, negative, neutral, and positive)

h is 3-days two features (historical return and compound scores)

i is 3-days three features (historical return, negative, and positive)

j is 3-days four features (historical return, negative, neutral, and positive)

k is 5-days two features (historical return and compound scores)

l is 5-days three features (historical return, negative, and positive)

m is 5-days four features (historical return, negative, neutral, and positive)

Figure 5-2 compares the set of epochs to the best window size ($w=21$). It shows that dataset j with *Sigmoid* maintained its strong prediction performance relative to the other 12 datasets, with an average prediction error of 18% when the epoch was 150. Obviously, epoch sizes greater than 50 enable the model to attain improved prediction performance across all 13 datasets. The dataset without sentiment scores tended to achieve a high level of predictive power as the epoch progressed but still received a higher average predictive error than some datasets (i and j), see more details in Figure G.1-3 in Appendix G. However, for the sentiment datasets, none of the epochs emerged as best across all 12 datasets and three activation functions. The network architecture was investigated, based on the characteristics of the best parameters for each dataset.

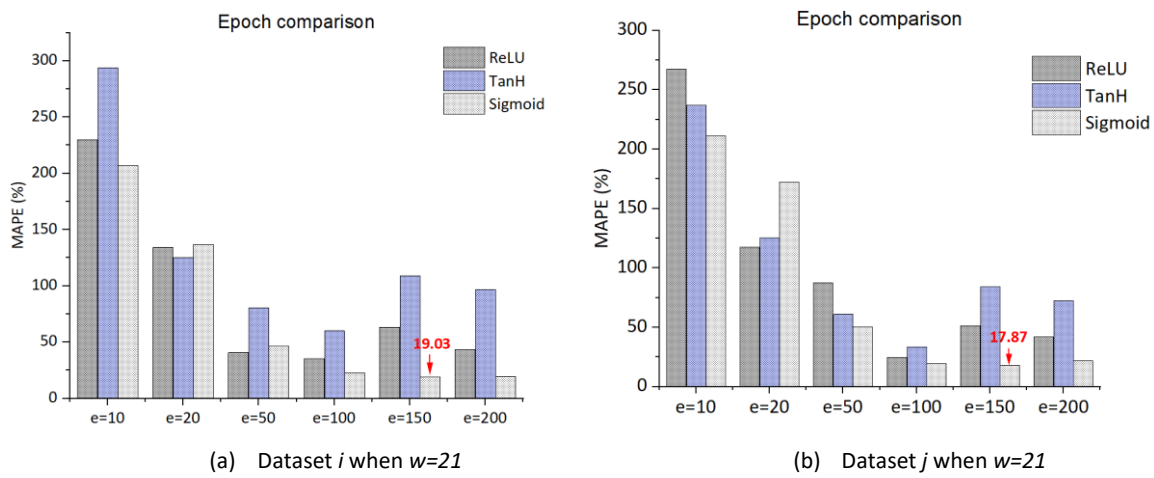
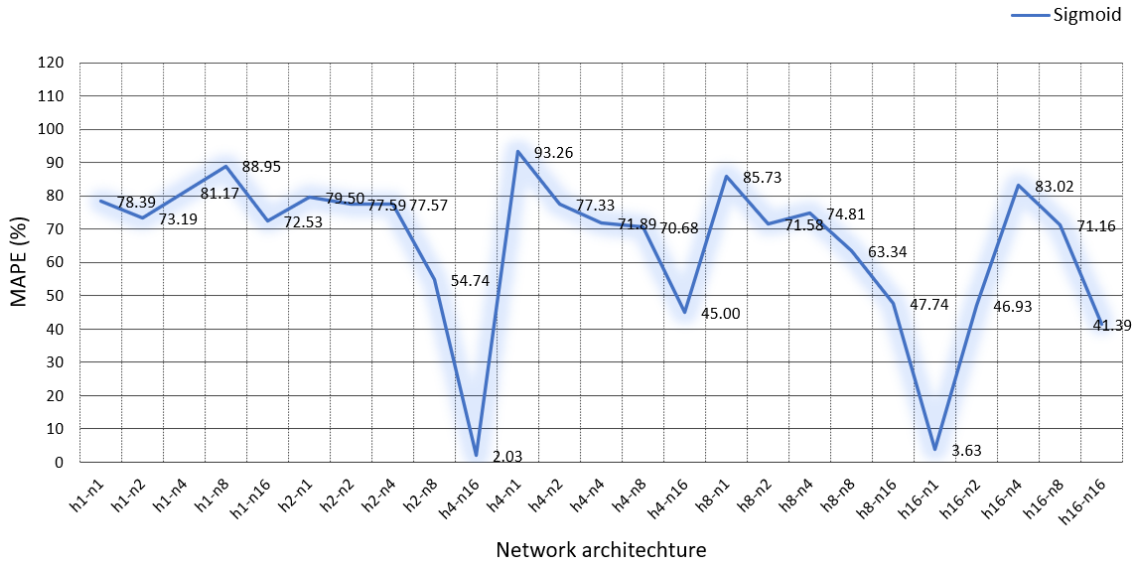
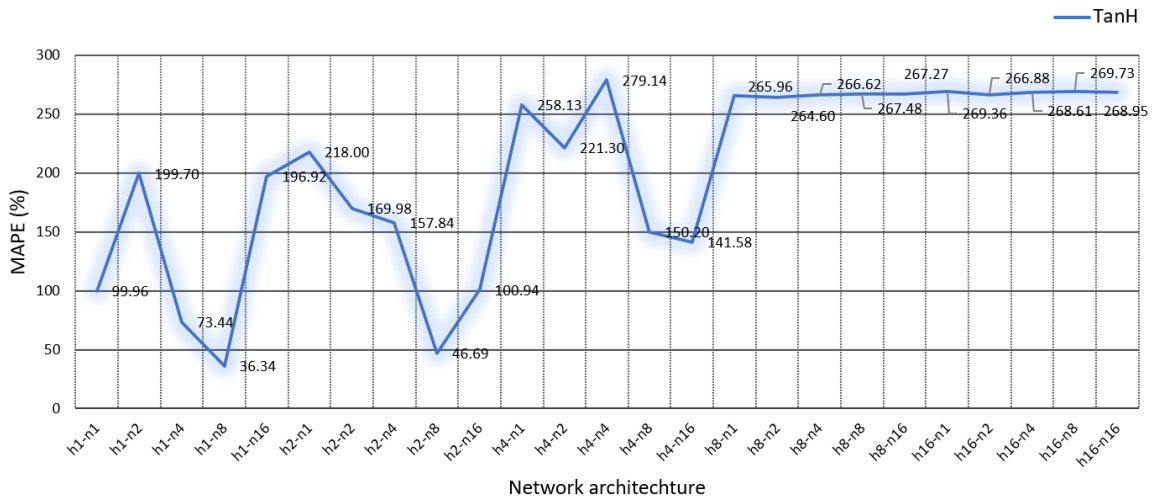


Figure 5-2: Epoch comparison for datasets i and j across three activation functions when $w = 21$

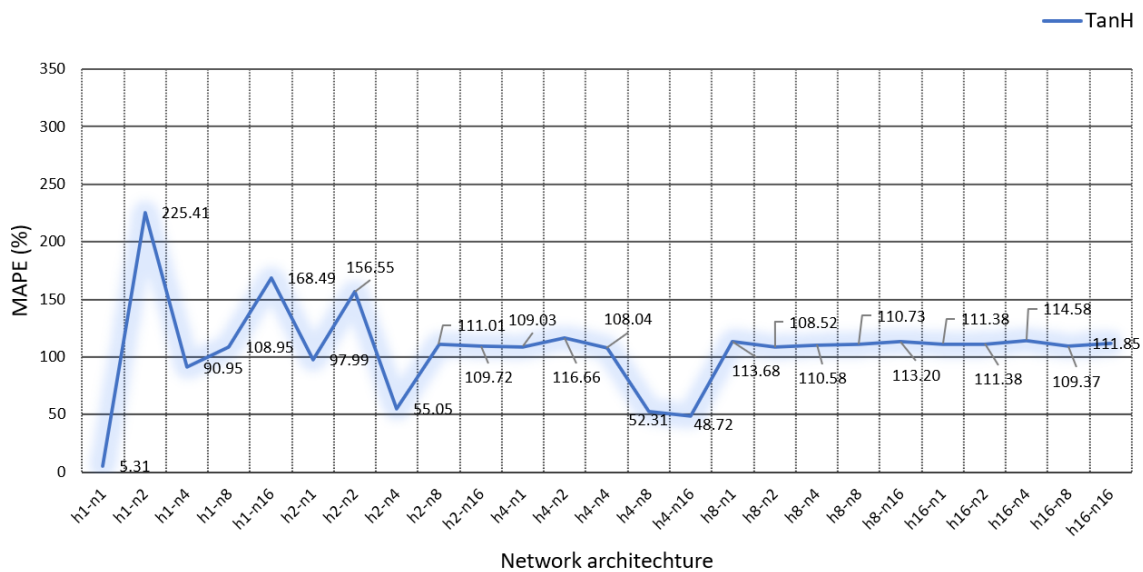
The best of each of the activation function, window size, and epoch, was used to investigate the network architecture based on the preceding results. Figure 5-3(a) shows that there was no discernible trend in network architecture (h and n) in dataset a . On the other hand, some sentiment datasets (b , c , d , e , f , and h) show that the trend of hidden layers and nodes exhibited significant fluctuations in average prediction error rates when the number of hidden layers and nodes was between $h1-n1$ and $h2-n16$. After $h2-n16$, h and n values altered the prediction error slightly. Focusing on dataset j , which achieved the lowest mean error. Figure 5-4(j) shows there was no discernible trend in the network. Likewise with the i and g datasets.



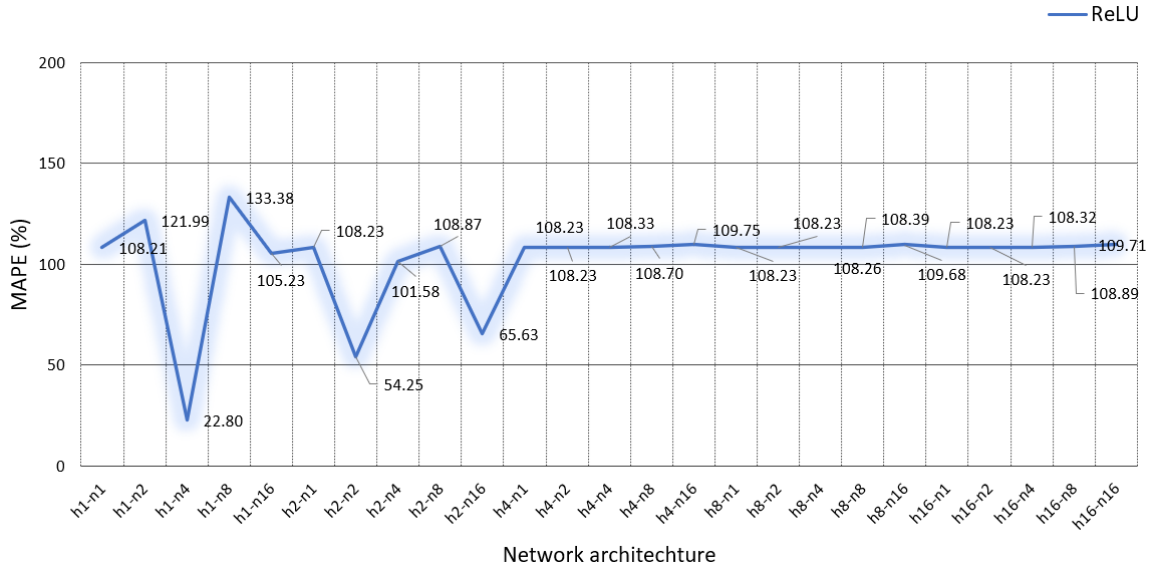
(a) Dataset *a* with *Sigmoid* when $w = 21$ and $e = 200$



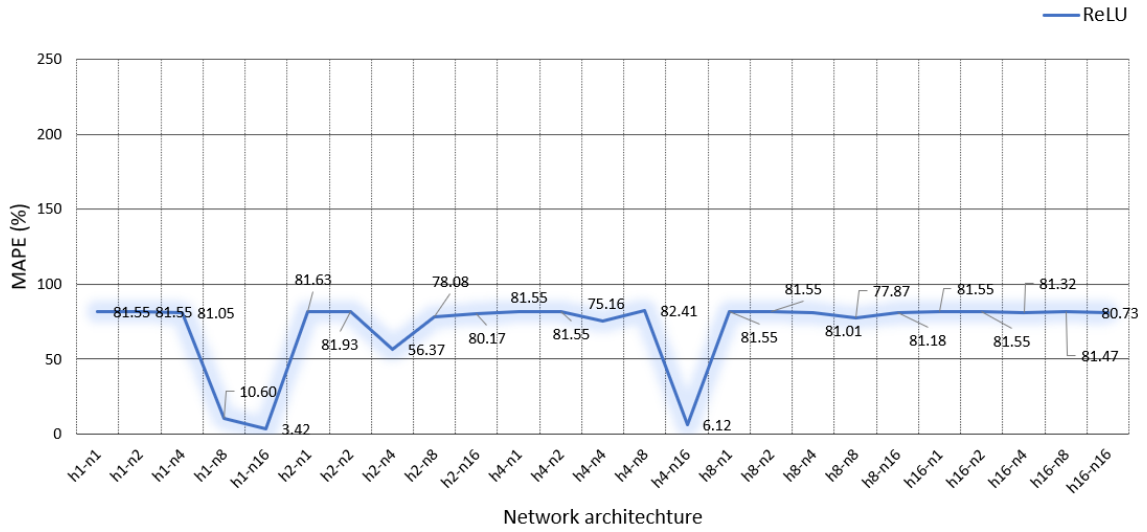
(b) Dataset *b* with *TanH* when $w = 21$ and $e = 200$



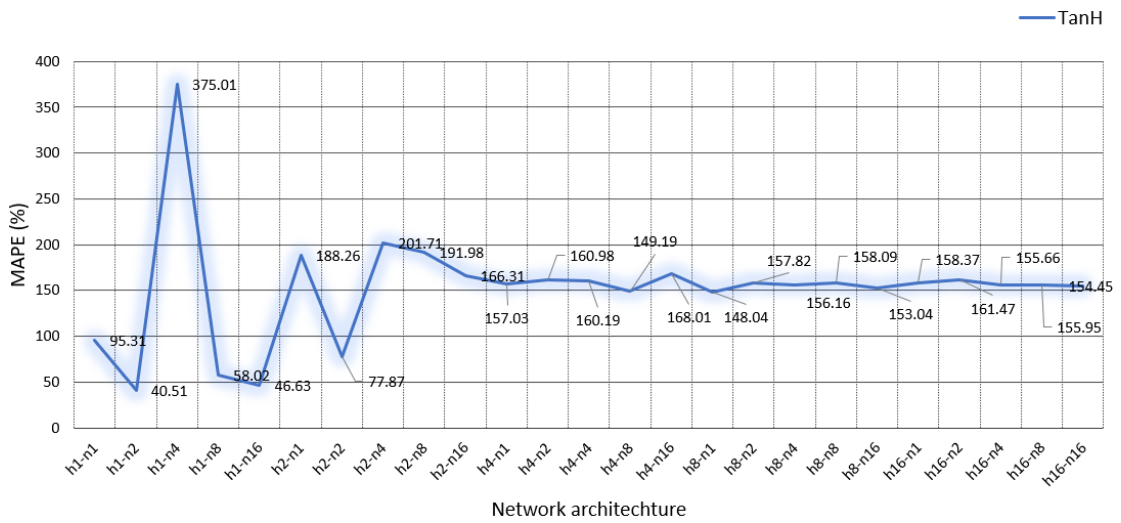
(c) Dataset *c* with *TanH* when $w = 21$ and $e = 200$



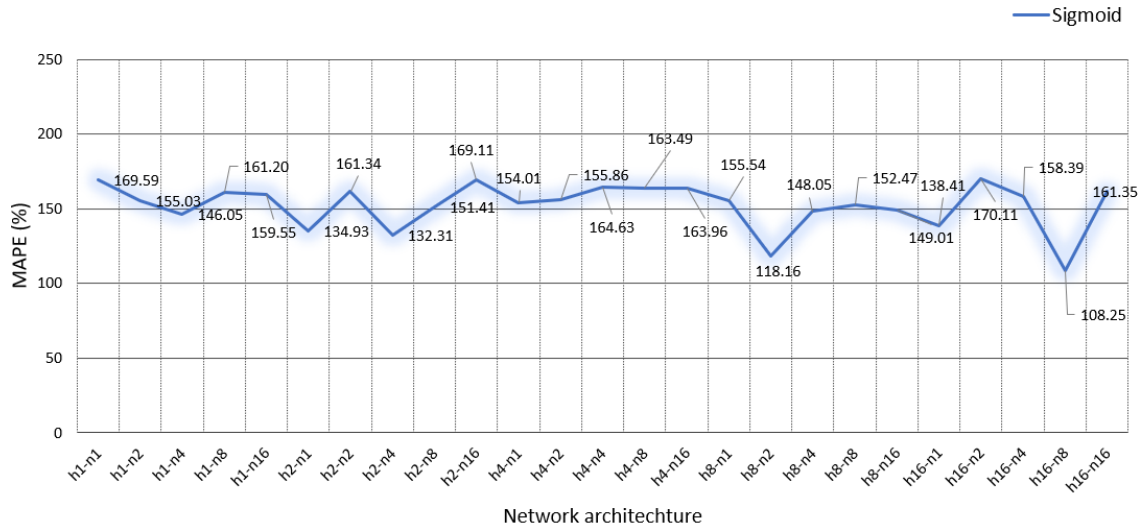
(d) Dataset *d* with ReLU when $w=21$ and $e=150$



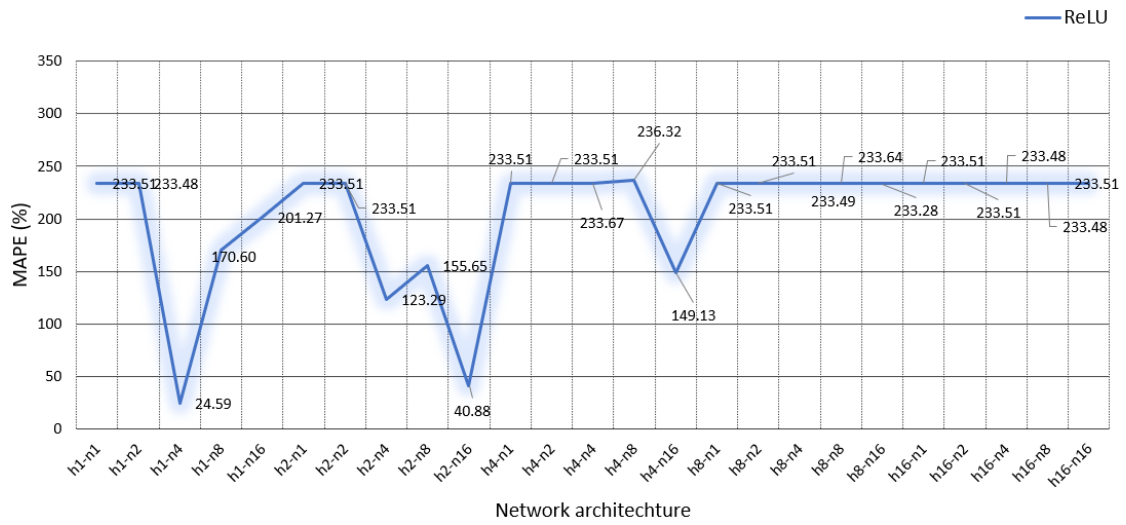
(e) Dataset *e* with ReLU when $w = 21$ and $e = 100$



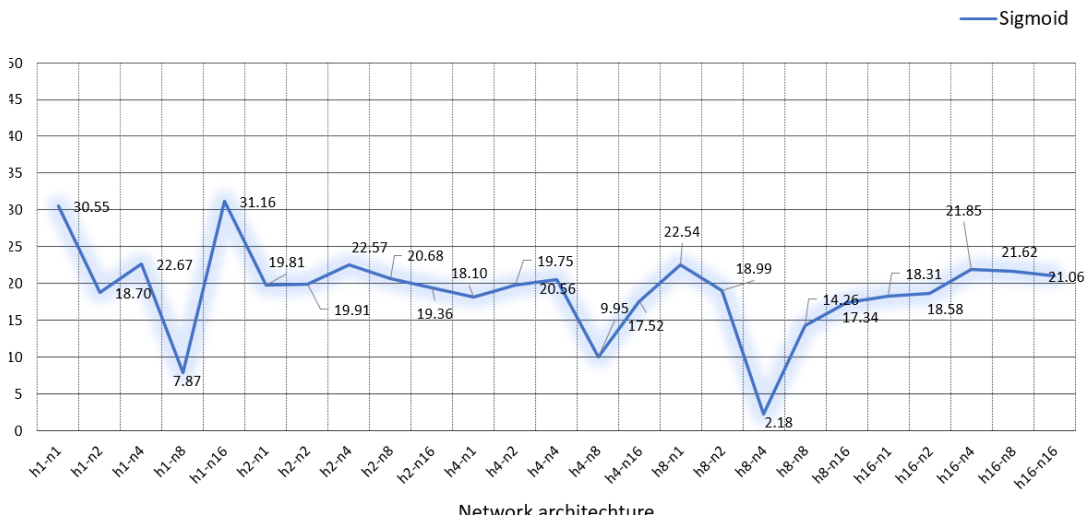
(f) Dataset *f* with TanH when $w = 21$ and $e = 150$



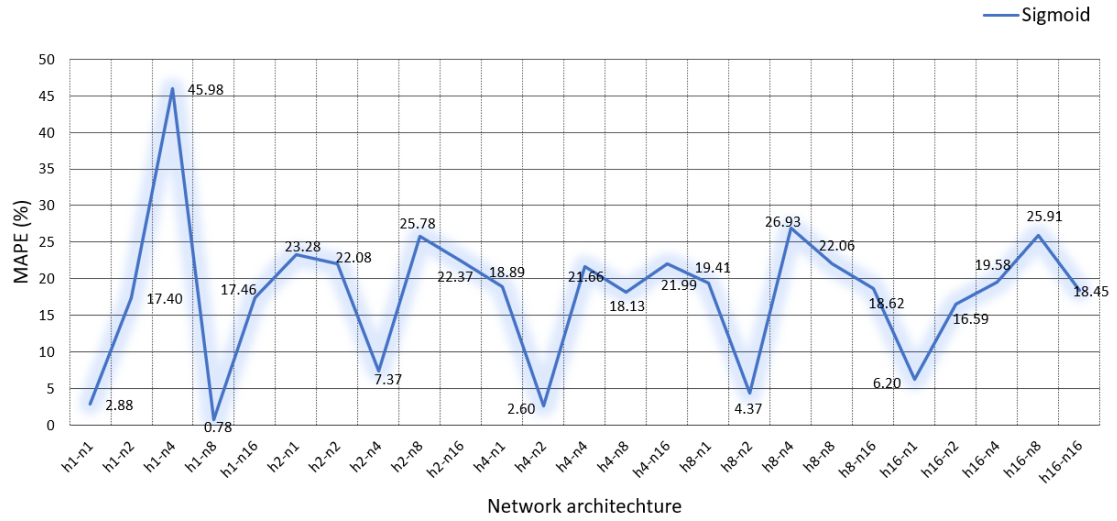
(g) Dataset *g* with *Sigmoid* when $w = 21$ and $e = 100$



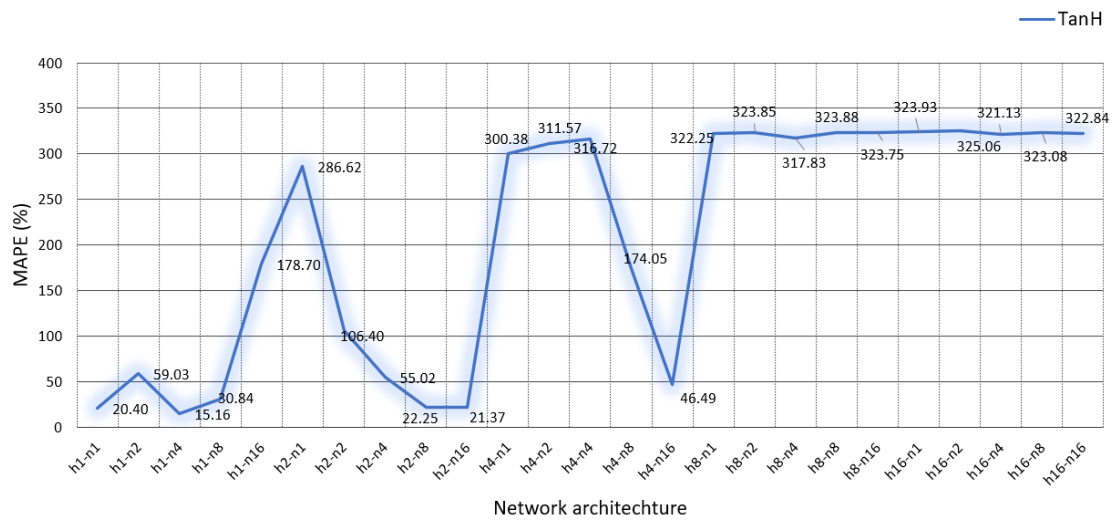
(h) Dataset *h* with *ReLU* when $w = 21$ and $e = 200$



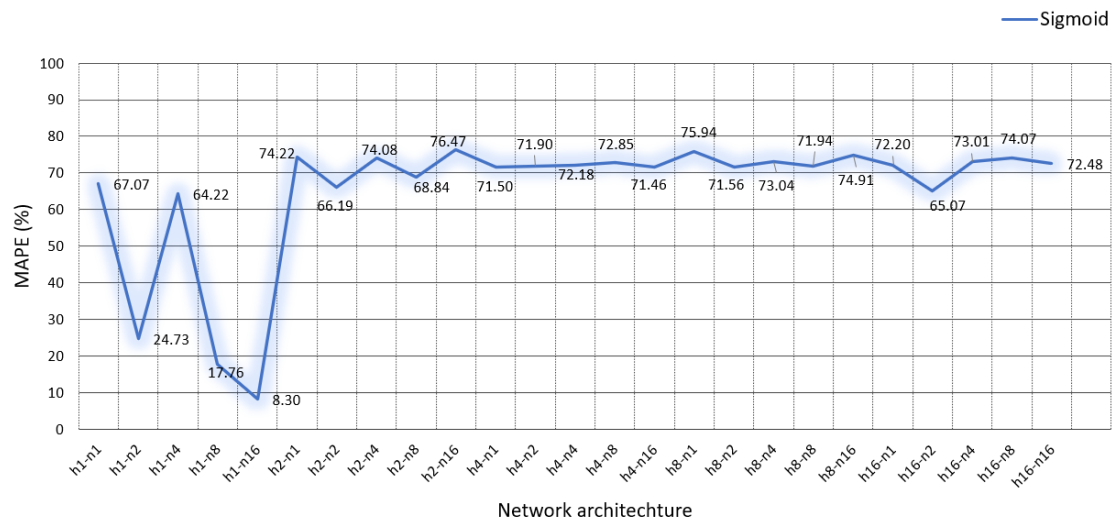
(i) Dataset *i* with *Sigmoid* when $w = 21$ and $e = 150$



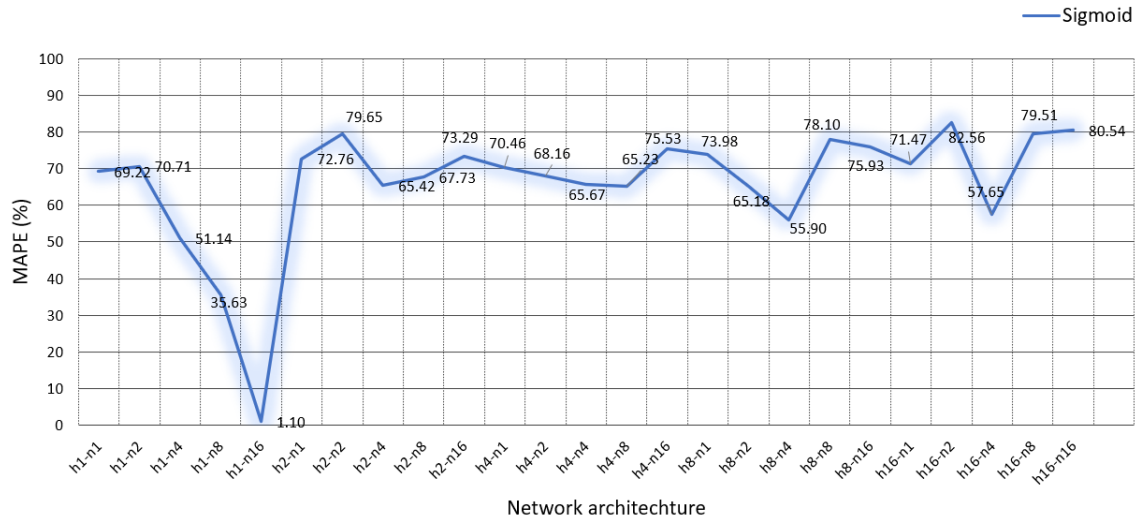
(j) Dataset *j* with *Sigmoid* when $w = 21$ and $e = 150$



(k) Dataset *k* with *TanH* when $w = 21$ and $e = 150$



(l) Dataset *l* with *Sigmoid* when $w = 21$ and $e = 200$

(m) Dataset m with *Sigmoid* when $w = 21$ and $e = 100$ Figure 5-3: Comparison of architecture for all 13 datasets with the best w , e ,

5.1.3 Training runtime

Figure 5-4(a-c) shows the average training runtime for all datasets with all activation functions. It is clear that, as the window size increases for all datasets containing sentiment scores, so the training time increases. However, the size of the window had little effect on dataset a . Further, the different activation functions did not affect training duration.

5.2 Statistical Analysis of the Results

The next task was to determine whether the activation function, window size, hidden layers, nodes, epoch, and datasets, impacted the predictive performance of the model. This test was conducted using one-way multivariate analysis of variance (MANOVA) because this approach is accessible for analysing statistical differences between the means of multiple dependent variables. MANOVA was performed to investigate the effects of the parameters on the predictive power. For this test, all 23,400 index return list results were utilised (see Appendix E.2). The investigation sought to identify any statistically significant difference between the mean model performance metrics ((MSE, RMSE, MAE, and MAPE in testing mode), prediction error (MAPE), and training runtime) for each parameter. Ateş et al. (2019) and Tabachnick and Fidell (2018) indicated that the Wilks' lambda test statistic should be employed to detect statistically significant differences, since it was the most powerful, most robust method and suitable for general use. Ateş et al., (2019) suggested that the significance threshold for many studies is reasonably fixed at 0.05 (5%). Full statistical results are show in Appendix E.2.1.

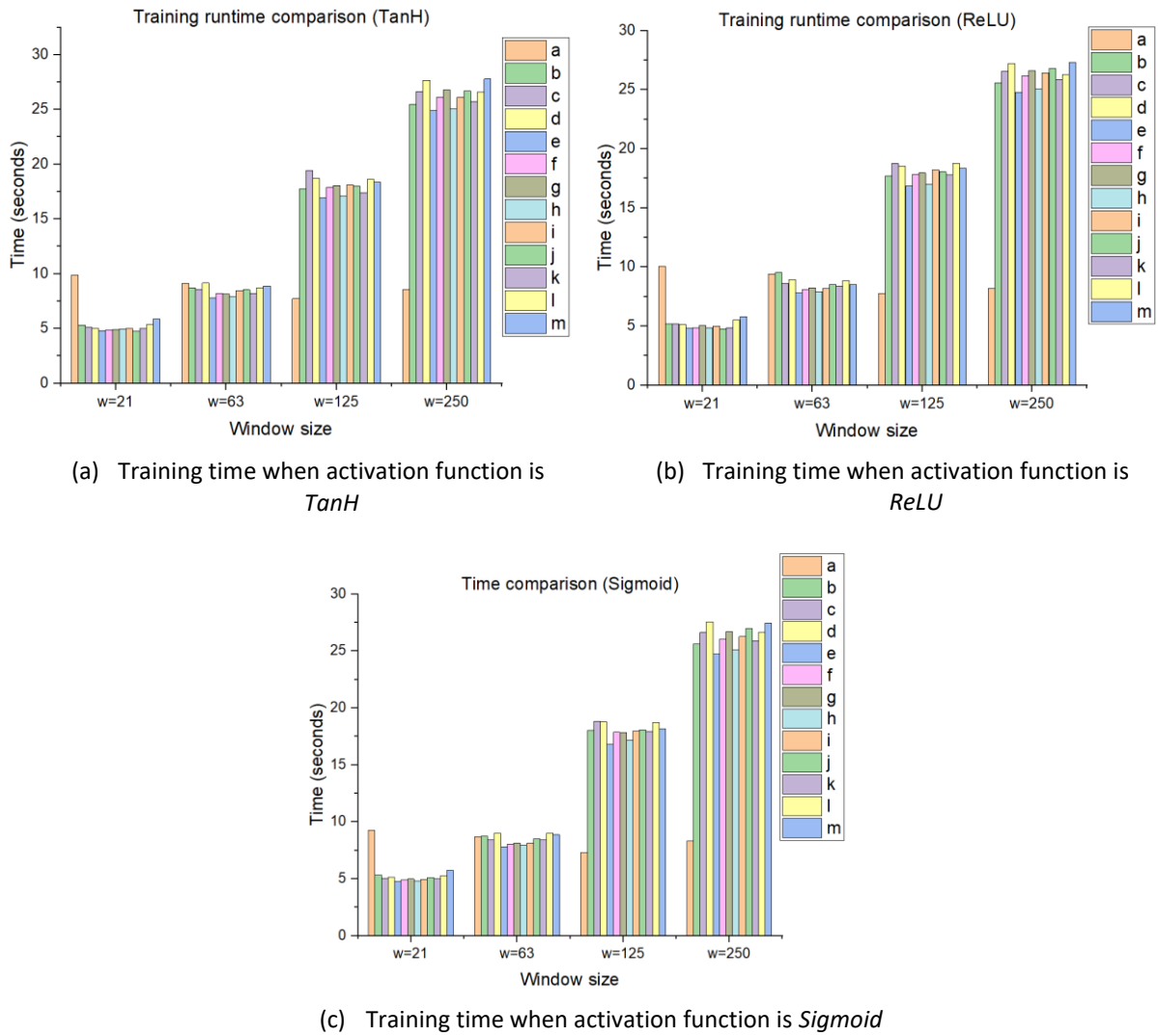


Figure 5-4: Average training time for all epochs and activation functions across 13 datasets

Table 5-2 highlights that all parameters and datasets had statistically significant effect on the performance of all measurements (MSE, RMSE, MAP, MAPE, prediction error, and training runtime) with $p < 0.05$. It can be concluded that each parameter and dataset had a significant effect on the forecasting performance of the model ($p < 0.001$).

Table 5-2: Summary of the multivariate analysis of the differences of all parameters and datasets

	Effect	Value	F	Hypothesis df	Error df	p
Wilks' Lambda	Activation Function	0.84	363.35 ^a	12	46728	<0.001
	Window size	0.28	2061.94	18	66083	<0.001
	Hidden	0.39	1053.70	24	81508	<0.001
	Node	0.92	77.37	24	81508	<0.001
	Epoch	0.07	3001.01	30	93458	<0.001
	Dataset	0.17	676.11	72	127119	<0.001

^a Exact statistic

To determine the mean differences between the groups of each parameter, univariate statistical tests (one-way ANOVA) was used. This test can tell which groups differed from which. Table 5-3 examines the tests of between-group effects of each parameter and dataset on the performance of MSE, RMSE, MAE, MAPE, prediction error, and training runtime. The result revealed window size, node, epoch, and dataset, had a significant effect on all prediction performances ($p < 0.001$). The type of activation function had a significant effect on the models' predictability ($p < 0.001$), but the effect on training runtime was insignificant ($p = 0.820$). The hidden layers affected MSE, RMSE, MAE, MAPE, and training runtime ($p < 0.001$) except for prediction error ($p = 0.229$).

Table 5-3 demonstrates that the parameters (except for the hidden) and data set can influence the prediction error of the model. The results of the pairwise comparison in Table G.2-2 in Appendix G, the parameters (activation function, window size, node, and epoch) and dataset were compared to determine the difference between their performance. The pairwise comparison were tested to discover the parameter and dataset types that result in the lowest prediction error for the model. Comparisons showing a significant level below 0.05 mean that the mean of the prediction error of the two was a significantly different effect on the prediction error and the lowest mean parameter difference was considered the winner. The mean analysis of all parameters and datasets can be found in Appendix E.2.2.

The activation function result revealed a significant difference between the means of all three activation functions at a level of less than 0.001. It can be concluded that the three activation functions have distinct effects on predictive ability. The *TanH* activation function achieved the lowest prediction across all 13 datasets.

Except for the pair *w63* and *w125*, the window size analysis revealed a significant difference between the means of practically all pairwise comparisons, and clearly that *w21* was the best mean over the other window sizes.

There was a significant difference between the means of all node layers at $p < 0.001$ and *n16* had the lowest mean prediction error across 13 datasets, although epochs 100, 150, and 200 did not differ greatly from the group mean ($p = 1.000$). Moreover, *e200* showed the lowest mean prediction error. This finding demonstrated that when the number of training epochs exceeded 100, there was little variance in the prediction error.

The analysis of datasets revealed that the majority had statistically different means ($p < 0.05$). The mean prediction error in Table E.10 (Appendix E) demonstrates that dataset *a* produced the lowest error percentage at 1046%, while datasets *i* and *j* (sentiment scores included) produced the lowest error percentage at 1231% and 1233%, respectively. Even though dataset *a* had the lowest mean

prediction error, it was discovered that dataset *a* had the highest standard deviation (SD) among the other 12 datasets, indicating that dataset *a* was more volatile than the others.

Table 5-3: The summary of the tests of between-group effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	p
Activation Function	MSE	0.004	2	0.002	240.332	<0.001*
	RMSE	0.121	2	0.061	358.519	<0.001*
	MAE	0.167	2	0.084	469.356	<0.001*
	MAPE	1.97E+08	2	98354155	470.167	<0.001*
	Prediction error	1.28E+08	2	63923503	72.336	<0.001*
	Runtime	2.82	2	1.41	0.199	0.820
Window size	MSE	0.000	3	8.51E-05	11.641	<0.001*
	RMSE	0.010	3	0.003	19.909	<0.001*
	MAE	0.012	3	0.004	22.964	<0.001*
	MAPE	16549290	3	5516430	26.37	<0.001*
	Prediction error	3.42E+10	3	1.14E+10	12906.33	<0.001*
	Runtime	2240.615	3	746.872	105.389	<0.001*
Hidden	MSE	0.000	4	7.48E-05	10.226	<0.001*
	RMSE	0.009	4	0.002	13.563	<0.001*
	MAE	0.025	4	0.006	35.165	<0.001*
	MAPE	28948099	4	7237025	34.596	<0.001*
	Prediction error	4966968	4	1241742	1.405	0.229
	Runtime	197737.8	4	49434.44	6975.544	<0.001*
Node	MSE	0.005	4	0.001	168.939	<0.001*
	RMSE	0.206	4	0.052	305.212	<0.001*
	MAE	0.228	4	0.057	319.472	<0.001*
	MAPE	2.66E+08	4	66500286	317.895	<0.001*
	Prediction error	3.49E+08	4	87258949	98.742	<0.001*
	Runtime	406.412	4	101.603	14.337	<0.001*
Epoch	MSE	0.033	5	0.007	897.891	<0.001*
	RMSE	1.656	5	0.331	1960.12	<0.001*
	MAE	1.736	5	0.347	1950.277	<0.001*
	MAPE	2.07E+09	5	4.13E+08	1976.013	<0.001*
	Prediction error	2.79E+09	5	5.58E+08	631.103	<0.001*
	Runtime	1653119	5	330623.8	46653.32	<0.001*
Dataset	MSE	0.025	12	0.002	280.428	<0.001*
	RMSE	2.510	12	0.209	1237.718	<0.001*
	MAE	2.958	12	0.246	1384.37	<0.001*
	MAPE	3.97E+09	12	3.31E+08	1580.067	<0.001*
	Prediction error	2.17E+09	12	1.81E+08	204.69	<0.001*
	Runtime	59706.33	12	4975.527	702.082	<0.001*

* Indicates significance at $\alpha = 0.05$

5.3 Discussion of the results

The comparative performance of the four sentiment windows (current-day, 1-day, 3-day, and 5-day) provides insight into how information released at t_0 propagates into market pricing at t_1 . The results indicate that neither current-day nor 1-day sentiment consistently produces the lowest prediction errors, suggesting that markets do not always fully react to news within a single session. Instead, the 3-day aggregated sentiment window shows the strongest predictive value, particularly in datasets i and j . This aligns with behavioural-finance findings that investor processing of news often unfolds over several days due to staggered trading, heterogeneous interpretation, and gradual information diffusion. Conversely, performance deterioration in the 5-day window suggests that sentiment becomes diluted and less informative when aggregated across a longer horizon. Overall, the results indicate that the most influential sentiment signal for next-day return prediction occurs within the first 2–3 trading days after news release, empirically validating the selection of these temporal windows in the experimental design.

The activation function for all 13 datasets were first compared. The outputs represent the average of all window size, hidden layers, nodes, and epoch, prediction errors. With the exception of datasets d , f , and g , the results suggested that the *TanH* activation function outperformed *ReLU* and *Sigmoid* in the other nine datasets. In addition, statistical analysis revealed that the three functions have significantly different effects on prediction errors. Comparing the means of pairs revealed that *TanH* had a smaller mean prediction error than the other two functions.

Window size was then explored; the findings revealed that $w21$ was the optimal window size for all 13 datasets and three activation functions. Moreover, the model produced the greatest error among the 13 datasets when $w250$ was used. Interestingly, $w63$ and $w125$ produced almost similar results across all 13 datasets, as reported in Section 6.2. There was not a single function that minimised errors in every dataset. When the dataset changed, the prediction error produced by the various activation functions differed. Following the determination of the best window size, dataset i with *Sigmoid* error rate of 75% displayed the lowest prediction error.

Since $w21$ was appropriate for all datasets and functions, the training epoch was studied with a focus on $w21$, and it was discovered that there was no “best” epoch among all 13 datasets. Interestingly, when the number of epochs exceeded 100, the model exhibited a low forecasting error. There are three competing epoch sets for datasets with a sentiment score: 100, 150, and 200 (see Table 6-5 below). This conclusion was backed by statistical analysis, which revealed no significant difference between the means of $e100$, $e150$, and $e200$. As a result, the best epoch was dependent on the dataset and activation function, but 100 or more epochs are required. Lastly, it was revealed that dataset j had the smallest average error (18%) when $w21$ was combined with $e150$ under *Sigmoid* activation.

For each dataset, the winner settings for window size, epoch, and activation function were used to study the architecture layers. It was found that there was no discernible pattern of hidden layers and nodes; nonetheless, statistical analysis revealed that nodes affected the prediction capacity of the model. The results of a test for differences between pairings suggested that all pairs were distinct but lacked a discernible pattern. The findings reveal that hidden layers have no effect on the prediction capacity of the model when employing these 13 datasets.

In conclusion, the average of all prediction errors indicates that *TanH* was the best function for the majority of datasets and statistical pairwise comparison results corroborated this. When focusing on the window size and the training epochs, the activation function that provided the lowest prediction error varied, based on the dataset. Interestingly, the sentiment datasets of 3 days (*h*, *i*, and *j*) and 5 days (*k*, *l*, and *m*) produced the same pattern of results. The datasets *h* (3 days) (203% of average error) and *k* (5 days) (207% of average error) that use historical return with compound scores as a feature, exhibited the greatest average prediction error of each group (3-day group and 5-day group). The datasets *i* (19%) (using historical return, positive, and negative scores) and *j* (18%) (using historical return, positive, neutral, and negative scores) had the lowest average prediction error among the other 11 datasets. In the same way, the dataset *l* (65%) (historical return, positive, and negative scores) and *m* (66%) (historical return, positive, neutral, and negative scores) also showed the lowest average prediction error in the group with 5-days' sentiment. It can be concluded that the datasets with three (historical return, negative, and positive) and four (historical return, negative, neutral, and positive) features yielded a lower average prediction error than the dataset with two features (historical return, and compound scores). In particular, 3-days of sentiment scores with three or four features when *w21* and *e150* cooperated with *Sigmoid* to produce the lowest prediction error in this experiment. The summary of all parameters for each dataset is shown in Table 5-5.

Table 5-4: Parameter summary of S&P 500 index return prediction using news sentiment

		Activation Function	Window size	Epoch	Hidden	Node
Benchmark	Dataset a	Sigmoid	w21	e200	N/E	N/A
Sentiment dataset	Dataset b	TanH	w21	e200	N/E	N/A
	Dataset c	TanH	w21	e200	N/E	N/A
	Dataset d	ReLU	w21	e150	N/E	N/A
	Dataset e	ReLU	w21	e100	N/E	N/A
	Dataset f	TanH	w21	e150	N/E	N/A
	Dataset g	Sigmoid	w21	e100	N/E	N/A
	Dataset h	ReLU	w21	e200	N/E	N/A
	Dataset i	Sigmoid	w21	e150	N/E	N/A
	Dataset j	Sigmoid	w21	e150	N/E	N/A
	Dataset k	TanH	w21	e150	N/E	N/A
	Dataset l	Sigmoid	w21	e200	N/E	N/A
	Dataset m	Sigmoid	w21	e100	N/E	N/A

N/E = No Effect, N/A = Not Applicable

5.4 Summary

To address the research question, this experiment evaluated the MLP model using 12 distinct confidence data sets and compared the outcomes to the baseline dataset. The experiment compared four different hyperparameters, including three activation functions, four window sizes, six training epoch sets, and five architecture layers. The window size of 21 (1-month data) provided the model with the lowest prediction error among the 13 datasets. In addition, the number of training epoch must be at least 100 for each dataset to have the lowest prediction error. It was impossible to determine which function produced the best error for the model, as it depended on the dataset. For example, *TanH* provided the lowest error when applied to datasets *b*, *c*, *f*, and *k*, whereas *Sigmoid* provided accurate predictions when applied to datasets *g*, *i*, *j*, *l*, and *m*. Neither were the optimal architectural layers identified, and the prediction error rate was highly volatile when hidden layers and nodes were small.

In conclusion, the experiment demonstrated that the datasets containing sentiment scores yielded superior model performance to the dataset without sentiment features. The average prediction error for the deep MLP model when using dataset *a* (without sentiment) was 65%. The model utilising dataset *j* with four characteristics (historical return, positive, negative, and neutral scores), which were generated by sentiment scores acquired three days before the trading day, had the lowest prediction error of 18%. Consequently, it can be concluded that the sentiment dataset can reduce the error of S&P 500 index return prediction using deep MLP.

Chapter 6 Discussion

This chapter discusses the outcomes of the two-phase experiment. Chapter 4 presented a large-scale comparative evaluation of three deep learning architectures—MLP, LSTM, and GRU—for forecasting the S&P 500 index price and return. Models were systematically tested across a structured hyperparameter space (activation functions, window sizes, network depths, and training epochs), enabling a clear understanding of how architectural and training choices influence predictive accuracy and computational efficiency. Statistical validation using MANOVA and t-tests further supported the robustness of the observed trends. Importantly, these analyses also established the practical viability of each architecture for real-world financial deployment, where speed, stability, and reliability are critical.

Chapter 5 addressed the central research question: whether integrating sentiment extracted from financial news can meaningfully improve the performance of deep learning models in forecasting S&P 500 index returns. The experiment introduced 12 sentiment-enhanced datasets to overcome the limitations identified in Chapter 4, where return-only models exhibited high error rates due to the weak signal and noise-dominated structure of daily returns. The chapter examined how different sentiment windows and polarity components affect predictive performance, revealing that multi-dimensional sentiment features can substantially reduce forecasting error. The study is both methodically sound and practically relevant, offering insights into how qualitative sentiment features complement traditional quantitative time series in financial prediction.

In addition, the training time is reported in this Chapter to provide investors and researchers with an alternative perspective when evaluating whether speed or predictive accuracy should be prioritised. The relative importance of these factors is dependent on the application context. In trading systems that require real-time responsiveness, such as high-frequency trading (HFT), rapid prediction speed is of paramount importance because execution delays can directly affect trading outcomes (X. Zhang et al., 2023). By contrast, investors who rely on daily, weekly, or monthly forecasts place greater emphasis on predictive accuracy, as cumulative returns are strongly influenced by the quality of the predictions. Consequently, model accuracy tends to have a greater impact on investment performance in these settings (Justus et al., 2018). Nevertheless, in comparative research, reporting the training time remains essential, as it enables an assessment of the model's computational efficiency and its practical viability for real-world implementation.

6.1 The S&P 500 experiment in deep learning

6.1.1 Index price prediction finding

GRU with TanH activation achieved the strongest performance in price prediction, obtaining an error as low as 19.54% using a minimal architecture (1 hidden layer, 16 nodes), a large window size ($w = 250$), and only 10 training epochs. MLP, though less accurate overall than GRU, delivered significantly faster training times ($\sim 10\times$ faster than GRU) and performed consistently across hyperparameter settings. Activation choice strongly influenced performance: TanH produced the lowest error rates, ReLU delivered stable convergence, and Sigmoid consistently produced high error and instability due to gradient saturation. Statistical analysis confirmed that activation function, hidden layer depth, and node count had significant effects on predictive accuracy, whereas window size and epochs had negligible impact on accuracy but did influence training time. This finding is domain-relevant because daily price movements contain smoother temporal structure than returns, meaning the models benefit modestly from longer historical windows but not from excessive training cycles.

6.1.2 Index return prediction finding

All models performed poorly, with average error rates above 90%, reflecting the well-established financial principle that daily returns approximate a random walk and offer very limited deterministic structure for predictive modelling. MLP with ReLU and window size 63 achieved the lowest error (90.64%)—still far too high for practical application. No single model–activation pairing consistently outperformed others, and hyperparameter variation produced minimal changes in accuracy. Increased complexity, deeper architectures, and additional epochs did not improve return prediction, demonstrating that the limitation resides in the data-generating process rather than the modelling framework. Statistical tests confirmed the absence of significant differences across groups.

6.1.3 Model efficiency

MLP is the most efficient model, with stable training times ($\sim 10.8s$ average) regardless of configuration. GRU, while most accurate for price, is computationally expensive ($\sim 1500+$ seconds average), especially with longer windows. Adding architectural complexity (more layers or nodes) generally increased training time and validation loss, with little to no gain in accuracy. A simpler configuration ($h = 1, n = 16$) offered the best price prediction accuracy, reinforcing the principle of architectural parsimony. This efficiency difference matters because financial forecasting models must be retrained frequently; therefore, architectures that require hours of retraining (like GRU) are unsuitable for operational use in most investment contexts.

6.1.4 Implications and Contribution

The results show that while historical price data can support moderately accurate forecasting, particularly using GRU-type architectures, return forecasting based solely on past return sequences is fundamentally constrained by noise and low signal strength. This finding aligns with financial theory and provides a methodological basis for introducing sentiment features in Chapter 5.

6.2 S&P 500 index return prediction with sentiment analysis

In the second phase of experimentation, a deep MLP model was evaluated using 13 sentiment-augmented datasets to determine which combination of sentiment structure and temporal aggregation yields meaningful improvements over the baseline return-only dataset. These datasets varied systematically in terms of sentiment components (compound only, polarities, multi-dimensional sentiment) and sentiment time windows (current day, 1-day lag, 3-day average, 5-day average). As in the preliminary experiment, the model was tested across multiple hyperparameters to ensure that performance improvements could be attributed to the structural contribution of sentiment features rather than to incidental tuning effects. The evaluation focused on forecasting error, prediction behaviour, and computational efficiency.

6.2.1 Index return prediction finding

The integration of sentiment features produced substantial performance improvements, especially when sentiment was represented using multiple polarity components (positive, negative, neutral) rather than a single compound score. This indicates that granular sentiment captures distinct information channels relevant to investor behaviour that are not present in the baseline return sequence. This finding reinforces previous work, such as that by Zhong and Enke (2019) and Bhowmik and Wang (2020), who emphasised the importance of external information in overcoming the limitations of purely historical models. Compound-only sentiment datasets produced modest improvements, but the strongest performance came from datasets that included all three polarity dimensions aggregated across short windows—particularly the 3-day window (dataset j), which achieved the lowest MAPE of 18.43%. The 3-day aggregation appears to capture the diffusion period during which news effects propagate into market prices, offering a stable balance between immediacy and noise reduction. This aligns with Hiransha et al. (2018), who suggested that recent market events and news influence stock behaviour in the short term and are best captured using deep learning architectures capable of extracting non-linear relationships.

The results demonstrate that sentiment features reduce error not by increasing model complexity, but by providing additional explanatory signals that complement the weak predictive content of historical

returns. The most effective datasets (especially dataset j) utilised three sentiment polarity features (positive, negative, and neutral) and short aggregation periods (3 days). This suggests that market reactions to news are most predictive when sentiment is disaggregated and recent.

6.2.2 Model Configuration Insights

Model configuration influenced prediction accuracy in non-uniform ways. While TanH generally performed well across many datasets, the best-performing configuration for the top dataset (j) unexpectedly used the Sigmoid activation function. This suggests that sentiment-augmented datasets interact differently with activation functions than return-only datasets, likely because sentiment introduces bounded, non-linear features that Sigmoid can exploit more effectively than ReLU or TanH. This suggests that no single activation function universally performs best across different feature sets, as also supported by the findings of Maguolo, Nanni, and Ghidoni (2020), who demonstrated that optimal activation function selection depends heavily on the characteristics of the dataset. The strong performance of Sigmoid in the best configuration indicates that sentiment-rich inputs benefit from smooth, saturating transformations, enabling the model to represent subtle distinctions between positive and negative news without overreacting to noise. This demonstrates the need for tailored tuning of activation functions and model structures depending on the feature representation and market context. The superiority of this dataset-specific configuration highlights the value of flexible model design when working with real-world financial data, which is inherently noisy and heterogeneous.

While TanH was generally the best-performing activation function across datasets, the best individual result was obtained using Sigmoid with dataset j, indicating that optimal configurations are dataset-specific. The combination of sentiment and return data enables the deep MLP model to capture hidden relationships not present in historical prices alone.

6.2.3 Architecture and efficiency considerations

The architectural choices significantly affected both prediction accuracy and training efficiency. Increasing node count improved learning capacity, but adding more hidden layers produced diminishing returns and often increased training time without improving accuracy. Shallow architectures (1 hidden layer) consistently outperformed deeper structures, indicating that excessive depth causes overfitting in this low-signal domain. This finding is consistent with research showing that noisy financial series benefit more from width than depth (Vujičić & Matijević, 2016; Nayak et al., 2014). Shallow networks also align better with real-world constraints of financial modelling, where retraining must occur frequently and latency must remain low. Complex architectures, while theoretically expressive, are operationally unsuitable for daily retraining workflows. In this study,

shallow architectures ($h = 1$) with moderate node counts ($n = 8$ or 16) consistently yielded the best trade-off between training time and prediction accuracy, reinforcing the practical value of model simplicity in financial forecasting scenarios.

Model complexity influenced performance, but not in the expected direction: wider models (more nodes) consistently improved predictive robustness, whereas deeper architectures (more layers) introduced instability without reducing error. This asymmetry again reflects the low signal-to-noise ratio of daily returns, where deeper networks tend to amplify noise rather than extract structure. Thus, shallow architectures paired with sentiment features offer the most practical balance of accuracy, interpretability, and computational viability. From a deployment perspective, these models are lightweight enough to be retrained daily—an essential requirement for real investment systems that must update forecasts as new information arrives.

A key reason sentiment features substantially reduce forecasting error is that they inject information not present in historical returns, thereby mitigating the fundamental limitations of return-only models. Daily equity returns are dominated by noise and exhibit little autocorrelation, making them extremely difficult to predict using past values alone. Sentiment features provide a structured proxy for market expectations, investor attention, and information diffusion—factors known to influence short-term price dynamics but not observable directly in return series. By combining numerical and text-derived inputs, the model effectively bridges the gap between *what has happened* (historical return behaviour) and *what the market anticipates* (news-derived sentiment). This hybridisation suppresses error not by overfitting, but by enriching the input space with economically meaningful signals that improve the model's capacity to discriminate between noise and informative variation.

The relevance of these findings extends beyond theoretical performance metrics. In real financial applications—such as automated trading systems, risk-management dashboards, and decision-support tools for portfolio managers—the objective is not simply to minimise a numerical error measure, but to obtain forecasts that more reliably reflect market conditions and investor behaviour. The identification of configurations that consistently reduce error (e.g., 3-day sentiment windows with multi-polarity inputs) demonstrates *which types of information* and *which modelling choices* materially enhance predictive reliability. This enables practitioners to prioritise inputs and model structures that offer the greatest informational value per unit of computational cost. Moreover, by showing that certain models (MLP) are both faster and more accurate than alternatives (LSTM, GRU), this research provides actionable guidance on which architectures are viable for daily retraining in production environments where latency and resource constraints are non-negotiable.

6.3 Integrated Discussion of Both Phases

Taken together, the two phases of experimentation clarify not only *which* models perform best, but *why* certain modelling strategies succeed or fail within the structural constraints of financial time-series prediction. Phase 1 demonstrates that stock returns, unlike prices, contain insufficient predictive structure for deep learning models to exploit. This is consistent with well-established empirical research showing that high-frequency equity returns approximate a random walk, with very low autocorrelation and strong noise dominance. As a result, purely historical models—regardless of architecture—generate high forecast errors because the input data lack the deterministic patterns these models rely on.

Phase 1 also demonstrates that the apparent complexity of LSTM and GRU does not translate into practical benefit under walk-forward training conditions. Their longer training times, coupled with sensitivity to window size and instability across configurations, make them poorly suited for environments where models must be retrained frequently. In contrast, deep MLP architectures converge quickly, maintain stable performance across hyperparameters, and operate efficiently on small datasets—a critical requirement in financial return forecasting where daily updates are necessary. This distinction establishes the *contextual appropriateness* of each architecture, linking model selection to domain-specific constraints rather than general performance.

Phase 2 builds upon these insights by testing whether sentiment can compensate for the fundamental informational deficiency of return-only forecasting. The results show that sentiment features—particularly multi-polarity scores aggregated over short (3-day) windows—introduce economically meaningful information absent in historical returns. These features capture aspects of investor attention, news tone, and market expectations that evolve more quickly and more predictably than price movements themselves. In doing so, they reduce both bias and variance in the prediction process, explaining the substantial decreases in forecast error observed in the sentiment-augmented models.

The contribution of this research does not lie in the mechanical adjustment of hyperparameters, but in demonstrating which modelling strategies meaningfully improve predictive reliability within a noisy and low-signal financial environment. By systematically decomposing the prediction problem into two stages—first evaluating the intrinsic limitations of historical data, then introducing external sentiment signals—the study shows why certain modelling choices are justified and others are not. This reflects a principled, domain-aware approach rather than a brute-force technological application. The findings guide practitioners toward configurations that balance accuracy, computational efficiency, and real-world deployability, which is of direct relevance to quantitative analysts, risk managers, and automated trading system designers.

Training time is not simply a technical statistic—it is a meaningful operational constraint in applied finance. Trading models must often be retrained daily or intraday as new information becomes available. Architectures with long training times (e.g., LSTM/GRU) are therefore impractical for real deployment despite their theoretical capacity for temporal learning. By contrast, the MLP’s speed enables frequent model refresh without sacrificing accuracy, ensuring that forecasts incorporate the most recent data. This practical dimension—balancing predictive skill with operational feasibility—is a central consideration for any stakeholder deploying these models in real decision-making.

The two-phase experimental structure strengthens the overall contribution by allowing the research to isolate the sources of predictive difficulty and then systematically test enhancements. Rather than assuming sentiment would help, the study first establishes the baseline predictive limits of historical data and identifies where the modelling bottleneck lies (i.e., insufficient signal in returns). This diagnostic step is essential: without it, the performance gains from sentiment could not be interpreted meaningfully. Phase 2 then demonstrates how additional information resolves the bottleneck, providing a clear rationale for hybrid modelling. The staged design therefore reflects analytical intent rather than mere procedural convenience.

6.4 Implications for Financial Prediction and Model Deployment

The findings of this study provide a deeper understanding of how predictive performance, computational demands, and informational content interact in financial forecasting contexts. Rather than merely comparing models, the results clarify *which modelling decisions are appropriate* for specific types of financial data and *why* certain approaches succeed or fail. This extends the contribution beyond technical optimisation and toward domain-specific methodological guidance.

6.4.1 Implications for Predicting Stock Returns

The consistently high error rates for return-only prediction highlight the structural difficulty of forecasting daily returns, which are dominated by noise and exhibit minimal temporal dependency. These results are not a failure of the models but a reflection of the empirical reality that returns possess very low inherent predictability. Recognising this limitation is essential: it signals that improving accuracy requires introducing external information rather than increasing model complexity.

This insight is crucial for practitioners because it demonstrates that more sophisticated architectures or deeper networks will not overcome the informational limits of historical returns. Instead, predictive improvement must come from enriching the feature space—precisely the motivation for incorporating sentiment signals in Phase 2.

6.4.2 Implications of Sentiment Integration

Sentiment features substantially reduced prediction errors because they provide structured, forward-looking information that historical prices cannot capture. Market behaviour often reacts to news and investor expectations more rapidly than to numerical trends in past prices. Sentiment polarity scores—especially when disaggregated into positive, negative, and neutral components—encode early signals of such reactions. This allows models to distinguish meaningful directional shifts from random volatility, thereby improving forecast stability and reducing noise sensitivity.

From an applied perspective, this demonstrates that hybrid models combining numerical and textual signals are more aligned with the information-processing mechanisms of real financial markets, where sentiment often precedes price movements. This finding supports the growing use of sentiment data in algorithmic trading, risk management, and portfolio analytics.

6.4.3 Implications for Hyperparameter Selection and Training Time

Training time emerges as a meaningful practical constraint, not merely a secondary metric. Financial models must often be retrained frequently—daily or even intra-day—to incorporate new market information. Models such as GRU and LSTM, which require long training times and exhibit instability across hyperparameter choices, are therefore operationally unsuitable despite their theoretical strengths.

MLP, by contrast, provides rapid convergence with stable performance across thousands of tested configurations. This makes MLP the most deployable architecture for environments in which computational resources, latency, and retraining frequency are key considerations.

This research contributes more than a simple application of existing tools. It demonstrates a principled and context-driven modelling workflow that identifies the informational limits of historical data, quantifies the benefits of integrating sentiment, and shows which model architectures are feasible to deploy under real-world operational constraints. The comparative findings across more than 10,000 configurations provide a robust empirical basis for guiding future financial prediction systems, moving beyond ad hoc experimentation toward a more systematic understanding of what works, why it works, and when it should be used.

In the broader context of financial investment and risk management, even small improvements in return prediction accuracy can materially affect portfolio allocation, hedging decisions, and algorithmic trading profitability. Equally, reducing model instability and computational cost improves system reliability and responsiveness—factors essential for real-time decision-making. By demonstrating that sentiment-enriched MLPs materially outperform traditional approaches while remaining

computationally practical, this research provides actionable insights that can directly inform the design of decision-support tools for investors, analysts, and automated trading systems.

6.5 Summary

This chapter synthesised the findings from both phases of the research, demonstrating how predictive limitations inherent in historical data can be addressed through model selection and the integration of alternative information sources such as sentiment. Rather than viewing the experiments as isolated performance tests, this discussion positioned them within the broader context of financial forecasting, clarifying the practical and theoretical reasons underlying the observed results.

The findings reaffirm that historical returns, due to their noise dominance and low serial correlation, inherently limit the forecasting capacity of deep learning models. This explains the consistently high error rates observed in Phase 1 and underscores that predictive improvement requires informational enrichment rather than model complexity alone.

Phase 2 demonstrated that sentiment-enhanced feature sets substantially reduce prediction errors by providing forward-looking information that complements the weak signal in return series. These results reveal that hybrid quantitative–textual models more closely reflect real financial behaviour, where investor expectations and news flow play a major role in shaping short-term market dynamics.

The analysis confirmed that MLP offers the most favourable balance between accuracy, training efficiency, and operational feasibility. While recurrent architectures such as LSTM and GRU are conceptually appealing for sequential modelling, they proved inefficient and unstable when applied to walk-forward financial forecasting, where models must be retrained frequently and quickly. The suitability of MLP in this context therefore reflects not only performance metrics but also practical deployment considerations.

Collectively, the findings demonstrate that model choice, data representation, and domain constraints must be treated as interconnected elements of the prediction task. The two-phase design makes this relationship explicit: Phase 1 isolates the core limitations of historical data, while Phase 2 tests a targeted enhancement (sentiment integration) under realistic modelling constraints. This approach moves beyond hyperparameter exploration toward a domain-aware modelling strategy that directly informs real-world system design.

For practitioners, the implications are clear: successful financial prediction requires models that are both informationally rich and computationally viable. The study identifies which configurations satisfy these criteria and shows how sentiment can be incorporated to meaningfully improve predictive reliability. These insights can guide the development of next-generation decision-support tools,

automated trading systems, and risk analytics frameworks that depend on rapid, accurate, and interpretable forecasting models.

The chapter also provides a conceptual foundation for future research, which can build upon these findings by integrating higher-resolution sentiment sources, exploring transformer-based architectures, or applying the modelling strategy to multi-asset portfolios. The methodological clarity established here ensures that such extensions will rest upon a well-justified analytical framework rather than ad hoc experimentation.

Chapter 7 Conclusion and Future Work

Stocks are considered among the most actively traded financial instruments owing to their high return potential, encompassing both dividends and capital gains. Consequently, they remain a preferred investment vehicle for a wide array of investors. This study was motivated by the challenge of improving the predictive accuracy of stock returns through the utilisation of historical financial data and sentiment derived from financial news sources. The overarching objective was to enhance predictive performance by identifying optimal deep learning parameters and exploring the utility of sentiment-based features.

To address the challenge of improving return prediction accuracy, this study posed the following research questions: **How can we improve the performance of predicting the stock return using deep learning to support investor investment?.**

To investigate the research question, five objectives were investigated:

Objective 1: Review and analysis of price prediction techniques for financial news.

Objective 2: Investigate how varying hyperparameters impact the predictive accuracy of the deep learning model.

Objective 3: Review and analyse sentiment techniques for financial news.

Objective 4: Investigate what lay period of financial news yields the more precise stock return prediction.

Objective 5: Investigate the trade-off between time to complete and precision of the output produced by DL techniques with and without news sentiment analysis.

Chapter 2 reviewed literature on machine learning and sentiment analysis for stock market prediction, emphasizing deep learning models (MLP, LSTM, GRU) for time-series forecasting and the integration of sentiment features—particularly using VADER—to improve predictive performance. It supports a hybrid framework combining quantitative and qualitative data, which forms the foundation for the experimental design in Chapter 3.

Chapter 3 designs a two-phase experimental framework to evaluate deep learning models for stock prediction, first comparing the predictability of index price and return using historical data, then enhancing return prediction by integrating sentiment from financial news; results from over 10,000 model configurations show that MLP is optimal for efficiency, and the final phase demonstrates that combining sentiment with return data improves forecasting accuracy

The experiment in Chapter 4 conducted a comparative analysis of deep learning models (MLP, LSTM, GRU) for predicting S&P 500 index price and return using historical closing prices and returns, revealing that while GRU achieved the highest price prediction accuracy, MLP offered faster training and slightly better return forecasting, though all models struggled with return predictability—supporting the need to incorporate external factors like investor sentiment to improve performance.

In Chapter 4, the techniques of sentiment analysis (SA) were explored in preparation for the next experiment. Literature revealed that investor sentiment, gathered from financial news and social media, considerably increased the accuracy of stock prediction. Comparing the advantages and disadvantages of the SA approach revealed that VADER was one of the best options, as it handles social media-style text and capitalisation quite well, uses fewer resources than Machine Learning models since it does not require massive volumes of training data, and is ideal for tasks that demand rapid processing. As a result, VADER was employed to analyse the financial news emotion in the experiments.

To address the research question, the experiment in Chapter 5 evaluated the MLP model across 13 datasets and found that incorporating sentiment features significantly improved prediction accuracy, with the best-performing dataset—combining historical returns with three-day lagged sentiment scores—reducing the error from 65% (baseline) to 18%, confirming the effectiveness of sentiment-enhanced models for forecasting S&P 500 index returns.

7.1 Contribution

The primary objective of this research was to improve the accuracy of stock return forecasting by reducing the error rate via a deep learning technique. The following is a summary of the contributions of this research:

7.1.1 Deep Learning Model Optimisation

This research presents a rigorous empirical comparison of three prominent deep learning models—GRU, LSTM, and MLP—for stock return forecasting. Unlike prior works that focused on fixed configurations (e.g., Zhong and Enke, 2019; Hiransha et al., 2018; Althelaya et al., 2018a), this research examined over 10,000 configurations, encompassing multiple activation functions, input windows, architectural depths, and epoch counts.

The finding include:

- GRU, when used with TanH, was most accurate for predicting index prices, although its prolonged training time limited its practicality.

- MLP with ReLU emerged as the most efficient and stable model for return prediction, achieving optimal performance with window size 63, 50 epochs, one hidden layer, and four nodes.
- While increasing node count improved performance, deeper architectures offered no significant advantage, corroborating earlier studies (Vujičić and Matijević, 2016; Nayak, Misra and Behera, 2014).

These insights provide concrete guidance for selecting and tuning deep learning models for financial applications. Moreover, the volume and diversity of model configurations tested in this study far exceed the scope of earlier research, lending robustness to the conclusions drawn. This large-scale experimentation also reinforces the importance of performance benchmarking under different hyperparameter regimes, a practice often overlooked in the literature.

7.1.2 Sentiment-Enriched Return Prediction

This research makes a novel contribution by evaluating how sentiment extracted from financial news can improve return forecasting. A total of 13 datasets were generated, incorporating combinations of sentiment scores (compound, positive, neutral, negative) across four timeframes.

These contributions include:

- Dataset j, incorporating a three-day average of sentiment scores alongside historical returns, was the most effective configuration.
- The inclusion of sentiment features significantly reduced prediction error, with the best configuration achieving a MAPE of 18.43%.
- Multi-dimensional sentiment (as opposed to compound-only scores) proved substantially more informative.
- Model performance varied by dataset, with the Sigmoid activation function performing best in the top sentiment-integrated configuration.

These findings underscore the value of structured, time-aware sentiment features in financial forecasting and provide a direction for future research on hybrid input design. Additionally, the ability of sentiment features to reduce forecasting error highlights their real-world potential in market analytics, algorithmic trading, and investor behaviour modelling. Integrating sentiment allows for a more nuanced interpretation of market signals, which could support both short-term trading decisions and longer-term strategic forecasting.

7.1.3 Methodological and Analytical Contributions

This research contributes a reproducible and statistically validated experimental framework. Notable methodological strengths include:

- Implementation of walk-forward validation to simulate real-world prediction scenarios while avoiding data leakage.
- Statistical validation through MANOVA and ANOVA, confirming the influence of hyperparameters on predictive accuracy.
- A modular, scalable design that can be adapted to other indices or extended with additional data inputs.

Collectively, the methodology strengthens the credibility and generalisability of the findings while offering a template for future financial AI research. By formalising the experimental workflow and validating it through statistical means, the study sets a standard for reproducibility and comparability, encouraging further exploration in both academic and applied contexts. This structured approach ensures that future enhancements—such as alternative data inputs or advanced model architectures—can be incorporated seamlessly into the existing framework. (Kingma and Ba, 2015; Ding and Qin, 2020; Palomino and Aider, 2022).

7.2 Limitations and Future Work

Despite the promising results, several limitations should be acknowledged. Firstly, the sentiment data retrieved from *Finnhub* was limited to a five-year period. While sufficient for the current study, longer datasets might capture broader market cycles and improve the robustness of findings.

Secondly, the study primarily focused on MLP in the final experiments. Future research may benefit from exploring more sophisticated architectures, such as Transformer models or hybrid networks that combine temporal and contextual learning.

In addition, future studies could incorporate a wider range of input variables, including macroeconomic indicators (e.g., interest rates, inflation), geopolitical events, and alternative sentiment sources (e.g., social media, earnings calls). More advanced sentiment analysis methods, such as BERT or domain-adapted transformers, could further enhance sentiment feature quality.

Finally, it would be valuable to apply the proposed models in simulated or real-world trading environments, assessing their utility within financial decision-support systems. Such extensions would enhance the practical relevance and industry applicability of this research.

Appendix A List of Machine Learning Techniques and Definitions

A

ANNs (Artificial Neural Networks): Computing systems with a set of models and algorithms that are brain-inspired, intended to imitate human learning (Frankenfield, 2018).

ARIMA (Autoregressive integrated moving average model): A prediction technique performed by a statistical analysis model using time series data (Zhang, 2003).

B

BPNN (Backpropagation neural network): An iterative process of tuning the weights in neural network models from errors provided by a loss function (Chen et al., 2008).

BSM (Black Scholes Model): A mathematical model for calculating price deviation over a period of time for financial instruments (Kenton, 2019a).

C

CART (Classification and Regression Trees): A binary decision tree model performed through a sequence of questions, the answers to which are input to the next question, and each terminal node is the result of prediction (Breiman et al., 2017; Pradeepkumar and Ravi, 2017).

F

FCM (Fuzzy c means): A clustering technique where an object can belong to more than one cluster with different probabilities (Zhang, Wang and Zhang, 2007).

G

GARCH (Generalized Autoregressive Conditional Heteroscedasticity): A statistical model for prediction through analysis of financial time-series data (Francq and Zakoian, 2019).

GAs (Genetic Algorithms): A search technique that imitates the process of natural selection to find optimal solutions (Pal and Wang, 2017).

GMDH (Group method of data handling): A type of inductive algorithm performed by a mathematical model that provides possible automatic discovery of relations in the data (Teng et al., 2017).

GP (Gaussian Processes): A collection of random variables that have a normal distribution (Swain et al., 2016).

GRNN (Generalized Regression Neural Network): A basic neural network-based function estimation algorithm used for classification, regression, and prediction (Chen and Wang, 2018).

H

HMM (Hidden Markov Model): A statistical model used for machine learning with hidden states, as opposed to a standard Markov chain where all states are disclosed (Degirmenci, 2014).

Hierarchical clustering: builds a multilevel hierarchy of clusters by creating a cluster tree (Rokach and Maimon, 2005a).

K

KNN (K Nearest Neighbour): A supervised learning technique use for classification, where an object is considered as a member of a cluster with a plurality voting of its neighbours (Jadhav and Channe, 2016).

k-means: A clustering technique where an object can belong to only one cluster and a cluster must contain at least one object, in which centroids of clusters are means of objects in each cluster (Rokach and Maimon, 2005b).

k-medoids (PAM): A clustering technique where an object can belong to only one cluster and a cluster must contain at least one object, in which centroids of clusters are the most central object in each cluster (Rokach and Maimon, 2005b).

L

LR (Logistic Regression): A machine learning algorithm for statistical classification, where an outcome is determined by one or more independent variables (Attigeri et al., 2015).

LSTM (Long Short-Term Memory): One of the most successful RNN architectures that introduce the memory cell, a unit of computation that replaces traditional artificial neurons in the hidden layer of the network. These memory cells make networks effectively associate memories with input remote in time (Roondiwala, Patel and Varma, 2017).

M

MCS (Monte Carlo Simulation): A technique used to model the probability of variant outcomes in hard to predict cases because of the interference of random variables (Morin, 2019).

MLP (Multilayer Perceptron): A type of ANN consisting of at least three layers: input layer, hidden layer, and output layer (Ramchoun et al., 2016).

P

PSO (Particle Swarm Optimization): A technique performing optimal solution searching, inspired by the behaviour of social creatures in groups (Martínez and Cao, 2018).

Q

QR (Quantile Regression): A regression mechanism that models the relationship between a dependent variable and independent variables at different quantiles (Pradeepkumar and Ravi, 2017).

QRNN (Quantile Regression Neural Network): A QR-based hybrid and a feedforward neural network that can be used to estimate the

nonlinear models at different quantiles
(Pradeepkumar and Ravi, 2017).

R

RBF (Radial Basis Function Neural Networks): A type of ANN performed by a linear model (Aljarah et al., 2018).

RF (Random Forest): An ensemble method used to construct a prediction model of both classification and regression problems (Janitza, Tutz and Boulesteix, 2016).

RNN (Recurrent neural networks): A powerful model for processing sequential data such as sound, time-series data or written natural language. Some designs of RNN are used to predict the stock market (Saad, Prokhorov and Wunsch, 1998; Chen, Zhou and Dai, 2015; Lipton, Berkowitz and Elkan, 2015; Rather, Agarwal and Sastry, 2015).

S

SOM (Self-organizing maps): A type of ANN using unsupervised learning in training to build a two-dimensional map of the problem space (Galutira, Fajardo and Medina, 2019).

SVM (Support Vector Machine): A supervised machine learning technique for classification and regression analysis (Auria and Moro, 2008).

SVR (Support Vector Regression): A supervised machine learning technique for classification and regression analysis (Basak, Pal and Patranabis, 2007).

Appendix B Machine Learning Techniques Applied to Financial Instruments

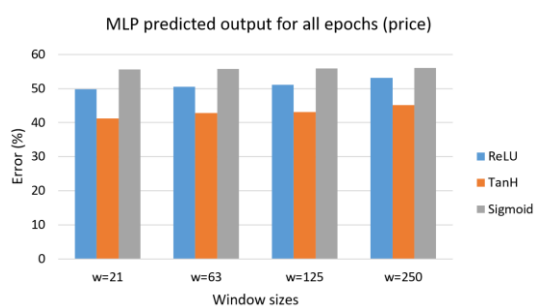
Table B - 1 : Machine learning applied to cluster, classify, and predict the financial instruments

	Stocks	Bonds	Derivatives	Foreign Exchange	Commodities
Clustering	- SOM - k-Means - Hierarchical Clustering				
Prediction	- RF (prices) - SVM (prices) - ARIMA (prices) - GARCH (prices) - MLP (prices) - LSTM (prices) - GAs (prices) - KNN (prices) - SVR (prices, value at risk) - MCS (prices, value at risk) - ANNs (prices, value at risk) - LR (prices)	- CART (credit risk) - KNN (credit risk) - SVR (value at risk) - MCS (volatility, value at risk, default probability) - NNs (value at risk)	- GP (pricing and hedging derivatives securities) - ANNs (pricing and hedging derivatives securities, value at risk, options pricing) - SVR (value at risk) - MCS (value at risk, default probability, options pricing) - BSM (pricing and hedging derivatives securities) - MLP (options pricing) - BSM (options pricing) - RBF (options pricing) - BPNN (options pricing) - GAs (options pricing) - KNN (options pricing) - LR (default probability)	- GARCH (exchange rates) - QR (exchange rates) - ARIMA (exchange rates) - Vector Autoregressive (exchange rates) - KNN (exchange rates) - SVR (value at risk, exchange rates) - MCS (value at risk) - MLP (value at risk, exchange rates) - LR (cryptocurrency) - Naïve Bayes (cryptocurrency) - SVM (cryptocurrency) - Deep Reinforcement Learning (cryptocurrency)	- MLP (Gold and Oil (prices, value at risk)) - GRNN (Gold and Oil prices) - GARCH (Gold and Oil prices) - RF (Gold and Oil prices) - GAs (Gold and Oil (prices, value at risk)) - RNN (Gold and Oil (prices, value at risk))
Classification	- SVM	- SVM (bond rating, credit rating) - KNN (bond rating) - LR (credit rating) - NNs (credit rating)			

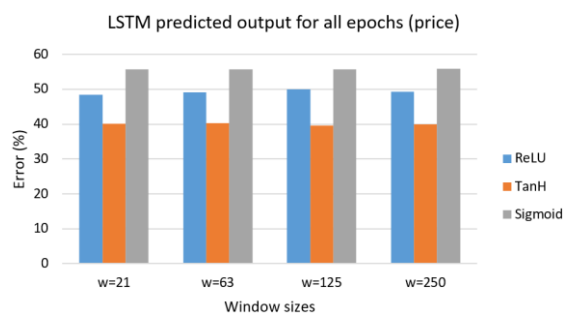
Appendix C The prediction results of the S&P 500 index price and return

C.1 The results of stock index price prediction

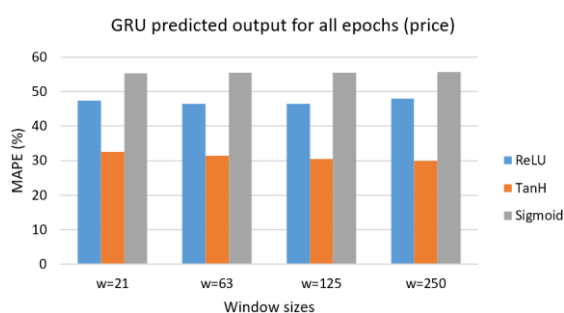
C.1.1 Predicted output error



(a) MLP average error for all epochs



(b) LSTM average error for all epochs



(c) GRU average error for all epochs

Figure C - 1 : Window size comparison of all epochs and architecture across three models with all activation functions (price)

Appendix C The prediction results of the S&P 500 index price and returns

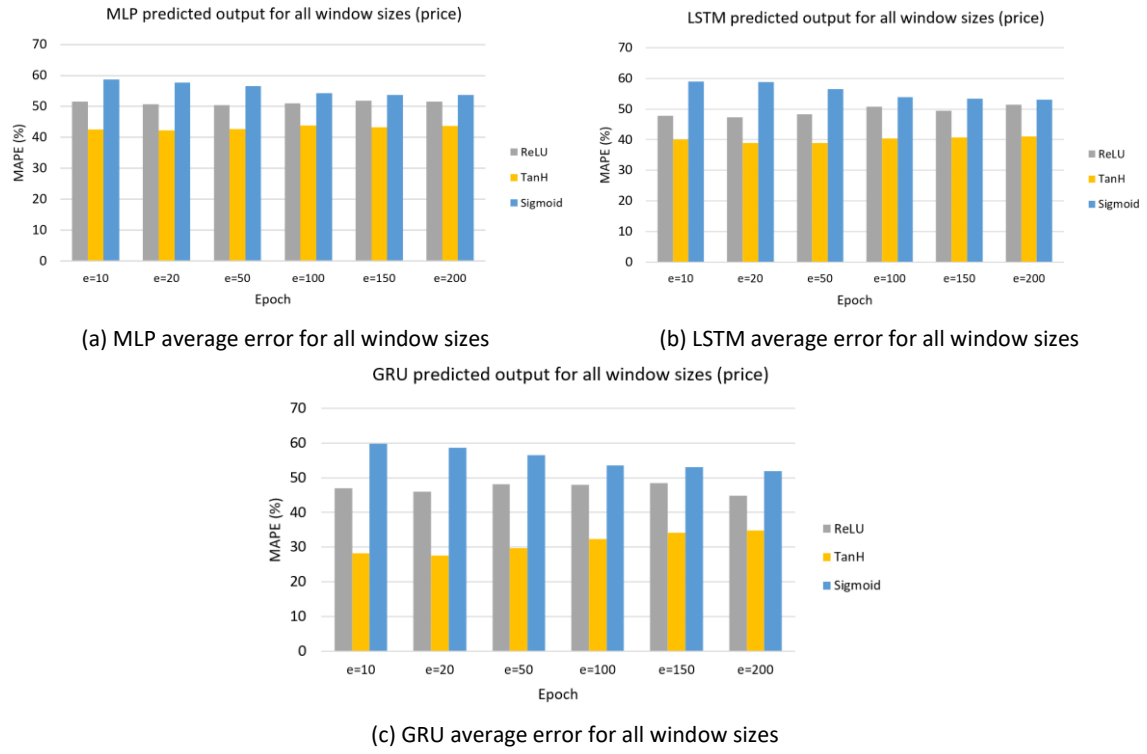


Figure C - 2 : Epoch comparison of all window sizes and architecture across three models with all activation functions (price)

Appendix C The prediction results of the S&P 500 index price and returns

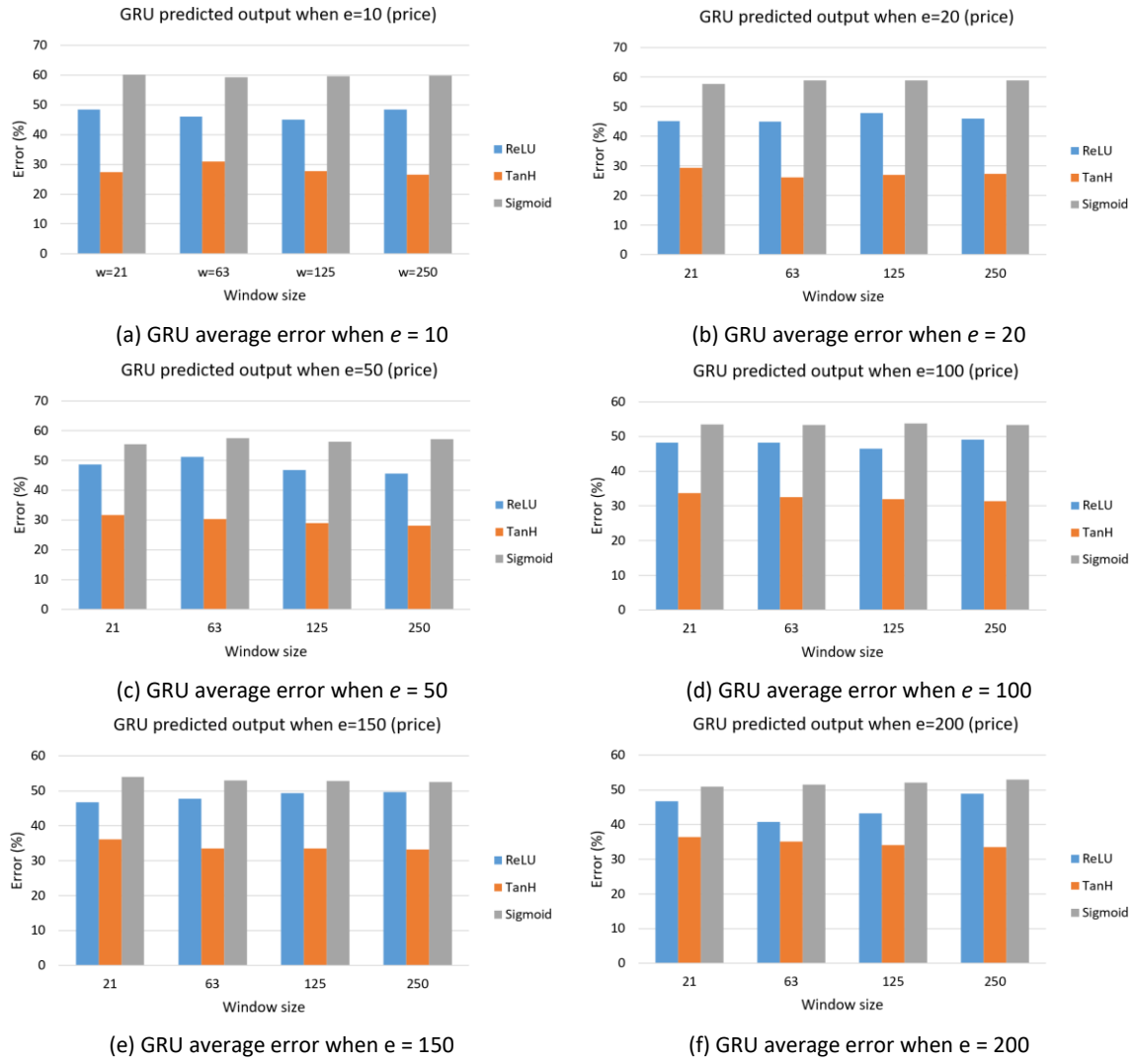


Figure C - 3 : Window size comparison of GRU of each epoch across all architectures on index price prediction

Appendix C The prediction results of the S&P 500 index price and returns

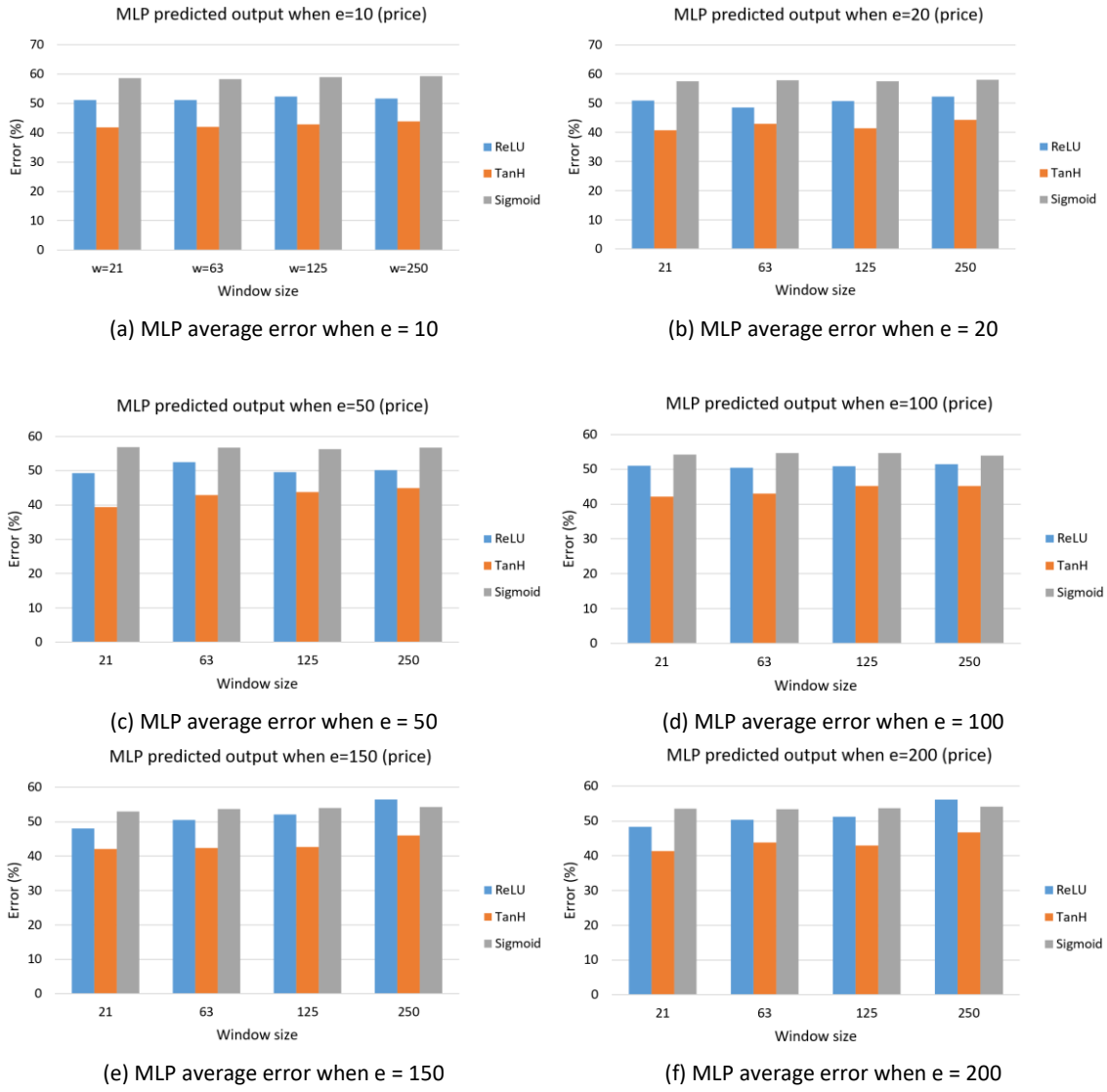


Figure C - 4 : Window size comparison of MLP of each epoch across all architectures on index price prediction

Appendix C The prediction results of the S&P 500 index price and returns

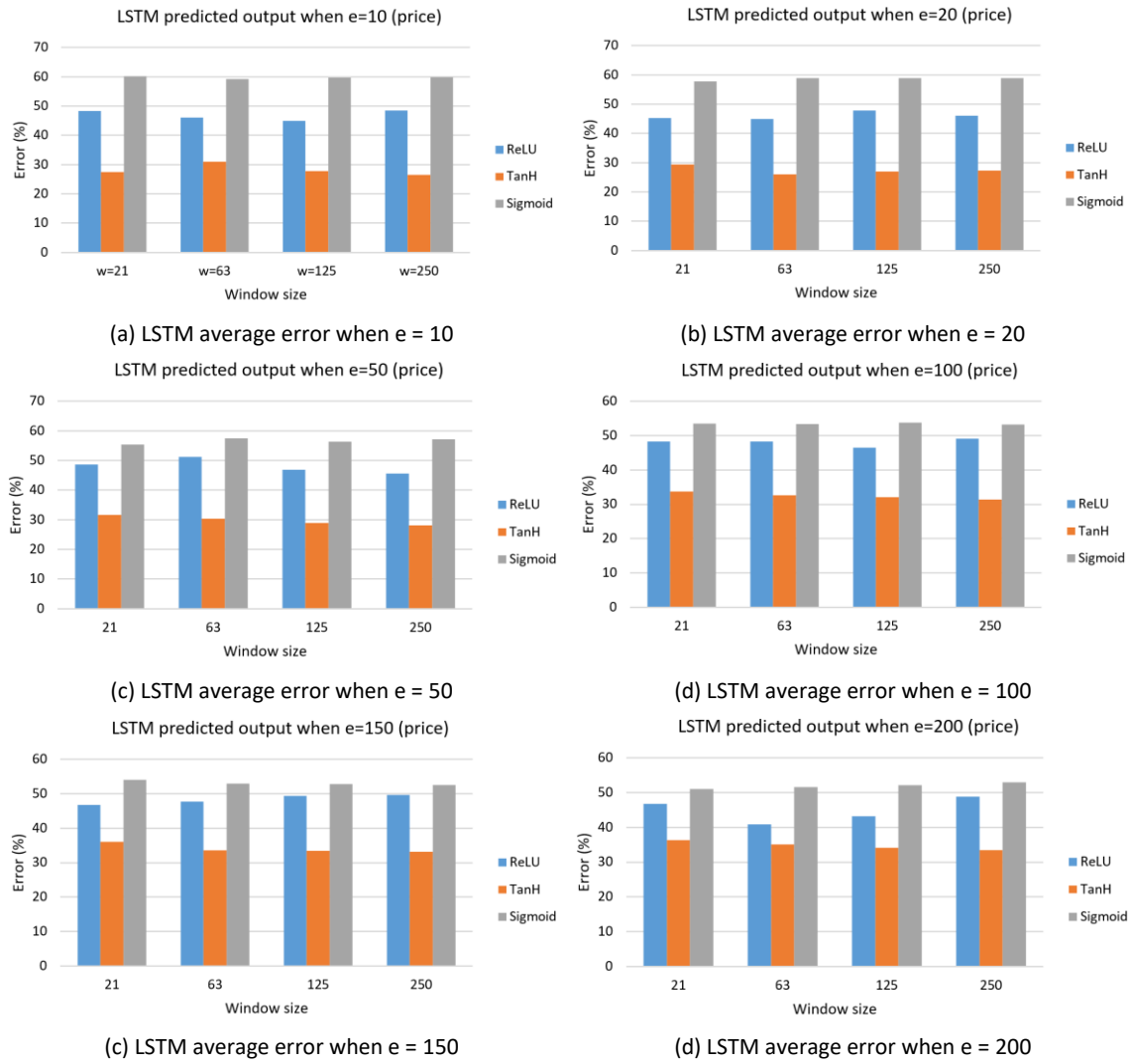


Figure C - 5 : Window size comparison of LSTM of each epoch across all architectures on index price prediction

Appendix C The prediction results of the S&P 500 index price and returns

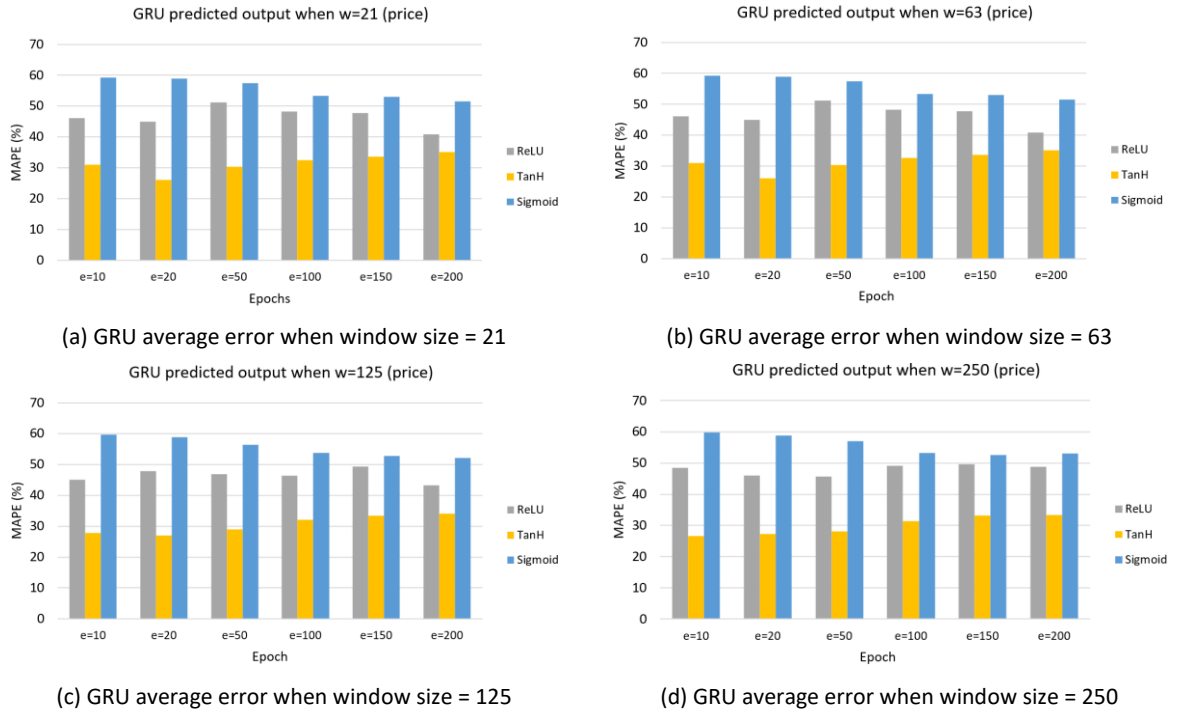


Figure C - 6 : Epoch comparison of GRU of each window size across all architectures on index price prediction

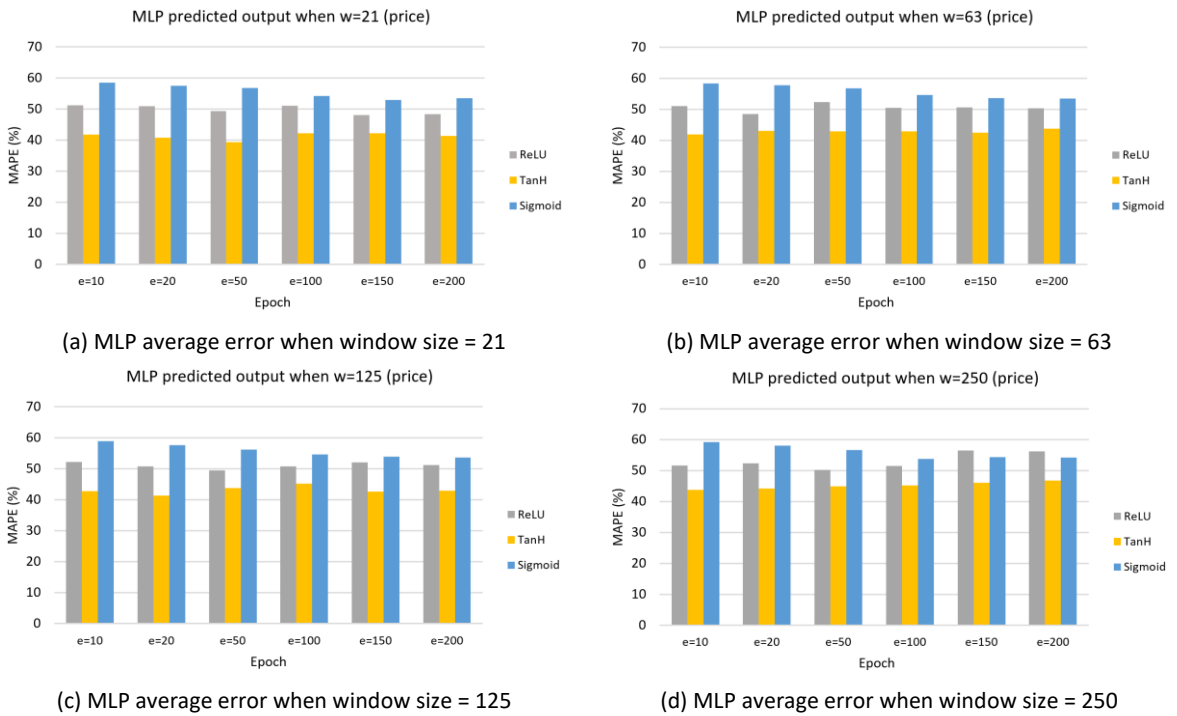
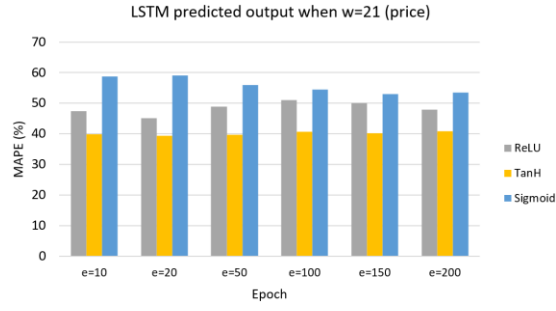
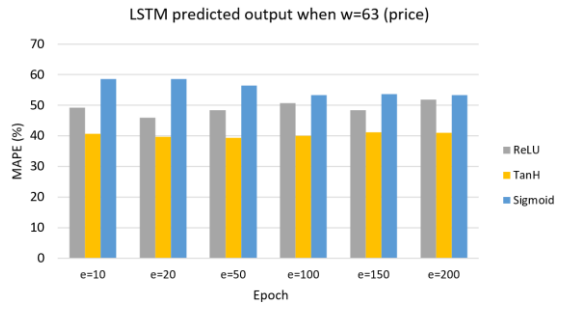


Figure C - 7 : Epoch comparison of MLP of each window size across all architectures on index price prediction

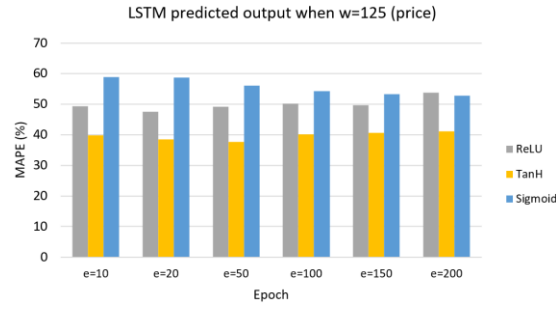
Appendix C The prediction results of the S&P 500 index price and returns



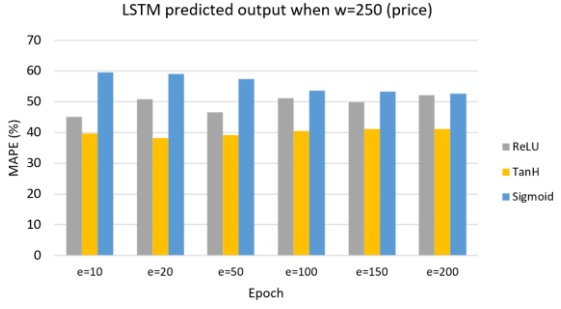
(a) LSTM average error when window size = 21



(b) LSTM average error when window size = 63



(c) LSTM average error when window size = 125



(d) LSTM average error when window size = 250

Figure C - 8 : Epoch comparison of LSTM of each window size across all architectures

C.1.2 The best average parameter value of three models across three activation functions on index return prediction

Table C - 1 : The best average parameter values of GRU model across three activation functions (return)

Activation Function	Parameters				Results		
	w	e	h*	n*	Best rrorr (%)	Mean error (%)	Mean time (sec)
ReLU	21	10	1	4	98.72	108.81	37.19
		20	1	16	90.26	98.19	67.80
		50	2	16	83.70	97.95	160.21
		100	1	4	86.76	96.93	305.82
		150	1	4	90.38	97.37	461.52
		200	1	8	86.00	97.91	607.10
	63	10	2	4	99.03	112.45	91.32
		20	1	4	94.42	98.46	176.99
		50	1	4	85.23	99.02	435.83
		100	2	4	84.95	97.92	872.75
		150	1	4	87.76	97.41	1316.83
		200	1	16	86.85	99.94	1762.17
	125	10	1	1	99.53	110.09	189.68
		20	1	4	88.39	98.76	370.12
		50	2	8	88.61	98.14	916.95
		100	1	1	89.62	97.70	1834.13
		150	2	4	87.94	97.86	2754.22
		200	8	16	90.57	98.38	3674.46
	250	10	4	16	99.63	110.72	393.47
		20	2	2	92.36	97.86	796.75
		50	1	16	88.76	97.12	2028.56
		100	1	4	92.43	98.13	4089.31
		150	1	16	90.87	98.11	6232.85
		200	1	4	88.47	97.06	8196.43
TanH	21	10	1	1	91.92	110.18	35.40
		20	1	1	78.10	100.38	64.30
		50	1	2	71.19	98.98	152.93
		100	4	8	89.05	98.20	298.24
		150	1	1	82.69	98.59	443.63
		200	1	1	84.05	97.59	590.89
	63	10	1	1	73.90	109.62	92.20
		20	1	1	84.76	96.55	178.67
		50	2	8	84.24	94.66	435.91
		100	2	2	89.89	100.13	867.95
		150	1	1	87.46	97.65	1331.06
		200	1	1	84.19	100.06	1767.55
	125	10	1	8	92.04	114.59	188.85
		20	1	16	79.34	97.87	371.70
		50	1	4	78.12	97.65	936.63
		100	1	2	79.59	95.94	1845.79

Appendix C The prediction results of the S&P 500 index price and returns

Activation Function	Parameters				Results		
	w	e	h*	n*	Best rrror (%)	Mean error (%)	Mean time (sec)
	125	150	2	8	84.23	96.74	2831.68
		200	1	8	84.91	97.63	3694.35
	250	10	1	1	90.48	110.54	395.11
		20	4	1	86.90	100.16	795.11
		50	2	16	83.93	95.46	2038.99
		100	2	8	84.95	98.04	4078.67
		150	8	1	80.59	97.37	6134.80
		200	2	8	90.94	97.59	8300.23
Sigmoid	21	10	1	4	58.54	145.23	26.02
		20	1	4	54.51	103.37	64.21
		50	1	16	80.92	99.68	150.76
		100	1	1	81.91	99.23	295.62
		150	1	1	84.78	96.90	441.03
		200	1	1	85.40	98.45	589.65
	63	10	1	4	92.41	153.52	93.12
		20	1	16	53.58	97.79	180.75
		50	1	16	73.40	96.56	447.65
		100	1	4	77.61	95.79	897.35
		150	1	4	85.13	99.29	1318.56
		200	1	2	91.98	98.70	1769.58
	125	10	1	2	67.79	153.32	189.89
		20	1	8	61.76	101.24	375.05
		50	1	1	84.51	97.42	924.39
		100	1	4	76.23	99.49	1852.09
		150	1	4	83.68	94.95	2779.94
		200	1	4	88.85	99.21	3679.85
	250	10	1	4	68.57	143.04	412.19
		20	1	4	56.34	102.18	847.15
		50	1	4	67.88	96.89	2048.00
		100	1	1	86.07	97.17	4132.24
		150	16	1	85.11	97.92	6154.59
		200	1	1	87.34	98.77	8297.60

Note: h*n* are the architecture of the best prediction of that window size

is the best w that shows the best average of the prediction accuracy of all epochs in that window size

Table C - 2 : The best average parameter values of MLP model across three activation functions (return)

Activation Function	Parameters				Results		
	w	e	h*	n*	Best rror (%)	Mean error (%)	Mean time (sec)
ReLU	21	10	1	4	80.09	99.59	2.17
		20	1	16	66.03	94.33	3.28
		50	2	16	82.78	96.28	6.62
		100	1	4	90.38	98.15	13.15
		150	1	4	89.37	98.27	17.71
		200	1	8	87.89	96.89	23.20
	63	10	2	4	52.73	96.70	2.19
		20	1	4	66.21	94.39	3.26
		50	1	4	65.02	90.64	6.65
		100	2	4	74.84	91.33	12.20
		150	1	4	78.21	94.25	17.38
		200	1	16	75.99	93.90	23.05
	125	10	1	1	45.68	98.61	2.15
		20	1	4	74.36	103.78	3.26
		50	2	8	78.19	96.36	6.56
		100	1	1	77.50	97.32	11.91
		150	2	4	87.09	98.92	17.38
		200	8	16	93.29	98.60	23.02
	250	10	4	16	65.65	90.99	2.16
		20	2	2	79.19	105.64	3.24
		50	1	16	86.70	100.19	6.49
		100	1	4	85.44	97.34	12.07
		150	1	16	93.38	99.08	17.31
		200	1	4	92.61	101.17	22.98
TanH	21	10	1	1	58.03	97.36	2.17
		20	1	1	32.19	96.35	3.29
		50	1	2	86.97	98.69	6.75
		100	4	8	87.06	97.48	12.16
		150	1	1	88.82	99.78	17.49
		200	1	1	83.71	98.34	23.17
	63	10	1	1	29.45	102.87	2.16
		20	1	1	76.77	98.50	3.26
		50	2	8	87.78	99.57	6.55
		100	2	2	80.70	98.91	12.01
		150	1	1	84.15	99.70	17.39
		200	1	1	84.09	100.96	23.19
	125	10	1	8	78.03	108.25	2.14
		20	1	16	93.27	101.61	3.25
		50	1	4	94.50	102.29	6.50
		100	1	2	93.11	102.98	12.05
		150	2	8	85.16	103.23	17.46
		200	1	8	88.77	102.77	22.72
	250	10	1	1	93.28	104.50	2.16

Appendix C The prediction results of the S&P 500 index price and returns

Activation Function	Parameters				Results		
	w	e	h*	n*	Best rror (%)	Mean error (%)	Mean time (sec)
	20	4	1		90.40	105.70	3.26
	50	2	16		91.23	106.58	6.57
	100	2	8		93.07	101.98	12.17
	150	8	1		97.98	108.97	17.57
	200	2	8		94.22	107.47	23.32
Sigmoid	21	10	1	4	91.64	104.30	2.25
		20	1	4	85.25	98.20	3.29
		50	1	16	93.23	101.31	6.60
		100	1	1	90.92	98.48	12.19
		150	1	1	89.00	98.14	17.77
		200	1	1	89.28	97.34	22.93
	63	10	1	4	71.33	105.41	2.17
		20	1	16	66.06	99.53	3.27
		50	1	16	58.71	95.71	6.52
		100	1	4	74.81	98.38	12.09
		150	1	4	82.39	98.02	17.57
		200	1	2	81.95	97.08	22.94
	125	10	1	2	57.43	107.68	2.16
		20	1	8	78.59	98.92	3.27
		50	1	1	93.08	100.37	6.57
		100	1	4	88.27	100.31	12.07
		150	1	4	83.12	101.13	17.35
		200	1	4	94.29	101.63	22.99
	250	10	1	4	62.97	113.54	2.14
		20	1	4	90.51	101.66	3.26
		50	1	4	93.50	101.12	6.67
		100	1	1	94.69	103.22	11.97
		150	16	1	96.27	104.16	17.52
		200	1	1	96.21	106.06	22.94

Note: h*n* are the architecture of the best prediction of that window size

is the best w that shows the best average of the prediction accuracy of all epochs in that window size

Table C - 3 : The best average parameter values of LSTM model across three activation functions
(return)

Activation Function	Parameters				Results		
	w	e	h*	n*	Best rrorr (%)	Mean error (%)	Mean time (sec)
ReLU	21	10	1	16	60.81	97.29	10.81
		20	1	16	68.46	96.92	18.46
		50	8	16	58.63	92.29	42.05
		100	16	8	56.31	98.04	81.15
		150	8	16	82.95	100.32	123.79
		200	2	8	72.16	98.52	162.08
	63	10	8	2	49.24	95.43	24.29
		20	8	16	60.53	96.03	47.10
		50	4	4	73.77	95.38	109.93
		100	2	16	75.21	98.69	217.98
		150	8	8	65.86	98.30	325.42
		200	4	16	66.03	97.88	432.65
	125	10	2	8	68.89	97.78	44.00
		20	16	4	75.39	96.40	85.79
		50	8	8	80.14	99.34	210.07
		100	2	16	70.20	96.25	422.81
		150	1	1	75.07	98.92	634.32
		200	1	8	82.17	96.84	843.48
	250	10	4	16	66.03	98.76	104.27
		20	2	8	67.81	98.25	194.03
		50	16	8	48.66	93.07	472.96
		100	4	16	75.90	97.86	953.46
		150	2	8	81.96	98.72	1420.90
		200	8	4	76.76	97.55	1906.21
TanH	21	10	16	16	65.60	96.06	10.33
		20	2	4	78.31	102.81	18.17
		50	2	16	56.33	97.74	41.75
		100	16	2	59.11	95.97	80.23
		150	2	16	78.91	97.97	122.59
		200	4	8	70.95	94.62	162.84
	63	10	8	8	53.07	95.41	23.51
		20	8	8	58.08	92.27	44.79
		50	16	2	51.86	90.75	108.96
		100	2	8	72.42	99.20	216.79
		150	2	2	81.67	102.27	327.79
		200	1	16	75.87	99.75	434.80
	125	10	2	4	65.84	92.62	45.11
		20	1	16	41.87	92.93	89.39
		50	1	16	54.63	94.02	225.02
		100	16	16	74.15	99.15	444.37
		150	2	8	81.19	99.29	674.34
		200	16	8	56.43	95.74	904.34

Appendix C The prediction results of the S&P 500 index price and returns

Activation Function	Parameters				Results		
	w	e	h*	n*	Best rrror (%)	Mean error (%)	Mean time (sec)
	250	10	4	4	62.38	96.44	95.67
		20	1	8	68.47	96.00	191.95
		50	1	16	60.53	99.70	478.01
		100	8	8	76.04	101.33	958.49
		150	4	8	64.70	98.74	1434.07
		200	16	4	75.51	95.10	1994.72
Sigmoid	21	10	4	8	73.82	101.50	10.35
		20	8	16	84.51	99.28	18.35
		50	4	8	70.86	94.27	42.41
		100	1	8	77.21	94.59	83.14
		150	8	16	62.25	98.34	120.77
		200	1	8	76.13	101.34	159.92
	63	10	8	16	86.00	109.54	23.90
		20	2	8	83.57	100.21	46.12
		50	8	2	76.62	99.60	110.26
		100	8	2	83.71	99.36	218.43
		150	1	16	79.29	95.74	325.70
		200	4	16	66.64	100.17	437.11
	125	10	16	16	81.06	100.02	44.77
		20	16	16	92.42	99.26	89.57
		50	1	2	75.26	103.28	222.61
		100	8	8	64.40	97.30	449.60
		150	4	2	80.27	99.60	675.63
		200	2	8	78.20	101.16	897.86
	250	10	1	8	74.07	100.42	97.10
		20	2	16	57.10	94.15	191.72
		50	2	8	74.24	96.81	477.88
		100	2	8	78.65	99.16	947.58
		150	4	4	78.68	97.80	1444.41
		200	2	16	57.52	95.13	1943.01

Note: h*n* are the architecture of the best prediction of that window size

is the best w that shows the best average of the prediction accuracy of all epochs in that window size

C.2 The result of stock index return prediction

C.2.1 Predicted output error

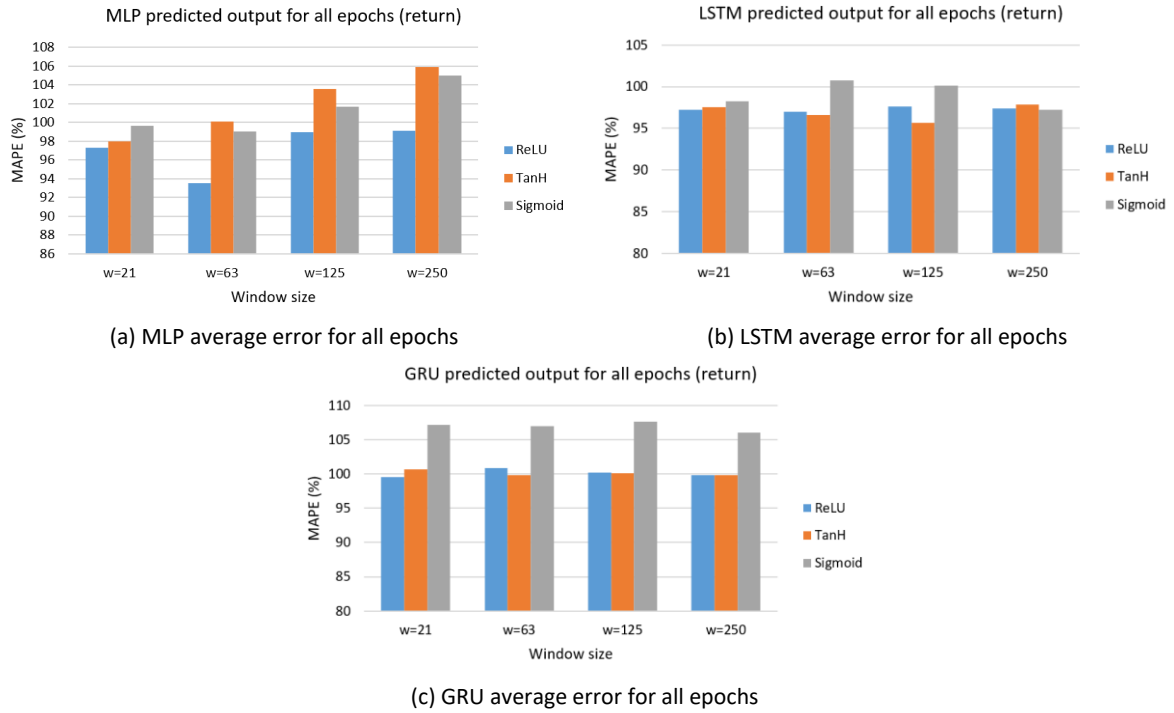


Figure C - 9 : Window size comparison of all epochs and architecture across three models with all activation functions (index return)

Appendix C The prediction results of the S&P 500 index price and returns

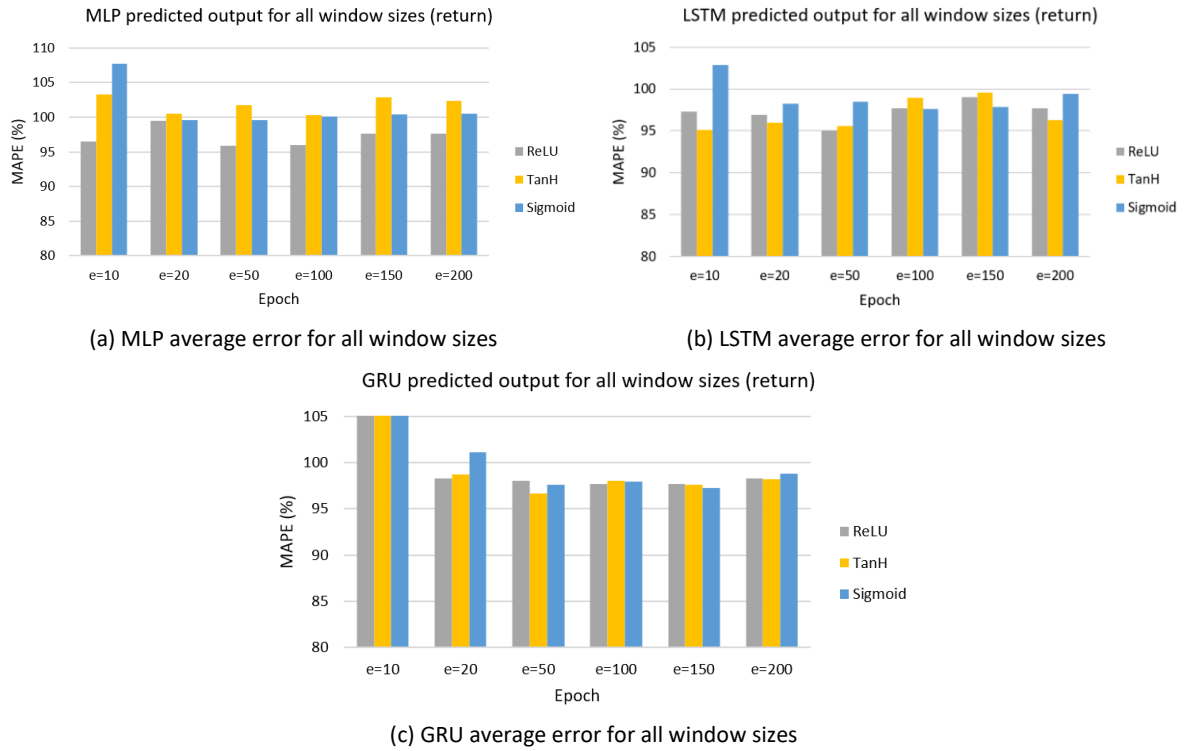


Figure C - 10 : Epoch comparison of all window sizes and architecture across three models with all activation functions (index return)

Appendix C The prediction results of the S&P 500 index price and returns

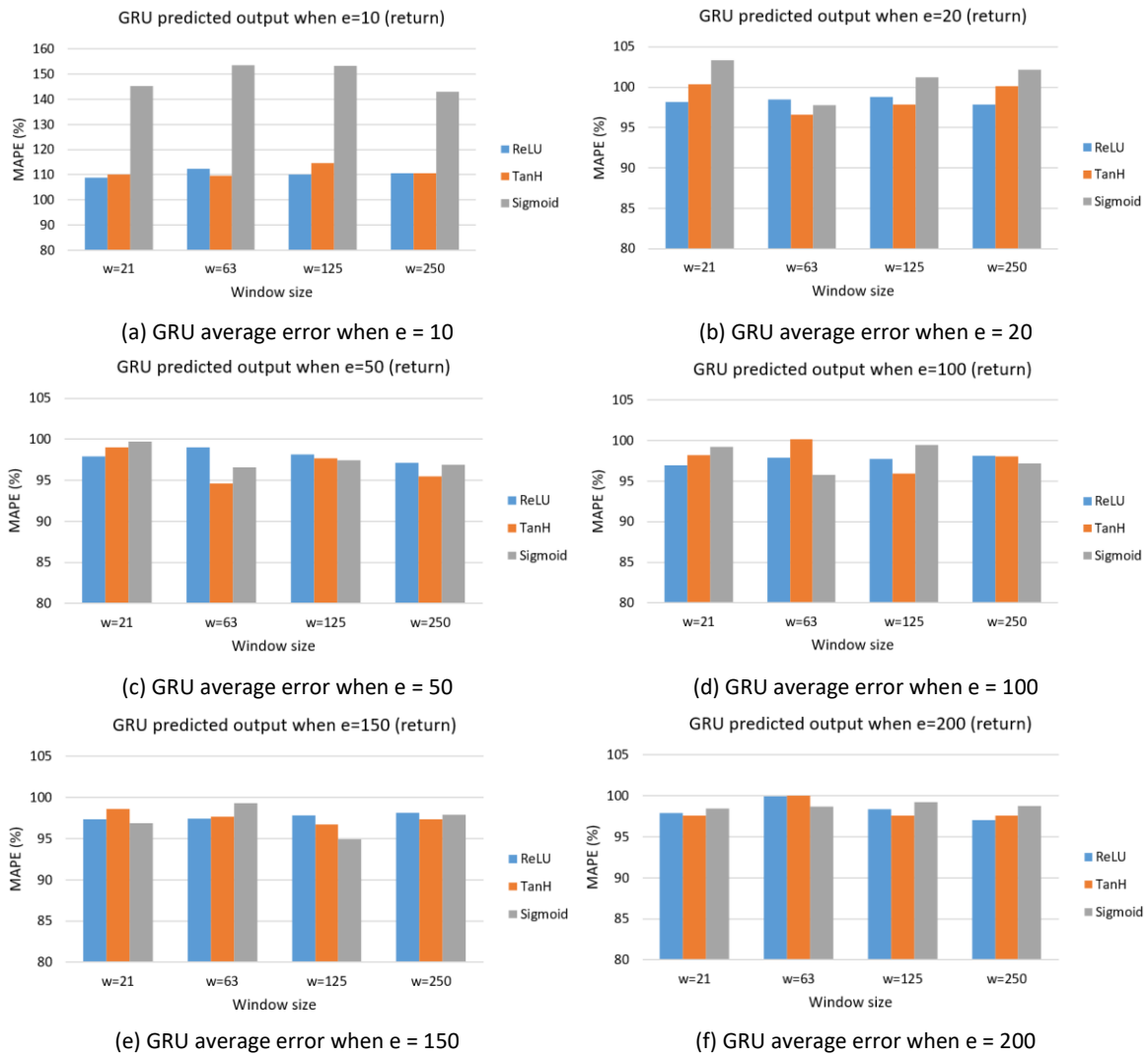


Figure C - 11 : Window size comparison of GRU of each epoch across all architectures on index return prediction

Appendix C The prediction results of the S&P 500 index price and returns

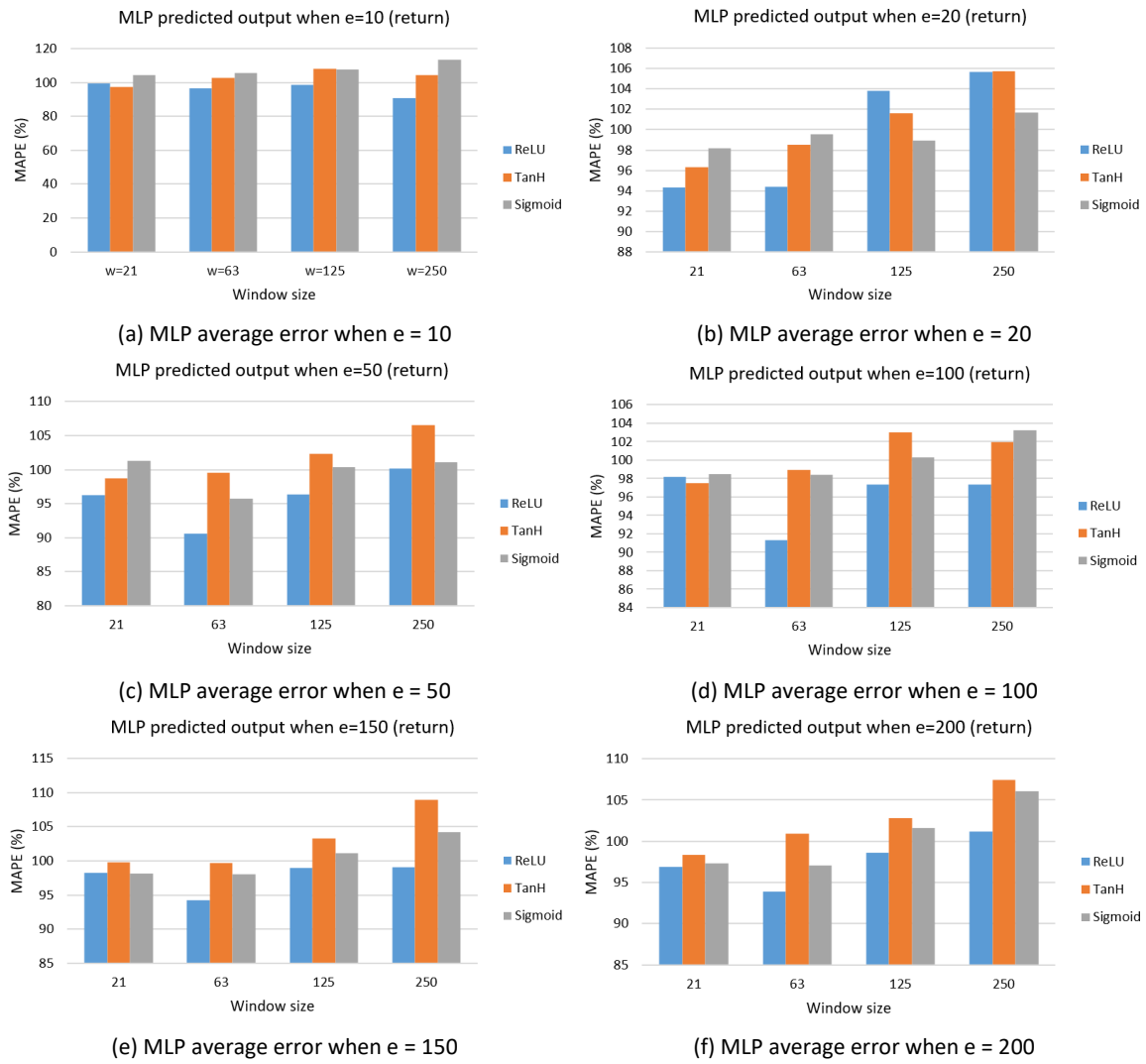


Figure C - 12 : Window size comparison of MLP of each epoch across all architectures on index return prediction

Appendix C The prediction results of the S&P 500 index price and returns

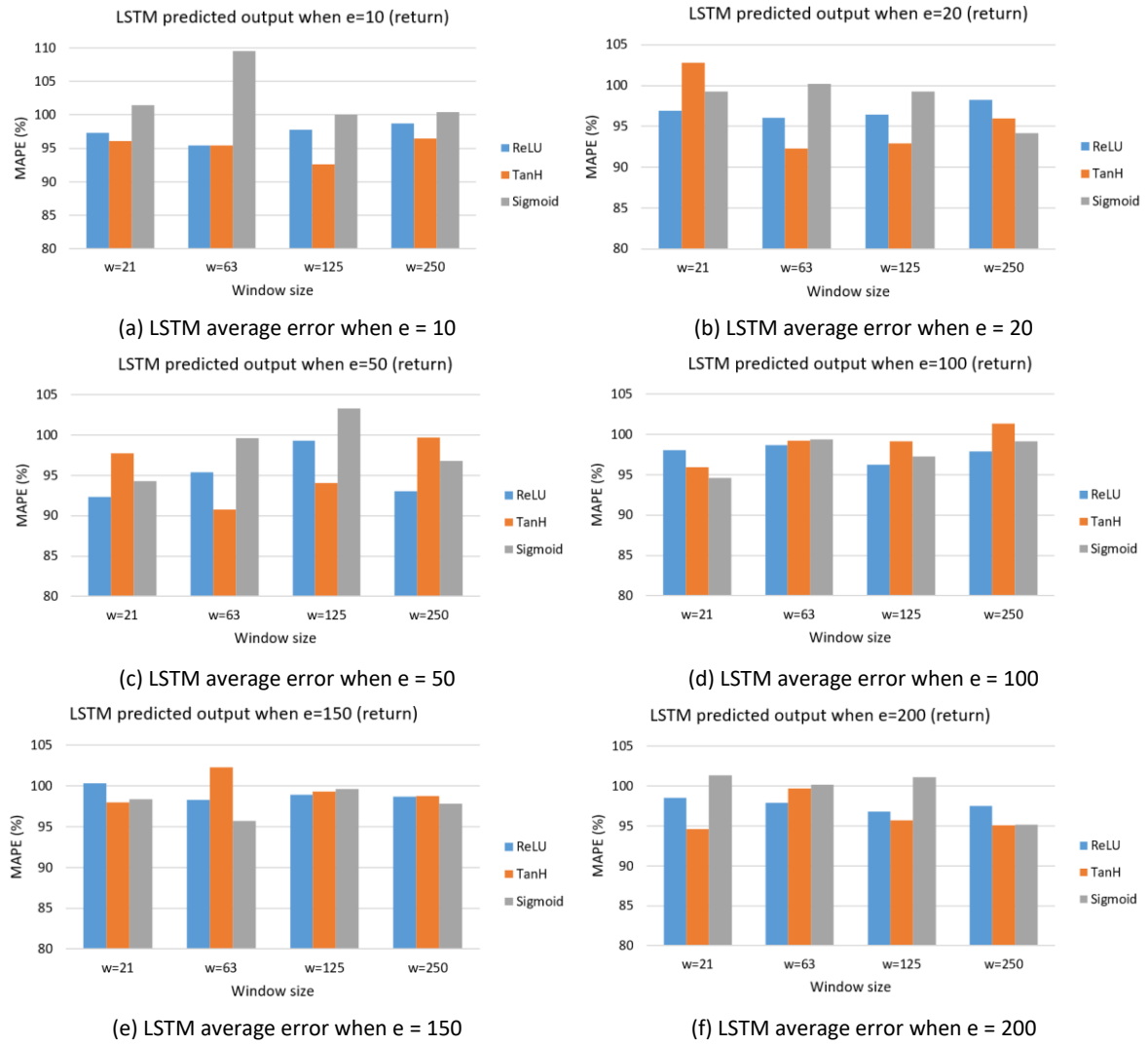


Figure C - 13 : Window size comparison of LSTM of each epoch across all architectures on index return prediction

Appendix C The prediction results of the S&P 500 index price and returns

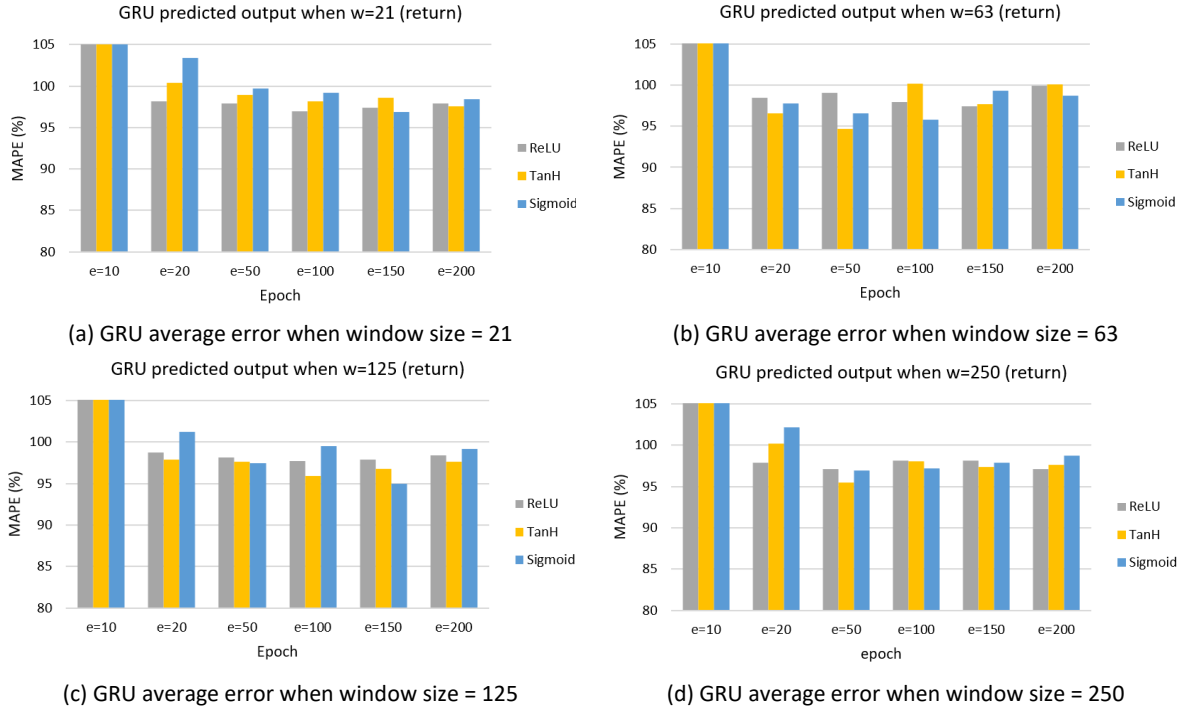


Figure C - 14 : Epoch comparison of GRU of each window size across all architectures on index return prediction

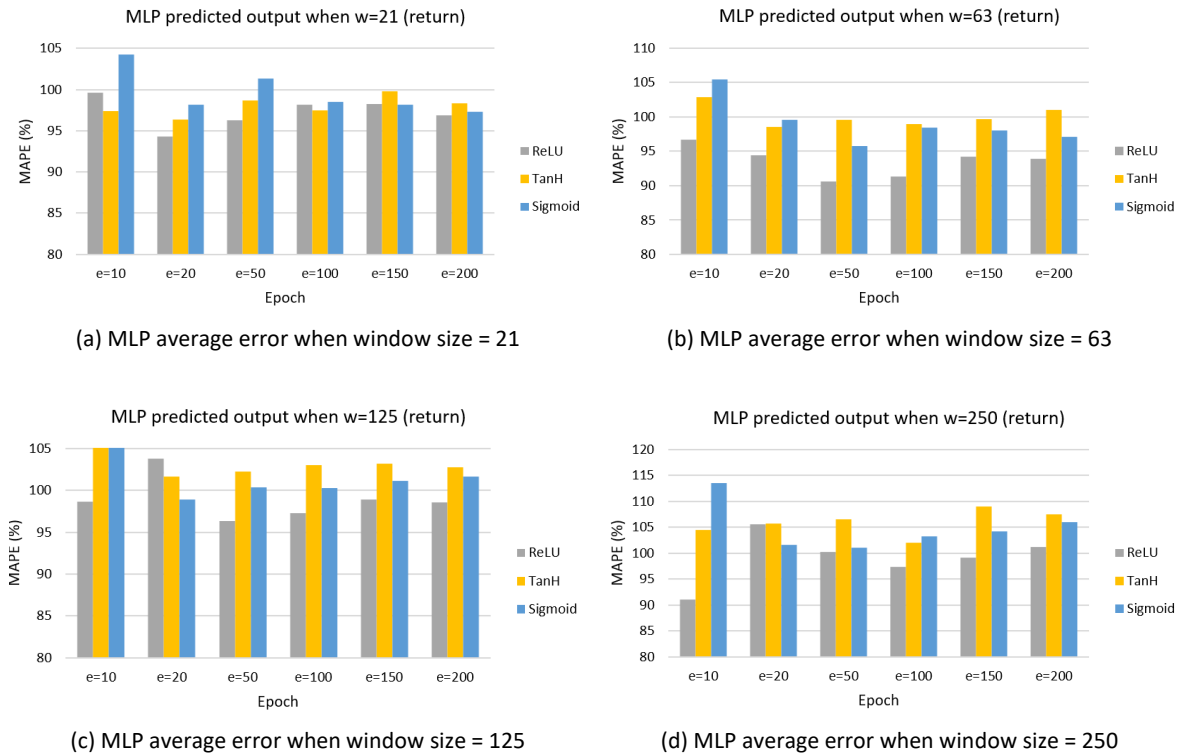


Figure C - 15 : Epoch comparison of MLP of each window size across all architectures on index return prediction

Appendix C The prediction results of the S&P 500 index price and returns

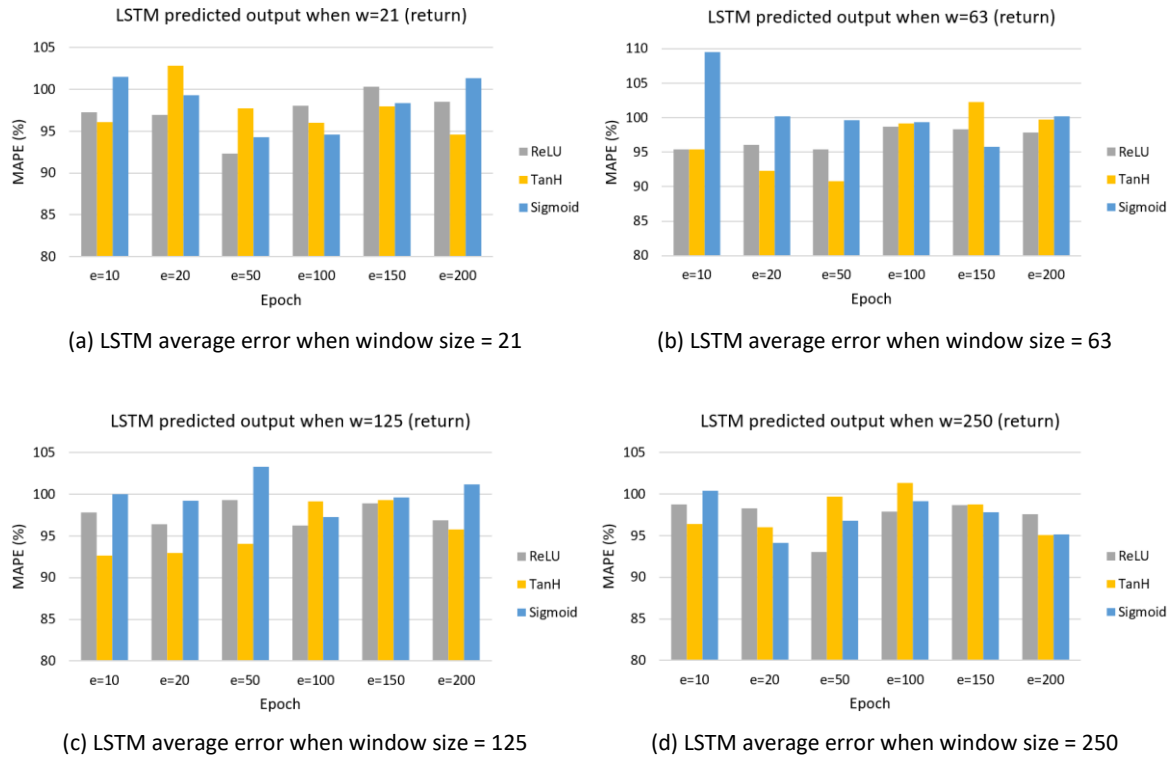
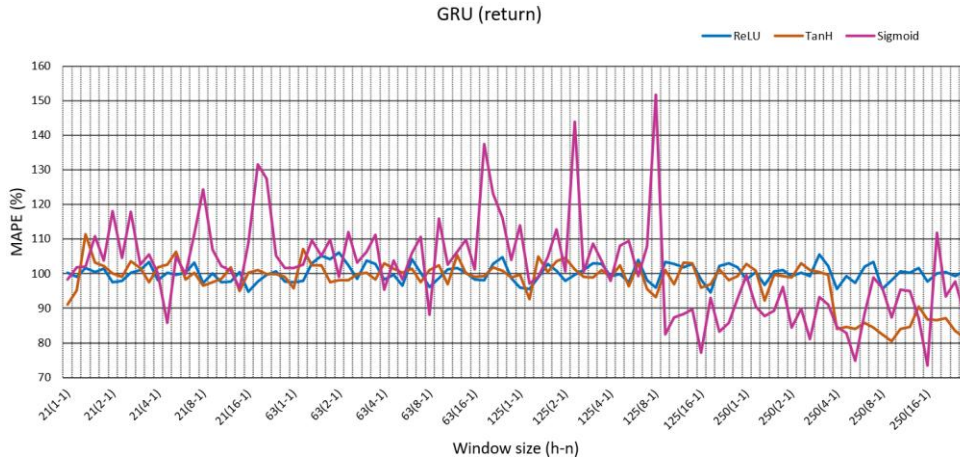
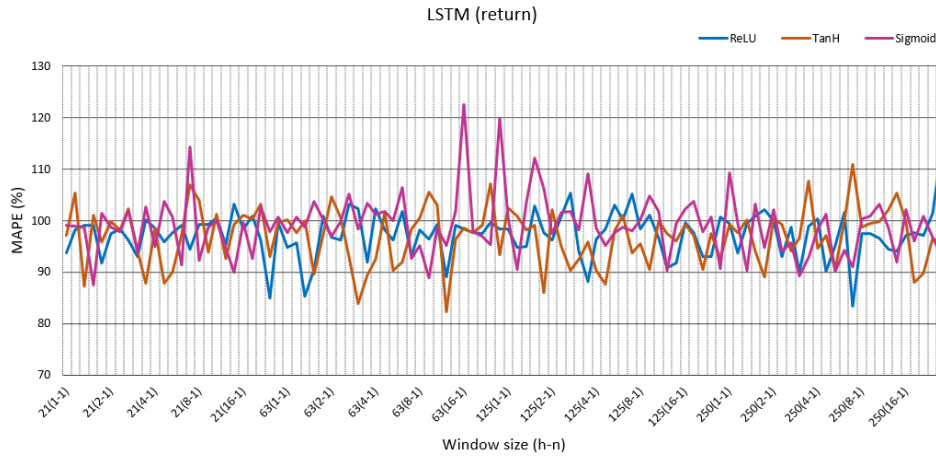


Figure C - 16 : Epoch comparison of LSTM of each window size across all architectures on index return prediction

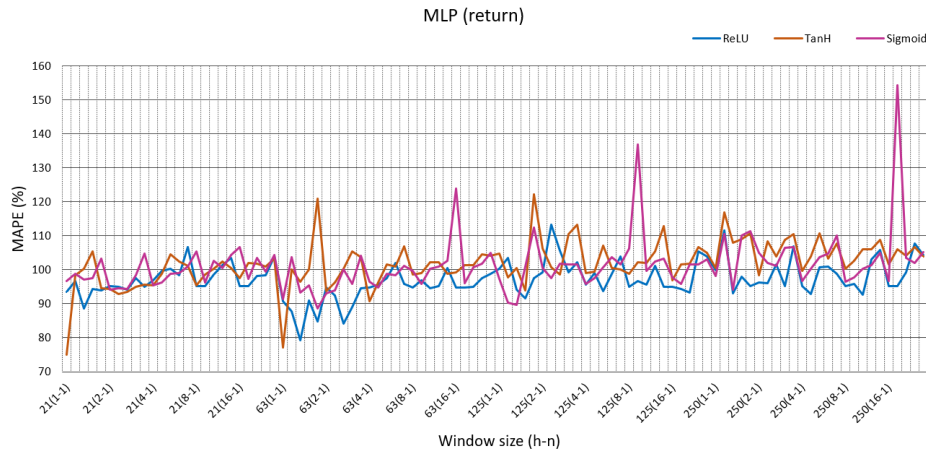
Appendix C The prediction results of the S&P 500 index price and returns



(n) GRU average error of all window sizes and all epochs



(o) LSTM average error of all window sizes and all epochs



(p) MLP average error of all window sizes and all epochs

Figure C - 17 : Model architecture comparison of all three models on index return prediction

C.2.2 The best average parameter value of three models across three activation functions on index return prediction

Table C - 4 : The best average parameter values of GRU model across three activation functions (return)

Activation	Parameters				Results		
Function	w	e	h*	n*	Best error (%)	Mean error (%)	Mean time (sec)
ReLU	21	10	1	4	98.72	108.81	37.19
		20	1	16	90.26	98.19	67.80
		50	2	16	83.70	97.95	160.21
		100	1	4	86.76	96.93	305.82
		150	1	4	90.38	97.37	461.52
		200	1	8	86.00	97.91	607.10
	63	10	2	4	99.03	112.45	91.32
		20	1	4	94.42	98.46	176.99
		50	1	4	85.23	99.02	435.83
		100	2	4	84.95	97.92	872.75
		150	1	4	87.76	97.41	1316.83
		200	1	16	86.85	99.94	1762.17
	125	10	1	1	99.53	110.09	189.68
		20	1	4	88.39	98.76	370.12
		50	2	8	88.61	98.14	916.95
		100	1	1	89.62	97.70	1834.13
		150	2	4	87.94	97.86	2754.22
		200	8	16	90.57	98.38	3674.46
	250	10	4	16	99.63	110.72	393.47
		20	2	2	92.36	97.86	796.75
		50	1	16	88.76	97.12	2028.56
		100	1	4	92.43	98.13	4089.31
		150	1	16	90.87	98.11	6232.85
		200	1	4	88.47	97.06	8196.43
TanH	21	10	1	1	91.92	110.18	35.40
		20	1	1	78.10	100.38	64.30
		50	1	2	71.19	98.98	152.93
		100	4	8	89.05	98.20	298.24
		150	1	1	82.69	98.59	443.63
		200	1	1	84.05	97.59	590.89
	63	10	1	1	73.90	109.62	92.20
		20	1	1	84.76	96.55	178.67
		50	2	8	84.24	94.66	435.91
		100	2	2	89.89	100.13	867.95
		150	1	1	87.46	97.65	1331.06
		200	1	1	84.19	100.06	1767.55
	125	10	1	8	92.04	114.59	188.85
		20	1	16	79.34	97.87	371.70
		50	1	4	78.12	97.65	936.63
		100	1	2	79.59	95.94	1845.79

Appendix C The prediction results of the S&P 500 index price and returns

Activation	Parameters				Results		
Function	w	e	h*	n*	Best error (%)	Mean error (%)	Mean time (sec)
	125	150	2	8	84.23	96.74	2831.68
		200	1	8	84.91	97.63	3694.35
	250	10	1	1	90.48	110.54	395.11
		20	4	1	86.90	100.16	795.11
		50	2	16	83.93	95.46	2038.99
		100	2	8	84.95	98.04	4078.67
		150	8	1	80.59	97.37	6134.80
		200	2	8	90.94	97.59	8300.23
Sigmoid	21	10	1	4	58.54	145.23	26.02
		20	1	4	54.51	103.37	64.21
		50	1	16	80.92	99.68	150.76
		100	1	1	81.91	99.23	295.62
		150	1	1	84.78	96.90	441.03
		200	1	1	85.40	98.45	589.65
	63	10	1	4	92.41	153.52	93.12
		20	1	16	53.58	97.79	180.75
		50	1	16	73.40	96.56	447.65
		100	1	4	77.61	95.79	897.35
		150	1	4	85.13	99.29	1318.56
		200	1	2	91.98	98.70	1769.58
	125	10	1	2	67.79	153.32	189.89
		20	1	8	61.76	101.24	375.05
		50	1	1	84.51	97.42	924.39
		100	1	4	76.23	99.49	1852.09
		150	1	4	83.68	94.95	2779.94
		200	1	4	88.85	99.21	3679.85
	250	10	1	4	68.57	143.04	412.19
		20	1	4	56.34	102.18	847.15
		50	1	4	67.88	96.89	2048.00
		100	1	1	86.07	97.17	4132.24
		150	16	1	85.11	97.92	6154.59
		200	1	1	87.34	98.77	8297.60

Note: h*n* are the architecture of the best prediction of that window size

is the best w that shows the best average of the prediction accuracy of all epochs in that window size

Table C - 5 : The best average parameter values of MLP model across three activation functions (return)

Activation	Parameters				Results		
Function	w	e	h*	n*	Best rrror (%)	Mean error (%)	Mean time (sec)
ReLU	21	10	1	4	80.09	99.59	2.17
		20	1	16	66.03	94.33	3.28
		50	2	16	82.78	96.28	6.62
		100	1	4	90.38	98.15	13.15
		150	1	4	89.37	98.27	17.71
		200	1	8	87.89	96.89	23.20
	63	10	2	4	52.73	96.70	2.19
		20	1	4	66.21	94.39	3.26
		50	1	4	65.02	90.64	6.65
		100	2	4	74.84	91.33	12.20
		150	1	4	78.21	94.25	17.38
		200	1	16	75.99	93.90	23.05
	125	10	1	1	45.68	98.61	2.15
		20	1	4	74.36	103.78	3.26
		50	2	8	78.19	96.36	6.56
		100	1	1	77.50	97.32	11.91
		150	2	4	87.09	98.92	17.38
		200	8	16	93.29	98.60	23.02
	250	10	4	16	65.65	90.99	2.16
		20	2	2	79.19	105.64	3.24
		50	1	16	86.70	100.19	6.49
		100	1	4	85.44	97.34	12.07
		150	1	16	93.38	99.08	17.31
		200	1	4	92.61	101.17	22.98
TanH	21	10	1	1	58.03	97.36	2.17
		20	1	1	32.19	96.35	3.29
		50	1	2	86.97	98.69	6.75
		100	4	8	87.06	97.48	12.16
		150	1	1	88.82	99.78	17.49
		200	1	1	83.71	98.34	23.17
	63	10	1	1	29.45	102.87	2.16
		20	1	1	76.77	98.50	3.26
		50	2	8	87.78	99.57	6.55
		100	2	2	80.70	98.91	12.01
		150	1	1	84.15	99.70	17.39
		200	1	1	84.09	100.96	23.19
	125	10	1	8	78.03	108.25	2.14
		20	1	16	93.27	101.61	3.25
		50	1	4	94.50	102.29	6.50
		100	1	2	93.11	102.98	12.05
		150	2	8	85.16	103.23	17.46
		200	1	8	88.77	102.77	22.72
	250	10	1	1	93.28	104.50	2.16

Appendix C The prediction results of the S&P 500 index price and returns

Activation Function	Parameters				Results		
	w	e	h*	n*	Best rrror (%)	Mean error (%)	Mean time (sec)
		20	4	1	90.40	105.70	3.26
		50	2	16	91.23	106.58	6.57
		100	2	8	93.07	101.98	12.17
		150	8	1	97.98	108.97	17.57
		200	2	8	94.22	107.47	23.32
Sigmoid	21	10	1	4	91.64	104.30	2.25
		20	1	4	85.25	98.20	3.29
		50	1	16	93.23	101.31	6.60
		100	1	1	90.92	98.48	12.19
		150	1	1	89.00	98.14	17.77
		200	1	1	89.28	97.34	22.93
	63	10	1	4	71.33	105.41	2.17
		20	1	16	66.06	99.53	3.27
		50	1	16	58.71	95.71	6.52
		100	1	4	74.81	98.38	12.09
		150	1	4	82.39	98.02	17.57
		200	1	2	81.95	97.08	22.94
	125	10	1	2	57.43	107.68	2.16
		20	1	8	78.59	98.92	3.27
		50	1	1	93.08	100.37	6.57
		100	1	4	88.27	100.31	12.07
		150	1	4	83.12	101.13	17.35
		200	1	4	94.29	101.63	22.99
	250	10	1	4	62.97	113.54	2.14
		20	1	4	90.51	101.66	3.26
		50	1	4	93.50	101.12	6.67
		100	1	1	94.69	103.22	11.97
		150	16	1	96.27	104.16	17.52
		200	1	1	96.21	106.06	22.94

Note: h*n* are the architecture of the best prediction of that window size

is the best w that shows the best average of the prediction accuracy of all epochs in that window size

Table C - 6 : The best average parameter values of LSTM model across three activation functions
(return)

Activation	Parameters				Results		
Function	w	e	h*	n*	Best rrorr (%)	Mean error (%)	Mean time (sec)
ReLU	21	10	1	16	60.81	97.29	10.81
		20	1	16	68.46	96.92	18.46
		50	8	16	58.63	92.29	42.05
		100	16	8	56.31	98.04	81.15
		150	8	16	82.95	100.32	123.79
		200	2	8	72.16	98.52	162.08
	63	10	8	2	49.24	95.43	24.29
		20	8	16	60.53	96.03	47.10
		50	4	4	73.77	95.38	109.93
		100	2	16	75.21	98.69	217.98
		150	8	8	65.86	98.30	325.42
		200	4	16	66.03	97.88	432.65
	125	10	2	8	68.89	97.78	44.00
		20	16	4	75.39	96.40	85.79
		50	8	8	80.14	99.34	210.07
		100	2	16	70.20	96.25	422.81
		150	1	1	75.07	98.92	634.32
		200	1	8	82.17	96.84	843.48
	250	10	4	16	66.03	98.76	104.27
		20	2	8	67.81	98.25	194.03
		50	16	8	48.66	93.07	472.96
		100	4	16	75.90	97.86	953.46
		150	2	8	81.96	98.72	1420.90
		200	8	4	76.76	97.55	1906.21
TanH	21	10	16	16	65.60	96.06	10.33
		20	2	4	78.31	102.81	18.17
		50	2	16	56.33	97.74	41.75
		100	16	2	59.11	95.97	80.23
		150	2	16	78.91	97.97	122.59
		200	4	8	70.95	94.62	162.84
	63	10	8	8	53.07	95.41	23.51
		20	8	8	58.08	92.27	44.79
		50	16	2	51.86	90.75	108.96
		100	2	8	72.42	99.20	216.79
		150	2	2	81.67	102.27	327.79
		200	1	16	75.87	99.75	434.80
	125	10	2	4	65.84	92.62	45.11
		20	1	16	41.87	92.93	89.39
		50	1	16	54.63	94.02	225.02
		100	16	16	74.15	99.15	444.37
		150	2	8	81.19	99.29	674.34
		200	16	8	56.43	95.74	904.34

Appendix C The prediction results of the S&P 500 index price and returns

Activation	Parameters				Results		
Function	w	e	h*	n*	Best rrror (%)	Mean error (%)	Mean time (sec)
	250	10	4	4	62.38	96.44	95.67
		20	1	8	68.47	96.00	191.95
		50	1	16	60.53	99.70	478.01
		100	8	8	76.04	101.33	958.49
		150	4	8	64.70	98.74	1434.07
		200	16	4	75.51	95.10	1994.72
Sigmoid	21	10	4	8	73.82	101.50	10.35
		20	8	16	84.51	99.28	18.35
		50	4	8	70.86	94.27	42.41
		100	1	8	77.21	94.59	83.14
		150	8	16	62.25	98.34	120.77
		200	1	8	76.13	101.34	159.92
	63	10	8	16	86.00	109.54	23.90
		20	2	8	83.57	100.21	46.12
		50	8	2	76.62	99.60	110.26
		100	8	2	83.71	99.36	218.43
		150	1	16	79.29	95.74	325.70
		200	4	16	66.64	100.17	437.11
	125	10	16	16	81.06	100.02	44.77
		20	16	16	92.42	99.26	89.57
		50	1	2	75.26	103.28	222.61
		100	8	8	64.40	97.30	449.60
		150	4	2	80.27	99.60	675.63
		200	2	8	78.20	101.16	897.86
	250	10	1	8	74.07	100.42	97.10
		20	2	16	57.10	94.15	191.72
		50	2	8	74.24	96.81	477.88
		100	2	8	78.65	99.16	947.58
		150	4	4	78.68	97.80	1444.41
		200	2	16	57.52	95.13	1943.01

Note: h*n* are the architecture of the best prediction of that window size

is the best w that shows the best average of the prediction accuracy of all epochs in that window size

C.3 Training runtime of different models across three activation functions on index price and return prediction

Table C - 7 : The training runtime in seconds of different models and activation functions on stock index price and return prediction across all window sizes

Average Training Time (Sec)								
Activation Function	Window size	Epoch	Index Price			Index Return		
			MLP	LSTM	GRU	MLP	LSTM	GRU
ReLU	21	10	2.85	11.1	35.13	2.17	10.81	37.19
		20	4.29	19.38	64.06	3.28	18.46	67.8
		50	8.72	44.49	150.24	6.62	42.05	160.21
		100	15.42	85.88	295.36	13.15	81.15	305.82
		150	22.55	127.45	439.01	17.71	123.79	461.52
		200	30.09	173.26	587.07	23.2	162.08	607.1
	63	10	2.89	24.88	91.74	2.19	24.29	91.32
		20	4.34	46.72	176.89	3.26	47.1	176.99
		50	8.67	113.28	431	6.65	109.93	435.83
		100	15.94	223.92	853.71	12.2	217.98	872.75
		150	22.51	336	1286.44	17.38	325.42	1316.83
		200	30.02	448.56	1708.86	23.05	432.65	1762.17
	125	10	2.85	45.14	186.75	2.15	44	189.68
		20	4.23	87.75	364.49	3.26	85.79	370.12
		50	8.4	216.72	963.29	6.56	210.07	916.95
		100	15.6	441.13	1831.75	11.91	422.81	1834.13
		150	23.1	695.87	2693.63	17.38	634.32	2754.22
		200	29.51	912.12	3631.12	23.02	843.48	3674.46
	250	10	2.85	96.86	385.7	2.16	104.27	393.47
		20	4.23	195.09	772.97	3.24	194.03	796.75
		50	8.44	485.45	1968.47	6.49	472.96	2028.56
		100	15.39	959	4011.99	12.07	953.46	4089.31
		150	22.75	1448.47	6476.3	17.31	1420.9	6232.85
		200	30.18	1923.14	8142.42	22.98	1906.21	8196.43
TanH	21	10	2.87	10.83	35.02	2.17	10.33	35.4
		20	4.27	19.34	63.59	3.29	18.17	64.3
		50	8.53	44.48	150	6.75	41.75	152.93
		100	15.36	86.78	294.12	12.16	80.23	298.24
		150	16.82	130.28	438.24	17.49	122.59	443.63
		200	29.69	168.4	582.31	23.17	162.84	590.89

Average Training Time (Sec)								
Activation Function	Window size	Epoch	Index Price			Index Return		
			MLP	LSTM	GRU	MLP	LSTM	GRU
TanH	63	10	2.81	24.64	91.59	2.16	23.51	92.2
		20	4.21	46.78	176.17	3.26	44.79	178.67
		50	8.36	112.65	433.49	6.55	108.96	435.91
		100	15.44	224.38	856.01	12.01	216.79	867.95
		150	22.48	335.47	1291.25	17.39	327.79	1331.06
		200	29.1	442.92	1728.34	23.19	434.8	1767.55
	125	10	2.85	46.07	186.44	2.14	45.11	188.85
		20	4.26	89.64	365.83	3.25	89.39	371.7
		50	8.49	224.09	906.81	6.5	225.02	936.63
		100	15.7	448.6	1790.29	12.05	444.37	1845.79
		150	22.43	670.61	2806.69	17.46	674.34	2831.68
		200	29.31	905.69	3643.22	22.72	904.34	3694.35
	250	10	2.93	98.78	387.94	2.16	95.67	395.11
		20	4.3	193.21	780.24	3.26	191.95	795.11
		50	8.46	482.1	1978.92	6.57	478.01	2038.99
		100	15.53	971.03	4026.79	12.17	958.49	4078.67
		150	22.25	1455.55	6132.4	17.57	1434.07	6134.8
		200	29.57	1944.61	8113.8	23.32	1994.72	8300.23
Sigmoid	21	10	2.86	10.95	35.36	2.25	10.35	26.02
		20	4.33	19.15	64.18	3.29	18.35	64.21
		50	8.51	44.16	150.41	6.6	42.41	150.76
		100	15.48	87.61	295.3	12.19	83.14	295.62
		150	22.38	128.8	442.88	17.77	120.77	441.03
		200	29.62	172.64	585.77	22.93	159.92	589.65
	63	10	2.82	24.67	91.14	2.17	23.9	93.12
		20	4.22	46.59	176.01	3.27	46.12	180.75
		50	8.4	113.64	432.27	6.52	110.26	447.65
		100	15.29	224.71	869.44	12.09	218.43	897.35
		150	22.34	337.93	1294.81	17.57	325.7	1318.56
		200	29.46	451.77	1720.8	22.94	437.11	1769.58
	250	10	2.9	98.45	401.99	2.14	97.1	412.19
		20	4.3	195.36	825.07	3.26	191.72	847.15
		50	8.41	484.44	2026.25	6.67	477.88	2048
		100	15.15	970.78	3987.32	11.97	947.58	4132.24
		150	22.36	1466.06	6051.9	17.52	1444.41	6154.59
		200	29.8	1957.36	8152.25	22.94	1943.01	8297.6

Appendix D The prediction results of the S&P 500 index price and return - Statistical tests

D.1 The statistical analysis of index price prediction

Table D.1 highlights that all the parameters of all three models had statistically significant effects on the performance of all measurements (MSE, RMSE, MAE, MAPE in testing mode, prediction error, and training runtime) with $p < 0.05$. In other words, each parameter affected the forecasting performance of each model differently. Likewise, the activation functions, hidden layers, node, window size, and epoch affected the performance differently in MSE, RMSE, MAE, MAPE in testing mode, prediction error, and training runtime, for all three models. Table D.1 in Appendix D reports the result for the tests of between-group effects of all parameters on the performance of MSE, RMSE, MAE, MAPE, prediction error, and training runtime. The results from Table D.1 are described below.

Table D - 1 : Summary of the multivariate analysis of index price prediction of the differences of all parameters for the three models

Model	Effect	Value	F	Hypothesis df	Error df	p
GRU	Activation Function	0.439	151.95 ^a	12	3584	< 0.001*
	Hidden layers	0.543	49.73	24	6245	< 0.001*
	Node	0.684	29.91	24	6245	< 0.001*
	Window size	0.809	21.87	18	5066	< 0.001*
	Epochs	0.781	15.21	30	7158	< 0.001*
LSTM	Activation Function	0.721	53.18 ^a	12	3584	< 0.001*
	Hidden layers	0.573	45.09	24	6245	< 0.001*
	Node	0.864	11.14	24	6245	< 0.001*
	Window size	0.621	51.60	18	5066	< 0.001*
	Epochs	0.593	33.25	30	7158	< 0.001*
MLP	Activation Function	0.685	62.16 ^a	12	3584	< 0.001*
	Hidden layers	0.378	83.73	24	6245	< 0.001*
	Node	0.789	18.34	24	6245	< 0.001*
	Window size	0.982	1.80	18	5066	0.020*
	Epochs	0.196	120.02	30	7158	< 0.001*

^a Exact statistic

* Indicates significance at $\alpha = 0.05$

GRU: The type of activation function and the number of nodes affected predictive performance measured by MSE, RMSE, MAE, MAPE, and prediction error, but the effect on training runtime was insignificant. The number of hidden layers affected the prediction performance (MSE, RMSE, MAE, MAPE, prediction error, and training runtime). For the window size and epoch, the training runtime performance was affected, but the effect on the prediction performance was insignificant.

LSTM: The activation functions, hidden layers, and nodes had insignificant effects on the levels of MSE. However, the number of hidden layers and number of nodes produced significant effects on the prediction performance measured by RMSE, MAE, MAPE, prediction error, and training time. The window size, and epoch had no significant effect on the prediction performance of MSE, RMSE, MAE, MAPE, and prediction error, but did affect training runtime.

MLP: The values of a significance level (p) indicated that there were insignificant effects in model performance caused by the window size, but the number of hidden layers had a significant effect on the models' predictability and training runtime. The type of activation function and the number of nodes affected the prediction error, but the effect on training runtime was insignificant. There was a significant difference between the epoch groups that changed the performance of MSE, MAE, MAPE, and training time. The model performance could also be affected by the number of epoch.

According to these test results, the activation function, hidden layers, and node parameters, could affect the predictive performance (prediction error) of the three models. The window size did not affect the predictive performance of any of the models, but it altered the training time for GRU and LSTM. The number of epochs could impact only the training times of the three models. In order to determine whether there is a statistically significant difference between the group of activation function, hidden layers, and node, in index price prediction, statistical hypothesis tests (t -tests) were conducted. The null hypothesis is that the group means are equal. The tables below give the results of the t -tests performed on the prediction error of each activation function, the number of hidden layers, and the total number of nodes, based on two-sided tests assuming equal variances with a significance level of 0.05.

Table D.2 to D.4 compare the results of activation functions for each model. The results showed that every pair yielded different predictive performances in both GRU and MLP ($p < 0.001$). Only the pair ReLU and TanH yielded no difference in predictive performance in the LSTM ($p = 0.289$). Further examination of the mean and t -values showed that the three models had the highest predictive efficiency with TanH. When the models were compared using the same activation function, it was found that TanH made all models work differently, but was more effective when working with GRU ($\bar{x} = 31.10$, $t = -9.953$ when compared to LSTM, and $t = -14.023$ when compared to MLP).

Table D - 2 : T-test result for the comparison of the activation function effects on GRU model's prediction error for index price

	Activation	N	Mean	Std. Dev.	t	p
Prediction error	ReLU	600	47.07	15.56	18.720	< 0.001*
	TanH	600	31.10	13.94		
Prediction error	ReLU	600	47.07	15.56	-11.982	< 0.001*
	Sigmoid	600	55.56	7.70		
Prediction error	TanH	600	31.10	13.94	-37.622	< 0.001*
	Sigmoid	600	55.56	7.70		

* Indicates significance at $\alpha = 0.05$

Table D - 3 : T-test result for the comparison of the activation function effects on LSTM model's prediction error for index price

	Activation	N	Mean	Std. Dev.	t	p
Prediction error	ReLU	600	49.91	22.08	8.722	0.289
	TanH	600	40.00	16.90		
Prediction error	ReLU	600	49.91	22.08	-6.164	< 0.001*
	Sigmoid	600	55.76	7.32		
Prediction error	TanH	600	40.00	16.90	-20.956	< 0.001*
	Sigmoid	600	55.76	7.32		

* Indicates significance at $\alpha = 0.05$

Table D - 4 : T-test result for the comparison of the activation function effects on MLP model's prediction error for index price

	Activation	N	Mean	Std. Dev.	t	p
Prediction error	ReLU	600	51.15	13.76	9.478	< 0.001*
	TanH	600	43.09	15.63		
Prediction error	ReLU	600	51.15	13.76	-7.537	< 0.001*
	Sigmoid	600	55.81	6.31		
Prediction error	TanH	600	43.09	15.63	-18.481	< 0.001*
	Sigmoid	600	55.81	6.31		

* Indicates significance at $\alpha = 0.05$

Tables D.5 to D.7 compare the prediction error between pairs of hidden layers for the models. For all models, they show that only five out of ten pairs possessed a statistically significant difference in the number of hidden layers. However, LSTM and MLP exhibited an additional significant difference pair (*h8* and *h16*). Focusing on the significant differences, *h1* outperformed *h8* and *h16*, which had a higher mean predictive error than *h1*, in all three models.

Table D - 5 : T-test result for the comparison of the hidden layer effects on GRU model's prediction error for index price when the activation function is TanH

	Hidden layers	N	Mean	Std. Dev.	t	p
Prediction error	h1	120	18.09	13.15	-5.405	0.514
	h2	120	27.13	12.76		
Prediction error	h1	120	18.09	13.15	-8.927	0.200
	h4	120	32.34	11.52		
Prediction error	h1	120	18.09	13.15	-12.167	0.006*
	h8	120	36.85	10.60		
Prediction error	h1	120	18.09	13.15	-16.009	< 0.001*
	h16	120	41.10	8.66		
Prediction error	h2	120	27.13	12.76	-3.318	0.572
	h4	120	32.34	11.52		
Prediction error	h2	120	27.13	12.76	-6.418	0.041*
	h8	120	36.85	10.60		
Prediction error	h2	120	27.13	12.76	-9.924	< 0.001*
	h16	120	41.10	8.66		
Prediction error	h4	120	32.34	11.52	-3.158	0.102
	h8	120	36.85	10.60		
Prediction error	h4	120	32.34	11.52	-6.662	0.002*
	h16	120	41.10	8.66		
Prediction error	h8	120	36.85	10.60	-3.402	0.243
	h16	120	41.10	8.66		

* Indicates significance at alpha = 0.05

Table D - 6 : T-test result for the comparison of the hidden layer effects on LSTM model's prediction error for index price when the activation function is TanH

	Hidden layers	N	Mean	Std. Dev.	t	p
Prediction error	h1	120	19.25	11.66	-8.048	0.079
	h2	120	30.83	10.60		
Prediction error	h1	120	19.25	11.66	-14.524	0.166
	h4	120	41.07	11.62		
Prediction error	h1	120	19.25	11.66	-23.395	< 0.001*
	h8	120	49.71	8.21		
Prediction error	h1	120	19.25	11.66	-37.288	< 0.001*
	h16	120	59.16	1.20		
Prediction error	h2	120	30.83	10.60	-7.137	0.866
	h4	120	41.07	11.62		
Prediction error	h2	120	30.83	10.60	-15.427	0.042*
	h8	120	49.71	8.21		
Prediction error	h2	120	30.83	10.60	-29.089	< 0.001*
	h16	120	59.16	1.20		
Prediction error	h4	120	41.07	11.62	-6.651	0.056
	h8	120	49.71	8.21		
Prediction error	h4	120	41.07	11.62	-16.960	< 0.001*
	h16	120	59.16	1.20		
Prediction error	h8	120	49.71	8.21	-12.466	< 0.001*
	h16	120	59.16	1.20		

* Indicates significance at alpha = 0.05

Table D - 7 : T-test result for the comparison of the hidden layer effects on MLP model's prediction error for index price when the activation function is TanH

	Hidden layers	N	Mean	Std. Dev.	t	p
Prediction error	h1	120	22.29	9.92	-9.421	0.974
	h2	120	34.89	10.78		
Prediction error	h1	120	22.29	9.92	-18.978	0.041*
	h4	120	45.30	8.83		
Prediction error	h1	120	22.29	9.92	-28.315	< 0.001*
	h8	120	53.73	7.04		
Prediction error	h1	120	22.29	9.92	-40.788	< 0.001*
	h16	120	59.25	0.28		
Prediction error	h2	120	34.89	10.78	-8.813	0.074
	h4	120	45.30	8.83		
Prediction error	h2	120	34.89	10.78	-16.034	< 0.001*
	h8	120	53.73	7.04		
Prediction error	h2	120	34.89	10.78	-24.743	< 0.001*
	h16	120	59.25	0.28		
Prediction error	h4	120	45.30	8.83	-8.184	0.056
	h8	120	53.73	7.04		
Prediction error	h4	120	45.30	8.83	-17.297	< 0.001*
	h16	120	59.25	0.28		
Prediction error	h8	120	53.73	7.04	-8.571	< 0.001*
	h16	120	59.25	0.28		

* Indicates significance at alpha = 0.05

Table D - 8 : T-test result for the comparison of the node effects on GRU model's prediction error for index price when the activation function is TanH

	Node	N	Mean	Std. Dev.	t	p
Prediction error	n1	120	46.10	9.62	7.934	0.709
	n2	120	36.34	9.44		
Prediction error	n1	120	46.10	9.62	14.593	0.633
	n4	120	28.26	9.32		
Prediction error	n1	120	46.10	9.62	16.506	0.002*
	n8	120	23.90	11.16		
Prediction error	n1	120	46.10	9.62	17.186	< 0.001*
	n16	120	20.91	12.86		
Prediction error	n2	120	36.34	9.44	6.669	0.378
	n4	120	28.26	9.32		
Prediction error	n2	120	36.34	9.44	9.321	< 0.001*
	n8	120	23.90	11.16		
Prediction error	n2	120	36.34	9.44	10.595	< 0.001
	n16	120	20.91	12.86		
Prediction error	n4	120	28.26	9.32	3.288	0.003*
	n8	120	23.90	11.16		
Prediction error	n4	120	28.26	9.32	5.071	< 0.001*
	n16	120	20.91	12.86		
Prediction error	n8	120	23.90	11.16	1.921	0.039*
	n16	120	20.91	12.86		

* Indicates significance at alpha = 0.05

Table D - 9 : T-test result for the comparison of the node effects on LSTM model's prediction error for index price when the activation function is TanH

	Node	N	Mean	Std. Dev.	t	p
Prediction error	n1	120	50.40	10.35	3.496	0.090
	n2	120	45.34	12.01		
Prediction error	n1	120	50.40	10.35	6.719	< 0.001*
	n4	120	38.96	15.52		
Prediction error	n1	120	50.40	10.35	8.368	< 0.001*
	n8	120	34.75	17.68		
Prediction error	n1	120	50.40	10.35	9.888	< 0.001*
	n16	120	30.56	19.39		
Prediction error	n2	120	45.34	12.01	3.563	< 0.001*
	n4	120	38.96	15.52		
Prediction error	n2	120	45.34	12.01	5.430	< 0.001*
	n8	120	34.75	17.68		
Prediction error	n2	120	45.34	12.01	7.100	< 0.001*
	n16	120	30.56	19.39		
Prediction error	n4	120	38.96	15.52	1.961	0.033*
	n8	120	34.75	17.68		
Prediction error	n4	120	38.96	15.52	3.706	< 0.001*
	n16	120	30.56	19.39		
Prediction error	n8	120	34.75	17.68	1.749	0.174
	n16	120	30.56	19.39		

* Indicates significance at alpha = 0.05

Table D - 10 : T-test result for the comparison of the node effects on MLP model's prediction error for index price when the activation function is TanH

	Node	N	Mean	Std. Deviation	t	p
Prediction error	n1	120	51.38	9.52	2.917	0.003*
	n2	120	47.26	12.23		
Prediction error	n1	120	51.38	9.52	5.485	< 0.001*
	n4	120	42.63	14.65		
Prediction error	n1	120	51.38	9.52	7.320	< 0.001*
	n8	120	38.55	16.68		
Prediction error	n1	120	51.38	9.52	8.397	< 0.001*
	n16	120	35.63	18.21		
Prediction error	n2	120	47.26	12.23	2.652	0.039*
	n4	120	42.63	14.65		
Prediction error	n2	120	47.26	12.23	4.610	< 0.001*
	n8	120	38.55	16.68		
Prediction error	n2	120	47.26	12.23	5.804	< 0.001*
	n16	120	35.63	18.21		
Prediction error	n4	120	42.63	14.65	2.015	0.155
	n8	120	38.55	16.68		
Prediction error	n4	120	42.63	14.65	3.282	0.017*
	n16	120	35.63	18.21		
Prediction error	n8	120	38.55	16.68	1.295	0.326
	n16	120	35.63	18.21		

* Indicates significance at $\alpha = 0.05$

D.2 The statistical analysis of index return prediction

Table D.11 summarises the results of the multivariate analysis. It shows that the activation function, hidden layers, node, window size, and epoch employed, had a significant effect on the performance of MSE, RMSE, MAE, MAPE, prediction error, and training runtime ($p < 0.001$). The next part of the output tested the effect between-group of all parameters on the performance (MSE, RMSE, MAE, MAPE, prediction error, and training runtime).

Table D - 11 : Summary of the multivariate analysis of index return prediction of the differences of all parameters for the three models

Model	Effect	Value	F	Hypothesis df	Error df	p
GRU	Activation Function	0.915	13.61 ^a	12	3584	< 0.001*
	Hidden layers	0.784	18.85	24	6246	< 0.001*
	Node	0.965	2.67	24	6246	< 0.001*
	Window size	0.819	20.54	18	5066	< 0.001*
	Epochs	0.512	43.45	30	7158	< 0.001*
LSTM	Activation Function	0.939	9.47 ^a	12	3584	< 0.001*
	Hidden layers	0.954	3.57	24	6246	< 0.001*
	Node	0.882	9.54	24	6246	< 0.001*
	Window size	0.636	48.79	18	5067	< 0.001*
	Epochs	0.584	34.40	30	7158	< 0.001*
MLP	Activation Function	0.922	12.35 ^a	12	3584	< 0.001*
	Hidden layers	0.603	40.57	24	6246	< 0.001*
	Node	0.906	7.49	24	6246	< 0.001*
	Window size	0.944	5.81	18	5066	< 0.001*
	Epochs	0.126	161.76	30	7158	< 0.001*

^a Exact statistic

* Indicates significance at $\alpha = 0.05$

GRU The epoch had a significant effect on the performance of model measured by MSE, RMSE, MAE, MAPE, prediction error, and training runtime. On the other hand, the number of nodes had no significant effect on all performance measurements. The window sizes and the number of hidden layers had a significant effect on all performance measurements, except training runtime. Last, the type of activation function had no significant effect on training runtime but affected prediction error.

LSTM The window sizes and hidden layers had a significant effect on the predictability but no significant effect on training runtime. The number of nodes had a significant effect on all the performance measurements except prediction error and training time. The epoch affected MSE,

RMSE, MAE, and training time while the activation function affected RMSE, MAE, MAPE, and prediction error.

MLP The activation function, the number of nodes, and window size had a significant effect only on prediction error. On the other hand, the epoch affected all measurements except prediction error. The number of hidden layers had a significant effect on RMSE, MAE, MAPE, prediction error, and training time.

The multivariate test result for the index return prediction indicated that the activation function significantly affected the forecasting ability of all three models, whereas the number of epochs significantly affected the predictive performance of GRU. In addition to the activation function, the window size, hidden layers, and nodes can impact MLP's predictive performance. The parameters (activation function, window size, hidden layers, node, and epoch) were compared to find the difference between their performance.

Table D - 12 : T-test result for the comparison of the activation function effect on GRU model's prediction error for index return

	Activation	N	Mean	Std. Dev.	t	p
Prediction error	ReLU	600	100.10	7.46	0.010	< 0.001*
	TanH	600	100.09	9.72		
Prediction error	ReLU	600	100.10	7.46	-5.335	< 0.001*
	Sigmoid	600	106.92	30.44		
Prediction error	TanH	600	100.09	9.72	-5.236	< 0.001*
	Sigmoid	600	106.92	30.44		

* Indicates significance at alpha = 0.05

Table D - 13 : T-test result for the comparison of the activation function effect on LSTM model's prediction error for index return

	Activation	N	Mean	Std. Dev.	t	p
Prediction error	ReLU	600	97.28	11.85	0.481	< 0.001*
	TanH	600	96.91	14.85		
Prediction error	ReLU	600	97.28	11.85	-2.465	< 0.001*
	Sigmoid	600	99.08	13.40		
Prediction error	TanH	600	96.91	14.85	-2.661	< 0.001*
	Sigmoid	600	99.08	13.40		

* Indicates significance at alpha = 0.05

Table D - 14 : T-test result for the comparison of the activation function effect on MLP model's prediction error for index return

	Activation	N	Mean	Std. Dev.	t	p
Prediction error	ReLU	600	97.20	11.46	-6.863	0.458
	TanH	600	101.87	12.12		
Prediction error	ReLU	600	97.20	11.46	-4.356	0.532
	Sigmoid	600	101.32	20.17		
Prediction error	TanH	600	101.87	12.12	0.570	0.883
	Sigmoid	600	101.32	20.17		

* Indicates significance at $\alpha = 0.05$

Table E.12 to E.14 show that for GRU and LSTM, every pair of activation functions had a statistically significant difference in predictability. The TanH activation function gave a lower prediction error than the other activation functions in both GRU and LSTM, but there was no difference between the three activation functions in the MLP model. The models for each of the three activation functions were also compared with the same activation function. When the activation function was ReLU, the results vary significantly across all three models, with the MLP model producing the lowest mean prediction error. There was no significant difference in prediction error between GRU and MLP for TanH, while LSTM had the lowest mean for both TanH and Sigmoid.

Table E.15 compares pairs of epochs in GRU and found that 11 out of 15 means were significantly different ($p < 0.001$). Epoch *e50* performed better than the other epoch sizes. Epoch significantly affected the prediction error of GRU model ($p < 0.001$).

Table D - 15 : T-test result for the comparison of the epoch size effect on GRU model's prediction error for index return

	Epoch	N	Mean	Std. Dev.	t	p
Prediction error	e10	300	123.51	37.24	10.680	< 0.001*
	e20	300	99.40	11.92		
Prediction error	e10	300	123.51	37.24	11.878	< 0.001*
	e50	300	97.46	7.48		
Prediction error	e10	300	123.51	37.24	11.757	< 0.001*
	e100	300	97.89	6.14		
Prediction error	e10	300	123.51	37.24	11.959	< 0.001*
	e150	300	97.51	5.56		
Prediction error	e10	300	123.51	37.24	11.555	< 0.001*
	e200	300	98.44	5.04		
Prediction error	e20	300	99.40	11.92	2.388	0.137
	e50	300	97.46	7.48		
Prediction error	e20	300	99.40	11.92	1.953	< 0.001*
	e100	300	97.89	6.14		
Prediction error	e20	300	99.40	11.92	2.487	< 0.001*
	e150	300	97.51	5.56		
Prediction error	e20	300	99.40	11.92	1.287	< 0.001*
	e200	300	98.44	5.04		
Prediction error	e50	300	97.46	7.48	-0.767	< 0.001*
	e100	300	97.89	6.14		
Prediction error	e50	300	97.46	7.48	-0.096	< 0.001*
	e150	300	97.51	5.56		
Prediction error	e50	300	97.46	7.48	-1.880	< 0.001*
	e200	300	98.44	5.04		
Prediction error	e100	300	97.89	6.14	0.789	0.552
	e150	300	97.51	5.56		
Prediction error	e100	300	97.89	6.14	-1.200	0.036
	e200	300	98.44	5.04		
Prediction error	e150	300	97.51	5.56	-2.141	0.100
	e200	300	98.44	5.04		

* Indicates significance at alpha = 0.05

Table E.16 compares window size pairs. It showed that some paired with w21 had a different predictive power from those with w125 and w250, but there was almost no difference between window size comparisons overall (number of insignificances over a neutral point).

Table D - 16 : T-test result for the comparison of the window size effect on MLP model's prediction error for index return

	Window size	N	Mean	Std. Dev.	t	p
Prediction error	w21	450	98.29	9.77	0.947	0.072
	w63	450	97.55	13.57		
Prediction error	w21	450	98.29	9.77	-3.373	0.034*
	w125	450	101.38	16.74		
Prediction error	w21	450	98.29	9.77	-5.030	0.037*
	w250	450	103.30	18.70		
Prediction error	w63	450	97.55	13.57	-3.769	0.573
	w125	450	101.38	16.74		
Prediction error	w63	450	97.55	13.57	-5.279	0.493
	w250	450	103.30	18.70		
Prediction error	w125	450	101.38	16.74	-1.624	0.878
	w250	450	103.30	18.70		

* Indicates significance at $\alpha = 0.05$

Table D - 17 : T-test result for the comparison of the hidden layer effect on MLP model's prediction error for index return

	Hidden layers	N	Mean	Std. Dev.	t	p
Prediction error	h1	360	98.31	18.72	-1.127	< 0.001*
	h2	360	99.60	10.81		
Prediction error	h1	360	98.31	18.72	-1.487	< 0.001*
	h4	360	99.89	7.48		
Prediction error	h1	360	98.31	18.72	-2.063	< 0.001*
	h8	360	100.89	14.50		
Prediction error	h1	360	98.31	18.72	-2.484	< 0.001*
	h16	360	101.96	20.59		
Prediction error	h2	360	99.60	10.81	-0.427	< 0.001*
	h4	360	99.89	7.48		
Prediction error	h2	360	99.60	10.81	-1.354	0.810
	h8	360	100.89	14.50		
Prediction error	h2	360	99.60	10.81	-1.924	0.317
	h16	360	101.96	20.59		
Prediction error	h4	360	99.89	7.48	-1.157	0.797
	h8	360	100.89	14.50		
Prediction error	h4	360	99.89	7.48	-1.786	0.64
	h16	360	101.96	20.59		
Prediction error	h8	360	100.89	14.50	-0.805	0.806
	h16	360	101.96	20.59		

* Indicates significance at alpha = 0.05

Table D - 18 : T-test result for the comparison of the node effect on MLP model's prediction error for index return

	Node	N	Mean	Std. Dev.	t	p
Prediction error	n1	360	97.16	14.25	-2.165	0.058
	n2	360	100.38	24.38		
Prediction error	n1	360	97.16	14.25	-1.854	0.181
	n4	360	98.86	10.00		
Prediction error	n1	360	97.16	14.25	-4.281	0.274
	n8	360	100.98	9.18		
Prediction error	n1	360	97.16	14.25	-6.061	0.029*
	n16	360	103.26	12.73		
Prediction error	n2	360	100.38	24.38	1.096	0.212
	n4	360	98.86	10.00		
Prediction error	n2	360	100.38	24.38	-0.438	0.151
	n8	360	100.98	9.18		
Prediction error	n2	360	100.38	24.38	-1.988	0.579
	n16	360	103.26	12.73		
Prediction error	n4	360	98.86	10.00	-2.968	0.674
	n8	360	100.98	9.18		
Prediction error	n4	360	98.86	10.00	-5.161	0.202
	n16	360	103.26	12.73		
Prediction error	n8	360	100.98	9.18	-2.756	0.094
	n16	360	103.26	12.73		

* Indicates significance at alpha = 0.05

Table E.18 shows that there was a significant difference between all the pairs of hidden layer $h1$ and some pairs of $h2$ ($p < 0.001$). It shows that $h1$ performed best for the MLP model. Table E.18 compares pairs of nodes, and shows that there was only a significant difference between the pair of nodes $n1$ and $n16$ ($p < 0.05$) with the lowest mean when applying $n1$ ($\bar{x} = 97.16$).

D.3 MANOVA: Tests of Between-Subjects Effects

Table D - 19 : The summary of the tests of between-subjects effects on index price prediction

Model	Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
GRU	ActivationFunc	MSE	3.11518E+14	2	1.55759E+14	696.571	<0.001*
		RMSE	114177830.8	2	57088915.41	684.582	<0.001*
		MAE	114184697.6	2	57092348.78	711.069	<0.001*
		MAPE	173701.253	2	86850.627	720.762	<0.001*
		Prediction error	185033.796	2	92516.898	559.944	<0.001*
		Runtime	44793.36	2	22396.68	0.002	0.998
	Hidden	MSE	9.06395E+13	4	2.26599E+13	65.319	<0.001*
		RMSE	38280788.29	4	9570197.073	76.094	<0.001*
		MAE	34887964.91	4	8721991.227	70.024	<0.001*
		MAPE	51461.436	4	12865.359	68.167	<0.001*
		Prediction error	85193.144	4	21298.286	96.359	<0.001*
		Runtime	3433593111	4	858398277.7	113.086	<0.001*
	Node	MSE	9.98283E+13	4	2.49571E+13	73.019	<0.001*
		RMSE	42796580.85	4	10699145.21	86.807	<0.001*
		MAE	42408206.53	4	10602051.63	88.081	<0.001*
		MAPE	63857.16	4	15964.29	87.799	<0.001*
		Prediction error	75357.337	4	18839.334	83.172	<0.001*
		Runtime	6212402.859	4	1553100.715	0.163	0.957
	Window size	MSE	2.47752E+11	3	82584023573	0.208	0.891
		RMSE	121222.62	3	40407.54	0.275	0.843
		MAE	107704.689	3	35901.563	0.25	0.862
		MAPE	152.012	3	50.671	0.233	0.873
		Prediction error	344.025	3	114.675	0.428	0.733
		Runtime	2898492222	3	966164074.1	122.541	<0.001*
	Epoch	MSE	2.72507E+12	5	5.45014E+11	1.376	0.230
		RMSE	195453.269	5	39090.654	0.266	0.932
		MAE	324264.191	5	64852.838	0.451	0.813
		MAPE	597.207	5	119.441	0.55	0.738
		Prediction error	276.52	5	55.304	0.206	0.960
		Runtime	2690176739	5	538035347.7	67.176	<0.001*
LSTM	ActivationFunc	MSE	2.66029E+24	2	1.33014E+24	1.802	0.165
		RMSE	45561395.37	2	22780697.69	162.479	<0.001*
		MAE	44151970.94	2	22075985.47	217.267	<0.001*
		MAPE	66972.78	2	33486.39	219.75	<0.001*
		Prediction error	76107.834	2	38053.917	138.07	<0.001*
		Runtime	4013.107	2	2006.553	0.008	0.992
	Hidden	MSE	5.32054E+24	4	1.33013E+24	1.804	0.125
		RMSE	80525031.68	4	20131257.92	166.532	<0.001*
		MAE	80989624.25	4	20247406.06	249.357	<0.001*
		MAPE	121917.516	4	30479.379	249.946	<0.001*
		Prediction error	147518.666	4	36879.667	156.179	<0.001*
		Runtime	13612947.17	4	3403236.792	13.846	<0.001*
	Node	MSE	2.36469E+24	4	5.91173E+23	0.8	0.525

Appendix D The prediction results of the S&P 500 index price and return - Statistical tests

Model	Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
MLP		RMSE	30677819.43	4	7669454.857	51.592	<0.001*
		MAE	28970477.47	4	7242619.367	65.735	<0.001*
		MAPE	43636.285	4	10909.071	65.894	<0.001*
		Prediction error	53825.424	4	13456.356	46.669	<0.001*
		Runtime	71435.432	4	17858.858	0.07	<0.001*
	Window size	MSE	3.9904E+24	3	1.33013E+24	1.803	0.145
		RMSE	207336.355	3	69112.118	0.417	0.740
		MAE	38160.43	3	12720.143	0.101	0.960
		MAPE	60.622	3	20.207	0.107	0.956
		Prediction error	450.026	3	150.009	0.472	0.702
		Runtime	158631759.9	3	52877253.31	320.629	<0.001*
	Epoch	MSE	6.65068E+24	5	1.33014E+24	1.805	0.109
		RMSE	1242085.47	5	248417.094	1.504	0.185
		MAE	1117799.926	5	223559.985	1.778	0.114
		MAPE	1908.783	5	381.757	2.021	0.073
		Prediction error	400.545	5	80.109	0.252	0.939
		Runtime	161714400.4	5	32342880.09	197.958	<0.001*
	ActivationFunc	MSE	8.3932E+13	2	4.1966E+13	167.796	<0.001*
		RMSE	28388176.56	2	14194088.28	167.549	<0.001*
		MAE	27917327.33	2	13958663.66	169.312	<0.001*
		MAPE	42266.632	2	21133.316	170.082	<0.001*
		Prediction Error	49651.291	2	24825.646	157.347	<0.001*
		Runtime	50.229	2	25.114	0.192	0.826
	Hidden	MSE	2.3791E+14	4	5.94775E+13	361.349	<0.001*
		RMSE	78222229.14	4	19555557.29	342.793	<0.001*
		MAE	75398068.8	4	18849517.2	336.096	<0.001*
		MAPE	113214.826	4	28303.707	333.508	<0.001*
		Prediction Error	143775.561	4	35943.89	340.652	<0.001*
		Runtime	44658.227	4	11164.557	105.053	<0.001*
	Node	MSE	5.32349E+13	4	1.33087E+13	49.756	<0.001*
		RMSE	19758477.43	4	4939619.357	55.119	<0.001*
		MAE	19909990.95	4	4977497.738	57.215	<0.001*
		MAPE	30340.209	4	7585.052	57.885	<0.001*
		Prediction Error	32685.997	4	8171.499	48.813	<0.001*
		Runtime	192.357	4	48.089	0.367	0.832
	Window size	MSE	1.40496E+12	3	4.68322E+11	1.581	0.192
		RMSE	480213.599	3	160071.2	1.596	0.188
		MAE	439607.287	3	146535.762	1.498	0.213
		MAPE	649.872	3	216.624	1.469	0.221
		Prediction Error	1107.993	3	369.331	1.998	0.112
		Runtime	24.947	3	8.316	0.063	0.979
	Epoch	MSE	5.22021E+12	5	1.04404E+12	3.546	0.003*
		RMSE	889503.58	5	177900.716	1.776	0.115
		MAE	1145815.807	5	229163.161	2.35	0.039*
		MAPE	1940.762	5	388.152	2.642	0.022*

Appendix D The prediction results of the S&P 500 index price and return - Statistical tests

Model	Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
		Prediction					
		Error	335.861	5	67.172	0.362	0.875
		Runtime	168258.429	5	33651.686	898.847	<0.001*

* Indicates significant at $p < 0.05$

Table D - 20 : The summary of the tests of between-subjects effects on index return prediction

Model	Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
GRU	ActivationFunc	MSE	1.863E-08	2	9.316E-09	17.995	<0.001*
		RMSE	0.00003603	2	0.00001802	27.475	<0.001*
		MAE	0.00005585	2	0.00002793	31.717	<0.001*
		MAPE	2422998.43	2	1211499.215	45.537	<0.001*
		Prediction Error	18647.119	2	9323.56	25.979	<0.001*
		Runtime	19768.578	2	9884.289	0.001	0.999
	Hidden	MSE	2.03E-09	4	5.08E-10	0.964	0.426
		RMSE	2.72E-06	4	6.79E-07	1.006	0.403
		MAE	3.51E-06	4	8.77E-07	0.963	0.427
		MAPE	88474.644	4	22118.661	0.792	0.530
		Prediction Error	1452.907	4	363.227	0.985	0.415
		Runtime	3511396886.894	4	877849221.7	115.485	<0.001*
	Node	MSE	2.12E-09	4	5.31E-10	1.007	0.403
		RMSE	1.85E-06	4	4.61E-07	0.683	0.604
		MAE	1.48E-06	4	3.71E-07	0.407	0.804
		MAPE	13614.098	4	3403.524	0.122	0.975
		Prediction Error	838.183	4	209.546	0.568	0.686
		Runtime	4785829.552	4	1196457.388	0.125	0.973
	Window size	MSE	8.07E-10	3	2.69E-10	0.509	0.676
		RMSE	6.42E-07	3	2.14E-07	0.316	0.813
		MAE	7.89E-07	3	2.63E-07	0.289	0.834
		MAPE	28433.432	3	9477.811	0.339	0.797
		Prediction Error	140.707	3	46.902	0.127	0.944
		Runtime	2960545319.712	3	986848439.9	124.856	<0.001*
	Epoch	MSE	5.85E-08	5	1.17E-08	23.568	<0.001*
		RMSE	0.000	5	2.47E-05	40.667	<0.001*
		MAE	0.000	5	4.20E-05	52.699	<0.001*
		MAPE	8756253.390	5	1751250.678	75.749	<0.001*
		Prediction Error	161661.825	5	32332.365	115.569	<0.001*
		Runtime	2754791230.383	5	550958246.077	68.635	<0.001*
LSTM	ActivationFunc	MSE	7.74E-11	2	3.87E-11	1.907	0.149
		RMSE	3.16E-07	2	1.58E-07	3.284	0.038*
		MAE	7.31E-07	2	3.66E-07	4.477	0.011*
		MAPE	234685.176	2	117342.588	18.193	<0.001*
		Prediction Error	1619.843	2	809.922	4.495	0.011*
		Runtime	33428.846	2	16714.423	0.067	0.935
	Hidden	MSE	1.10E-10	4	2.75E-11	1.354	0.248
		RMSE	2.64E-07	4	6.60E-08	1.368	0.243
		MAE	4.36E-07	4	1.09E-07	1.329	0.257
		MAPE	32398.014	4	8099.504	1.233	0.295
		Prediction Error	343.84	4	85.96	0.475	0.754
		Runtime	12406321.53	4	3101580.383	12.813	<0.001*
	Node	MSE	5.05E-10	4	1.26E-10	6.285	<0.001*
		RMSE	1.97E-06	4	4.93E-07	10.426	<0.001*
		MAE	4.48E-06	4	1.12E-06	14.057	<0.001*

Appendix D The prediction results of the S&P 500 index price and return - Statistical tests

Model	Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.
MLP		MAPE	907601.206	4	226900.302	37.306	<0.001*
		Prediction Error	1484.28	4	371.07	2.056	0.084
		Runtime	37740.644	4	9435.161	0.038	0.997
	Window size	MSE	5.14E-11	3	1.71E-11	0.843	0.470
		RMSE	1.06E-07	3	3.52E-08	0.728	0.535
		MAE	1.44E-07	3	4.81E-08	0.586	0.624
		MAPE	3783.859	3	1261.286	0.192	0.902
		Prediction Error	89.869	3	29.956	0.165	0.920
		Runtime	157777113.4	3	52592371.13	326.699	<0.001*
	Epoch	MSE	3.55E-10	5	7.10E-11	3.522	0.004*
		RMSE	1.01E-06	5	2.02E-07	4.224	0.001*
		MAE	1.22E-06	5	2.44E-07	2.987	0.011*
		MAPE	60458.527	5	12091.705	1.844	0.101
		Prediction Error	1261.341	5	252.268	1.396	0.223
		Runtime	156428211	5	31285642.2	193.226	<0.001*
	ActivationFunc	MSE	9.20E-10	2	4.60E-10	0.873	0.418
		RMSE	2.74E-07	2	1.37E-07	0.281	0.755
		MAE	5.03E-07	2	2.52E-07	0.454	0.635
		MAPE	20073.809	2	10036.905	0.651	0.521
		Prediction Error	7831.264	2	3915.632	17.146	<0.001*
		Runtime	0.438	2	0.219	0.003	0.997
	Hidden	MSE	2.16E-09	4	5.41E-10	1.026	0.393
		RMSE	6.60E-06	4	1.65E-06	3.405	0.009*
		MAE	8.09E-06	4	2.02E-06	3.673	0.006*
		MAPE	1298613.07	4	324653.267	22.068	<0.001*
		Prediction Error	2717.478	4	679.37	2.935	0.020*
		Runtime	13359.013	4	3339.753	54.553	<0.001*
	Node	MSE	3.19E-09	4	7.98E-10	1.515	0.195
		RMSE	2.18E-06	4	5.46E-07	1.12	0.345
		MAE	2.49E-06	4	6.22E-07	1.122	0.344
		MAPE	144760.994	4	36190.248	2.357	0.052
		Prediction Error	7578.572	4	1894.643	8.282	<0.001*
		Runtime	18.468	4	4.617	0.067	0.992
	Window size	MSE	1.19E-09	3	3.97E-10	0.754	0.520
		RMSE	1.53E-06	3	5.09E-07	1.043	0.372
		MAE	2.17E-06	3	7.22E-07	1.304	0.272
		MAPE	124345.374	3	41448.458	2.699	0.044*
		Prediction Error	9733.107	3	3244.369	14.265	<0.001*
		Runtime	8.542	3	2.847	0.041	0.989
	Epoch	MSE	1.36E-08	5	2.73E-09	5.239	<0.001*
		RMSE	2.05E-05	5	4.10E-06	8.579	<0.001*
		MAE	1.96E-05	5	3.93E-06	7.212	<0.001*
		MAPE	658745.205	5	131749.041	8.739	<0.001*
		Prediction Error	2522.681	5	504.536	2.177	0.054
		Runtime	103637.37	5	20727.474	1895.939	<0.001*

* Indicates significant at $p < 0.05$

D.4 t-test: One-Tailed Hypothesis Tests

Table D - 21 : Comparing the mean of three models in index price prediction by the t-tests at 95% confidence interval when activation function is ReLU

	Model	N	Mean	Std. Deviation	t	Sig.
Prediction error	GRU	600	47.0687	15.5599	-2.572	0.733
	LSTM	600	49.9048	22.0833		
Prediction error	GRU	600	47.0687	15.5599	-4.809	<0.001*
	MLP	600	51.1471	13.7605		
Prediction error	LSTM	600	49.9048	22.0833	-1.169	0.002*
	MLP	600	51.1471	13.7605		

* Indicates significance at $p < 0.05$

Table D - 22 : Comparing the mean of three models in index price prediction by the t-tests at 95% confidence interval when activation function is ReLU

	Model	N	Mean	Std. Deviation	t	Sig.
Prediction error	GRU	600	31.1026	13.9408	-9.953	<0.001*
	LSTM	600	40.0037	16.8989		
Prediction error	GRU	600	31.1026	13.9408	-14.023	<0.001*
	MLP	600	43.0905	15.6256		
Prediction error	LSTM	600	40.0037	16.8989	-3.285	0.028*
	MLP	600	43.0905	15.6256		

* Indicates significance at $p < 0.05$

Table D - 23 : Comparing the mean of three models in index price prediction by the t-tests at 95% confidence interval when activation function is Sigmoid

	Model	N	Mean	Std. Deviation	t	Sig.
Prediction error	GRU	600	55.5598	7.6952	-0.46	0.193
	LSTM	600	55.7591	7.3209		
Prediction error	GRU	600	55.5598	7.6952	-0.603	<0.001*
	MLP	600	55.8048	6.3100		
Prediction error	LSTM	600	55.7591	7.3209	-0.116	0.040*
	MLP	600	55.8048	6.3100		

* Indicates significance at $p < 0.05$

Table D - 24 : Comparing the mean of three models in index return prediction by the t-tests at 95% confidence interval when activation function is ReLU

	Model	N	Mean	Std. Deviation	t	Sig.
Prediction error	GRU	600	100.0953	7.4579	4.917	<0.001*
	LSTM	600	97.2847	11.8491		
Prediction error	GRU	600	100.0953	7.4579	5.194	<0.001*
	MLP	600	97.1964	11.4592		
Prediction error	LSTM	600	97.2847	11.8491	0.131	<0.014*
	MLP	600	97.1964	11.4592		

* Indicates significance at $p < 0.05$

Table D - 25 : Comparing the mean of three models in index return prediction by the t-tests at 95% confidence interval when activation function is TanH

	Model	N	Mean	Std. Deviation	t	Sig.
Prediction error	GRU	600	100.0902	9.7213	4.386	<0.001*
	LSTM	600	96.9117	14.8543		
Prediction error	GRU	600	100.0902	9.7213	-2.805	0.440
	MLP	600	101.8695	12.1190		
Prediction error	LSTM	600	96.9117	14.8543	-6.335	<0.001*
	MLP	600	101.8695	12.1190		

* Indicates significance at $p < 0.05$

Table D - 26 : Comparing the mean of three models in index return prediction by the t-tests at 95% confidence interval when activation function is Sigmoid

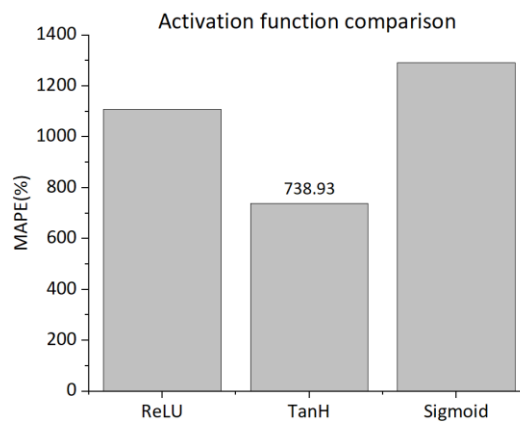
	Model	N	Mean	Std. Deviation	t	Sig.
Prediction error	GRU	600	106.9205	30.4390	5.772	<0.001*
	LSTM	600	99.0845	13.3962		
Prediction error	GRU	600	106.9205	30.4390	3.756	<0.001*
	MLP	600	101.3218	20.1722		
Prediction error	LSTM	600	99.0845	13.3962	-2.263	0.520
	MLP	600	101.3218	20.1722		

* Indicates significance at $p < 0.05$

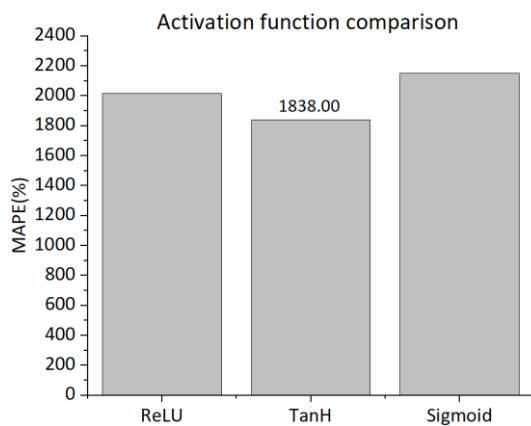
Appendix E The S&P 500 index return with sentiment analysis prediction – outputs and statistical tests

E.1 Prediction output

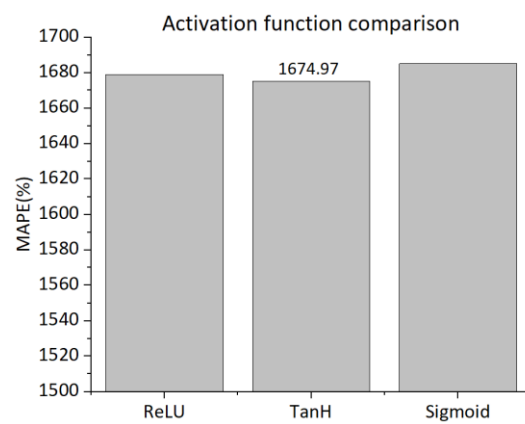
E.1.1 The prediction outcomes



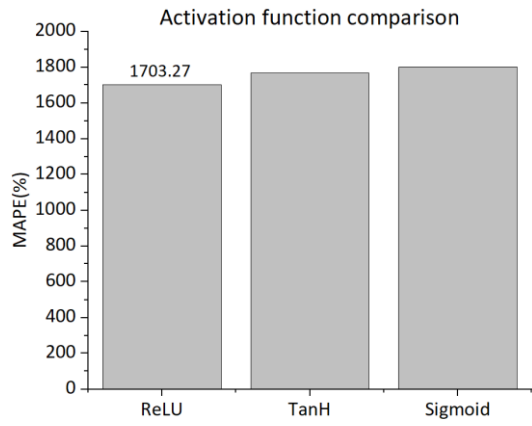
(a) Dataset *a* – one feature



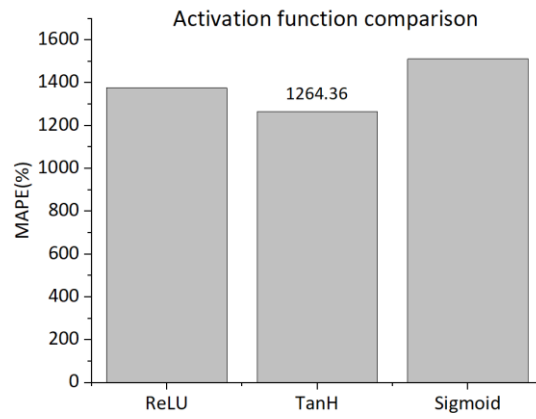
(b) Dataset *b* (current-day two features)



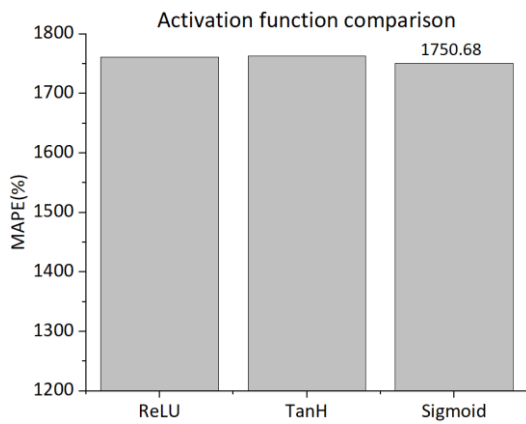
(c) Dataset *c* - current-day three features



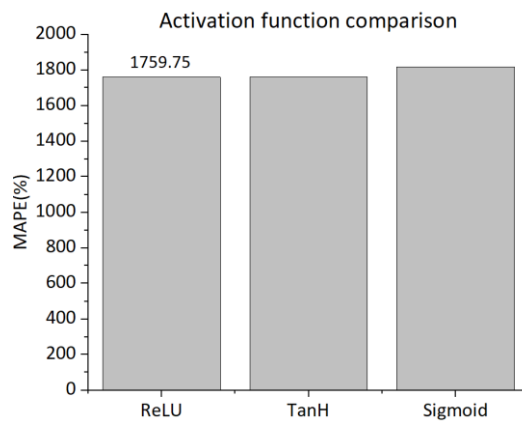
(d) Dataset *d* (current-day four features)



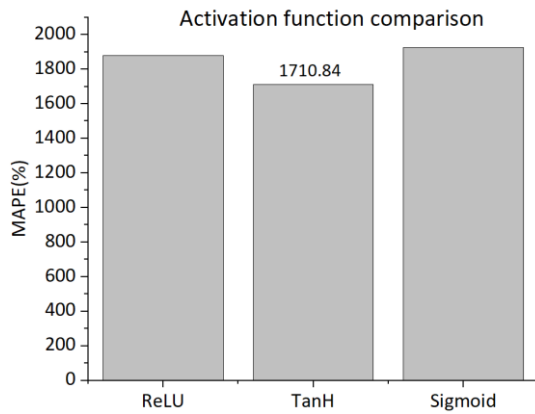
(e) Dataset *e* (1-day two features)



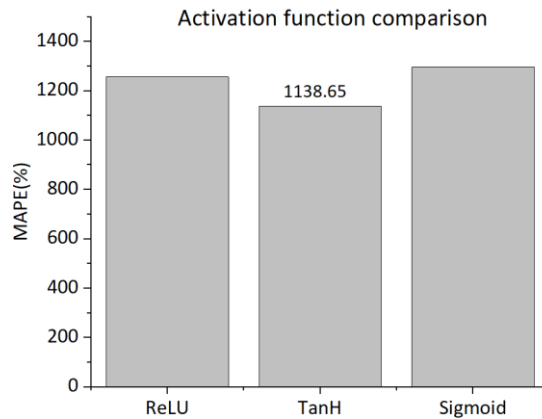
(f) Dataset *f* (1-day three features)



(g) Dataset *g* (1-day four features)



(h) Dataset *h* (3-days two features)



(i) Dataset *i* (3-days four features)

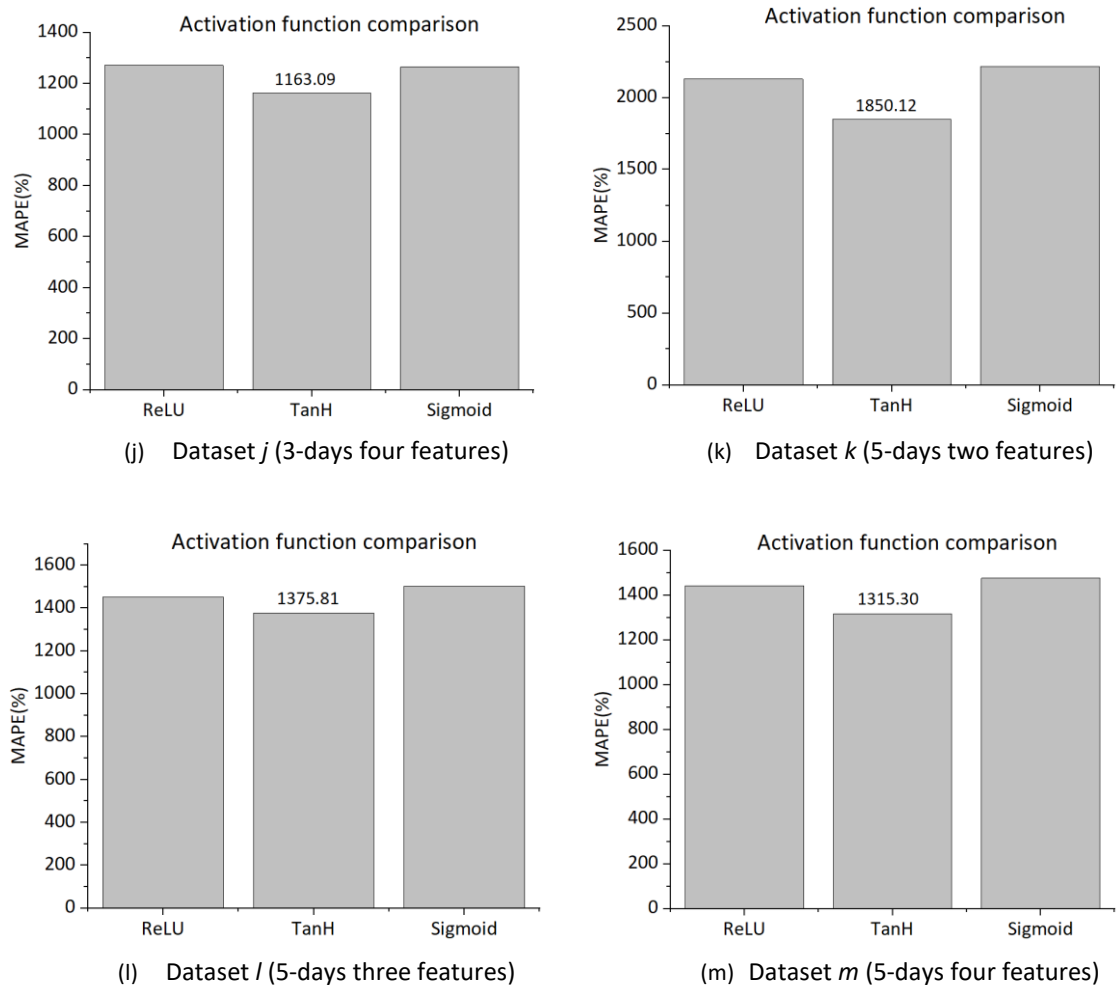
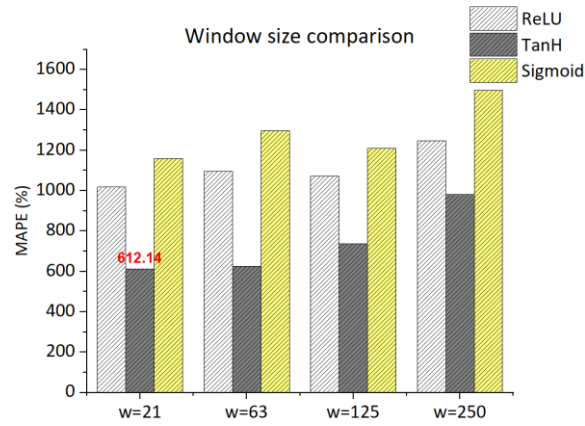
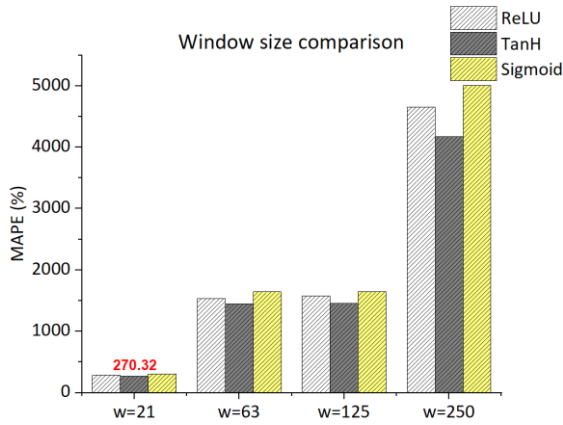


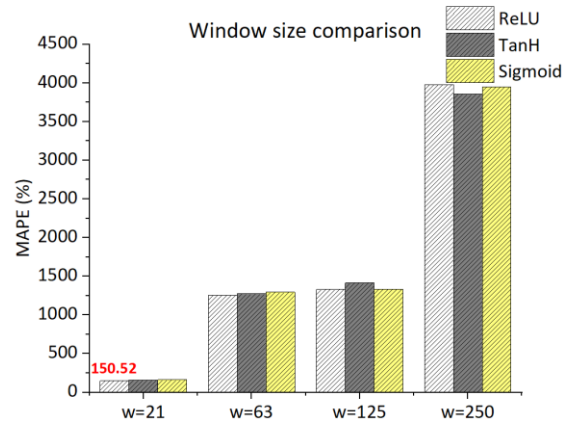
Figure E - 1 : Average error rate for all window sizes, epochs, and architecture across three activation functions of all 13 datasets



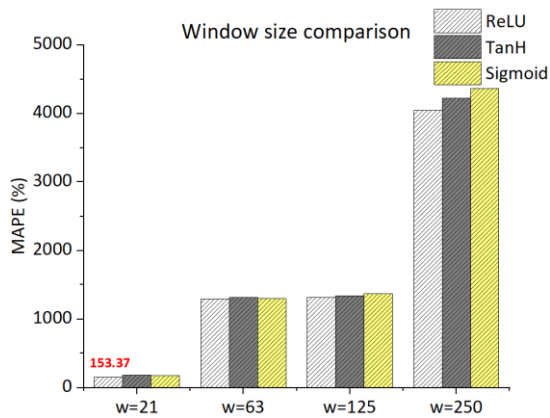
(a) Dataset a – one feature



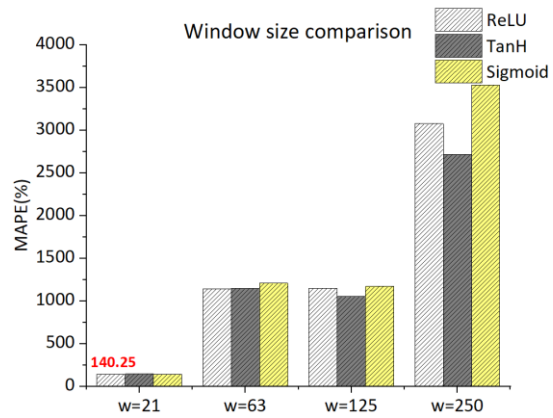
(b) Dataset b (current-day two features)



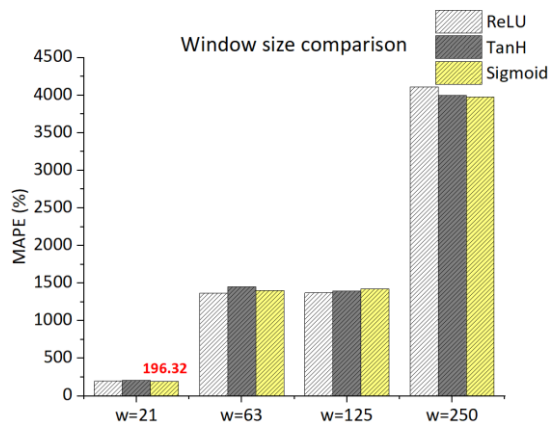
(c) Dataset c (current-day three features)



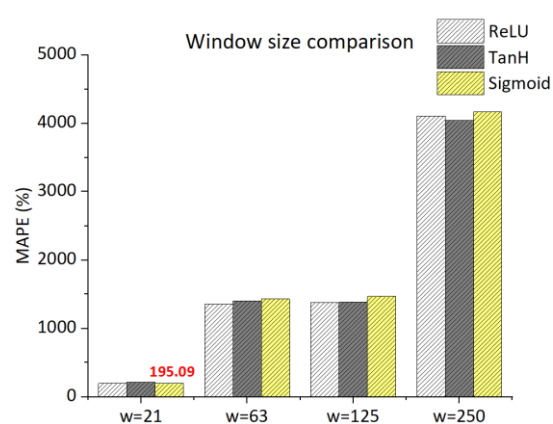
(d) Dataset d (current-day four features)



(e) Dataset e (1-day two features)



(f) Dataset f (1-day three features)



(g) Dataset g (1-day four features)

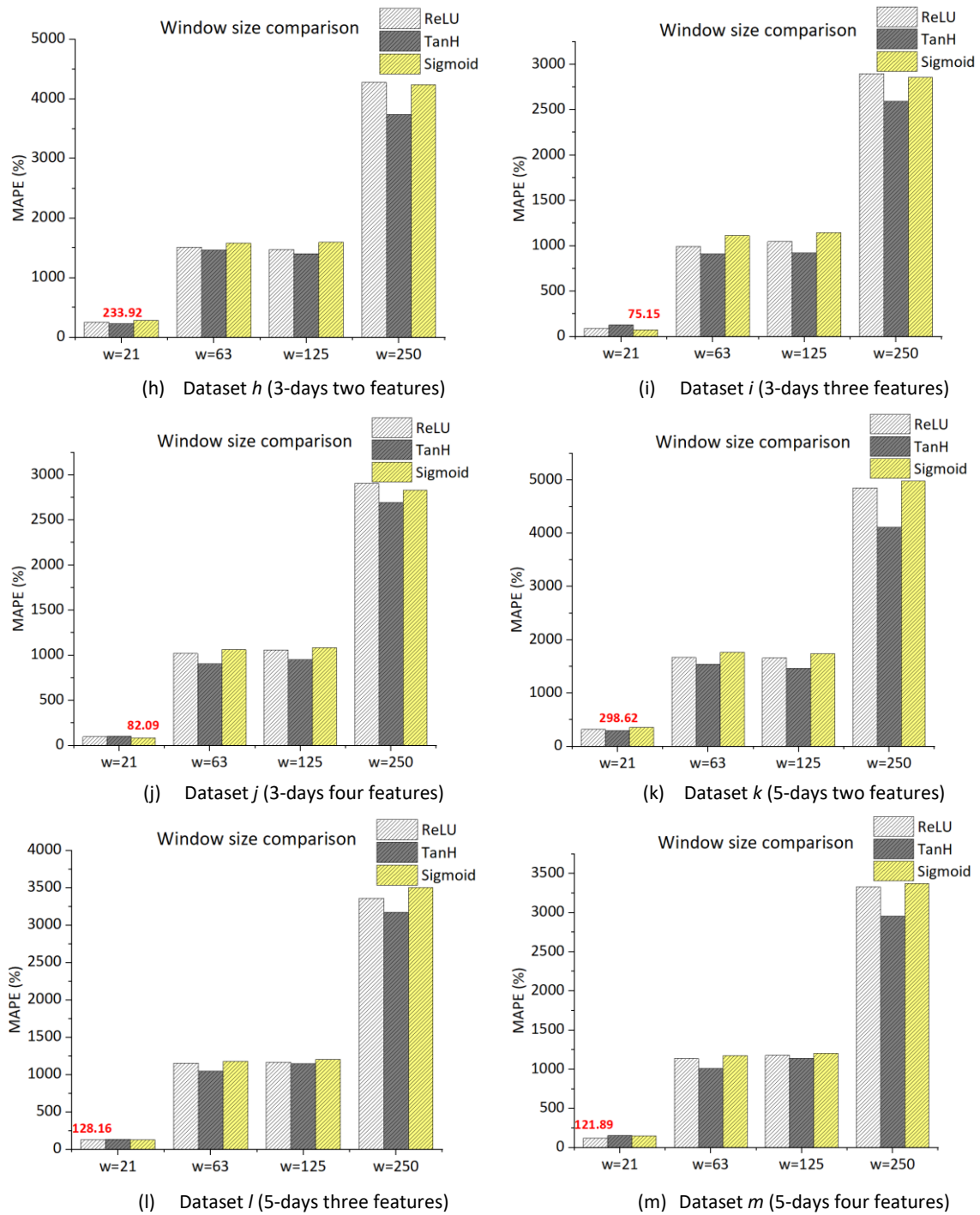
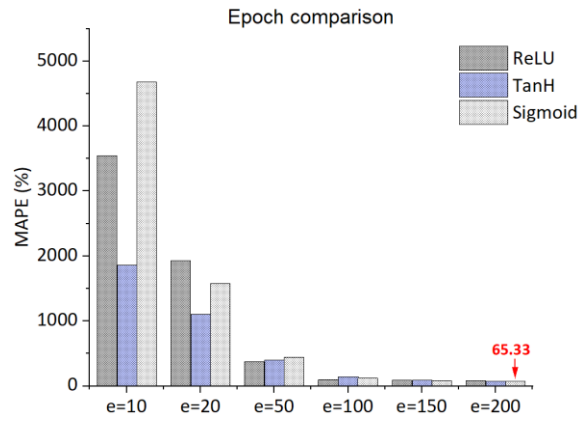
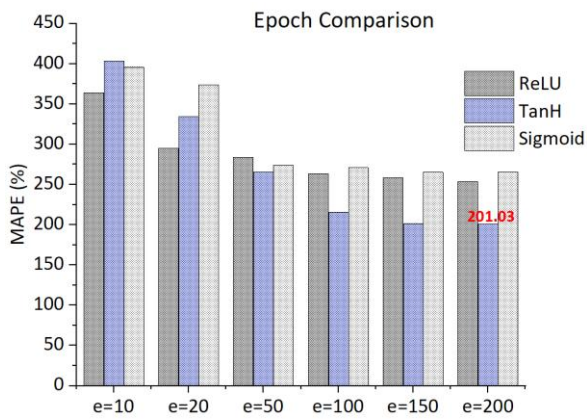


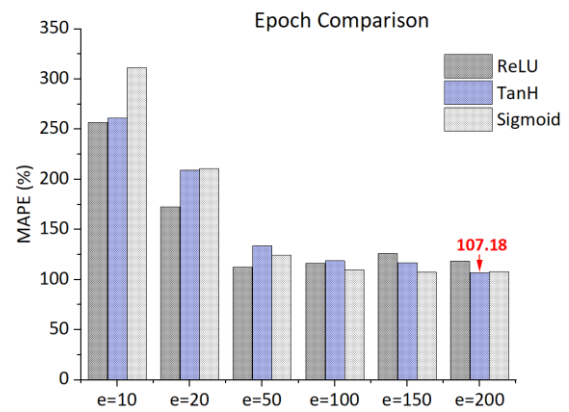
Figure E - 2 : Window size comparison for all epoch and all 13 datasets across three activation functions



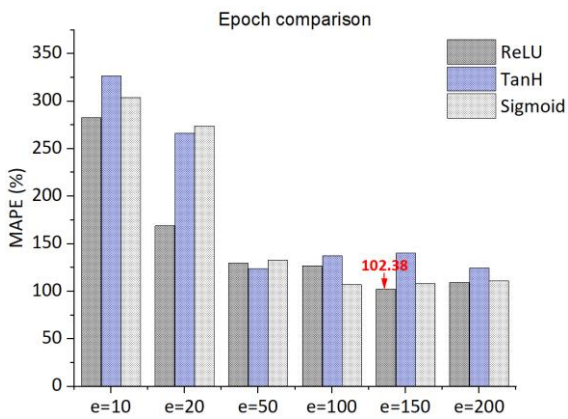
(c) Dataset *a* when $w=21$



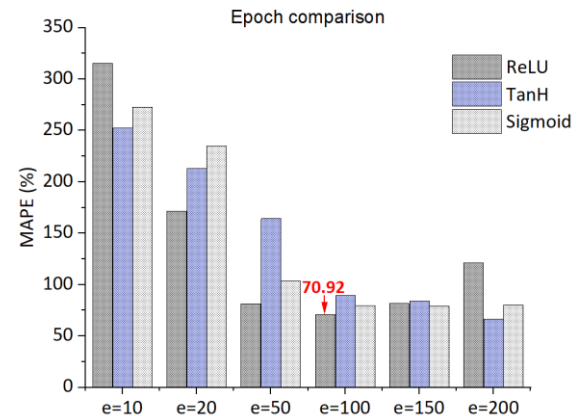
(d) Dataset *b* when $w=21$



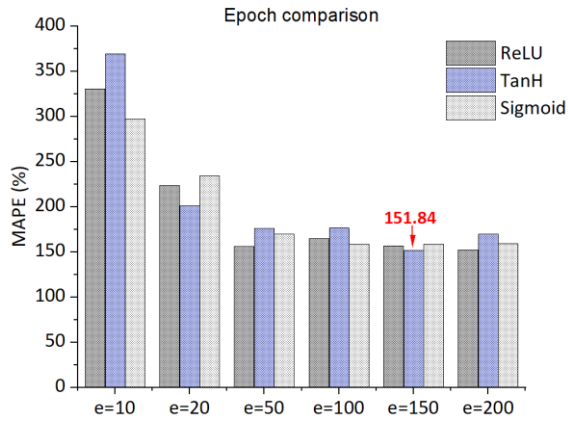
(e) Dataset *c* when $w=21$



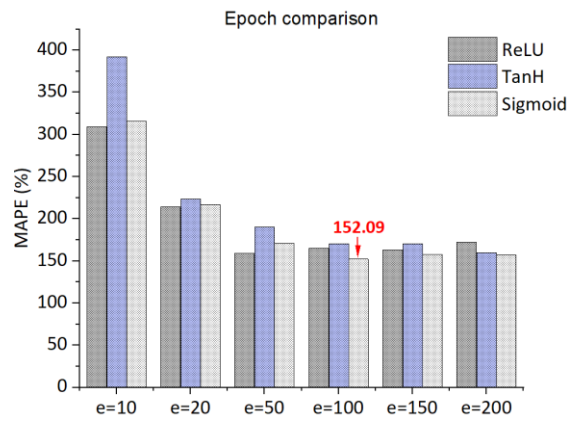
(f) Dataset *d* when $w=21$



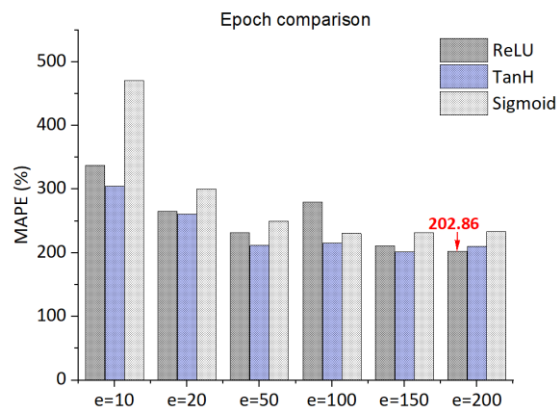
(g) Dataset *e* when $w=21$



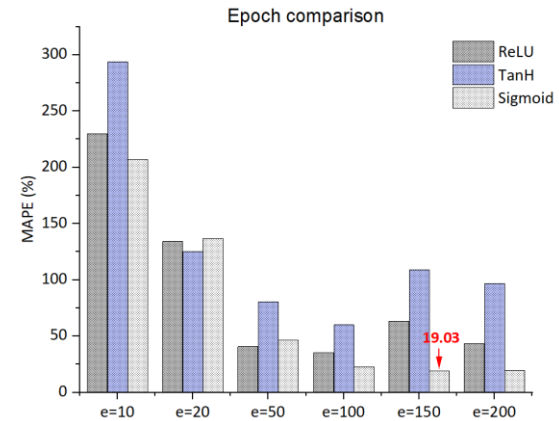
(h) Dataset *f* when $w=21$



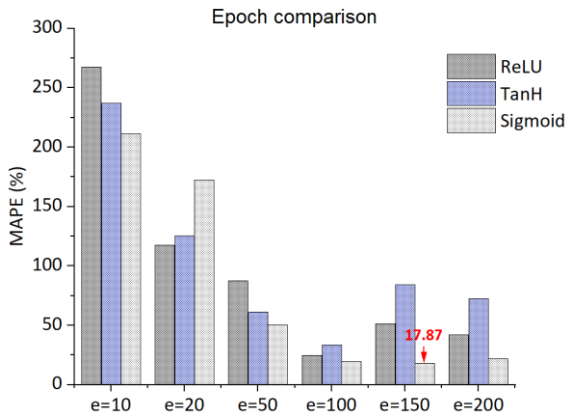
(i) Dataset *g* when $w=21$



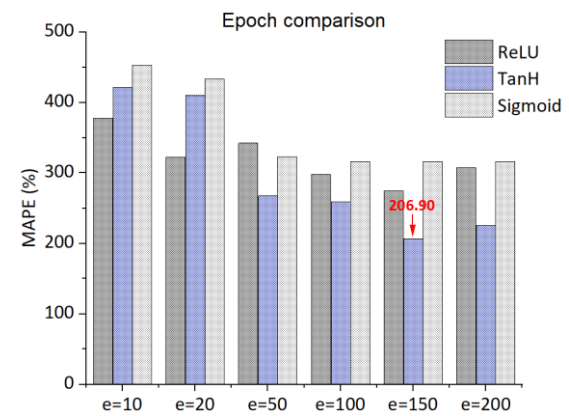
(j) Dataset *h* when $w=21$



(k) Dataset *i* when $w=21$



(l) Dataset *j* when $w=21$



(m) Dataset *k* when $w=21$

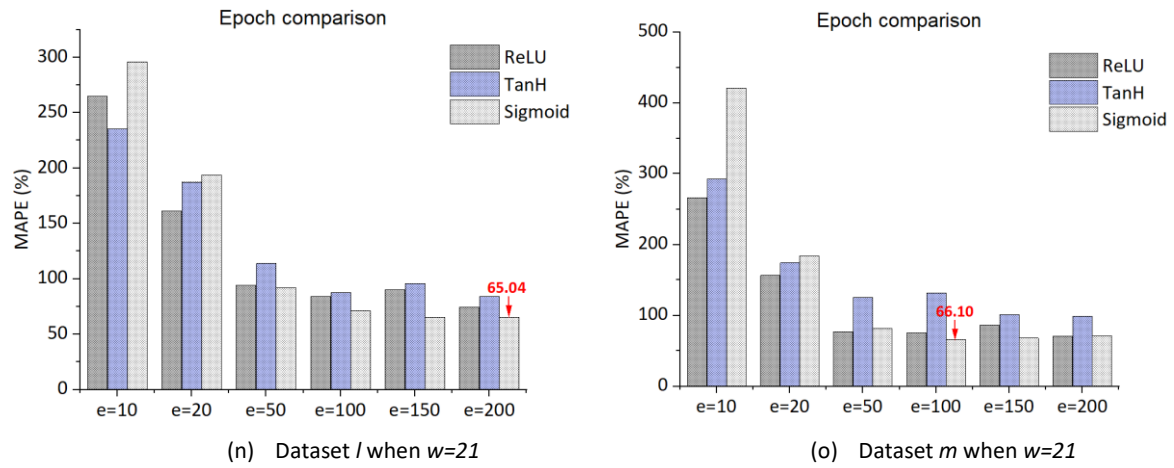
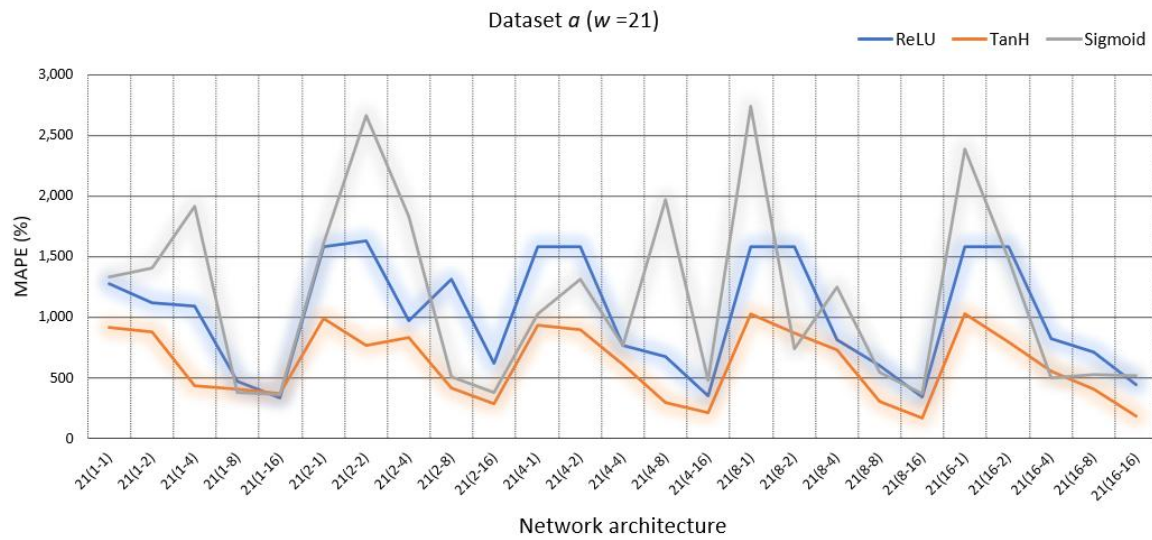


Figure E - 3 : Epoch comparison for all 13 datasets across three activation functions when $w = 21$

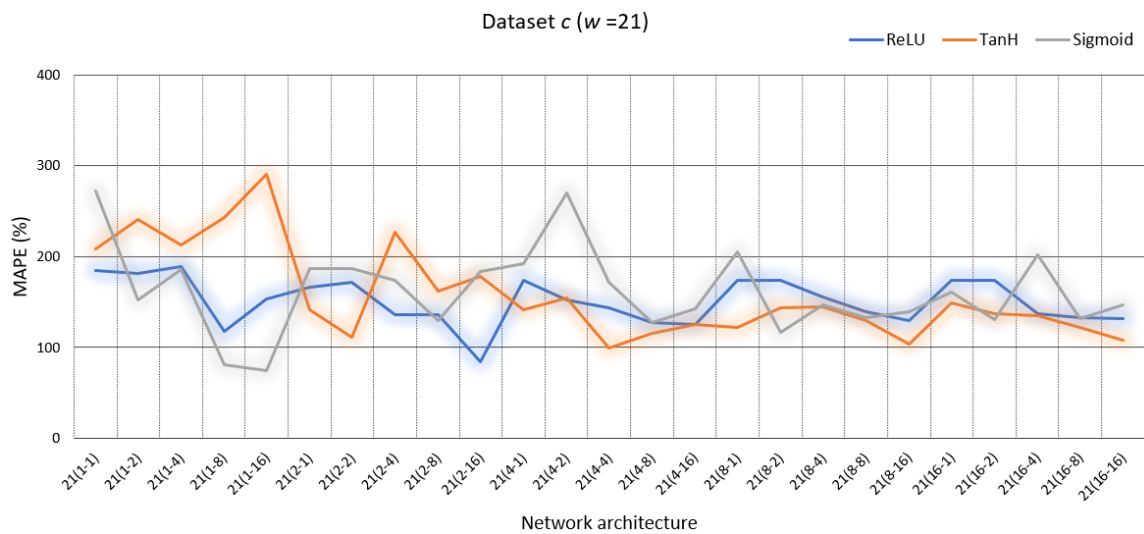
E.1.2 The architecture layer comparison of all 13 datasets



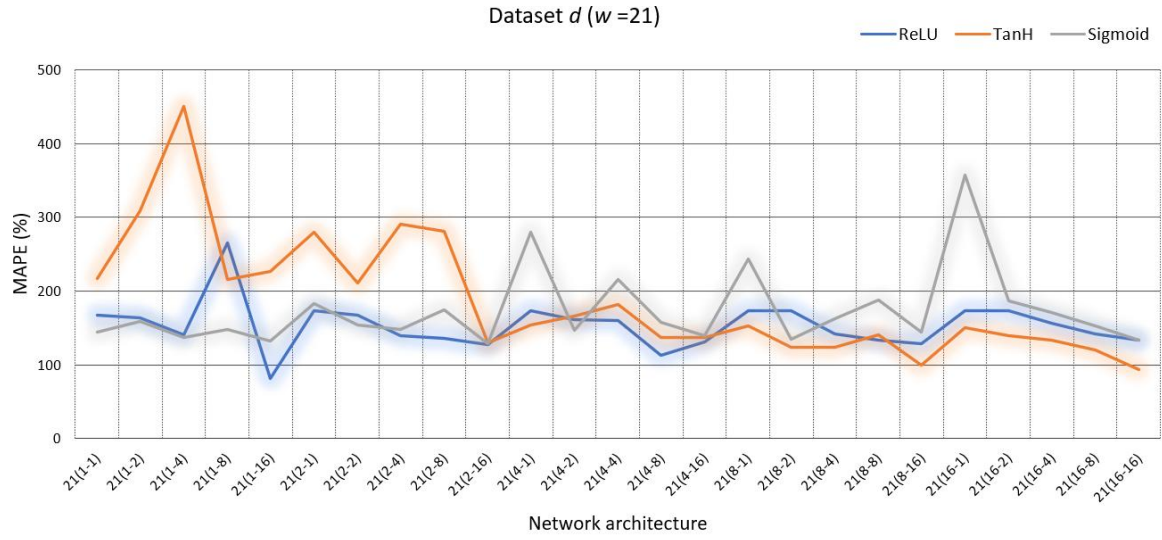
(a) Dataset *a*



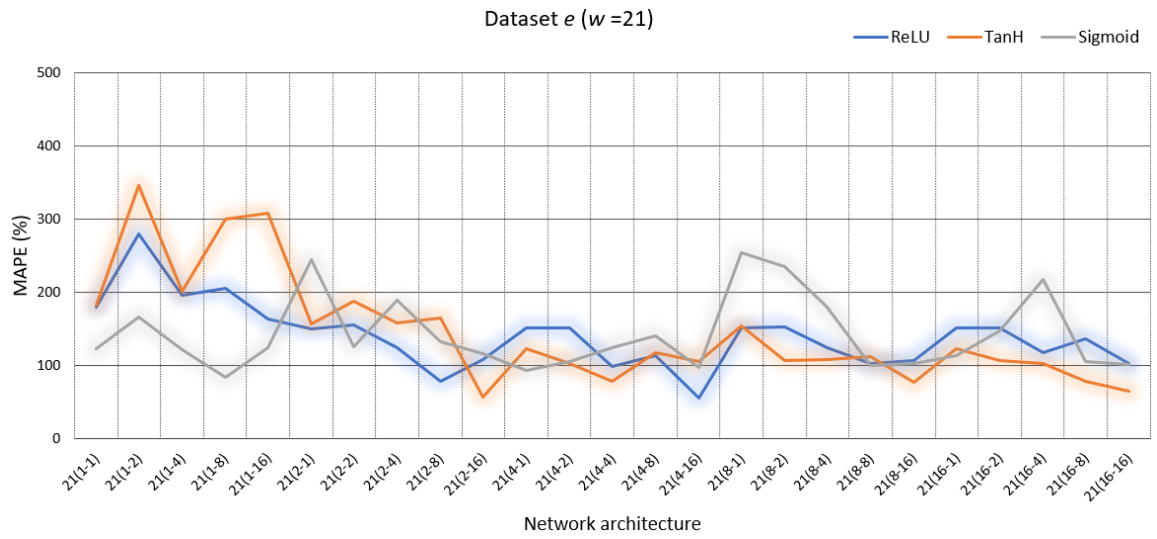
(b) Dataset *b*



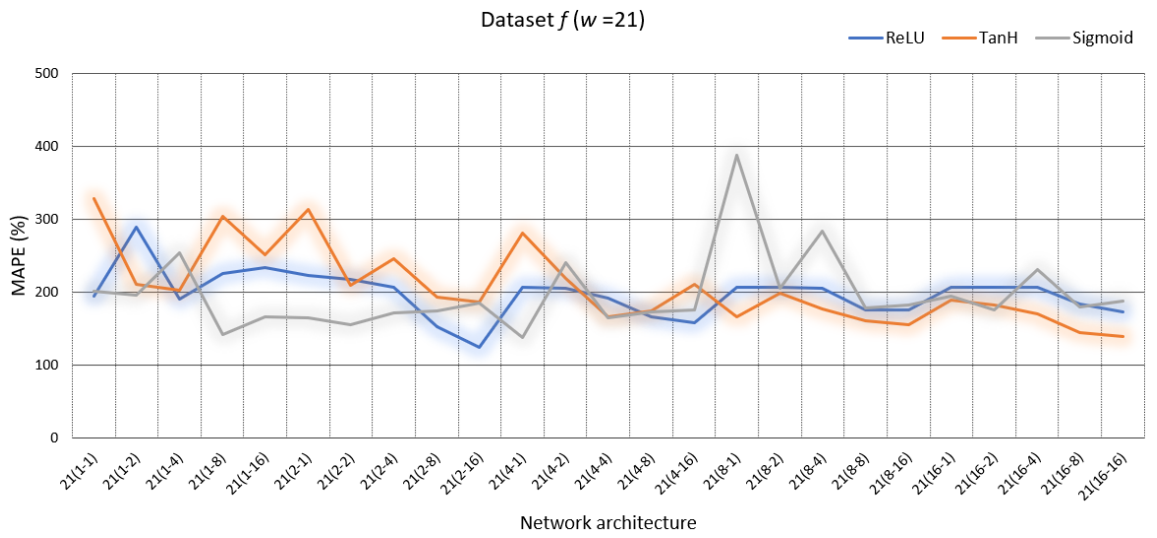
(c) Dataset *c*



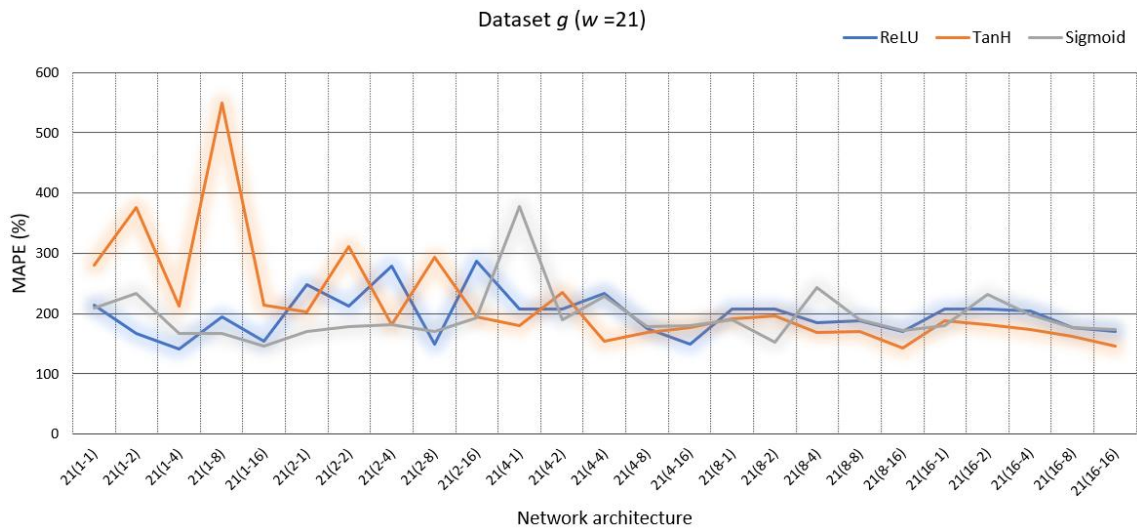
(d) Dataset d



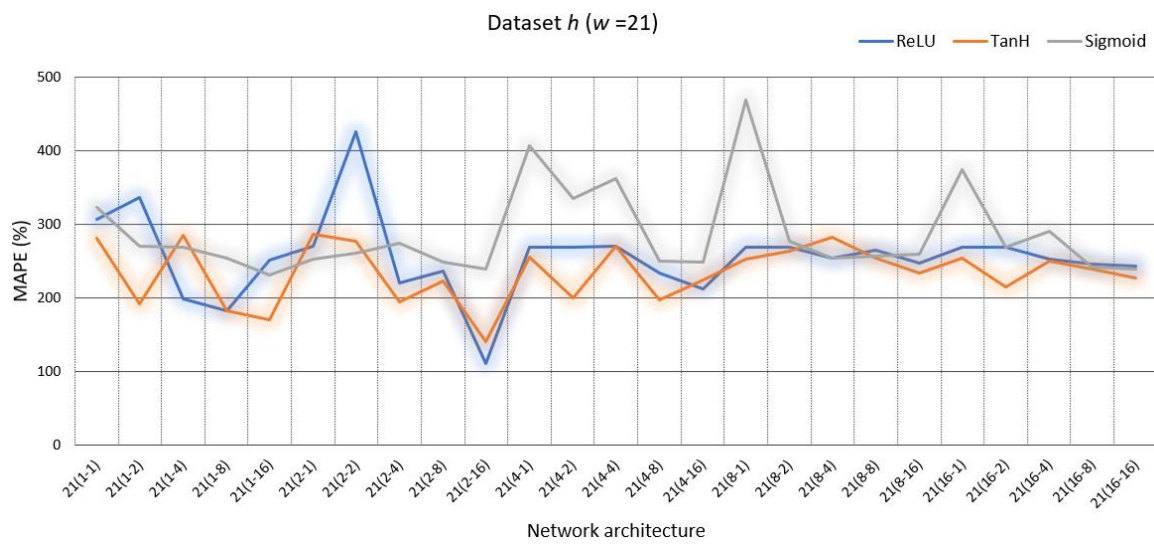
(e) Dataset e



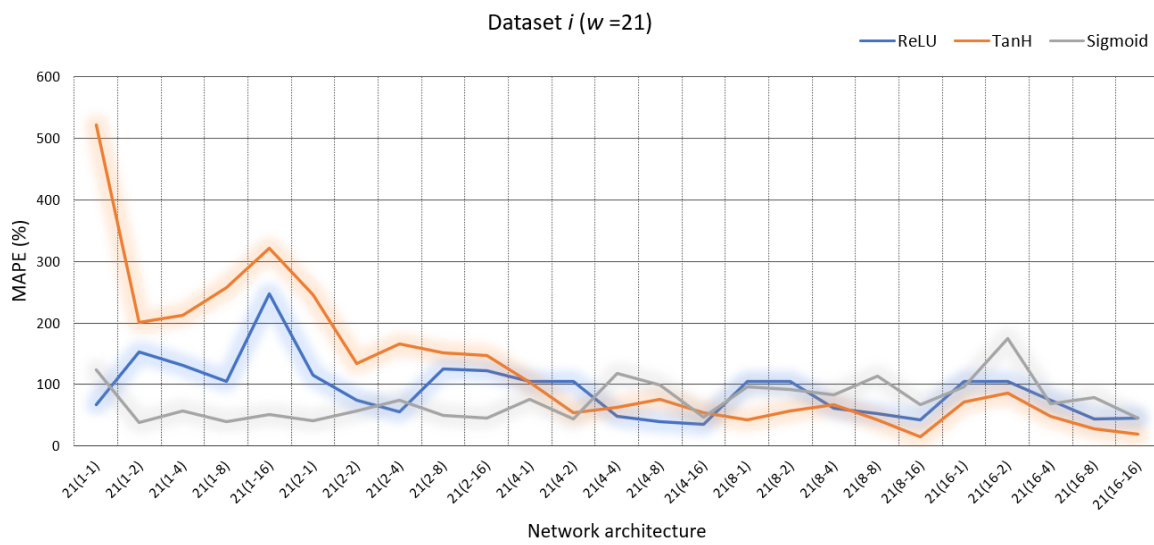
(f) Dataset f



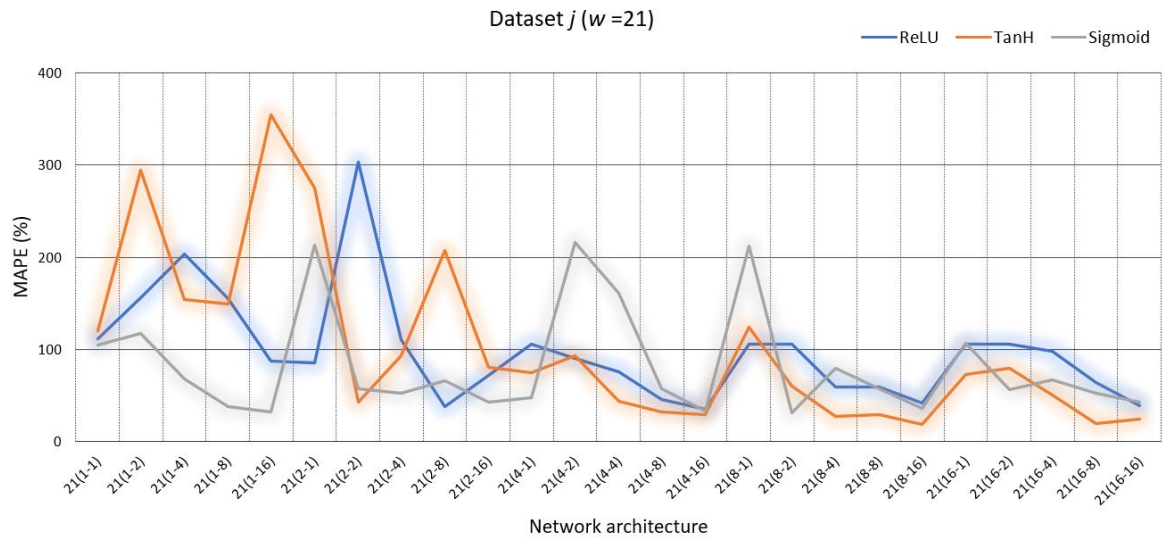
(g) Dataset g



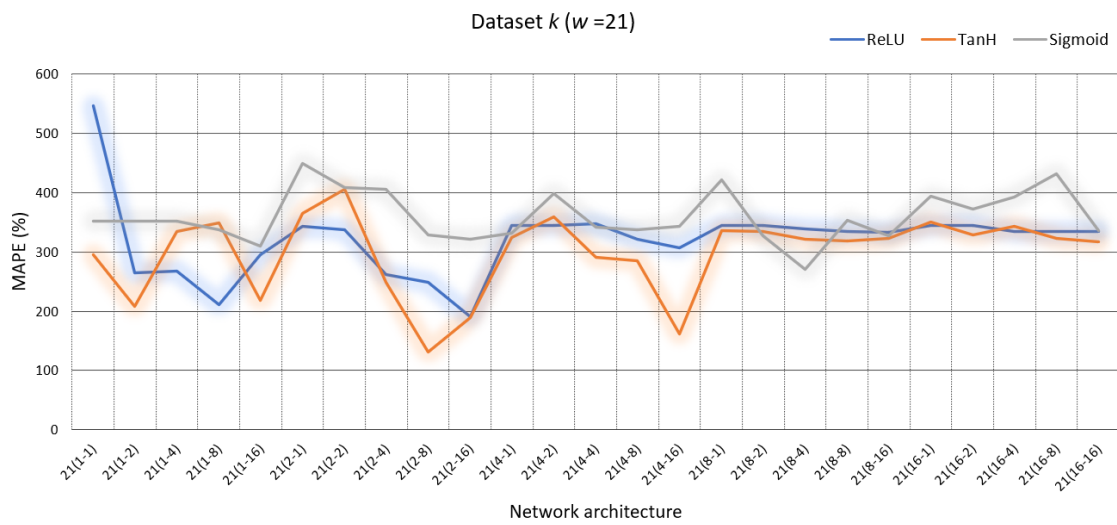
(h) Dataset h



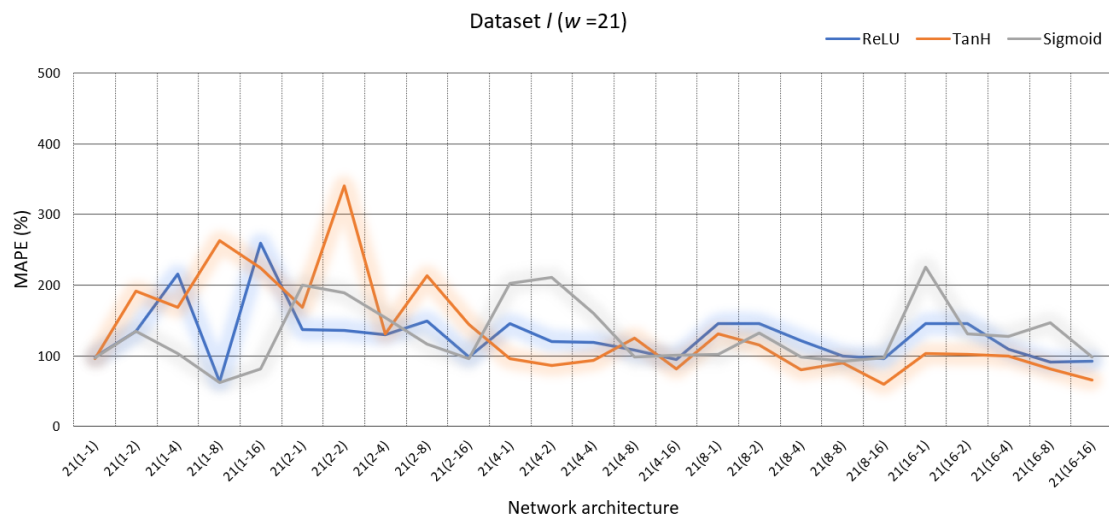
(i) Dataset i



(j) Dataset j



(k) Dataset k



(l) Dataset l

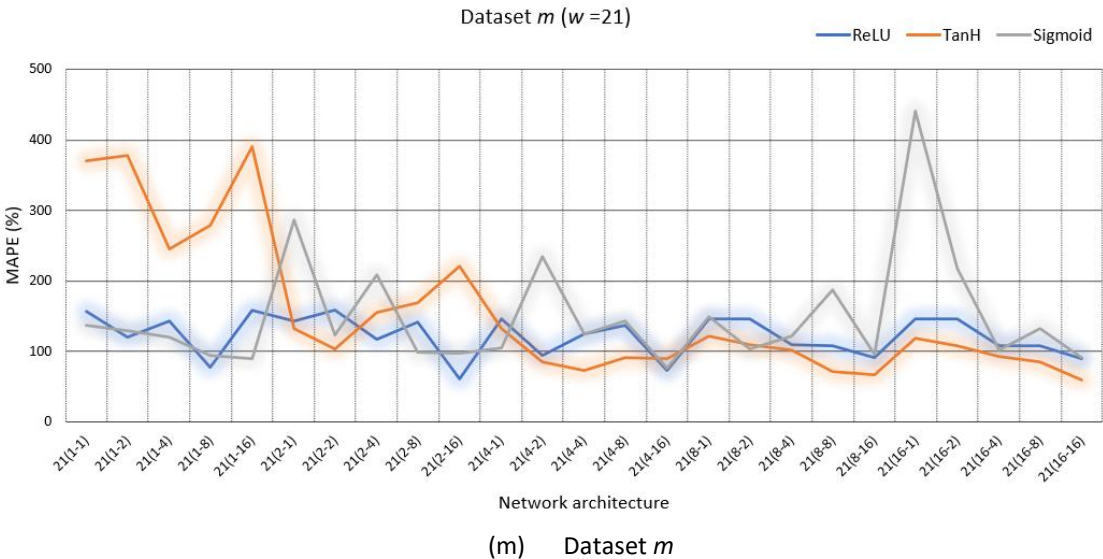


Figure E - 4 : Architecture comparison of all 13 datasets across three activation function when $w = 21$

E.2 Statistical tests

E.2.1 MANOVA: Difference of all parameters and datasets

Table E - 1 : Multivariate Tests^a of all parameters and datasets

Effect		Value	F	Hypothesis df	Error df	p
Intercept	Pillai's Trace	0.99	662144.901 ^b	6	23364.00	<0.001*
	Wilks' Lambda	0.01	662144.901 ^b	6	23364.00	<0.001*
	Hotelling's Trace	170.04	662144.901 ^b	6	23364.00	<0.001*
	Roy's Largest Root	170.04	662144.901 ^b	6	23364.00	<0.001*
Activation Function	Pillai's Trace	0.17	349.71	12	46730.00	<0.001*
	Wilks' Lambda	0.84	363.353 ^b	12	46728.00	<0.001*
	Hotelling's Trace	0.19	377.04	12	46726.00	<0.001*
	Roy's Largest Root	0.19	718.987 ^c	6	23365.00	<0.001*
Window size	Pillai's Trace	0.73	1246.54	18	70098.00	<0.001*
	Wilks' Lambda	0.28	2061.94	18	66083.86	<0.001*
	Hotelling's Trace	2.49	3231.43	18	70088.00	<0.001*
	Roy's Largest Root	2.47	9635.607 ^c	6	23366.00	<0.001*
Epoch	Pillai's Trace	1.11	1113.51	30	116840.00	<0.001*
	Wilks' Lambda	0.07	3001.01	30	93458.00	<0.001*
	Hotelling's Trace	11.22	8734.12	30	116812.00	<0.001*
	Roy's Largest Root	10.98	42750.011 ^c	6	23368.00	<0.001*
Hidden	Pillai's Trace	0.66	774.14	24	93468.00	<0.001*
	Wilks' Lambda	0.39	1053.70	24	81508.47	<0.001*
	Hotelling's Trace	1.43	1393.29	24	93450.00	<0.001*
	Roy's Largest Root	1.33	5177.271 ^c	6	23367.00	<0.001*
Node	Pillai's Trace	0.08	75.11	24	93468.00	<0.001*
	Wilks' Lambda	0.92	77.37	24	81508.47	<0.001*
	Hotelling's Trace	0.08	79.46	24	93450.00	<0.001*
	Roy's Largest Root	0.08	311.876 ^c	6	23367.00	<0.001*
Dataset	Pillai's Trace	1.14	456.88	72	140214.00	<0.001*
	Wilks' Lambda	0.17	676.11	72	127119.71	<0.001*
	Hotelling's Trace	3.07	995.35	72	140174.00	<0.001*
	Roy's Largest Root	2.34	4563.481 ^c	12	23369.00	<0.001*

^a Design: Intercept + Activation Function + Window size + Epoch + Hidden + Node + Dataset

^b Exact statistic

^c The statistic is an upper bound on F that yields a lower bound on the significance level.

Table E - 2 : The multiple comparisons of all parameters which affect the prediction error

Dependent Variable	Independent (I)	Independent (J)	Mean Difference (I-J)	Std. Error	95% Confidence Interval		<i>p</i>
					Lower Bound	Upper Bound	
Prediction error	ReLU	TanH	112.8995*	15.05	76.86	148.94	<0.001*
		Sigmoid	-66.1318*	15.05	-102.17	-30.09	<0.001*
	TanH	ReLU	-112.8995*	15.05	-148.94	-76.86	<0.001*
		Sigmoid	-179.0313*	15.05	-215.07	-142.99	<0.001*
	Sigmoid	ReLU	66.1318*	15.05	30.09	102.17	<0.001*
		TanH	179.0313*	15.05	142.99	215.07	<0.001*
	w=21	w=63	-1028.3948*	17.38	-1074.26	-982.53	<0.001*
		w=125	-1045.2099*	17.38	-1091.07	-999.35	<0.001*
		w=250	-3307.0820*	17.38	-3352.94	-3261.22	<0.001*
	w=63	w=21	1028.3948*	17.38	982.53	1074.26	<0.001*
		w=125	-16.8152	17.38	-62.68	29.05	1.000
		w=250	-2278.6872*	17.38	-2324.55	-2232.83	<0.001*
	w=125	w=21	1045.2099*	17.38	999.35	1091.07	<0.001*
		w=63	16.8152	17.38	-29.05	62.68	1.000
		w=250	-2261.8720*	17.38	-2307.73	-2216.01	<0.001*
	w=250	w=21	3307.0820*	17.38	3261.22	3352.94	<0.001*
		w=63	2278.6872*	17.38	2232.83	2324.55	<0.001*
		w=125	2261.8720*	17.38	2216.01	2307.73	<0.001*
	n1	n2	70.0175*	19.43	15.46	124.57	0.003*
		n4	146.1958*	19.43	91.64	200.75	<0.001*
		n8	254.1793*	19.43	199.62	308.73	<0.001*
		n16	338.4341*	19.43	283.88	392.99	<0.001*
	n2	n1	-70.0175*	19.43	-124.57	-15.46	0.003*
		n4	76.1783*	19.43	21.62	130.73	<0.001*
		n8	184.1617*	19.43	129.61	238.72	<0.001*
		n16	268.4166*	19.43	213.86	322.97	<0.001*
	n4	n1	-146.1958*	19.43	-200.75	-91.64	<0.001*
		n2	-76.1783*	19.43	-130.73	-21.62	<0.001*
		n8	107.9835*	19.43	53.43	162.54	<0.001*
		n16	192.2383*	19.43	137.68	246.79	<0.001*
	n8	n1	-254.1793*	19.43	-308.73	-199.62	<0.001*
		n2	-184.1617*	19.43	-238.72	-129.61	<0.001*
		n4	-107.9835*	19.43	-162.54	-53.43	<0.001*
		n16	84.2549*	19.43	29.70	138.81	<0.001*
	n16	n1	-338.4341*	19.43	-392.99	-283.88	<0.001*
		n2	-268.4166*	19.43	-322.97	-213.86	<0.001*
		n4	-192.2383*	19.43	-246.79	-137.68	<0.001*
		n8	-84.2549*	19.43	-138.81	-29.70	<0.001*
	10e	20e	396.6440*	35.51	292.41	500.88	<0.001*
		50e	789.0402*	35.51	684.80	893.28	<0.001*
		100e	904.6260*	35.51	800.39	1008.86	<0.001*
		150e	913.0963*	35.51	808.86	1017.33	<0.001*
		200e	923.9692*	35.51	819.73	1028.21	<0.001*
	20e	10e	-396.6440*	35.51	-500.88	-292.41	<0.001*
		50e	392.3962*	35.51	288.16	496.63	<0.001*
		100e	507.9820*	35.51	403.75	612.22	<0.001*
		150e	516.4523*	35.51	412.22	620.69	<0.001*

Dependent Variable	Independent (I)	Independent (J)	Mean Difference (I-J)	Std. Error	95% Confidence Interval		<i>p</i>
					Lower Bound	Upper Bound	
	50e	200e	527.3253*	35.51	423.09	631.56	<0.001*
		10e	-789.0402*	35.51	-893.28	-684.80	<0.001*
		20e	-392.3962*	35.51	-496.63	-288.16	<0.001*
		100e	115.5859*	35.51	11.35	219.82	0.017*
	100e	150e	124.0561*	35.51	19.82	228.29	0.007*
		200e	134.9291*	35.51	30.69	239.17	0.002*
		10e	-904.6260*	35.51	-1008.86	-800.39	<0.001*
		20e	-507.9820*	35.51	-612.22	-403.75	<0.001*
	150e	50e	-115.5859*	35.51	-219.82	-11.35	0.017*
		150e	8.4702	35.51	-95.77	112.71	1.000
		200e	19.3432	35.51	-84.89	123.58	1.000
		10e	-913.0963*	35.51	-1017.33	-808.86	<0.001*
	200e	20e	-516.4523*	35.51	-620.69	-412.22	<0.001*
		50e	-124.0561*	35.51	-228.29	-19.82	0.007*
		100e	-8.4702	35.51	-112.71	95.77	1.000
		200e	10.873	35.51	-93.36	115.11	1.000
	200e	10e	-923.9692*	35.51	-1028.21	-819.73	<0.001*
		20e	-527.3253*	35.51	-631.56	-423.09	<0.001*
		50e	-134.9291*	35.51	-239.17	-30.69	0.002*
		100e	-19.3432	35.51	-123.58	84.89	1.000
		150e	-10.873	35.51	-115.11	93.36	1.000
	dataset a	dataset b	-954.7911*	52.56	-1134.22	-775.36	<0.001*
		dataset c	-633.4250*	52.56	-812.86	-453.99	<0.001*
		dataset d	-710.6775*	52.56	-890.11	-531.25	<0.001*
		dataset e	-337.7239*	52.56	-517.15	-158.29	<0.001*
		dataset f	-712.2328*	52.56	-891.66	-532.80	<0.001*
		dataset g	-732.8309*	52.56	-912.26	-553.40	<0.001*
		dataset h	-791.6771*	52.56	-971.11	-612.25	<0.001*
		dataset i	-184.6195*	52.56	-364.05	-5.19	0.035*
		dataset j	-187.0522*	52.56	-366.48	-7.62	0.029*
		dataset k	-1021.0333*	52.56	-1200.46	-841.60	<0.001*
		dataset l	-397.5547*	52.56	-576.99	-218.12	<0.001*
		dataset m	-364.6797*	52.56	-544.11	-185.25	<0.001*
	dataset b	dataset a	954.7911*	52.56	775.36	1134.22	<0.001*
		dataset c	321.3661*	52.56	141.94	500.80	<0.001*
		dataset d	244.1136*	52.56	64.68	423.54	<0.001*
		dataset e	617.0672*	52.56	437.64	796.50	<0.001*
		dataset f	242.5583*	52.56	63.13	421.99	<0.001*
		dataset g	221.9602*	52.56	42.53	401.39	0.002*
		dataset h	163.114	52.56	-16.32	342.54	0.149
		dataset i	770.1715*	52.56	590.74	949.60	<0.001*
		dataset j	767.7389*	52.56	588.31	947.17	<0.001*
		dataset k	-66.2422	52.56	-245.67	113.19	1.000
		dataset l	557.2364*	52.56	377.81	736.67	<0.001*
		dataset m	590.1114*	52.56	410.68	769.54	<0.001*
	dataset c	dataset a	633.4250*	52.56	453.99	812.86	<0.001*
		dataset b	-321.3661*	52.56	-500.80	-141.94	<0.001*
		dataset d	-77.2525	52.56	-256.68	102.18	1.000
		dataset e	295.7011*	52.56	116.27	475.13	<0.001*

Dependent Variable	Independent (I)	Independent (J)	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
dataset d		dataset f	-78.8078	52.56	-258.24	100.62	1.000
		dataset g	-99.4059	52.56	-278.84	80.02	1.000
		dataset h	-158.2521	52.56	-337.68	21.18	0.203
		dataset i	448.8054*	52.56	269.38	628.24	<0.001*
		dataset j	446.3728*	52.56	266.94	625.80	<0.001*
		dataset k	-387.6083*	52.56	-567.04	-208.18	<0.001*
		dataset l	235.8703*	52.56	56.44	415.30	<0.001*
		dataset m	268.7453*	52.56	89.31	448.18	<0.001*
		dataset a	710.6775*	52.56	531.25	890.11	<0.001*
		dataset b	-244.1136*	52.56	-423.54	-64.68	<0.001*
		dataset c	77.2525	52.56	-102.18	256.68	1.000
		dataset e	372.9536*	52.56	193.52	552.38	<0.001*
		dataset f	-1.5553	52.56	-180.99	177.88	1.000
		dataset g	-22.1533	52.56	-201.58	157.28	1.000
		dataset h	-80.9995	52.56	-260.43	98.43	1.000
		dataset i	526.0580*	52.56	346.63	705.49	<0.001*
		dataset j	523.6253*	52.56	344.19	703.06	<0.001*
		dataset k	-310.3557*	52.56	-489.79	-130.93	<0.001*
		dataset l	313.1228*	52.56	133.69	492.55	<0.001*
		dataset m	345.9978*	52.56	166.57	525.43	<0.001*
dataset e		dataset a	337.7239*	52.56	158.29	517.15	<0.001*
		dataset b	-617.0672*	52.56	-796.50	-437.64	<0.001*
		dataset c	-295.7011*	52.56	-475.13	-116.27	<0.001*
		dataset d	-372.9536*	52.56	-552.38	-193.52	<0.001*
		dataset f	-374.5088*	52.56	-553.94	-195.08	<0.001*
		dataset g	-395.1069*	52.56	-574.54	-215.68	<0.001*
		dataset h	-453.9531*	52.56	-633.38	-274.52	<0.001*
		dataset i	153.1044	52.56	-26.33	332.53	0.279
		dataset j	150.6717	52.56	-28.76	330.10	0.324
		dataset k	-683.3093*	52.56	-862.74	-503.88	<0.001*
dataset f		dataset l	-59.8308	52.56	-239.26	119.60	1.000
		dataset m	-26.9558	52.56	-206.39	152.47	1.000
		dataset a	712.2328*	52.56	532.80	891.66	<0.001*
		dataset b	-242.5583*	52.56	-421.99	-63.13	<0.001*
		dataset c	78.8078	52.56	-100.62	258.24	1.000
		dataset d	1.5553	52.56	-177.88	180.99	1.000
		dataset e	374.5088*	52.56	195.08	553.94	<0.001*
		dataset g	-20.5981	52.56	-200.03	158.83	1.000
		dataset h	-79.4443	52.56	-258.87	99.99	1.000
		dataset i	527.6132*	52.56	348.18	707.04	<0.001*
dataset g		dataset j	525.1806*	52.56	345.75	704.61	<0.001*
		dataset k	-308.8005*	52.56	-488.23	-129.37	<0.001*
		dataset l	314.6781*	52.56	135.25	494.11	<0.001*
		dataset m	347.5530*	52.56	168.12	526.98	<0.001*
		dataset a	732.8309*	52.56	553.40	912.26	<0.001*
		dataset b	-221.9602*	52.56	-401.39	-42.53	0.002*
		dataset c	99.4059	52.56	-80.02	278.84	1.000
		dataset d	22.1533	52.56	-157.28	201.58	1.000
		dataset e	395.1069*	52.56	215.68	574.54	<0.001*

Dependent Variable	Independent (I)	Independent (J)	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
		dataset f	20.5981	52.56	-158.83	200.03	1.000
		dataset h	-58.8462	52.56	-238.28	120.58	1.000
		dataset i	548.2113*	52.56	368.78	727.64	<0.001*
		dataset j	545.7787*	52.56	366.35	725.21	<0.001*
		dataset k	-288.2024*	52.56	-467.63	-108.77	<0.001*
		dataset l	335.2761*	52.56	155.85	514.71	<0.001*
		dataset m	368.1511*	52.56	188.72	547.58	<0.001*
	dataset h	dataset a	791.6771*	52.56	612.25	971.11	<0.001*
	dataset h	dataset b	-163.114	52.56	-342.54	16.32	0.149
	dataset h	dataset c	158.2521	52.56	-21.18	337.68	0.203
	dataset h	dataset d	80.9995	52.56	-98.43	260.43	1.000
	dataset h	dataset e	453.9531*	52.56	274.52	633.38	<0.001*
	dataset h	dataset f	79.4443	52.56	-99.99	258.87	1.000
	dataset h	dataset g	58.8462	52.56	-120.58	238.28	1.000
	dataset h	dataset i	607.0575*	52.56	427.63	786.49	<0.001*
	dataset h	dataset j	604.6249*	52.56	425.19	784.06	<0.001*
	dataset h	dataset k	-229.3562*	52.56	-408.79	-49.93	0.001*
	dataset h	dataset l	394.1223*	52.56	214.69	573.55	<0.001*
	dataset h	dataset m	426.9973*	52.56	247.57	606.43	<0.001*
	dataset i	dataset a	184.6195*	52.56	5.19	364.05	0.035*
	dataset i	dataset b	-770.1715*	52.56	-949.60	-590.74	<0.001*
	dataset i	dataset c	-448.8054*	52.56	-628.24	-269.38	<0.001*
	dataset i	dataset d	-526.0580*	52.56	-705.49	-346.63	<0.001*
	dataset i	dataset e	-153.1044	52.56	-332.53	26.33	0.279
	dataset i	dataset f	-527.6132*	52.56	-707.04	-348.18	<0.001*
	dataset i	dataset g	-548.2113*	52.56	-727.64	-368.78	<0.001*
	dataset i	dataset h	-607.0575*	52.56	-786.49	-427.63	<0.001*
	dataset i	dataset j	-2.4326	52.56	-181.86	177.00	1.000
	dataset i	dataset k	-836.4137*	52.56	-1015.84	-656.98	<0.001*
	dataset i	dataset l	-212.9352*	52.56	-392.37	-33.50	0.004*
	dataset i	dataset m	-180.0602*	52.56	-359.49	-0.63	0.048*
	dataset j	dataset a	187.0522*	52.56	7.62	366.48	0.029
	dataset j	dataset b	-767.7389*	52.56	-947.17	-588.31	<0.001*
	dataset j	dataset c	-446.3728*	52.56	-625.80	-266.94	<0.001*
	dataset j	dataset d	-523.6253*	52.56	-703.06	-344.19	<0.001*
	dataset j	dataset e	-150.6717	52.56	-330.10	28.76	0.324
	dataset j	dataset f	-525.1806*	52.56	-704.61	-345.75	<0.001*
	dataset j	dataset g	-545.7787*	52.56	-725.21	-366.35	<0.001*
	dataset j	dataset h	-604.6249*	52.56	-784.06	-425.19	<0.001*
	dataset j	dataset i	2.4326	52.56	-177.00	181.86	1.000
	dataset j	dataset k	-833.9811*	52.56	-1013.41	-654.55	<0.001*
	dataset j	dataset l	-210.5025*	52.56	-389.93	-31.07	0.005*
	dataset j	dataset m	-177.6275	52.56	-357.06	1.80	0.057
	dataset k	dataset a	1021.0333*	52.56	841.60	1200.46	<0.001*
	dataset k	dataset b	66.2422	52.56	-113.19	245.67	1.000
	dataset k	dataset c	387.6083*	52.56	208.18	567.04	<0.001*
	dataset k	dataset d	310.3557*	52.56	130.93	489.79	<0.001*
	dataset k	dataset e	683.3093*	52.56	503.88	862.74	<0.001*
	dataset k	dataset f	308.8005*	52.56	129.37	488.23	<0.001*

Dependent Variable	Independent (I)	Independent (J)	Mean Difference (I-J)	Std. Error	95% Confidence Interval		<i>p</i>
					Lower Bound	Upper Bound	
	dataset l	dataset g	288.2024*	52.56	108.77	467.63	<0.001*
		dataset h	229.3562*	52.56	49.93	408.79	0.001
		dataset i	836.4137*	52.56	656.98	1015.84	<0.001*
		dataset j	833.9811*	52.56	654.55	1013.41	<0.001*
		dataset l	623.4785*	52.56	444.05	802.91	<0.001*
		dataset m	656.3535*	52.56	476.92	835.78	<0.001*
		dataset a	397.5547*	52.56	218.12	576.99	<0.001*
		dataset b	-557.2364*	52.56	-736.67	-377.81	<0.001*
		dataset c	-235.8703*	52.56	-415.30	-56.44	<0.001*
		dataset d	-313.1228*	52.56	-492.55	-133.69	<0.001*
		dataset e	59.8308	52.56	-119.60	239.26	1.000
		dataset f	-314.6781*	52.56	-494.11	-135.25	<0.001*
		dataset g	-335.2761*	52.56	-514.71	-155.85	<0.001*
		dataset h	-394.1223*	52.56	-573.55	-214.69	<0.001*
		dataset i	212.9352*	52.56	33.50	392.37	0.004*
	dataset m	dataset j	210.5025*	52.56	31.07	389.93	0.005*
		dataset k	-623.4785*	52.56	-802.91	-444.05	<0.001*
		dataset m	32.875	52.56	-146.56	212.31	1.000
		dataset a	364.6797*	52.56	185.25	544.11	<0.001*
		dataset b	-590.1114*	52.56	-769.54	-410.68	<0.001*
		dataset c	-268.7453*	52.56	-448.18	-89.31	<0.001*
		dataset d	-345.9978*	52.56	-525.43	-166.57	<0.001*
		dataset e	26.9558	52.56	-152.47	206.39	1.000
		dataset f	-347.5530*	52.56	-526.98	-168.12	<0.001*
		dataset g	-368.1511*	52.56	-547.58	-188.72	<0.001*
		dataset h	-426.9973*	52.56	-606.43	-247.57	<0.001*
		dataset i	180.0602*	52.56	0.63	359.49	0.048*
		dataset j	177.6275	52.56	-1.80	357.06	0.057
		dataset k	-656.3535*	52.56	-835.78	-476.92	<0.001*
		dataset l	-32.875	52.56	-212.31	146.56	1.000

Table E - 3 : Test of Between-Subjects Effects of all parameters and datasets

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	p
Corrected Model	MSE	0.066 ^a	30	0.002	302.89	<0.001*
	RMSE	4.513 ^b	30	0.150	890.17	<0.001*
	MAE	5.126 ^c	30	0.171	959.67	<0.001*
	MAPE	6541418919.577 ^d	30	218047297.319	1042.34	<0.001*
	Prediction error	39657090216.862 ^e	30	1321903007.229	1495.87	<0.001*
	Runtime	1913213.044 ^f	30	63773.768	8998.92	<0.001*
Intercept	MSE	0.222	1	0.222	30306.82	<0.001*
	RMSE	63.55	1	63.550	376009.56	<0.001*
	MAE	54.46	1	54.460	305897.69	<0.001*
	MAPE	53478626736	1	53478626736.029	255646.63	<0.001*
	Prediction error	58923154530	1	58923154530.213	66677.58	<0.001*
	Runtime	4591040.941	1	4591040.941	647827.86	<0.001*
Activation function	MSE	0.004	2	0.002	240.33	<0.001*
	RMSE	0.121	2	0.061	358.52	<0.001*
	MAE	0.167	2	0.084	469.36	<0.001*
	MAPE	196708309.8	2	98354154.920	470.17	<0.001*
	Prediction error	127847005.2	2	63923502.612	72.34	<0.001*
	Runtime	2.82	2	1.410	0.20	0.820
Window size	MSE	0.000	3	0.000	11.64	<0.001*
	RMSE	0.01	3	0.003	19.91	<0.001*
	MAE	0.012	3	0.004	22.96	<0.001*
	MAPE	16549290.35	3	5516430.116	26.37	<0.001*
	Prediction error	34216085246	3	11405361748.786	12906.33	<0.001*
	Runtime	2240.615	3	746.872	105.39	<0.001*
Hidden	MSE	0.000	4	0.000	10.23	<0.001*
	RMSE	0.009	4	0.002	13.56	<0.001*
	MAE	0.025	4	0.006	35.17	<0.001*
	MAPE	28948098.95	4	7237024.738	34.60	<0.001*
	Prediction error	4966967.764	4	1241741.941	1.41	0.229
	Runtime	197737.762	4	49434.440	6975.54	<0.001*
Node	MSE	0.005	4	0.001	168.94	<0.001*
	RMSE	0.206	4	0.052	305.21	<0.001*
	MAE	0.228	4	0.057	319.47	<0.001*
	MAPE	266001142.2	4	66500285.555	317.90	<0.001*
	Prediction error	349035796.5	4	87258949.113	98.74	<0.001*
	Runtime	406.412	4	101.603	14.34	<0.001*
Epoch	MSE	0.033	5	0.007	897.89	<0.001*
	RMSE	1.656	5	0.331	1960.12	<0.001*
	MAE	1.736	5	0.347	1950.28	<0.001*
	MAPE	2066807154	5	413361430.848	1976.01	<0.001*
	Prediction error	2788537944	5	557707588.815	631.10	<0.001*
	Runtime	1653119.109	5	330623.822	46653.32	<0.001*
Dataset	MSE	0.025	12	0.002	280.43	<0.001*
	RMSE	2.51	12	0.209	1237.72	<0.001*
	MAE	2.958	12	0.246	1384.37	<0.001*
	MAPE	3966404924	12	330533743.665	1580.07	<0.001*
	Prediction error	2170617257	12	180884771.415	204.69	<0.001*

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	p
	Runtime	59706.326	12	4975.527	702.08	<0.001*
Error	MSE	0.171	23369	0.000007		
	RMSE	3.95	23369	0.000000		
	MAE	4.16	23369	0.000000		
	MAPE	4888552791	23369	209189.644		
	Prediction error	20651247756	23369	883702.673		
	Runtime	165611.952	23369	7.087		
Total	MSE	0.459	23400			
	RMSE	72.013	23400			
	MAE	63.746	23400			
	MAPE	64908598447	23400			
	Prediction error	1.19231E+11	23400			
	Runtime	6669865.937	23400			
Corrected Total	MSE	0.237	23399			
	RMSE	8.463	23399			
	MAE	9.286	23399			
	MAPE	11429971711	23399			
	Prediction error	60308337973	23399			
	Runtime	2078824.996	23399			

a R Squared = 0.280 (Adjusted R Squared = 0.279)

b R Squared = 0.533 (Adjusted R Squared = 0.533)

c R Squared = 0.552 (Adjusted R Squared = 0.551)

d R Squared = 0.572 (Adjusted R Squared = 0.572)

e R Squared = 0.658 (Adjusted R Squared = 0.657)

f R Squared = 0.920 (Adjusted R Squared = 0.920)

* Indicates significance at $p < 0.05$

Table E - 4 : The multiple comparisons of the activation function

Dependent Variable	(I) Window	(J) Window	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
MSE	ReLU	TanH	0.000337*	0.0000	0.0002	0.0004	<0.001
		Sigmoid	-0.000600*	0.0000	-0.0007	-0.0005	<0.001
	TanH	ReLU	-0.000337*	0.0000	-0.0004	-0.0002	<0.001
		Sigmoid	-0.000937*	0.0000	-0.0010	-0.0008	<0.001
	Sigmoid	ReLU	0.000600*	0.0000	0.0005	0.0007	<0.001
		TanH	0.000937*	0.0000	0.0008	0.0010	<0.001
RMSE	ReLU	TanH	0.003229*	0.0002	0.0027	0.0037	<0.001
		Sigmoid	-0.002321*	0.0002	-0.0028	-0.0018	<0.001
	TanH	ReLU	-0.003229*	0.0002	-0.0037	-0.0027	<0.001
		Sigmoid	-0.005550*	0.0002	-0.0060	-0.0051	<0.001
	Sigmoid	ReLU	0.002321*	0.0002	0.0018	0.0028	<0.001
		TanH	0.005550*	0.0002	0.0051	0.0060	<0.001
MAE	ReLU	TanH	0.004046*	0.0002	0.0035	0.0046	<0.001
		Sigmoid	-0.002433*	0.0002	-0.0029	-0.0019	<0.001
	TanH	ReLU	-0.004046*	0.0002	-0.0046	-0.0035	<0.001
		Sigmoid	-0.006480*	0.0002	-0.0070	-0.0060	<0.001
	Sigmoid	ReLU	0.002433*	0.0002	0.0019	0.0029	<0.001
		TanH	0.006480*	0.0002	0.0060	0.0070	<0.001
MAPE	ReLU	TanH	141.022901*	7.32	123.49	158.56	<0.001
		Sigmoid	-80.858716*	7.32	-98.39	-63.32	<0.001
	TanH	ReLU	-141.022901*	7.32	-158.56	-123.49	<0.001
		Sigmoid	-221.881617*	7.32	-239.42	-204.35	<0.001
	Sigmoid	ReLU	80.858716*	7.32	63.32	98.39	<0.001
		TanH	221.881617*	7.32	204.35	239.42	<0.001
Prediction error	ReLU	TanH	112.8995*	15.05	76.86	148.94	<0.001*
		Sigmoid	-66.1318*	15.05	-102.17	-30.09	<0.001*
	TanH	ReLU	-112.8995*	15.05	-148.94	-76.86	<0.001*
		Sigmoid	-179.0313*	15.05	-215.07	-142.99	<0.001*
	Sigmoid	ReLU	66.1318*	15.05	30.09	102.17	<0.001*
		TanH	179.0313*	15.05	142.99	215.07	<0.001*

Based on observed means.

The error term is Mean Square (Error) = 7.087.

* The mean difference is significant at the 0.05 level.

Table E - 5 : The multiple comparisons of window size

Dependent Variable	(I) Window	(J) Window	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
MSE	w=21	w=63	-0.00007	0.0001	-0.0002	0.0001	0.940
		w=125	-.000217*	0.0001	-0.0003	-0.0001	<0.001*
		w=250	-.000256*	0.0001	-0.0004	-0.0001	<0.001*
	w=63	w=21	0.00007	0.0001	-0.0001	0.0002	0.940
		w=125	-.000146*	0.0001	-0.0003	0.0000	0.021*
		w=250	-.000185*	0.0001	-0.0003	-0.0001	0.001*
	w=125	w=21	.000217*	0.0001	0.0001	0.0003	<0.001*
		w=63	.000146*	0.0001	0.0000	0.0003	0.021*
		w=250	-0.00004	0.0001	-0.0002	0.0001	1.000
	w=250	w=21	.000256*	0.0001	0.0001	0.0004	<0.001*
		w=63	.000185*	0.0001	0.0001	0.0003	0.001*
		w=125	0.00004	0.0001	-0.0001	0.0002	1.000
RMSE	w=21	w=63	-0.000582	0.0002	-0.0012	0.0001	0.093
		w=125	-.001451*	0.0002	-0.0021	-0.0008	<0.001*
		w=250	-.001615*	0.0002	-0.0022	-0.0010	<0.001*
	w=63	w=21	0.000582	0.0002	-0.0001	0.0012	0.093
		w=125	-.000869*	0.0002	-0.0015	-0.0002	0.002*
		w=250	-.001033*	0.0002	-0.0017	-0.0004	<0.001*
	w=125	w=21	.001451*	0.0002	0.0008	0.0021	<0.001*
		w=63	.000869*	0.0002	0.0002	0.0015	0.002*
		w=250	-0.000164	0.0002	-0.0008	0.0005	1.000
	w=250	w=21	.001615*	0.0002	0.0010	0.0022	<0.001*
		w=63	.001033*	0.0002	0.0004	0.0017	<0.001*
		w=125	0.000164	0.0002	-0.0005	0.0008	1.000
MAE	w=21	w=63	-.000652*	0.0002	-0.0013	0.0000	0.049*
		w=125	-.001575*	0.0002	-0.0022	-0.0009	<0.001*
		w=250	-.001803*	0.0002	-0.0025	-0.0012	<0.001*
	w=63	w=21	.000652*	0.0002	0.0000	0.0013	0.049*
		w=125	-.000923*	0.0002	-0.0016	-0.0003	0.001*
		w=250	-.001151*	0.0002	-0.0018	-0.0005	<0.001*
	w=125	w=21	.001575*	0.0002	0.0009	0.0022	<0.001*
		w=63	.000923*	0.0002	0.0003	0.0016	0.001*
		w=250	-0.000227	0.0002	-0.0009	0.0004	1.000
	w=250	w=21	.001803*	0.0002	0.0012	0.0025	<0.001*
		w=63	.001151*	0.0002	0.0005	0.0018	<0.001*
		w=125	0.000227	0.0002	-0.0004	0.0009	1.000
MAPE	w=21	w=63	-27.437352*	8.46	-49.75	-5.12	0.007*
		w=125	-60.037539*	8.46	-82.35	-37.72	<0.001*
		w=250	-66.077000*	8.46	-88.39	-43.76	<0.001*
	w=63	w=21	27.437352*	8.46	5.12	49.75	0.007*
		w=125	-32.600187*	8.46	-54.91	-10.29	<0.001*
		w=250	-38.639649*	8.46	-60.95	-16.33	<0.001*
	w=125	w=21	60.037539*	8.46	37.72	82.35	<0.001*
		w=63	32.600187*	8.46	10.29	54.91	<0.001*
		w=250	-6.039462	8.46	-28.35	16.27	1.000

Dependent Variable	(I) Window	(J) Window	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	w=250	w=21	66.077000*	8.46	43.76	88.39	<0.001*
		w=63	38.639649*	8.46	16.33	60.95	<0.001*
		w=125	6.039462	8.46	-16.27	28.35	1.000
Prediction error	w=21	w=63	-1028.3948*	17.38	-1074.26	-982.53	<0.001*
		w=125	-1045.2099*	17.38	-1091.07	-999.35	<0.001*
		w=250	-3307.0820*	17.38	-3352.94	-3261.22	<0.001*
	w=63	w=21	1028.3948*	17.38	982.53	1074.26	<0.001*
		w=125	-16.8152	17.38	-62.68	29.05	1.000
		w=250	-2278.6872*	17.38	-2324.55	-2232.83	<0.001*
	w=125	w=21	1045.2099*	17.38	999.35	1091.07	<0.001*
		w=63	16.8152	17.38	-29.05	62.68	1.000
		w=250	-2261.8720*	17.38	-2307.73	-2216.01	<0.001*
	w=250	w=21	3307.0820*	17.38	3261.22	3352.94	<0.001*
		w=63	2278.6872*	17.38	2232.83	2324.55	<0.001*
		w=125	2261.8720*	17.38	2216.01	2307.73	<0.001*
Runtime	w=21	w=63	-.8474*	0.05	-0.98	-0.72	<0.001*
		w=125	-.2579*	0.05	-0.39	-0.13	<0.001*
		w=250	-.4550*	0.05	-0.58	-0.33	<0.001*
	w=63	w=21	.8474*	0.05	0.72	0.98	<0.001*
		w=125	.5895*	0.05	0.46	0.72	<0.001*
		w=250	.3924*	0.05	0.26	0.52	<0.001*
	w=125	w=21	.2579*	0.05	0.13	0.39	<0.001*
		w=63	-.5895*	0.05	-0.72	-0.46	<0.001*
		w=250	-.1972*	0.05	-0.33	-0.07	<0.001*
	w=250	w=21	.4550*	0.05	0.33	0.58	<0.001*
		w=63	-.3924*	0.05	-0.52	-0.26	<0.001*
		w=125	.1972*	0.05	0.07	0.33	<0.001*

Based on observed means.

The error term is Mean Square(Error) = 7.087.

* The mean difference is significant at the 0.05 level.

Table E - 6 : The multiple comparisons of epoch

Dependent Variable	(I) Epoch	(J) Epoch	Mean Difference (I-J)	Std. Error	95% Confidence Interval		<i>p</i>
					Lower Bound	Upper Bound	
MSE	10e	20e	0.001734*	0.0001	0.0016	0.0019	<0.001*
		50e	0.002953*	0.0001	0.0028	0.0031	<0.001*
		100e	0.003173*	0.0001	0.0030	0.0034	<0.001*
		150e	0.003204*	0.0001	0.0030	0.0034	<0.001*
		200e	0.003217*	0.0001	0.0030	0.0034	<0.001*
	20e	10e	-0.001734	0.0001	-0.0019	-0.0016	<0.001*
		50e	0.001219*	0.0001	0.0010	0.0014	<0.001*
		100e	0.001439*	0.0001	0.0013	0.0016	<0.001*
		150e	0.001470*	0.0001	0.0013	0.0017	<0.001*
		200e	0.001483*	0.0001	0.0013	0.0017	<0.001*
	50e	10e	-0.002953	0.0001	-0.0031	-0.0028	<0.001*
		20e	-0.001219	0.0001	-0.0014	-0.0010	<0.001*
		100e	0.000219*	0.0001	0.0000	0.0004	0.005
		150e	0.000251*	0.0001	0.0001	0.0004	<0.001*
		200e	0.000263*	0.0001	0.0001	0.0004	<0.001*
	100e	10e	-0.003173	0.0001	-0.0034	-0.0030	<0.001*
		20e	-0.001439	0.0001	-0.0016	-0.0013	<0.001*
		50e	-0.000219	0.0001	-0.0004	0.0000	0.005*
		150e	0.000031	0.0001	-0.0001	0.0002	1.000
		200e	0.000044	0.0001	-0.0001	0.0002	1.000
	150e	10e	-0.003204	0.0001	-0.0034	-0.0030	<0.001*
		20e	-0.00147	0.0001	-0.0017	-0.0013	<0.001*
		50e	-0.000251	0.0001	-0.0004	-0.0001	<0.001*
		100e	-0.000031	0.0001	-0.0002	0.0001	1.000
		200e	0.000013	0.0001	-0.0002	0.0002	1.000
	200e	10e	-0.003217	0.0001	-0.0034	-0.0030	<0.001*
		20e	-0.001483	0.0001	-0.0017	-0.0013	<0.001*
		50e	-0.000263	0.0001	-0.0004	-0.0001	<0.001*
		100e	-0.000044	0.0001	-0.0002	0.0001	1.000
		150e	-0.000013	0.0001	-0.0002	0.0002	1.000
RMSE	10e	20e	0.010246*	0.0003	0.0094	0.0111	<0.001*
		50e	0.019885*	0.0003	0.0190	0.0207	<0.001*
		100e	0.022077*	0.0003	0.0212	0.0229	<0.001*
		150e	0.022405*	0.0003	0.0215	0.0233	<0.001*
		200e	0.022541*	0.0003	0.0217	0.0234	<0.001*
	20e	10e	-0.010246	0.0003	-0.0111	-0.0094	<0.001*
		50e	0.009639*	0.0003	0.0088	0.0105	<0.001*
		100e	0.011831*	0.0003	0.0110	0.0127	<0.001*
		150e	0.012159*	0.0003	0.0113	0.0130	<0.001*
		200e	0.012295*	0.0003	0.0114	0.0132	<0.001*
	50e	10e	-0.019885	0.0003	-0.0207	-0.0190	<0.001*
		20e	-0.009639*	0.0003	-0.0105	-0.0088	<0.001*
		100e	.002192*	0.0003	0.0013	0.0031	<0.001*
		150e	.002520*	0.0003	0.0017	0.0034	<0.001*
		200e	.002657*	0.0003	0.0018	0.0035	<0.001*
	100e	10e	-.022077*	0.0003	-0.0229	-0.0212	<0.001*
		20e	-.011831*	0.0003	-0.0127	-0.0110	<0.001*
		50e	-.002192*	0.0003	-0.0031	-0.0013	<0.001*

Dependent Variable	(I) Epoch	(J) Epoch	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	150e	150e	0.000328	0.0003	-0.0005	0.0012	1.000
		200e	0.000464	0.0003	-0.0004	0.0013	1.000
		10e	-.022405*	0.0003	-0.0233	-0.0215	<0.001*
		20e	-.012159*	0.0003	-0.0130	-0.0113	<0.001*
		50e	-.002520*	0.0003	-0.0034	-0.0017	<0.001*
	200e	100e	-0.000328	0.0003	-0.0012	0.0005	1.000
		200e	0.000136	0.0003	-0.0007	0.0010	1.000
		10e	-.022541*	0.0003	-0.0234	-0.0217	<0.001*
		20e	-.012295*	0.0003	-0.0132	-0.0114	<0.001*
		50e	-.002657*	0.0003	-0.0035	-0.0018	<0.001*
		100e	-0.000464	0.0003	-0.0013	0.0004	1.000
		150e	-0.000136	0.0003	-0.0010	0.0007	1.000
MAE	10e	20e	0.010342*	0.0003	0.0095	0.0112	<0.001*
		50e	0.020268*	0.0003	0.0194	0.0212	<0.001*
		100e	0.022545*	0.0003	0.0217	0.0234	<0.001*
		150e	0.022904*	0.0003	0.0220	0.0238	<0.001*
		200e	0.023075*	0.0003	0.0222	0.0240	<0.001*
	20e	10e	-0.010342	0.0003	-0.0112	-0.0095	<0.001*
		50e	0.009926*	0.0003	0.0090	0.0108	<0.001*
		100e	0.012202*	0.0003	0.0113	0.0131	<0.001*
		150e	0.012562*	0.0003	0.0117	0.0134	<0.001*
		200e	0.012733*	0.0003	0.0118	0.0136	<0.001*
	50e	10e	-0.020268	0.0003	-0.0212	-0.0194	<0.001*
		20e	-0.009926	0.0003	-0.0108	-0.0090	<0.001*
		100e	0.002276*	0.0003	0.0014	0.0032	<0.001*
		150e	0.002636*	0.0003	0.0017	0.0035	<0.001*
		200e	0.002807*	0.0003	0.0019	0.0037	<0.001*
	100e	10e	-0.022545	0.0003	-0.0234	-0.0217	<0.001*
		20e	-0.012202	0.0003	-0.0131	-0.0113	<0.001*
		50e	-0.002276	0.0003	-0.0032	-0.0014	<0.001*
		150e	0.000359	0.0003	-0.0005	0.0012	1.000
		200e	0.000531	0.0003	-0.0004	0.0014	1.000
	150e	10e	-0.022904	0.0003	-0.0238	-0.0220	<0.001*
		20e	-0.012562	0.0003	-0.0134	-0.0117	<0.001*
		50e	-0.002636	0.0003	-0.0035	-0.0017	<0.001*
		100e	-0.000359	0.0003	-0.0012	0.0005	1.000
		200e	0.000172	0.0003	-0.0007	0.0011	1.000
	200e	10e	-0.023075	0.0003	-0.0240	-0.0222	<0.001*
		20e	-0.012733	0.0003	-0.0136	-0.0118	<0.001*
		50e	-0.002807	0.0003	-0.0037	-0.0019	<0.001*
		100e	-0.000531	0.0003	-0.0014	0.0004	1.000
		150e	-0.000172	0.0003	-0.0011	0.0007	1.000
MAPE	10e	20e	347.186869*	10.36	316.78	377.59	<0.001*
		50e	693.362550*	10.36	662.96	723.77	<0.001*
		100e	775.628356*	10.36	745.22	806.03	<0.001*
		150e	788.569304*	10.36	758.17	818.97	<0.001*
		200e	794.066489*	10.36	763.66	824.47	<0.001*
	20e	10e	-347.186869*	10.36	-377.59	-316.78	<0.001*
		50e	346.175681*	10.36	315.77	376.58	<0.001*
		100e	428.441487*	10.36	398.04	458.85	<0.001*

Dependent Variable	(I) Epoch	(J) Epoch	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	50e	150e	441.382435*	10.36	410.98	471.79	<0.001*
		200e	446.879620*	10.36	416.48	477.28	<0.001*
		10e	-693.362550*	10.36	-723.77	-662.96	<0.001*
		20e	-346.175681*	10.36	-376.58	-315.77	<0.001*
		100e	82.265806*	10.36	51.86	112.67	<0.001*
		150e	95.206754*	10.36	64.80	125.61	<0.001*
	100e	200e	100.703939*	10.36	70.30	131.11	<0.001*
		10e	-775.628356*	10.36	-806.03	-745.22	<0.001*
		20e	-428.441487*	10.36	-458.85	-398.04	<0.001*
		50e	-82.265806*	10.36	-112.67	-51.86	<0.001*
		150e	12.940948	10.36	-17.46	43.35	1.000
		200e	18.438134	10.36	-11.97	48.84	1.000
	150e	10e	-788.569304*	10.36	-818.97	-758.17	<0.001*
		20e	-441.382435*	10.36	-471.79	-410.98	<0.001*
		50e	-95.206754*	10.36	-125.61	-64.80	<0.001*
		100e	-12.940948	10.36	-43.35	17.46	1.000
		200e	5.497185	10.36	-24.91	35.90	1.000
	200e	10e	-794.066489*	10.36	-824.47	-763.66	<0.001*
		20e	-446.879620*	10.36	-477.28	-416.48	<0.001*
		50e	-100.703939*	10.36	-131.11	-70.30	<0.001*
		100e	-18.438134	10.36	-48.84	11.97	1.000
		150e	-5.497185	10.36	-35.90	24.91	1.000
Prediction error	10e	20e	396.6440*	21.29	334.15	459.14	<0.001*
		50e	789.0402*	21.29	726.55	851.53	<0.001*
		100e	904.6260*	21.29	842.13	967.12	<0.001*
		150e	913.0963*	21.29	850.61	975.59	<0.001*
		200e	923.9692*	21.29	861.48	986.46	<0.001*
	20e	10e	-396.6440*	21.29	-459.14	-334.15	<0.001*
		50e	392.3962*	21.29	329.91	454.89	<0.001*
		100e	507.9820*	21.29	445.49	570.47	<0.001*
		150e	516.4523*	21.29	453.96	578.94	<0.001*
		200e	527.3253*	21.29	464.83	589.82	<0.001*
	50e	10e	-789.0402*	21.29	-851.53	-726.55	<0.001*
		20e	-392.3962*	21.29	-454.89	-329.91	<0.001*
		100e	115.5859*	21.29	53.09	178.08	<0.001*
		150e	124.0561*	21.29	61.57	186.55	<0.001*
		200e	134.9291*	21.29	72.44	197.42	<0.001*
	100e	10e	-904.6260*	21.29	-967.12	-842.13	<0.001*
		20e	-507.9820*	21.29	-570.47	-445.49	<0.001*
		50e	-115.5859*	21.29	-178.08	-53.09	<0.001*
		150e	8.4702	21.29	-54.02	70.96	1.000
		200e	19.3432	21.29	-43.15	81.83	1.000
	150e	10e	-913.0963*	21.29	-975.59	-850.61	<0.001*
		20e	-516.4523*	21.29	-578.94	-453.96	<0.001*
		50e	-124.0561*	21.29	-186.55	-61.57	<0.001*
		100e	-8.4702	21.29	-70.96	54.02	1.000
		200e	10.873	21.29	-51.62	73.36	1.000
	200e	10e	-923.9692*	21.29	-986.46	-861.48	<0.001*
		20e	-527.3253*	21.29	-589.82	-464.83	<0.001*

Dependent Variable	(I) Epoch	(J) Epoch	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
Runtime		50e	-134.9291*	21.29	-197.42	-72.44	<0.001*
		100e	-19.3432	21.29	-81.83	43.15	1.000
		150e	-10.873	21.29	-73.36	51.62	1.000
	10e	20e	-1.2219*	0.06	-1.40	-1.04	<0.001*
		50e	-4.9690*	0.06	-5.15	-4.79	<0.001*
		100e	-11.1321*	0.06	-11.31	-10.96	<0.001*
		150e	-16.9813*	0.06	-17.16	-16.80	<0.001*
		200e	-23.1370*	0.06	-23.31	-22.96	<0.001*
	20e	10e	1.2219*	0.06	1.04	1.40	<0.001*
		50e	-3.7472*	0.06	-3.92	-3.57	<0.001*
		100e	-9.9102*	0.06	-10.09	-9.73	<0.001*
		150e	-15.7594*	0.06	-15.94	-15.58	<0.001*
		200e	-21.9152*	0.06	-22.09	-21.74	<0.001*
	50e	10e	4.9690*	0.06	4.79	5.15	<0.001*
		20e	3.7472*	0.06	3.57	3.92	<0.001*
		100e	-6.1631*	0.06	-6.34	-5.99	<0.001*
		150e	-12.0123*	0.06	-12.19	-11.84	<0.001*
		200e	-18.1680*	0.06	-18.35	-17.99	<0.001*
	100e	10e	11.1321*	0.06	10.96	11.31	<0.001*
		20e	9.9102*	0.06	9.73	10.09	<0.001*
		50e	6.1631*	0.06	5.99	6.34	<0.001*
		150e	-5.8492*	0.06	-6.03	-5.67	<0.001*
		200e	-12.0049*	0.06	-12.18	-11.83	<0.001*
	150e	10e	16.9813*	0.06	16.80	17.16	<0.001*
		20e	15.7594*	0.06	15.58	15.94	<0.001*
		50e	12.0123*	0.06	11.84	12.19	<0.001*
		100e	5.8492*	0.06	5.67	6.03	<0.001*
		200e	-6.1557*	0.06	-6.33	-5.98	<0.001*
	200e	10e	23.1370*	0.06	22.96	23.31	<0.001*
		20e	21.9152*	0.06	21.74	22.09	<0.001*
		50e	18.1680*	0.06	17.99	18.35	<0.001*
		100e	12.0049*	0.06	11.83	12.18	<0.001*
		150e	6.1557*	0.06	5.98	6.33	<0.001*

Based on observed means.

The error term is Mean Square(Error) = 7.087.

* The mean difference is significant at the 0.05 level.

Table E - 7 : The multiple comparisons of hidden

Dependent Variable	(I) Hidden	(J) Hidden	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
MSE	h1	h2	-0.000212*	0.0001	-0.0004	-0.0001	0.001
		h4	-0.000295*	0.0001	-0.0005	-0.0001	<0.001*
		h8	-0.000280*	0.0001	-0.0004	-0.0001	<0.001*
		h16	-0.000299*	0.0001	-0.0005	-0.0001	<0.001*
	h2	h1	0.000212*	0.0001	0.0001	0.0004	0.001
		h4	-0.000082	0.0001	-0.0002	0.0001	1.000
		h8	-0.000068	0.0001	-0.0002	0.0001	1.000
		h16	-0.000087	0.0001	-0.0002	0.0001	1.000
	h4	h1	0.000295*	0.0001	0.0001	0.0005	<0.001*
		h2	0.000082	0.0001	-0.0001	0.0002	1.000
		h8	0.000014	0.0001	-0.0001	0.0002	1.000
		h16	-0.000005	0.0001	-0.0002	0.0002	1.000
	h8	h1	0.000280*	0.0001	0.0001	0.0004	<0.001*
		h2	0.000068	0.0001	-0.0001	0.0002	1.000
		h4	-0.000014	0.0001	-0.0002	0.0001	1.000
		h16	-0.000019	0.0001	-0.0002	0.0001	1.000
	h16	h1	0.000299*	0.0001	0.0001	0.0005	<0.001*
		h2	0.000087	0.0001	-0.0001	0.0002	1.000
		h4	0.000005	0.0001	-0.0002	0.0002	1.000
		h8	0.000019	0.0001	-0.0001	0.0002	1.000
RMSE	h1	h2	-0.001225*	0.0003	-0.0020	-0.0005	<0.001*
		h4	-0.001557*	0.0003	-0.0023	-0.0008	<0.001*
		h8	-0.001446*	0.0003	-0.0022	-0.0007	<0.001*
		h16	-0.001775*	0.0003	-0.0025	-0.0010	<0.001*
	h2	h1	0.001225*	0.0003	0.0005	0.0020	<0.001*
		h4	-0.000332	0.0003	-0.0011	0.0004	1.000
		h8	-0.000221	0.0003	-0.0010	0.0005	1.000
		h16	-0.00055	0.0003	-0.0013	0.0002	0.407
	h4	h1	0.001557*	0.0003	0.0008	0.0023	<0.001*
		h2	0.000332	0.0003	-0.0004	0.0011	1.000
		h8	0.000111	0.0003	-0.0006	0.0009	1.000
		h16	-0.000218	0.0003	-0.0010	0.0005	1.000
	h8	h1	0.001446*	0.0003	0.0007	0.0022	<0.001*
		h2	0.000221	0.0003	-0.0005	0.0010	1.000
		h4	-0.000111	0.0003	-0.0009	0.0006	1.000
		h16	-0.000329	0.0003	-0.0011	0.0004	1.000
	h16	h1	0.001775*	0.0003	0.0010	0.0025	<0.001*
		h2	0.00055	0.0003	-0.0002	0.0013	0.407
		h4	0.000218	0.0003	-0.0005	0.0010	1.000
		h8	0.000329	0.0003	-0.0004	0.0011	1.000
MAE	h1	h2	-0.001903*	0.0003	-0.0027	-0.0011	<0.001*
		h4	-0.002575*	0.0003	-0.0033	-0.0018	<0.001*
		h8	-0.002510*	0.0003	-0.0033	-0.0017	<0.001*
		h16	-0.002869*	0.0003	-0.0036	-0.0021	<0.001*
	h2	h1	0.001903*	0.0003	0.0011	0.0027	<0.001*
		h4	-0.000672	0.0003	-0.0014	0.0001	0.148
		h8	-0.000607	0.0003	-0.0014	0.0002	0.278
		h16	-0.000966*	0.0003	-0.0017	-0.0002	0.005

Dependent Variable	(I) Hidden	(J) Hidden	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	h4	h1	0.002575*	0.0003	0.0018	0.0033	<0.001*
		h2	0.000672	0.0003	-0.0001	0.0014	0.148
		h8	0.000065	0.0003	-0.0007	0.0008	1.000
		h16	-0.000294	0.0003	-0.0011	0.0005	1.000
	h8	h1	0.002510*	0.0003	0.0017	0.0033	<0.001*
		h2	0.000607	0.0003	-0.0002	0.0014	0.278
		h4	-0.000065	0.0003	-0.0008	0.0007	1.000
		h16	-0.000359	0.0003	-0.0011	0.0004	1.000
	h16	h1	0.002869*	0.0003	0.0021	0.0036	<0.001*
		h2	0.000966*	0.0003	0.0002	0.0017	0.005
		h4	0.000294	0.0003	-0.0005	0.0011	1.000
		h8	0.000359	0.0003	-0.0004	0.0011	1.000
MAPE	h1	h2	-65.618892*	9.46	-92.16	-39.08	<0.001*
		h4	-87.836168*	9.46	-114.38	-61.29	<0.001*
		h8	-84.875805*	9.46	-111.42	-58.33	<0.001*
		h16	-97.677300*	9.46	-124.22	-71.13	<0.001*
	h2	h1	65.618892*	9.46	39.08	92.16	<0.001*
		h4	-22.217276	9.46	-48.76	4.33	0.188
		h8	-19.256913	9.46	-45.80	7.29	0.417
		h16	-32.058408*	9.46	-58.60	-5.52	0.007
	h4	h1	87.836168*	9.46	61.29	114.38	<0.001*
		h2	22.217276	9.46	-4.33	48.76	0.188
		h8	2.960362	9.46	-23.58	29.50	1.000
		h16	-9.841132	9.46	-36.38	16.70	1.000
	h8	h1	84.875805*	9.46	58.33	111.42	<0.001*
		h2	19.256913	9.46	-7.29	45.80	0.417
		h4	-2.960362	9.46	-29.50	23.58	1.000
		h16	-12.801495	9.46	-39.34	13.74	1.000
	h16	h1	97.677300*	9.46	71.13	124.22	<0.001*
		h2	32.058408*	9.46	5.52	58.60	0.007
		h4	9.841132	9.46	-16.70	36.38	1.000
		h8	12.801495	9.46	-13.74	39.34	1.000
Runtime	h1	h2	-0.3413*	0.06	-0.50	-0.19	<0.001*
		h4	-1.4241*	0.06	-1.58	-1.27	<0.001*
		h8	-3.6712*	0.06	-3.83	-3.52	<0.001*
		h16	-7.8801*	0.06	-8.03	-7.73	<0.001*
	h2	h1	0.3413*	0.06	0.19	0.50	<0.001*
		h4	-1.0828*	0.06	-1.24	-0.93	<0.001*
		h8	-3.3299*	0.06	-3.48	-3.18	<0.001*
		h16	-7.5388*	0.06	-7.69	-7.38	<0.001*
	h4	h1	1.4241*	0.06	1.27	1.58	<0.001*
		h2	1.0828*	0.06	0.93	1.24	<0.001*
		h8	-2.2471*	0.06	-2.40	-2.09	<0.001*
		h16	-6.4560*	0.06	-6.61	-6.30	<0.001*
	h8	h1	3.6712*	0.06	3.52	3.83	<0.001*
		h2	3.3299*	0.06	3.18	3.48	<0.001*
		h4	2.2471*	0.06	2.09	2.40	<0.001*
		h16	-4.2090*	0.06	-4.36	-4.05	<0.001*
	h16	h1	7.8801*	0.06	7.73	8.03	<0.001*
		h2	7.5388*	0.06	7.38	7.69	<0.001*

Dependent Variable	(I) Hidden	(J) Hidden	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
		h4	6.4560*	0.06	6.30	6.61	<0.001*
		h8	4.2090*	0.06	4.05	4.36	<0.001*

Based on observed means.

The error term is Mean Square(Error) = 7.087.

* The mean difference is significant at the 0.05 level.

Table E - 8 : The multiple comparisons of node

Dependent Variable	(I) Hidden	(J) Hidden	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
MSE	n1	n2	0.000262*	0.0001	0.0001	0.0004	<0.001*
		n4	0.000612*	0.0001	0.0005	0.0008	<0.001*
		n8	0.001014*	0.0001	0.0009	0.0012	<0.001*
		n16	0.001243*	0.0001	0.0011	0.0014	<0.001*
	n2	n1	-0.000262	0.0001	-0.0004	-0.0001	<0.001*
		n4	0.000350*	0.0001	0.0002	0.0005	<0.001*
		n8	0.000752*	0.0001	0.0006	0.0009	<0.001*
		n16	0.000981*	0.0001	0.0008	0.0011	<0.001*
	n4	n1	-0.000612	0.0001	-0.0008	-0.0005	<0.001*
		n2	-0.00035	0.0001	-0.0005	-0.0002	<0.001*
		n8	0.000402*	0.0001	0.0002	0.0006	<0.001*
		n16	0.000631*	0.0001	0.0005	0.0008	<0.001*
	n8	n1	-0.001014	0.0001	-0.0012	-0.0009	<0.001*
		n2	-0.000752	0.0001	-0.0009	-0.0006	<0.001*
		n4	-0.000402	0.0001	-0.0006	-0.0002	<0.001*
		n16	0.000229*	0.0001	0.0001	0.0004	<0.001*
	n16	n1	-0.001243	0.0001	-0.0014	-0.0011	<0.001*
		n2	-0.000981	0.0001	-0.0011	-0.0008	<0.001*
		n4	-0.000631	0.0001	-0.0008	-0.0005	<0.001*
		n8	-0.000229*	0.0001	-0.0004	-0.0001	<0.001*
RMSE	n1	n2	0.001476*	0.0003	0.0007	0.0022	<0.001*
		n4	0.003487*	0.0003	0.0027	0.0042	<0.001*
		n8	0.006154*	0.0003	0.0054	0.0069	<0.001*
		n16	0.008115*	0.0003	0.0074	0.0089	<0.001*
	n2	n1	-0.001476	0.0003	-0.0022	-0.0007	<0.001*
		n4	0.002012*	0.0003	0.0013	0.0028	<0.001*
		n8	0.004679*	0.0003	0.0039	0.0054	<0.001*
		n16	0.006639*	0.0003	0.0059	0.0074	<0.001*
	n4	n1	-0.003487	0.0003	-0.0042	-0.0027	<0.001*
		n2	-0.002012	0.0003	-0.0028	-0.0013	<0.001*
		n8	0.002667*	0.0003	0.0019	0.0034	<0.001*
		n16	0.004628*	0.0003	0.0039	0.0054	<0.001*
	n8	n1	-0.006154*	0.0003	-0.0069	-0.0054	<0.001*
		n2	-0.004679	0.0003	-0.0054	-0.0039	<0.001*
		n4	-0.002667	0.0003	-0.0034	-0.0019	<0.001*
		n16	0.001960*	0.0003	0.0012	0.0027	<0.001*
	n16	n1	-0.008115	0.0003	-0.0089	-0.0074	<0.001*
		n2	-0.006639	0.0003	-0.0074	-0.0059	<0.001*
		n4	-0.004628	0.0003	-0.0054	-0.0039	<0.001*
		n8	-0.00196	0.0003	-0.0027	-0.0012	<0.001*
MAE	n1	n2	0.001572*	0.0003	0.0008	0.0023	<0.001*
		n4	0.003686*	0.0003	0.0029	0.0045	<0.001*
		n8	0.006461*	0.0003	0.0057	0.0072	<0.001*
		n16	0.008536*	0.0003	0.0078	0.0093	<0.001*
	n2	n1	-0.001572	0.0003	-0.0023	-0.0008	<0.001*
		n4	0.002114*	0.0003	0.0013	0.0029	<0.001*
		n8	0.004889*	0.0003	0.0041	0.0057	<0.001*
		n16	0.006964*	0.0003	0.0062	0.0077	<0.001*

Dependent Variable	(I) Hidden	(J) Hidden	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	n4	n1	-0.003686	0.0003	-0.0045	-0.0029	<0.001*
		n2	-0.002114	0.0003	-0.0029	-0.0013	<0.001*
		n8	0.002775*	0.0003	0.0020	0.0035	<0.001*
		n16	0.004850*	0.0003	0.0041	0.0056	<0.001*
	n8	n1	-0.006461	0.0003	-0.0072	-0.0057	<0.001*
		n2	-0.004889	0.0003	-0.0057	-0.0041	<0.001*
		n4	-0.002775	0.0003	-0.0035	-0.0020	<0.001*
		n16	0.002075*	0.0003	0.0013	0.0029	<0.001*
	n16	n1	-0.008536	0.0003	-0.0093	-0.0078	<0.001*
		n2	-0.006964	0.0003	-0.0077	-0.0062	<0.001*
		n4	-0.00485	0.0003	-0.0056	-0.0041	<0.001*
		n8	-0.002075	0.0003	-0.0029	-0.0013	<0.001*
MAPE	n1	n2	52.396966*	9.46	25.853902	78.94003	<0.001*
		n4	124.529735*	9.46	97.986671	151.072799	<0.001*
		n8	219.268923*	9.46	192.725859	245.811987	<0.001*
		n16	291.885094*	9.46	265.34203	318.428159	<0.001*
	n2	n1	-52.396966*	9.46	-78.94003	-25.853902	<0.001*
		n4	72.132769*	9.46	45.589705	98.675833	<0.001*
		n8	166.871957*	9.46	140.328893	193.415021	<0.001*
		n16	239.488128*	9.46	212.945064	266.031192	<0.001*
	n4	n1	-124.529735*	9.46	-151.072799	-97.986671	<0.001*
		n2	-72.132769*	9.46	-98.675833	-45.589705	<0.001*
		n8	94.739188*	9.46	68.196124	121.282252	<0.001*
		n16	167.355360*	9.46	140.812296	193.898424	<0.001*
	n8	n1	-219.268923*	9.46	-245.811987	-192.725859	<0.001*
		n2	-166.871957*	9.46	-193.415021	-140.328893	<0.001*
		n4	-94.739188*	9.46	-121.282252	-68.196124	<0.001*
		n16	72.616171*	9.46	46.073107	99.159235	<0.001*
	n16	n1	-291.885094*	9.46	-318.428159	-265.34203	<0.001*
		n2	-239.488128*	9.46	-266.031192	-212.945064	<0.001*
		n4	-167.355360*	9.46	-193.898424	-140.812296	<0.001*
		n8	-72.616171*	9.46	-99.159235	-46.073107	<0.001*
Prediction error	n1	n2	70.0175*	19.43	15.4626	124.5725	0.003
		n4	146.1958*	19.43	91.6409	200.7507	<0.001*
		n8	254.1793*	19.43	199.6244	308.7342	<0.001*
		n16	338.4341*	19.43	283.8792	392.9891	<0.001*
	n2	n1	-70.0175*	19.43	-124.5725	-15.4626	0.003
		n4	76.1783*	19.43	21.6233	130.7332	<0.001*
		n8	184.1617*	19.43	129.6068	238.7167	<0.001*
		n16	268.4166*	19.43	213.8617	322.9715	<0.001*
	n4	n1	-146.1958*	19.43	-200.7507	-91.6409	<0.001*
		n2	-76.1783*	19.43	-130.7332	-21.6233	<0.001*
		n8	107.9835*	19.43	53.4286	162.5384	<0.001*
		n16	192.2383*	19.43	137.6834	246.7933	<0.001*
	n8	n1	-254.1793*	19.43	-308.7342	-199.6244	<0.001*
		n2	-184.1617*	19.43	-238.7167	-129.6068	<0.001*
		n4	-107.9835*	19.43	-162.5384	-53.4286	<0.001*
		n16	84.2549*	19.43	29.6999	138.8098	<0.001*
	n16	n1	-338.4341*	19.43	-392.9891	-283.8792	<0.001*

Dependent Variable	(I) Hidden	(J) Hidden	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
		n2	-268.4166*	19.43	-322.9715	-213.8617	<0.001*
		n4	-192.2383*	19.43	-246.7933	-137.6834	<0.001*
		n8	-84.2549*	19.43	-138.8098	-29.6999	<0.001*
Runtime	n1	n2	-0.13	0.06	-0.2845	0.0245	0.181
		n4	-0.1767	0.06	-0.3312	-0.0222	0.013
		n8	-0.2769	0.06	-0.4314	-0.1224	<0.001*
		n16	-0.3888	0.06	-0.5433	-0.2343	<0.001*
	n2	n1	0.13	0.06	-0.0245	0.2845	0.181
		n4	-0.0467	0.06	-0.2012	0.1078	1.000
		n8	-0.1469	0.06	-0.3014	0.0076	0.076
		n16	-0.2587	0.06	-0.4132	-0.1043	<0.001*
	n4	n1	0.1767*	0.06	0.0222	0.3312	0.013
		n2	0.0467	0.06	-0.1078	0.2012	1.000
		n8	-0.1002	0.06	-0.2547	0.0543	0.686
		n16	-0.2121	0.06	-0.3666	-0.0576	0.001
	n8	n1	0.2769*	0.06	0.1224	0.4314	<0.001*
		n2	0.1469	0.06	-0.0076	0.3014	0.076
		n4	0.1002	0.06	-0.0543	0.2547	0.686
		n16	-0.1118	0.06	-0.2663	0.0426	0.421
	n16	n1	0.3888*	0.06	0.2343	0.5433	<0.001*
		n2	0.2587*	0.06	0.1043	0.4132	<0.001*
		n4	0.2121*	0.06	0.0576	0.3666	0.001
		n8	0.1118	0.06	-0.0426	0.2663	0.421

Based on observed means.

The error term is Mean Square(Error) = 7.087.

* The mean difference is significant at the 0.05 level.

Table E - 9 : The multiple comparisons of epoch

Dependent Variable	(I) Epoch	(J) Epoch	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
MSE	10e	20e	0.001734*	0.0001	0.0015	0.0019	<0.001*
		50e	.002953*	0.0001	0.0028	0.0032	<0.001*
		100e	.003173*	0.0001	0.0030	0.0034	<0.001*
		150e	.003204*	0.0001	0.0030	0.0034	<0.001*
		200e	.003217*	0.0001	0.0030	0.0034	<0.001*
	20e	10e	-.001734*	0.0001	-0.0019	-0.0015	<0.001*
		50e	.001219*	0.0001	0.0010	0.0014	<0.001*
		100e	.001439*	0.0001	0.0012	0.0016	<0.001*
		150e	.001470*	0.0001	0.0013	0.0017	<0.001*
		200e	.001483*	0.0001	0.0013	0.0017	<0.001*
	50e	10e	-.002953*	0.0001	-0.0032	-0.0028	<0.001*
		20e	-.001219*	0.0001	-0.0014	-0.0010	<0.001*
		100e	.000219*	0.0001	0.0000	0.0004	0.016*
		150e	.000251*	0.0001	0.0001	0.0004	0.003*
		200e	.000263*	0.0001	0.0001	0.0005	0.001*
	100e	10e	-.003173*	0.0001	-0.0034	-0.0030	<0.001*
		20e	-.001439*	0.0001	-0.0016	-0.0012	<0.001*
		50e	-.000219*	0.0001	-0.0004	0.0000	0.016*
		150e	0.000031	0.0001	-0.0002	0.0002	1.000
		200e	0.000044	0.0001	-0.0002	0.0002	1.000
	150e	10e	-.003204*	0.0001	-0.0034	-0.0030	<0.001*
		20e	-.001470*	0.0001	-0.0017	-0.0013	<0.001*
		50e	-.000251*	0.0001	-0.0004	-0.0001	0.003*
		100e	-3.1E-05	0.0001	-0.0002	0.0002	1.000
		200e	0.000013	0.0001	-0.0002	0.0002	1.000
	200e	10e	-.003217*	0.0001	-0.0034	-0.0030	<0.001*
		20e	-.001483*	0.0001	-0.0017	-0.0013	<0.001*
		50e	-.000263*	0.0001	-0.0005	-0.0001	0.001*
		100e	-4.4E-05	0.0001	-0.0002	0.0002	1.000
		150e	-1.3E-05	0.0001	-0.0002	0.0002	1.000
RMSE	10e	20e	.010246*	0.0004	0.0091	0.0114	<0.001*
		50e	.019885*	0.0004	0.0188	0.0210	<0.001*
		100e	.022077*	0.0004	0.0209	0.0232	<0.001*
		150e	.022405*	0.0004	0.0213	0.0235	<0.001*
		200e	.022541*	0.0004	0.0214	0.0237	<0.001*
	20e	10e	-.010246*	0.0004	-0.0114	-0.0091	<0.001*
		50e	.009639*	0.0004	0.0085	0.0108	<0.001*
		100e	.011831*	0.0004	0.0107	0.0130	<0.001*
		150e	.012159*	0.0004	0.0110	0.0133	<0.001*
		200e	.012295*	0.0004	0.0112	0.0134	<0.001*
	50e	10e	-.019885*	0.0004	-0.0210	-0.0188	<0.001*
		20e	-.009639*	0.0004	-0.0108	-0.0085	<0.001*
		100e	.002192*	0.0004	0.0011	0.0033	<0.001*
		150e	.002520*	0.0004	0.0014	0.0037	<0.001*
		200e	.002657*	0.0004	0.0015	0.0038	<0.001*
	100e	10e	-.022077*	0.0004	-0.0232	-0.0209	<0.001*
		20e	-.011831*	0.0004	-0.0130	-0.0107	<0.001*

Dependent Variable	(I) Epoch	(J) Epoch	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
		50e	-.002192*	0.0004	-0.0033	-0.0011	<0.001*
		150e	0.000328	0.0004	-0.0008	0.0015	1.000
		200e	0.000464	0.0004	-0.0007	0.0016	1.000
	150e	10e	-.022405*	0.0004	-0.0235	-0.0213	<0.001*
		20e	-.012159*	0.0004	-0.0133	-0.0110	<0.001*
		50e	-.002520*	0.0004	-0.0037	-0.0014	<0.001*
	100e	100e	-0.00033	0.0004	-0.0015	0.0008	1.000
		200e	0.000136	0.0004	-0.0010	0.0013	1.000
	200e	10e	-.022541*	0.0004	-0.0237	-0.0214	<0.001*
		20e	-.012295*	0.0004	-0.0134	-0.0112	<0.001*
		50e	-.002657*	0.0004	-0.0038	-0.0015	<0.001*
	100e	100e	-0.00046	0.0004	-0.0016	0.0007	1.000
		150e	-0.00014	0.0004	-0.0013	0.0010	1.000
MAE	10e	20e	.010342*	0.0004	0.0091	0.0115	<0.001*
		50e	.020268*	0.0004	0.0191	0.0215	<0.001*
		100e	.022545*	0.0004	0.0214	0.0237	<0.001*
		150e	.022904*	0.0004	0.0217	0.0241	<0.001*
		200e	.023075*	0.0004	0.0219	0.0243	<0.001*
	20e	10e	-.010342*	0.0004	-0.0115	-0.0091	<0.001*
		50e	.009926*	0.0004	0.0087	0.0111	<0.001*
		100e	.012202*	0.0004	0.0110	0.0134	<0.001*
		150e	.012562*	0.0004	0.0114	0.0138	<0.001*
		200e	.012733*	0.0004	0.0115	0.0139	<0.001*
	50e	10e	-.020268*	0.0004	-0.0215	-0.0191	<0.001*
		20e	-.009926*	0.0004	-0.0111	-0.0087	<0.001*
		100e	.002276*	0.0004	0.0011	0.0035	<0.001*
		150e	.002636*	0.0004	0.0014	0.0038	<0.001*
		200e	.002807*	0.0004	0.0016	0.0040	<0.001*
	100e	10e	-.022545*	0.0004	-0.0237	-0.0214	<0.001*
		20e	-.012202*	0.0004	-0.0134	-0.0110	<0.001*
		50e	-.002276*	0.0004	-0.0035	-0.0011	<0.001*
		150e	0.000359	0.0004	-0.0008	0.0016	1.000
		200e	0.000531	0.0004	-0.0007	0.0017	1.000
	150e	10e	-.022904*	0.0004	-0.0241	-0.0217	<0.001*
		20e	-.012562*	0.0004	-0.0138	-0.0114	<0.001*
		50e	-.002636*	0.0004	-0.0038	-0.0014	<0.001*
		100e	-0.00036	0.0004	-0.0016	0.0008	1.000
		200e	0.000172	0.0004	-0.0010	0.0014	1.000
	200e	10e	-.023075*	0.0004	-0.0243	-0.0219	<0.001*
		20e	-.012733*	0.0004	-0.0139	-0.0115	<0.001*
		50e	-.002807*	0.0004	-0.0040	-0.0016	<0.001*
		100e	-0.00053	0.0004	-0.0017	0.0007	1.000
		150e	-0.00017	0.0004	-0.0014	0.0010	1.000
MAPE	10e	20e	347.186869*	14.33	305.13	389.24	<0.001*
		50e	693.362550*	14.33	651.31	735.42	<0.001*
		100e	775.628356*	14.33	733.57	817.68	<0.001*
		150e	788.569304*	14.33	746.51	830.62	<0.001*
		200e	794.066489*	14.33	752.01	836.12	<0.001*
	20e	10e	-347.186869*	14.33	-389.24	-305.13	<0.001*

Dependent Variable	(I) Epoch	(J) Epoch	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	50e	50e	346.175681*	14.33	304.12	388.23	<0.001*
		100e	428.441487*	14.33	386.39	470.50	<0.001*
		150e	441.382435*	14.33	399.33	483.44	<0.001*
		200e	446.879620*	14.33	404.82	488.94	<0.001*
		10e	-693.362550*	14.33	-735.42	-651.31	<0.001*
		20e	-346.175681*	14.33	-388.23	-304.12	<0.001*
		100e	82.265806*	14.33	40.21	124.32	<0.001*
		150e	95.206754*	14.33	53.15	137.26	<0.001*
		200e	100.703939*	14.33	58.65	142.76	<0.001*
		10e	-775.628356*	14.33	-817.68	-733.57	<0.001*
		20e	-428.441487*	14.33	-470.50	-386.39	<0.001*
		50e	-82.265806*	14.33	-124.32	-40.21	<0.001*
	100e	150e	12.94095	14.33	-29.11	55.00	1.000
		200e	18.43813	14.33	-23.62	60.49	1.000
		10e	-788.569304*	14.33	-830.62	-746.51	<0.001*
		20e	-441.382435*	14.33	-483.44	-399.33	<0.001*
		50e	-95.206754*	14.33	-137.26	-53.15	<0.001*
		100e	-12.9409	14.33	-55.00	29.11	1.000
		200e	5.497185	14.33	-36.56	47.55	1.000
		10e	-794.066489*	14.33	-836.12	-752.01	<0.001*
		20e	-446.879620*	14.33	-488.94	-404.82	<0.001*
		50e	-100.703939*	14.33	-142.76	-58.65	<0.001*
		100e	-18.4381	14.33	-60.49	23.62	1.000
		150e	-5.49719	14.33	-47.55	36.56	1.000
Prediction error	10e	20e	396.6440*	35.51	292.41	500.88	<0.001*
		50e	789.0402*	35.51	684.80	893.28	<0.001*
		100e	904.6260*	35.51	800.39	1008.86	<0.001*
		150e	913.0963*	35.51	808.86	1017.33	<0.001*
		200e	923.9692*	35.51	819.73	1028.21	<0.001*
		20e	-396.6440*	35.51	-500.88	-292.41	<0.001*
		50e	392.3962*	35.51	288.16	496.63	<0.001*
		100e	507.9820*	35.51	403.75	612.22	<0.001*
		150e	516.4523*	35.51	412.22	620.69	<0.001*
		200e	527.3253*	35.51	423.09	631.56	<0.001*
		50e	-789.0402*	35.51	-893.28	-684.80	<0.001*
		20e	-392.3962*	35.51	-496.63	-288.16	<0.001*
	50e	100e	115.5859*	35.51	11.35	219.82	0.017*
		150e	124.0561*	35.51	19.82	228.29	0.007*
		200e	134.9291*	35.51	30.69	239.17	0.002*
		10e	-904.6260*	35.51	-1008.86	-800.39	<0.001*
		20e	-507.9820*	35.51	-612.22	-403.75	<0.001*
		50e	-115.5859*	35.51	-219.82	-11.35	0.017*
		150e	8.4702	35.51	-95.77	112.71	1.000
		200e	19.3432	35.51	-84.89	123.58	1.000
		10e	-913.0963*	35.51	-1017.33	-808.86	<0.001*
		20e	-516.4523*	35.51	-620.69	-412.22	<0.001*
		50e	-124.0561*	35.51	-228.29	-19.82	0.007*
		100e	-8.4702	35.51	-112.71	95.77	1.000
		200e	10.873	35.51	-93.36	115.11	1.000

Dependent Variable	(I) Epoch	(J) Epoch	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	200e	10e	-923.9692*	35.51	-1028.21	-819.73	<0.001*
		20e	-527.3253*	35.51	-631.56	-423.09	<0.001*
		50e	-134.9291*	35.51	-239.17	-30.69	0.002*
		100e	-19.3432	35.51	-123.58	84.89	1.000
		150e	-10.873	35.51	-115.11	93.36	1.000
Runtime	10e	20e	-1.2219*	0.10	-1.51	-0.94	<0.001*
		50e	-4.9690*	0.10	-5.25	-4.69	<0.001*
		100e	-11.1321*	0.10	-11.42	-10.85	<0.001*
		150e	-16.9813*	0.10	-17.26	-16.70	<0.001*
		200e	-23.1370*	0.10	-23.42	-22.85	<0.001*
	20e	10e	1.2219*	0.10	0.94	1.51	<0.001*
		50e	-3.7472*	0.10	-4.03	-3.46	<0.001*
		100e	-9.9102*	0.10	-10.19	-9.63	<0.001*
		150e	-15.7594*	0.10	-16.04	-15.48	<0.001*
		200e	-21.9152*	0.10	-22.20	-21.63	<0.001*
	50e	10e	4.9690*	0.10	4.69	5.25	<0.001*
		20e	3.7472*	0.10	3.46	4.03	<0.001*
		100e	-6.1631*	0.10	-6.45	-5.88	<0.001*
		150e	-12.0123*	0.10	-12.30	-11.73	<0.001*
		200e	-18.1680*	0.10	-18.45	-17.88	<0.001*
	100e	10e	11.1321*	0.10	10.85	11.42	<0.001*
		20e	9.9102*	0.10	9.63	10.19	<0.001*
		50e	6.1631*	0.10	5.88	6.45	<0.001*
		150e	-5.8492*	0.10	-6.13	-5.57	<0.001*
		200e	-12.0049*	0.10	-12.29	-11.72	<0.001*
	150e	10e	16.9813*	0.10	16.70	17.26	<0.001*
		20e	15.7594*	0.10	15.48	16.04	<0.001*
		50e	12.0123*	0.10	11.73	12.30	<0.001*
		100e	5.8492*	0.10	5.57	6.13	<0.001*
		200e	-6.1557*	0.10	-6.44	-5.87	<0.001*
	200e	10e	23.1370*	0.10	22.85	23.42	<0.001*
		20e	21.9152*	0.10	21.63	22.20	<0.001*
		50e	18.1680*	0.10	17.88	18.45	<0.001*
		100e	12.0049*	0.10	11.72	12.29	<0.001*
		150e	6.1557*	0.10	5.87	6.44	<0.001*

Based on observed means.

The error term is Mean Square(Error) = 18.197.

* The mean difference is significant at the 0.05 level.

Table E - 10 : The multiple comparisons of datasets

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
MSE	dataset a	dataset b	-0.003*	0.0001	-0.004	-0.003	<0.001*
		dataset c	-0.002*	0.0001	-0.002	-0.001	<0.001*
		dataset d	-0.002*	0.0001	-0.002	-0.002	<0.001*
		dataset e	-0.001*	0.0001	-0.002	-0.001	<0.001*
		dataset f	-0.002*	0.0001	-0.002	-0.002	<0.001*
		dataset g	-0.002*	0.0001	-0.003	-0.002	<0.001*
		dataset h	-0.003*	0.0001	-0.003	-0.002	<0.001*
		dataset i	-0.001*	0.0001	-0.001	0.000	<0.001*
		dataset j	-0.001*	0.0001	-0.001	0.000	<0.001*
		dataset k	-0.004*	0.0001	-0.004	-0.003	<0.001*
		dataset l	-0.001*	0.0001	-0.002	-0.001	<0.001*
		dataset m	-0.001*	0.0001	-0.002	-0.001	<0.001*
	dataset b	dataset a	0.003*	0.0001	0.003	0.004	<0.001*
		dataset c	0.002*	0.0001	0.001	0.002	<0.001*
		dataset d	0.001*	0.0001	0.001	0.002	<0.001*
		dataset e	0.002*	0.0001	0.002	0.002	<0.001*
		dataset f	0.001*	0.0001	0.001	0.002	<0.001*
		dataset g	0.001*	0.0001	0.001	0.001	<0.001*
		dataset h	0.001*	0.0001	0.000	0.001	<0.001*
		dataset i	0.003*	0.0001	0.002	0.003	<0.001*
		dataset j	0.003*	0.0001	0.002	0.003	<0.001*
		dataset k	-0.001*	0.0001	-0.001	0.000	<0.001*
		dataset l	0.002*	0.0001	0.002	0.002	<0.001*
		dataset m	0.002*	0.0001	0.002	0.002	<0.001*
	dataset c	dataset a	0.002*	0.0001	0.001	0.002	<0.001*
		dataset b	-0.002*	0.0001	-0.002	-0.001	<0.001*
		dataset d	-0.0001	0.0001	0.000	0.000	1.000
		dataset e	0.001*	0.0001	0.000	0.001	<0.001*
		dataset f	-0.0003	0.0001	-0.001	0.000	0.130
		dataset g	-0.0005*	0.0001	-0.001	0.000	<0.001*
		dataset h	-0.001*	0.0001	-0.001	-0.001	<0.001*
		dataset i	0.001*	0.0001	0.001	0.001	<0.001*
		dataset j	0.001*	0.0001	0.001	0.001	<0.001*
		dataset k	-0.002*	0.0001	-0.002	-0.002	<0.001*
		dataset l	0.001*	0.0001	0.000	0.001	<0.001*
		dataset m	0.001*	0.0001	0.000	0.001	<0.001*
	dataset d	dataset a	0.002*	0.0001	0.002	0.002	<0.001*
		dataset b	-0.001*	0.0001	-0.002	-0.001	<0.001*
		dataset c	0.0001	0.0001	0.000	0.000	1.000
		dataset e	0.001*	0.0001	0.000	0.001	<0.001*
		dataset f	-0.0002	0.0001	-0.001	0.000	1.000
		dataset g	-0.00033	0.0001	-0.001	0.000	0.083
		dataset h	-0.001*	0.0001	-0.001	0.000	<0.001*
		dataset i	0.001*	0.0001	0.001	0.001	<0.001*
		dataset j	0.001*	0.0001	0.001	0.001	<0.001*
		dataset k	-0.002*	0.0001	-0.002	-0.002	<0.001*
		dataset l	0.001*	0.0001	0.000	0.001	<0.001*
		dataset m	0.001*	0.0001	0.000	0.001	<0.001*
	dataset e	dataset a	0.001*	0.0001	0.001	0.002	<0.001*
		dataset b	-0.002*	0.0001	-0.002	-0.002	<0.001*
		dataset c	-0.001*	0.0001	-0.001	0.000	<0.001*
		dataset d	-0.001*	0.0001	-0.001	0.000	<0.001*
		dataset f	-0.001*	0.0001	-0.001	-0.001	<0.001*

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	dataset f	dataset g	-0.001*	0.0001	-0.001	-0.001	<0.001*
		dataset h	-0.002*	0.0001	-0.002	-0.001	<0.001*
		dataset i	.0004*	0.0001	0.000	0.001	0.003*
		dataset j	.0004*	0.0001	0.000	0.001	0.016*
		dataset k	-.003*	0.0001	-0.003	-0.002	<0.001*
		dataset l	-2.1E-05	0.0001	0.000	0.000	1.000
		dataset m	-7.6E-05	0.0001	0.000	0.000	1.000
		dataset a	0.002*	0.0001	0.002	0.002	<0.001*
		dataset b	-0.001*	0.0001	-0.002	-0.001	<0.001*
		dataset c	0.0003	0.0001	0.000	0.001	0.130
		dataset d	0.0002	0.0001	0.000	0.001	1.000
		dataset e	0.001*	0.0001	0.001	0.001	<0.001*
		dataset g	-0.0001	0.0001	0.000	0.000	1.000
		dataset h	-0.001*	0.0001	-0.001	0.000	<0.001*
		dataset i	0.001*	0.0001	0.001	0.002	<0.001*
	dataset g	dataset j	0.001*	0.0001	0.001	0.002	<0.001*
		dataset k	-0.002*	0.0001	-0.002	-0.001	<0.001*
		dataset l	0.001*	0.0001	0.001	0.001	<0.001*
		dataset m	0.001*	0.0001	0.000	0.001	<0.001*
		dataset a	0.002*	0.0001	0.002	0.003	<0.001*
		dataset b	-0.001*	0.0001	-0.001	-0.001	<0.001*
		dataset c	0.001*	0.0001	0.000	0.001	<0.001*
		dataset d	0.0003	0.0001	0.000	0.001	0.083
		dataset e	0.001*	0.0001	0.001	0.001	<0.001*
		dataset f	0.0001	0.0001	0.000	0.000	1.000
		dataset h	-0.0005*	0.0001	-0.001	0.000	<0.001*
		dataset i	0.002*	0.0001	0.001	0.002	<0.001*
		dataset j	0.001*	0.0001	0.001	0.002	<0.001*
		dataset k	-0.002*	0.0001	-0.002	-0.001	<0.001*
		dataset l	0.001*	0.0001	0.001	0.001	<0.001*
		dataset m	0.001*	0.0001	0.001	0.001	<0.001*
	dataset h	dataset a	0.003*	0.0001	0.002	0.003	<0.001*
		dataset b	-0.001*	0.0001	-0.001	0.000	<0.001*
		dataset c	0.001*	0.0001	0.001	0.001	<0.001*
		dataset d	0.001*	0.0001	0.000	0.001	<0.001*
		dataset e	0.002*	0.0001	0.001	0.002	<0.001*
		dataset f	0.0006*	0.0001	0.000	0.001	<0.001*
		dataset g	0.0005*	0.0001	0.000	0.001	<0.001*
		dataset i	0.002*	0.0001	0.002	0.002	<0.001*
		dataset j	0.002*	0.0001	0.002	0.002	<0.001*
		dataset k	-0.001*	0.0001	-0.001	-0.001	<0.001*
		dataset l	0.002*	0.0001	0.001	0.002	<0.001*
		dataset m	0.001*	0.0001	0.001	0.002	<0.001*
	dataset i	dataset a	0.001*	0.0001	0.000	0.001	<0.001*
		dataset b	-0.003*	0.0001	-0.003	-0.002	<0.001*
		dataset c	-0.001*	0.0001	-0.001	-0.001	<0.001*
		dataset d	-0.001*	0.0001	-0.001	-0.001	<0.001*
		dataset e	-0.0004*	0.0001	-0.001	0.000	0.003*
		dataset f	-0.001*	0.0001	-0.002	-0.001	<0.001*
		dataset g	-0.002*	0.0001	-0.002	-0.001	<0.001*
		dataset h	-0.002*	0.0001	-0.002	-0.002	<0.001*
		dataset j	-0.00004	0.0001	0.000	0.000	1.000
		dataset k	-0.003*	0.0001	-0.003	-0.003	<0.001*
		dataset l	-0.0004*	0.0001	-0.001	0.000	0.001
		dataset m	-0.001*	0.0001	-0.001	0.000	<0.001*

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	dataset j	dataset a	0.001*	0.0001	0.000	0.001	<0.001*
		dataset b	-0.003*	0.0001	-0.003	-0.002	<0.001*
		dataset c	-0.001*	0.0001	-0.001	-0.001	<0.001*
		dataset d	-0.001*	0.0001	-0.001	-0.001	<0.001*
		dataset e	-0.0004*	0.0001	-0.001	0.000	0.016*
		dataset f	-0.001*	0.0001	-0.002	-0.001	<0.001*
		dataset g	-0.001*	0.0001	-0.002	-0.001	<0.001*
		dataset h	-0.002*	0.0001	-0.002	-0.002	<0.001*
		dataset i	0.00004	0.0001	0.000	0.000	1.000
		dataset k	-0.003*	0.0001	-0.003	-0.003	<0.001*
		dataset l	-0.0004*	0.0001	-0.001	0.000	0.007*
		dataset m	-0.001*	0.0001	-0.001	0.000	<0.001*
	dataset k	dataset a	0.004*	0.0001	0.003	0.004	<0.001*
		dataset b	0.001*	0.0001	0.000	0.001	<0.001*
		dataset c	0.002*	0.0001	0.002	0.002	<0.001*
		dataset d	0.002*	0.0001	0.002	0.002	<0.001*
		dataset e	0.003*	0.0001	0.002	0.003	<0.001*
		dataset f	0.002*	0.0001	0.001	0.002	<0.001*
		dataset g	0.002*	0.0001	0.001	0.002	<0.001*
		dataset h	0.001*	0.0001	0.001	0.001	<0.001*
		dataset i	0.003*	0.0001	0.003	0.003	<0.001*
		dataset j	0.003*	0.0001	0.003	0.003	<0.001*
		dataset l	0.003*	0.0001	0.002	0.003	<0.001*
		dataset m	0.003*	0.0001	0.002	0.003	<0.001*
	dataset l	dataset a	0.001*	0.0001	0.001	0.002	<0.001*
		dataset b	-0.002*	0.0001	-0.002	-0.002	<0.001*
		dataset c	-0.001*	0.0001	-0.001	0.000	<0.001*
		dataset d	-0.001*	0.0001	-0.001	0.000	<0.001*
		dataset e	0.00002	0.0001	0.000	0.000	1.000
		dataset f	-0.001*	0.0001	-0.001	-0.001	<0.001*
		dataset g	-0.001*	0.0001	-0.001	-0.001	<0.001*
		dataset h	-0.002*	0.0001	-0.002	-0.001	<0.001*
		dataset i	0.0004*	0.0001	0.000	0.001	0.001*
		dataset j	0.0004*	0.0001	0.000	0.001	0.007*
		dataset k	-0.003*	0.0001	-0.003	-0.002	<0.001*
		dataset m	-5.5E-05	0.0001	0.000	0.000	1.000
	dataset m	dataset a	0.001*	0.0001	0.001	0.002	<0.001*
		dataset b	-0.002*	0.0001	-0.002	-0.002	<0.001*
		dataset c	-0.001*	0.0001	-0.001	0.000	<0.001*
		dataset d	-0.001*	0.0001	-0.001	0.000	<0.001*
		dataset e	0.0001	0.0001	0.000	0.000	1.000
		dataset f	-0.001*	0.0001	-0.001	0.000	<0.001*
		dataset g	-0.001*	0.0001	-0.001	-0.001	<0.001*
		dataset h	-0.001*	0.0001	-0.002	-0.001	<0.001*
		dataset i	0.001*	0.0001	0.000	0.001	<0.001*
		dataset j	0.001*	0.0001	0.000	0.001	<0.001*
		dataset k	-0.003*	0.0001	-0.003	-0.002	<0.001*
		dataset l	0.00006	0.0001	0.000	0.000	1.000
RMSE	dataset a	dataset b	-0.04*	0.0005	-0.038	-0.034	<0.001*
		dataset c	-0.02*	0.0005	-0.025	-0.022	<0.001*
		dataset d	-0.02*	0.0005	-0.026	-0.022	<0.001*
		dataset e	-0.02*	0.0005	-0.018	-0.015	<0.001*
		dataset f	-0.03*	0.0005	-0.029	-0.025	<0.001*
		dataset g	-0.03*	0.0005	-0.029	-0.026	<0.001*
		dataset h	-0.03*	0.0005	-0.033	-0.030	<0.001*

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	dataset b	dataset i	-0.01*	0.0005	-0.015	-0.011	<0.001*
		dataset j	-0.01*	0.0005	-0.015	-0.011	<0.001*
		dataset k	-0.04*	0.0005	-0.042	-0.038	<0.001*
		dataset l	-0.02*	0.0005	-0.020	-0.016	<0.001*
		dataset m	-0.02*	0.0005	-0.020	-0.016	<0.001*
		dataset a	0.04*	0.0005	0.034	0.038	<0.001*
		dataset c	0.01*	0.0005	0.011	0.014	<0.001*
		dataset d	0.01*	0.0005	0.010	0.014	<0.001*
		dataset e	0.02*	0.0005	0.018	0.021	<0.001*
		dataset f	0.01*	0.0005	0.007	0.011	<0.001*
		dataset g	0.01*	0.0005	0.007	0.010	<0.001*
		dataset h	0.01*	0.0005	0.003	0.006	<0.001*
		dataset i	0.02*	0.0005	0.022	0.025	<0.001*
		dataset j	0.02*	0.0005	0.021	0.025	<0.001*
		dataset k	-.004*	0.0005	-0.006	-0.002	<0.001*
	dataset c	dataset l	0.02*	0.0005	0.016	0.020	<0.001*
		dataset m	0.02*	0.0005	0.016	0.020	<0.001*
		dataset a	0.02*	0.0005	0.022	0.025	<0.001*
		dataset b	-0.01*	0.0005	-0.014	-0.011	<0.001*
		dataset d	0.00	0.0005	-0.002	0.001	1.000
		dataset e	0.01*	0.0005	0.005	0.009	<0.001*
		dataset f	-0.004*	0.0005	-0.005	-0.002	<0.001*
		dataset g	-0.004*	0.0005	-0.006	-0.002	<0.001*
		dataset h	-0.01*	0.0005	-0.010	-0.006	<0.001*
		dataset i	0.01*	0.0005	0.009	0.013	<0.001*
		dataset j	0.01*	0.0005	0.009	0.012	<0.001*
		dataset k	-0.02*	0.0005	-0.018	-0.015	<0.001*
		dataset l	0.01*	0.0005	0.004	0.008	<0.001*
		dataset m	0.01*	0.0005	0.004	0.007	<0.001*
	dataset d	dataset a	0.02*	0.0005	0.022	0.026	<0.001*
		dataset b	-0.01*	0.0005	-0.014	-0.010	<0.001*
		dataset c	0.00	0.0005	-0.001	0.002	1.000
		dataset e	0.01*	0.0005	0.006	0.009	<0.001*
		dataset f	-0.003*	0.0005	-0.005	-0.001	<0.001*
		dataset g	-0.003*	0.0005	-0.005	-0.002	<0.001*
		dataset h	-0.007*	0.0005	-0.009	-0.006	<0.001*
		dataset i	0.01*	0.0005	0.010	0.013	<0.001*
		dataset j	0.01*	0.0005	0.009	0.013	<0.001*
		dataset k	-0.02*	0.0005	-0.018	-0.014	<0.001*
		dataset l	0.01*	0.0005	0.004	0.008	<0.001*
		dataset m	0.01*	0.0005	0.004	0.008	<0.001*
	dataset e	dataset a	0.02*	0.0005	0.015	0.018	<0.001*
		dataset b	-0.02*	0.0005	-0.021	-0.018	<0.001*
		dataset c	-0.01*	0.0005	-0.009	-0.005	<0.001*
		dataset d	-0.01*	0.0005	-0.009	-0.006	<0.001*
		dataset f	-0.01*	0.0005	-0.012	-0.009	<0.001*
		dataset g	-0.01*	0.0005	-0.013	-0.009	<0.001*
		dataset h	-0.02*	0.0005	-0.017	-0.013	<0.001*
		dataset i	0.01*	0.0005	0.002	0.006	<0.001*
		dataset j	0.004*	0.0005	0.002	0.006	<0.001*
		dataset k	-0.02*	0.0005	-0.025	-0.022	<0.001*
		dataset l	0.00	0.0005	-0.003	0.001	1.000
		dataset m	0.00	0.0005	-0.003	0.000	0.765
	dataset f	dataset a	0.03*	0.0005	0.025	0.029	<0.001*
		dataset b	-0.01*	0.0005	-0.011	-0.007	<0.001*

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	dataset g	dataset c	0.004*	0.0005	0.002	0.005	<0.001*
		dataset d	0.003*	0.0005	0.001	0.005	<0.001*
		dataset e	0.01*	0.0005	0.009	0.012	<0.001*
		dataset g	0.00	0.0005	-0.002	0.001	1.000
		dataset h	-0.004*	0.0005	-0.006	-0.003	<0.001*
		dataset i	0.01*	0.0005	0.013	0.016	<0.001*
		dataset j	0.01*	0.0005	0.012	0.016	<0.001*
		dataset k	-0.01*	0.0005	-0.015	-0.011	<0.001*
		dataset l	0.01*	0.0005	0.007	0.011	<0.001*
		dataset m	0.01*	0.0005	0.007	0.011	<0.001*
		dataset a	0.03*	0.0005	0.026	0.029	<0.001*
		dataset b	-0.01*	0.0005	-0.010	-0.007	<0.001*
	dataset h	dataset c	0.004*	0.0005	0.002	0.006	<0.001*
		dataset d	0.003*	0.0005	0.002	0.005	<0.001*
		dataset e	0.01*	0.0005	0.009	0.013	<0.001*
		dataset f	0.00	0.0005	-0.001	0.002	1.000
		dataset h	-0.004*	0.0005	-0.006	-0.002	<0.001*
		dataset i	0.02*	0.0005	0.013	0.017	<0.001*
		dataset j	0.02*	0.0005	0.013	0.016	<0.001*
		dataset k	-0.01*	0.0005	-0.015	-0.011	<0.001*
		dataset l	0.01*	0.0005	0.008	0.011	<0.001*
		dataset m	0.01*	0.0005	0.008	0.011	<0.001*
		dataset a	00.03*	0.0005	0.030	0.033	<0.001*
		dataset b	-0.01*	0.0005	-0.006	-0.003	<0.001*
	dataset i	dataset c	0.01*	0.0005	0.006	0.010	<0.001*
		dataset d	0.01*	0.0005	0.006	0.009	<0.001*
		dataset e	0.02*	0.0005	0.013	0.017	<0.001*
		dataset f	.004*	0.0005	0.003	0.006	<0.001*
		dataset g	.004*	0.0005	0.002	0.006	<0.001*
		dataset i	0.02*	0.0005	0.017	0.021	<0.001*
		dataset j	0.02*	0.0005	0.017	0.020	<0.001*
		dataset k	-0.01*	0.0005	-0.011	-0.007	<0.001*
		dataset l	0.01*	0.0005	0.012	0.015	<0.001*
		dataset m	0.01*	0.0005	0.012	0.015	<0.001*
		dataset a	0.01*	0.0005	0.011	0.015	<0.001*
		dataset b	-0.02*	0.0005	-0.025	-0.022	<0.001*
	dataset j	dataset c	-0.01*	0.0005	-0.013	-0.009	<0.001*
		dataset d	-0.01*	0.0005	-0.013	-0.010	<0.001*
		dataset e	-0.004*	0.0005	-0.006	-0.002	<0.001*
		dataset f	-0.01*	0.0005	-0.016	-0.013	<0.001*
		dataset g	-0.02*	0.0005	-0.017	-0.013	<0.001*
		dataset h	-0.02*	0.0005	-0.021	-0.017	<0.001*
		dataset j	0.00	0.0005	-0.002	0.002	1.000
		dataset k	-0.03*	0.0005	-0.029	-0.026	<0.001*
		dataset l	-0.01*	0.0005	-0.007	-0.003	<0.001*
		dataset m	-0.01*	0.0005	-0.007	-0.004	<0.001*
		dataset a	0.01*	0.0005	0.011	0.015	<0.001*
		dataset b	-0.02*	0.0005	-0.025	-0.021	<0.001*
		dataset c	-0.01*	0.0005	-0.012	-0.009	<0.001*
		dataset d	-0.01*	0.0005	-0.013	-0.009	<0.001*
		dataset e	-0.004*	0.0005	-0.006	-0.002	<0.001*
		dataset f	-0.01*	0.0005	-0.016	-0.012	<0.001*
		dataset g	-0.02*	0.0005	-0.016	-0.013	<0.001*
		dataset h	-0.02*	0.0005	-0.020	-0.017	<0.001*
		dataset i	0.00	0.0005	-0.002	0.002	1.000

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	dataset k	dataset k	-0.03*	0.0005	-0.029	-0.025	<0.001*
		dataset l	-0.01*	0.0005	-0.007	-0.003	<0.001*
		dataset m	-0.01*	0.0005	-0.007	-0.003	<0.001*
		dataset a	0.04*	0.0005	0.038	0.042	<0.001*
		dataset b	0.004*	0.0005	0.002	0.006	<0.001*
		dataset c	0.02*	0.0005	0.015	0.018	<0.001*
		dataset d	0.02*	0.0005	0.014	0.018	<0.001*
		dataset e	0.02*	0.0005	0.022	0.025	<0.001*
		dataset f	0.01*	0.0005	0.011	0.015	<0.001*
		dataset g	0.01*	0.0005	0.011	0.015	<0.001*
		dataset h	0.01*	0.0005	0.007	0.011	<0.001*
		dataset i	0.03*	0.0005	0.026	0.029	<0.001*
	dataset l	dataset j	0.03*	0.0005	0.025	0.029	<0.001*
		dataset l	0.02*	0.0005	0.021	0.024	<0.001*
		dataset m	0.02*	0.0005	0.020	0.024	<0.001*
		dataset a	0.02*	0.0005	0.016	0.020	<0.001*
		dataset b	-0.02*	0.0005	-0.020	-0.016	<0.001*
		dataset c	-0.01*	0.0005	-0.008	-0.004	<0.001*
		dataset d	-0.01*	0.0005	-0.008	-0.004	<0.001*
		dataset e	0.00	0.0005	-0.001	0.003	1.000
		dataset f	-0.01*	0.0005	-0.011	-0.007	<0.001*
		dataset g	-0.01*	0.0005	-0.011	-0.008	<0.001*
		dataset h	-0.01*	0.0005	-0.015	-0.012	<0.001*
		dataset i	0.01*	0.0005	0.003	0.007	<0.001*
	dataset m	dataset j	0.01*	0.0005	0.003	0.007	<0.001*
		dataset k	-0.02*	0.0005	-0.024	-0.021	<0.001*
		dataset m	0.00	0.0005	-0.002	0.002	1.000
		dataset a	0.02*	0.0005	0.016	0.020	<0.001*
		dataset b	-0.02*	0.0005	-0.020	-0.016	<0.001*
		dataset c	-0.01*	0.0005	-0.007	-0.004	<0.001*
		dataset d	-0.01*	0.0005	-0.008	-0.004	<0.001*
		dataset e	0.00	0.0005	0.000	0.003	0.765
		dataset f	-0.01*	0.0005	-0.011	-0.007	<0.001*
		dataset g	-0.01*	0.0005	-0.011	-0.008	<0.001*
		dataset h	-0.013*	0.0005	-0.015	-0.012	<0.001*
		dataset i	0.005*	0.0005	0.004	0.007	<0.001*
		dataset j	0.005*	0.0005	0.003	0.007	<0.001*
MAE	dataset a	dataset k	-0.022*	0.0005	-0.024	-0.020	<0.001*
		dataset l	0.00	0.0005	-0.002	0.002	1.000
		dataset b	-0.04*	0.0005	-0.042	-0.038	<0.001*
		dataset c	-0.03*	0.0005	-0.029	-0.025	<0.001*
		dataset d	-0.03*	0.0005	-0.030	-0.026	<0.001*
		dataset e	-0.02*	0.0005	-0.022	-0.018	<0.001*
		dataset f	-0.03*	0.0005	-0.033	-0.029	<0.001*
		dataset g	-0.03*	0.0005	-0.033	-0.030	<0.001*
		dataset h	-0.04*	0.0005	-0.037	-0.033	<0.001*
		dataset i	-0.02*	0.0005	-0.018	-0.014	<0.001*
		dataset j	-0.02*	0.0005	-0.018	-0.014	<0.001*
		dataset k	-0.04*	0.0005	-0.046	-0.042	<0.001*
	dataset b	dataset l	-0.02*	0.0005	-0.023	-0.019	<0.001*
		dataset m	-0.02*	0.0005	-0.023	-0.019	<0.001*
		dataset a	0.04*	0.0005	0.038	0.042	<0.001*
		dataset c	0.01*	0.0005	0.011	0.015	<0.001*
		dataset d	0.01*	0.0005	0.011	0.014	<0.001*
		dataset e	0.02*	0.0005	0.018	0.022	<0.001*

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	dataset c	dataset f	0.01*	0.0005	0.007	0.011	<0.001*
		dataset g	0.01*	0.0005	0.007	0.011	<0.001*
		dataset h	0.01*	0.0005	0.003	0.007	<0.001*
		dataset i	0.03*	0.0005	0.023	0.026	<0.001*
		dataset j	0.02*	0.0005	0.022	0.026	<0.001*
		dataset k	-0.004*	0.0005	-0.006	-0.002	<0.001*
		dataset l	0.02*	0.0005	0.017	0.021	<0.001*
		dataset m	0.01*	0.0005	0.017	0.021	<0.001*
		dataset a	0.03*	0.0005	0.025	0.029	<0.001*
		dataset b	-0.01*	0.0005	-0.015	-0.011	<0.001*
		dataset d	0.00	0.0005	-0.002	0.001	1.000
		dataset e	0.01*	0.0005	0.005	0.009	<0.001*
		dataset f	-0.004*	0.0005	-0.006	-0.002	<0.001*
		dataset g	-0.004*	0.0005	-0.006	-0.002	<0.001*
		dataset h	-0.01*	0.0005	-0.010	-0.006	<0.001*
	dataset d	dataset i	0.01*	0.0005	0.010	0.013	<0.001*
		dataset j	0.01*	0.0005	0.009	0.013	<0.001*
		dataset k	-0.02*	0.0005	-0.019	-0.015	<0.001*
		dataset l	0.01*	0.0005	0.004	0.008	<0.001*
		dataset m	0.01*	0.0005	0.004	0.008	<0.001*
		dataset a	0.03*	0.0005	0.026	0.030	<0.001*
		dataset b	-0.01*	0.0005	-0.014	-0.011	<0.001*
		dataset c	0.00	0.0005	-0.001	0.002	1.000
		dataset e	0.01*	0.0005	0.006	0.010	<0.001*
		dataset f	-0.003*	0.0005	-0.005	-0.001	<0.001*
		dataset g	-0.004*	0.0005	-0.006	-0.002	<0.001*
		dataset h	-0.01*	0.0005	-0.009	-0.006	<0.001*
		dataset i	0.01*	0.0005	0.010	0.014	<0.001*
		dataset j	0.01*	0.0005	0.010	0.014	<0.001*
		dataset k	-0.02*	0.0005	-0.018	-0.015	<0.001*
	dataset e	dataset l	0.01*	0.0005	0.005	0.009	<0.001*
		dataset m	0.01*	0.0005	0.005	0.008	<0.001*
		dataset a	0.02*	0.0005	0.018	0.022	<0.001*
		dataset b	-0.02*	0.0005	-0.022	-0.018	<0.001*
		dataset c	-0.01*	0.0005	-0.009	-0.005	<0.001*
		dataset d	-0.01*	0.0005	-0.010	-0.006	<0.001*
		dataset f	-0.01*	0.0005	-0.013	-0.009	<0.001*
		dataset g	-0.01*	0.0005	-0.013	-0.010	<0.001*
		dataset h	-0.02*	0.0005	-0.017	-0.014	<0.001*
		dataset i	0.004*	0.0005	0.002	0.006	<0.001*
		dataset j	0.004*	0.0005	0.002	0.006	<0.001*
		dataset k	-0.02*	0.0005	-0.026	-0.022	<0.001*
		dataset l	0.00	0.0005	-0.003	0.001	1.000
		dataset m	0.00	0.0005	-0.003	0.001	1.000
	dataset f	dataset a	0.03*	0.0005	0.029	0.033	<0.001*
		dataset b	-0.01*	0.0005	-0.011	-0.007	<0.001*
		dataset c	0.004*	0.0005	0.002	0.006	<0.001*
		dataset d	0.003*	0.0005	0.001	0.005	<0.001*
		dataset e	0.01*	0.0005	0.009	0.013	<0.001*
		dataset g	0.00	0.0005	-0.002	0.001	1.000
		dataset h	-0.004*	0.0005	-0.006	-0.002	<0.001*
		dataset i	0.02*	0.0005	0.013	0.017	<0.001*
		dataset j	0.02*	0.0005	0.013	0.017	<0.001*
		dataset k	-0.01*	0.0005	-0.015	-0.011	<0.001*
		dataset l	0.01*	0.0005	0.008	0.012	<0.001*

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	dataset g	dataset m	0.01*	0.0005	0.008	0.012	<0.001*
		dataset a	0.03*	0.0005	0.030	0.033	<0.001*
		dataset b	-0.01*	0.0005	-0.011	-0.007	<0.001*
		dataset c	0.004*	0.0005	0.002	0.006	<0.001*
		dataset d	0.004*	0.0005	0.002	0.006	<0.001*
		dataset e	0.01*	0.0005	0.010	0.013	<0.001*
		dataset f	0.00	0.0005	-0.001	0.002	1.000
		dataset h	-.004*	0.0005	-0.006	-0.002	<0.001*
		dataset i	0.02*	0.0005	0.014	0.018	<0.001*
		dataset j	0.02*	0.0005	0.014	0.017	<0.001*
		dataset k	-0.01*	0.0005	-0.015	-0.011	<0.001*
		dataset l	0.01*	0.0005	0.009	0.012	<0.001*
	dataset h	dataset m	0.01*	0.0005	0.008	0.012	<0.001*
		dataset a	0.04*	0.0005	0.033	0.037	<0.001*
		dataset b	-0.01*	0.0005	-0.007	-0.003	<0.001*
		dataset c	0.01*	0.0005	0.006	0.010	<0.001*
		dataset d	0.01*	0.0005	0.006	0.009	<0.001*
		dataset e	0.02*	0.0005	0.014	0.017	<0.001*
		dataset f	0.004*	0.0005	0.002	0.006	<0.001*
		dataset g	0.004*	0.0005	0.002	0.006	<0.001*
		dataset i	0.02*	0.0005	0.018	0.021	<0.001*
		dataset j	0.02*	0.0005	0.017	0.021	<0.001*
		dataset k	-0.01*	0.0005	-0.011	-0.007	<0.001*
		dataset l	0.01*	0.0005	0.012	0.016	<0.001*
	dataset i	dataset m	0.01*	0.0005	0.012	0.016	<0.001*
		dataset a	0.02*	0.0005	0.014	0.018	<0.001*
		dataset b	-0.03*	0.0005	-0.026	-0.023	<0.001*
		dataset c	-0.01*	0.0005	-0.013	-0.010	<0.001*
		dataset d	-0.01*	0.0005	-0.014	-0.010	<0.001*
		dataset e	-0.004*	0.0005	-0.006	-0.002	<0.001*
		dataset f	-0.02*	0.0005	-0.017	-0.013	<0.001*
		dataset g	-0.02*	0.0005	-0.018	-0.014	<0.001*
		dataset h	-0.02*	0.0005	-0.021	-0.018	<0.001*
		dataset j	0.00	0.0005	-0.002	0.002	1.000
		dataset k	-0.03*	0.0005	-0.030	-0.027	<0.001*
		dataset l	-0.01*	0.0005	-0.007	-0.003	<0.001*
	dataset j	dataset m	-0.01*	0.0005	-0.007	-0.004	<0.001*
		dataset a	0.02*	0.0005	0.014	0.018	<0.001*
		dataset b	-0.02*	0.0005	-0.026	-0.022	<0.001*
		dataset c	-0.01*	0.0005	-0.013	-0.009	<0.001*
		dataset d	-0.01*	0.0005	-0.014	-0.010	<0.001*
		dataset e	-0.04*	0.0005	-0.006	-0.002	<0.001*
		dataset f	-0.02*	0.0005	-0.017	-0.013	<0.001*
		dataset g	-0.02*	0.0005	-0.017	-0.014	<0.001*
		dataset h	-0.02*	0.0005	-0.021	-0.017	<0.001*
		dataset i	0.00	0.0005	-0.002	0.002	1.000
		dataset k	-0.03*	0.0005	-0.030	-0.026	<0.001*
		dataset l	-0.01*	0.0005	-0.007	-0.003	<0.001*
	dataset k	dataset m	-0.01*	0.0005	-0.007	-0.003	<0.001*
		dataset a	0.044*	0.0005	0.042	0.046	<0.001*
		dataset b	0.004*	0.0005	0.002	0.006	<0.001*
		dataset c	0.02*	0.0005	0.015	0.019	<0.001*
		dataset d	0.02*	0.0005	0.015	0.018	<0.001*
		dataset e	0.02*	0.0005	0.022	0.026	<0.001*
		dataset f	0.01*	0.0005	0.011	0.015	<0.001*

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	dataset l	dataset g	0.01*	0.0005	0.011	0.015	<0.001*
		dataset h	0.01*	0.0005	0.007	0.011	<0.001*
		dataset i	0.03*	0.0005	0.027	0.030	<0.001*
		dataset j	0.03*	0.0005	0.026	0.030	<0.001*
		dataset l	0.02*	0.0005	0.021	0.025	<0.001*
		dataset m	0.02*	0.0005	0.021	0.025	<0.001*
		dataset a	0.02*	0.0005	0.019	0.023	<0.001*
		dataset b	-0.02*	0.0005	-0.021	-0.017	<0.001*
		dataset c	-0.01*	0.0005	-0.008	-0.004	<0.001*
		dataset d	-0.01*	0.0005	-0.009	-0.005	<0.001*
		dataset e	0.00	0.0005	-0.001	0.003	1.000
		dataset f	-0.01*	0.0005	-0.012	-0.008	<0.001*
		dataset g	-0.01*	0.0005	-0.012	-0.009	<0.001*
		dataset h	-0.01*	0.0005	-0.016	-0.012	<0.001*
		dataset i	0.01*	0.0005	0.003	0.007	<0.001*
	dataset m	dataset j	0.01*	0.0005	0.003	0.007	<0.001*
		dataset k	-.02*	0.0005	-0.025	-0.021	<0.001*
		dataset m	0.00	0.0005	-0.002	0.002	1.000
		dataset a	0.02*	0.0005	0.019	0.023	<0.001*
		dataset b	-0.02*	0.0005	-0.021	-0.017	<0.001*
		dataset c	-0.01*	0.0005	-0.008	-0.004	<0.001*
		dataset d	-0.01*	0.0005	-0.008	-0.005	<0.001*
		dataset e	0.00	0.0005	-0.001	0.003	1.000
		dataset f	-0.01*	0.0005	-0.012	-0.008	<0.001*
		dataset g	-0.01*	0.0005	-0.012	-0.008	<0.001*
		dataset h	-0.01*	0.0005	-0.016	-0.012	<0.001*
		dataset i	0.01*	0.0005	0.004	0.007	<0.001*
		dataset j	0.01*	0.0005	0.003	0.007	<0.001*
		dataset k	-0.023*	0.0005	-0.025	-0.021	<0.001*
		dataset l	0.00	0.0005	-0.002	0.002	1.000
MAPE	dataset a	dataset b	-1523.80*	18.83	-1588.09	-1459.51	<0.001*
		dataset c	-1086.69*	18.83	-1150.98	-1022.40	<0.001*
		dataset d	-1104.26*	18.83	-1168.54	-1039.97	<0.001*
		dataset e	-820.31*	18.83	-884.59	-756.02	<0.001*
		dataset f	-1214.11*	18.83	-1278.40	-1149.82	<0.001*
		dataset g	-1230.81*	18.83	-1295.10	-1166.52	<0.001*
		dataset h	-1352.53*	18.83	-1416.81	-1288.24	<0.001*
		dataset i	-681.32*	18.83	-745.61	-617.03	<0.001*
		dataset j	-693.02*	18.83	-757.31	-628.73	<0.001*
		dataset k	-1654.38*	18.83	-1718.67	-1590.09	<0.001*
		dataset l	-871.11*	18.83	-935.40	-806.82	<0.001*
		dataset m	-875.89*	18.83	-940.18	-811.60	<0.001*
	dataset b	dataset a	1523.80*	18.83	1459.51	1588.09	<0.001*
		dataset c	437.11*	18.83	372.82	501.40	<0.001*
		dataset d	419.54*	18.83	355.25	483.83	<0.001*
		dataset e	703.49*	18.83	639.20	767.78	<0.001*
		dataset f	309.69*	18.83	245.40	373.98	<0.001*
		dataset g	292.98*	18.83	228.69	357.27	<0.001*
		dataset h	171.27*	18.83	106.98	235.56	<0.001*
		dataset i	842.48*	18.83	778.19	906.77	<0.001*
		dataset j	830.78*	18.83	766.49	895.07	<0.001*
		dataset k	-130.59*	18.83	-194.87	-66.30	<0.001*
	dataset c	dataset l	652.69*	18.83	588.40	716.98	<0.001*
		dataset m	647.91*	18.83	583.62	712.20	<0.001*
		dataset a	1086.69*	18.83	1022.40	1150.98	<0.001*

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	dataset d	dataset b	-437.11*	18.83	-501.40	-372.82	<0.001*
		dataset d	-17.57	18.83	-81.86	46.72	1.000
		dataset e	266.38*	18.83	202.09	330.67	<0.001*
		dataset f	-127.42*	18.83	-191.71	-63.13	<0.001*
		dataset g	-144.13*	18.83	-208.42	-79.84	<0.001*
		dataset h	-265.84*	18.83	-330.13	-201.55	<0.001*
		dataset i	405.37*	18.83	341.08	469.66	<0.001*
		dataset j	393.67*	18.83	329.38	457.96	<0.001*
		dataset k	-567.69*	18.83	-631.98	-503.40	<0.001*
		dataset l	215.58*	18.83	151.29	279.87	<0.001*
		dataset m	210.80*	18.83	146.51	275.09	<0.001*
		dataset a	1104.26*	18.83	1039.97	1168.54	<0.001*
		dataset b	-419.54*	18.83	-483.83	-355.25	<0.001*
		dataset c	17.57	18.83	-46.72	81.86	1.000
		dataset e	283.95*	18.83	219.66	348.24	<0.001*
	dataset e	dataset f	-109.85*	18.83	-174.14	-45.56	<0.001*
		dataset g	-126.56*	18.83	-190.85	-62.27	<0.001*
		dataset h	-248.27*	18.83	-312.56	-183.98	<0.001*
		dataset i	422.94*	18.83	358.65	487.23	<0.001*
		dataset j	411.24*	18.83	346.95	475.53	<0.001*
		dataset k	-550.13*	18.83	-614.42	-485.84	<0.001*
		dataset l	233.14*	18.83	168.85	297.43	<0.001*
		dataset m	228.37*	18.83	164.08	292.66	<0.001*
		dataset a	820.30*	18.83	756.02	884.59	<0.001*
		dataset b	-703.49*	18.83	-767.78	-639.20	<0.001*
		dataset c	-266.38*	18.83	-330.67	-202.09	<0.001*
		dataset d	-283.95*	18.83	-348.24	-219.66	<0.001*
		dataset f	-393.80*	18.83	-458.09	-329.51	<0.001*
		dataset g	-410.51*	18.83	-474.80	-346.22	<0.001*
		dataset h	-532.22*	18.83	-596.51	-467.93	<0.001*
	dataset f	dataset i	138.99*	18.83	74.70	203.28	<0.001*
		dataset j	127.29*	18.83	63.00	191.58	<0.001*
		dataset k	-834.08*	18.83	-898.37	-769.79	<0.001*
		dataset l	-50.81	18.83	-115.10	13.48	0.544
		dataset m	-55.58	18.83	-119.87	8.71	0.247
		dataset a	1214.11*	18.83	1149.82	1278.40	<0.001*
		dataset b	-309.69*	18.83	-373.98	-245.40	<0.001*
		dataset c	127.42*	18.83	63.13	191.71	<0.001*
		dataset d	109.85*	18.83	45.56	174.14	<0.001*
		dataset e	393.80*	18.83	329.51	458.09	<0.001*
		dataset g	-16.71	18.83	-81.00	47.58	1.000
		dataset h	-138.42*	18.83	-202.71	-74.13	<0.001*
	dataset g	dataset i	532.79*	18.83	468.50	597.08	<0.001*
		dataset j	521.09*	18.83	456.80	585.38	<0.001*
		dataset k	-440.28*	18.83	-504.56	-375.99	<0.001*
		dataset l	343.00*	18.83	278.71	407.29	<0.001*
		dataset m	338.22*	18.83	273.93	402.51	<0.001*
		dataset a	1230.81*	18.83	1166.52	1295.10	<0.001*
		dataset b	-292.98*	18.83	-357.27	-228.69	<0.001*
		dataset c	144.13*	18.83	79.84	208.42	<0.001*
		dataset d	126.56*	18.83	62.27	190.85	<0.001*
		dataset e	410.51*	18.83	346.22	474.80	<0.001*
		dataset f	16.71	18.83	-47.58	81.00	1.000
		dataset h	-121.71*	18.83	-186.00	-57.42	<0.001*
		dataset i	549.50*	18.83	485.21	613.78	<0.001*

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	dataset h	dataset j	537.80*	18.83	473.51	602.09	<0.001*
		dataset k	-423.57*	18.83	-487.86	-359.28	<0.001*
		dataset l	359.70*	18.83	295.41	423.99	<0.001*
		dataset m	354.93*	18.83	290.64	419.22	<0.001*
		dataset a	1352.53*	18.83	1288.24	1416.81	<0.001*
		dataset b	-171.27*	18.83	-235.56	-106.98	<0.001*
		dataset c	265.84*	18.83	201.55	330.13	<0.001*
		dataset d	248.27*	18.83	183.98	312.56	<0.001*
		dataset e	532.22*	18.83	467.93	596.51	<0.001*
		dataset f	138.42*	18.83	74.13	202.71	<0.001*
		dataset g	121.71*	18.83	57.42	186.00	<0.001*
		dataset i	671.21*	18.83	606.92	735.50	<0.001*
		dataset j	659.51*	18.83	595.22	723.80	<0.001*
		dataset k	-301.86*	18.83	-366.15	-237.57	<0.001*
		dataset l	481.41*	18.83	417.12	545.70	<0.001*
	dataset i	dataset m	476.64*	18.83	412.35	540.93	<0.001*
		dataset a	681.32*	18.83	617.03	745.61	<0.001*
		dataset b	-842.48*	18.83	-906.77	-778.19	<0.001*
		dataset c	-405.37*	18.83	-469.66	-341.08	<0.001*
		dataset d	-422.94*	18.83	-487.23	-358.65	<0.001*
		dataset e	-138.99*	18.83	-203.28	-74.70	<0.001*
		dataset f	-532.79*	18.83	-597.08	-468.50	<0.001*
		dataset g	-549.50*	18.83	-613.78	-485.21	<0.001*
		dataset h	-671.21*	18.83	-735.50	-606.92	<0.001*
		dataset j	-11.70	18.83	-75.99	52.59	1.000
		dataset k	-973.06*	18.83	-1037.35	-908.77	<0.001*
		dataset l	-189.79*	18.83	-254.08	-125.50	<0.001*
		dataset m	-194.57*	18.83	-258.86	-130.28	<0.001*
	dataset j	dataset a	693.02*	18.83	628.73	757.31	<0.001*
		dataset b	-830.78*	18.83	-895.07	-766.49	<0.001*
		dataset c	-393.67*	18.83	-457.96	-329.38	<0.001*
		dataset d	-411.24*	18.83	-475.53	-346.95	<0.001*
		dataset e	-127.29*	18.83	-191.58	-63.00	<0.001*
		dataset f	-521.09*	18.83	-585.38	-456.80	<0.001*
		dataset g	-537.80*	18.83	-602.09	-473.51	<0.001*
		dataset h	-659.51*	18.83	-723.80	-595.22	<0.001*
		dataset i	11.70	18.83	-52.59	75.99	1.000
		dataset k	-961.37*	18.83	-1025.66	-897.08	<0.001*
		dataset l	-178.10*	18.83	-242.39	-113.81	<0.001*
		dataset m	-182.87*	18.83	-247.16	-118.58	<0.001*
	dataset k	dataset a	1654.38*	18.83	1590.09	1718.67	<0.001*
		dataset b	130.59*	18.83	66.30	194.87	<0.001*
		dataset c	567.69*	18.83	503.40	631.98	<0.001*
		dataset d	550.13*	18.83	485.84	614.42	<0.001*
		dataset e	834.08*	18.83	769.79	898.37	<0.001*
		dataset f	440.28*	18.83	375.99	504.56	<0.001*
		dataset g	423.57*	18.83	359.28	487.86	<0.001*
		dataset h	301.86*	18.83	237.57	366.15	<0.001*
		dataset i	973.06*	18.83	908.77	1037.35	<0.001*
		dataset j	961.37*	18.83	897.08	1025.66	<0.001*
		dataset l	783.27*	18.83	718.98	847.56	<0.001*
		dataset m	778.50*	18.83	714.21	842.79	<0.001*
	dataset l	dataset a	871.11*	18.83	806.82	935.40	<0.001*
		dataset b	-652.69*	18.83	-716.98	-588.40	<0.001*
		dataset c	-215.58*	18.83	-279.87	-151.29	<0.001*

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	dataset m	dataset d	-233.14*	18.83	-297.43	-168.85	<0.001*
		dataset e	50.81	18.83	-13.48	115.10	0.544
		dataset f	-343.00*	18.83	-407.29	-278.71	<0.001*
		dataset g	-359.70*	18.83	-423.99	-295.41	<0.001*
		dataset h	-481.41*	18.83	-545.70	-417.12	<0.001*
		dataset i	189.79*	18.83	125.50	254.08	<0.001*
		dataset j	178.10*	18.83	113.81	242.39	<0.001*
		dataset k	-783.27*	18.83	-847.56	-718.98	<0.001*
		dataset m	-4.77	18.83	-69.06	59.52	1.000
		dataset a	875.89*	18.83	811.60	940.18	<0.001*
		dataset b	-647.91*	18.83	-712.20	-583.62	<0.001*
		dataset c	-210.80*	18.83	-275.09	-146.51	<0.001*
		dataset d	-228.37*	18.83	-292.66	-164.08	<0.001*
		dataset e	55.58	18.83	-8.71	119.87	0.247
		dataset f	-338.22*	18.83	-402.51	-273.93	<0.001*
		dataset g	-354.93*	18.83	-419.22	-290.64	<0.001*
		dataset h	-476.64*	18.83	-540.93	-412.35	<0.001*
		dataset i	194.57*	18.83	130.28	258.86	<0.001*
		dataset j	182.87*	18.83	118.58	247.16	<0.001*
		dataset k	-778.50*	18.83	-842.79	-714.21	<0.001*
		dataset l	4.77	18.83	-59.52	69.06	1.000
Prediction error	dataset a	dataset b	-954.79*	52.56	-1134.22	-775.36	<0.001*
		dataset c	-633.43*	52.56	-812.86	-453.99	<0.001*
		dataset d	-710.68*	52.56	-890.11	-531.25	<0.001*
		dataset e	-337.72*	52.56	-517.15	-158.29	<0.001*
		dataset f	-712.23*	52.56	-891.66	-532.80	<0.001*
		dataset g	-732.83*	52.56	-912.26	-553.40	<0.001*
		dataset h	-791.68*	52.56	-971.11	-612.25	<0.001*
		dataset i	-184.62*	52.56	-364.05	-5.19	0.035*
		dataset j	-187.05*	52.56	-366.48	-7.62	0.029*
		dataset k	-1021.03*	52.56	-1200.46	-841.60	<0.001*
		dataset l	-397.56*	52.56	-576.99	-218.12	<0.001*
		dataset m	-364.68*	52.56	-544.11	-185.25	<0.001*
	dataset b	dataset a	954.79*	52.56	775.36	1134.22	<0.001*
		dataset c	321.37*	52.56	141.94	500.80	<0.001*
		dataset d	244.11*	52.56	64.68	423.54	<0.001*
		dataset e	617.07*	52.56	437.64	796.50	<0.001*
		dataset f	242.56*	52.56	63.13	421.99	<0.001*
		dataset g	221.96*	52.56	42.53	401.39	0.002*
		dataset h	163.11	52.56	-16.32	342.54	0.149
		dataset i	770.17*	52.56	590.74	949.60	<0.001*
		dataset j	767.74*	52.56	588.31	947.17	<0.001*
		dataset k	-66.24	52.56	-245.67	113.19	1.000
		dataset l	557.24*	52.56	377.81	736.67	<0.001*
		dataset m	590.11*	52.56	410.68	769.54	<0.001*
	dataset c	dataset a	633.43*	52.56	453.99	812.86	<0.001*
		dataset b	-321.37*	52.56	-500.80	-141.94	<0.001*
		dataset d	-77.25	52.56	-256.68	102.18	1.000
		dataset e	295.70*	52.56	116.27	475.13	<0.001*
		dataset f	-78.81	52.56	-258.24	100.62	1.000
		dataset g	-99.41	52.56	-278.84	80.02	1.000
		dataset h	-158.25	52.56	-337.68	21.18	0.203
		dataset i	448.81*	52.56	269.38	628.24	<0.001*
		dataset j	446.37*	52.56	266.94	625.80	<0.001*

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	dataset d	dataset k	-387.61*	52.56	-567.04	-208.18	<0.001*
		dataset l	235.87*	52.56	56.44	415.30	<0.001*
		dataset m	268.75*	52.56	89.31	448.18	<0.001*
		dataset a	710.68*	52.56	531.25	890.11	<0.001*
		dataset b	-244.11*	52.56	-423.54	-64.68	<0.001*
		dataset c	77.25	52.56	-102.18	256.68	1.000
		dataset e	372.95*	52.56	193.52	552.38	<0.001*
		dataset f	-1.56	52.56	-180.99	177.88	1.000
		dataset g	-22.15	52.56	-201.58	157.28	1.000
		dataset h	-81.00	52.56	-260.43	98.43	1.000
		dataset i	526.06*	52.56	346.63	705.49	<0.001*
		dataset j	523.63*	52.56	344.19	703.06	<0.001*
		dataset k	-310.36*	52.56	-489.79	-130.93	<0.001*
		dataset l	313.12*	52.56	133.69	492.55	<0.001*
		dataset m	346.00*	52.56	166.57	525.43	<0.001*
	dataset e	dataset a	337.72*	52.56	158.29	517.15	<0.001*
		dataset b	-617.07*	52.56	-796.50	-437.64	<0.001*
		dataset c	-295.70*	52.56	-475.13	-116.27	<0.001*
		dataset d	-372.95*	52.56	-552.38	-193.52	<0.001*
		dataset f	-374.51*	52.56	-553.94	-195.08	<0.001*
		dataset g	-395.11*	52.56	-574.54	-215.68	<0.001*
		dataset h	-453.95*	52.56	-633.38	-274.52	<0.001*
		dataset i	153.10	52.56	-26.33	332.53	0.279
		dataset j	150.67	52.56	-28.76	330.10	0.324
		dataset k	-683.31*	52.56	-862.74	-503.88	<0.001*
		dataset l	-59.83	52.56	-239.26	119.60	1.000
		dataset m	-26.96	52.56	-206.39	152.47	1.000
	dataset f	dataset a	712.23*	52.56	532.80	891.66	<0.001*
		dataset b	-242.56*	52.56	-421.99	-63.13	<0.001*
		dataset c	78.81	52.56	-100.62	258.24	1.000
		dataset d	1.56	52.56	-177.88	180.99	1.000
		dataset e	374.51*	52.56	195.08	553.94	<0.001*
		dataset g	-20.60	52.56	-200.03	158.83	1.000
		dataset h	-79.44	52.56	-258.87	99.99	1.000
		dataset i	527.61*	52.56	348.18	707.04	<0.001*
		dataset j	525.18*	52.56	345.75	704.61	<0.001*
		dataset k	-308.80*	52.56	-488.23	-129.37	<0.001*
		dataset l	314.68*	52.56	135.25	494.11	<0.001*
		dataset m	347.55*	52.56	168.12	526.98	<0.001*
	dataset g	dataset a	732.83*	52.56	553.40	912.26	<0.001*
		dataset b	-221.96*	52.56	-401.39	-42.53	0.002*
		dataset c	99.41	52.56	-80.02	278.84	1.000
		dataset d	22.15	52.56	-157.28	201.58	1.000
		dataset e	395.11*	52.56	215.68	574.54	<0.001*
		dataset f	20.60	52.56	-158.83	200.03	1.000
		dataset h	-58.85	52.56	-238.28	120.58	1.000
		dataset i	548.21*	52.56	368.78	727.64	<0.001*
		dataset j	545.78*	52.56	366.35	725.21	<0.001*
		dataset k	-288.20*	52.56	-467.63	-108.77	<0.001*
		dataset l	335.28*	52.56	155.85	514.71	<0.001*
		dataset m	368.15*	52.56	188.72	547.58	<0.001*
	dataset h	dataset a	791.68*	52.56	612.25	971.11	<0.001*
		dataset b	-163.11	52.56	-342.54	16.32	0.149
		dataset c	158.25	52.56	-21.18	337.68	0.203
		dataset d	81.00	52.56	-98.43	260.43	1.000

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
		dataset e	453.95*	52.56	274.52	633.38	<0.001*
		dataset f	79.44	52.56	-99.99	258.87	1.000
		dataset g	58.85	52.56	-120.58	238.28	1.000
		dataset i	607.06*	52.56	427.63	786.49	<0.001*
		dataset j	604.63*	52.56	425.19	784.06	<0.001*
		dataset k	-229.36*	52.56	-408.79	-49.93	0.001*
		dataset l	394.12*	52.56	214.69	573.55	<0.001*
		dataset m	427.00*	52.56	247.57	606.43	<0.001*
	dataset i	dataset a	184.62*	52.56	5.19	364.05	0.035*
		dataset b	-770.17*	52.56	-949.60	-590.74	<0.001*
		dataset c	-448.81*	52.56	-628.24	-269.38	<0.001*
		dataset d	-526.06*	52.56	-705.49	-346.63	<0.001*
		dataset e	-153.10	52.56	-332.53	26.33	0.279
		dataset f	-527.61*	52.56	-707.04	-348.18	<0.001*
		dataset g	-548.21*	52.56	-727.64	-368.78	<0.001*
		dataset h	-607.06*	52.56	-786.49	-427.63	<0.001*
		dataset j	-2.43	52.56	-181.86	177.00	1.000
		dataset k	-836.41*	52.56	-1015.84	-656.98	<0.001*
		dataset l	-212.94*	52.56	-392.37	-33.50	0.004*
		dataset m	-180.06*	52.56	-359.49	-0.63	0.048*
	dataset j	dataset a	187.05*	52.56	7.62	366.48	0.029*
		dataset b	-767.74*	52.56	-947.17	-588.31	<0.001*
		dataset c	-446.37*	52.56	-625.80	-266.94	<0.001*
		dataset d	-523.63*	52.56	-703.06	-344.19	<0.001*
		dataset e	-150.67	52.56	-330.10	28.76	0.324
		dataset f	-525.18*	52.56	-704.61	-345.75	<0.001*
		dataset g	-545.78*	52.56	-725.21	-366.35	<0.001*
		dataset h	-604.63*	52.56	-784.06	-425.19	<0.001*
		dataset i	2.43	52.56	-177.00	181.86	1.000
		dataset k	-833.98*	52.56	-1013.41	-654.55	<0.001*
		dataset l	-210.50*	52.56	-389.93	-31.07	0.005*
		dataset m	-177.63	52.56	-357.06	1.80	0.057
	dataset k	dataset a	1021.03*	52.56	841.60	1200.46	<0.001*
		dataset b	66.24	52.56	-113.19	245.67	1.000
		dataset c	387.61*	52.56	208.18	567.04	<0.001*
		dataset d	310.36*	52.56	130.93	489.79	<0.001*
		dataset e	683.31*	52.56	503.88	862.74	<0.001*
		dataset f	308.80*	52.56	129.37	488.23	<0.001*
		dataset g	288.20*	52.56	108.77	467.63	<0.001*
		dataset h	229.36*	52.56	49.93	408.79	0.001*
		dataset i	836.41*	52.56	656.98	1015.84	<0.001*
		dataset j	833.98*	52.56	654.55	1013.41	<0.001*
		dataset l	623.48*	52.56	444.05	802.91	<0.001*
		dataset m	656.35*	52.56	476.92	835.78	<0.001*
	dataset l	dataset a	397.56*	52.56	218.12	576.99	<0.001*
		dataset b	-557.24*	52.56	-736.67	-377.81	<0.001*
		dataset c	-235.87*	52.56	-415.30	-56.44	<0.001*
		dataset d	-313.12*	52.56	-492.55	-133.69	<0.001*
		dataset e	59.83	52.56	-119.60	239.26	1.000
		dataset f	-314.68*	52.56	-494.11	-135.25	<0.001*
		dataset g	-335.28*	52.56	-514.71	-155.85	<0.001*
		dataset h	-394.12*	52.56	-573.55	-214.69	<0.001*
		dataset i	212.94*	52.56	33.50	392.37	0.004*
		dataset j	210.50*	52.56	31.07	389.93	0.005*
		dataset k	-623.48*	52.56	-802.91	-444.05	<0.001*

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
	dataset m	dataset m	32.88	52.56	-146.56	212.31	1.000
		dataset a	364.6797*	52.56	185.25	544.11	<0.001*
		dataset b	-590.11*	52.56	-769.54	-410.68	<0.001*
		dataset c	-268.75*	52.56	-448.18	-89.31	<0.001*
		dataset d	-346.00*	52.56	-525.43	-166.57	<0.001*
		dataset e	26.96	52.56	-152.47	206.39	1.000
		dataset f	-347.55*	52.56	-526.98	-168.12	<0.001*
		dataset g	-368.15*	52.56	-547.58	-188.72	<0.001*
		dataset h	-427.00*	52.56	-606.43	-247.57	<0.001*
		dataset i	180.06*	52.56	0.63	359.49	0.048*
		dataset j	177.63	52.56	-1.80	357.06	0.057
		dataset k	-656.35*	52.56	-835.78	-476.92	<0.001*
		dataset l	-32.88	52.56	-212.31	146.56	1.000
Runtime	dataset a	dataset b	-5.72*	0.31	-6.78	-4.67	<0.001*
		dataset c	-6.13*	0.31	-7.18	-5.07	<0.001*
		dataset d	-6.38*	0.31	-7.44	-5.32	<0.001*
		dataset e	-4.88*	0.31	-5.94	-3.82	<0.001*
		dataset f	-5.56*	0.31	-6.61	-4.50	<0.001*
		dataset g	-5.76*	0.31	-6.82	-4.71	<0.001*
		dataset h	-5.06*	0.31	-6.12	-4.00	<0.001*
		dataset i	-5.71*	0.31	-6.77	-4.65	<0.001*
		dataset j	-5.88*	0.31	-6.94	-4.82	<0.001*
		dataset k	-5.53*	0.31	-6.58	-4.47	<0.001*
		dataset l	-6.18*	0.31	-7.24	-5.12	<0.001*
		dataset m	-6.40*	0.31	-7.46	-5.34	<0.001*
	dataset b	dataset a	5.72*	0.31	4.67	6.78	<0.001*
		dataset c	-0.40	0.31	-1.46	0.65	1.000
		dataset d	-0.66	0.31	-1.72	0.40	1.000
		dataset e	0.84	0.31	-0.22	1.90	0.511
		dataset f	0.17	0.31	-0.89	1.22	1.000
		dataset g	-0.04	0.31	-1.10	1.02	1.000
		dataset h	0.66	0.31	-0.40	1.72	1.000
		dataset i	0.01	0.31	-1.05	1.07	1.000
		dataset j	-0.16	0.31	-1.21	0.90	1.000
		dataset k	0.20	0.31	-0.86	1.25	1.000
		dataset l	-0.46	0.31	-1.51	0.60	1.000
		dataset m	-0.68	0.31	-1.74	0.38	1.000
	dataset c	dataset a	6.13*	0.31	5.07	7.18	<0.001*
		dataset b	0.40	0.31	-0.65	1.46	1.000
		dataset d	-0.26	0.31	-1.31	0.80	1.000
		dataset e	1.25*	0.31	0.19	2.30	0.005*
		dataset f	0.57	0.31	-0.49	1.63	1.000
		dataset g	0.36	0.31	-0.70	1.42	1.000
		dataset h	1.07*	0.31	0.01	2.12	0.046*
		dataset i	0.41	0.31	-0.64	1.47	1.000
		dataset j	0.25	0.31	-0.81	1.30	1.000
		dataset k	0.60	0.31	-0.46	1.66	1.000
		dataset l	-0.05	0.31	-1.11	1.00	1.000
		dataset m	-0.28	0.31	-1.33	0.78	1.000
	dataset d	dataset a	6.38*	0.31	5.32	7.44	<0.001*
		dataset b	0.66	0.31	-0.40	1.72	1.000
		dataset c	0.26	0.31	-0.80	1.31	1.000
		dataset e	1.50*	0.31	0.44	2.56	<0.001*
		dataset f	0.83	0.31	-0.23	1.88	0.590
		dataset g	0.62	0.31	-0.44	1.68	1.000

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
		dataset h	1.32*	0.31	0.26	2.38	0.002*
		dataset i	0.67	0.31	-0.39	1.73	1.000
		dataset j	0.50	0.31	-0.55	1.56	1.000
		dataset k	0.86	0.31	-0.20	1.91	0.450
		dataset l	0.20	0.31	-0.85	1.26	1.000
		dataset m	-0.02	0.31	-1.08	1.04	1.000
	dataset e	dataset a	4.88*	0.31	3.82	5.94	<0.001*
		dataset b	-0.84	0.31	-1.90	0.22	0.511
		dataset c	-1.25*	0.31	-2.30	-0.19	0.005*
		dataset d	-1.50*	0.31	-2.56	-0.44	<0.001*
		dataset f	-0.67	0.31	-1.73	0.38	1.000
		dataset g	-0.88	0.31	-1.94	0.17	0.337
		dataset h	-0.18	0.31	-1.24	0.88	1.000
		dataset i	-0.83	0.31	-1.89	0.23	0.570
		dataset j	-1.00	0.31	-2.06	0.06	0.099
		dataset k	-0.65	0.31	-1.70	0.41	1.000
		dataset l	-1.30*	0.31	-2.36	-0.24	0.002*
		dataset m	-1.52*	0.31	-2.58	-0.46	<0.001*
	dataset f	dataset a	5.56*	0.31	4.50	6.61	<0.001*
		dataset b	-0.17	0.31	-1.22	0.89	1.000
		dataset c	-0.57	0.31	-1.63	0.49	1.000
		dataset d	-0.83	0.31	-1.88	0.23	0.590
		dataset e	0.67	0.31	-0.38	1.73	1.000
		dataset g	-0.21	0.31	-1.27	0.85	1.000
		dataset h	0.49	0.31	-0.56	1.55	1.000
		dataset i	-0.16	0.31	-1.21	0.90	1.000
		dataset j	-0.32	0.31	-1.38	0.73	1.000
		dataset k	0.03	0.31	-1.03	1.09	1.000
		dataset l	-0.62	0.31	-1.68	0.43	1.000
		dataset m	-0.85	0.31	-1.90	0.21	0.491
	dataset g	dataset a	5.76*	0.31	4.71	6.82	<0.001*
		dataset b	0.04	0.31	-1.02	1.10	1.000
		dataset c	-0.36	0.31	-1.42	0.70	1.000
		dataset d	-0.62	0.31	-1.68	0.44	1.000
		dataset e	0.88	0.31	-0.17	1.94	0.337
		dataset f	0.21	0.31	-0.85	1.27	1.000
		dataset h	0.70	0.31	-0.35	1.76	1.000
		dataset i	0.05	0.31	-1.00	1.11	1.000
		dataset j	-0.11	0.31	-1.17	0.94	1.000
		dataset k	0.24	0.31	-0.82	1.29	1.000
		dataset l	-0.41	0.31	-1.47	0.64	1.000
		dataset m	-0.64	0.31	-1.69	0.42	1.000
	dataset h	dataset a	5.06*	0.31	4.00	6.12	<0.001*
		dataset b	-0.66	0.31	-1.72	0.40	1.000
		dataset c	-1.07*	0.31	-2.12	-0.01	0.046*
		dataset d	-1.32*	0.31	-2.38	-0.26	0.002*
		dataset e	0.18	0.31	-0.88	1.24	1.000
		dataset f	-0.49	0.31	-1.55	0.56	1.000
		dataset g	-0.70	0.31	-1.76	0.35	1.000
		dataset i	-0.65	0.31	-1.71	0.41	1.000
		dataset j	-0.82	0.31	-1.88	0.24	0.647
		dataset k	-0.47	0.31	-1.52	0.59	1.000
		dataset l	-1.12*	0.31	-2.18	-0.06	0.024*
		dataset m	-1.34*	0.31	-2.40	-0.28	0.001*
	dataset i	dataset a	5.71*	0.31	4.65	6.77	<0.001*

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
					Lower Bound	Upper Bound	
		dataset b	-0.01	0.31	-1.07	1.05	1.000
		dataset c	-0.41	0.31	-1.47	0.64	1.000
		dataset d	-0.67	0.31	-1.73	0.39	1.000
		dataset e	0.83	0.31	-0.23	1.89	0.570
		dataset f	0.16	0.31	-0.90	1.21	1.000
		dataset g	-0.05	0.31	-1.11	1.00	1.000
		dataset h	0.65	0.31	-0.41	1.71	1.000
		dataset j	-0.17	0.31	-1.22	0.89	1.000
		dataset k	0.18	0.31	-0.87	1.24	1.000
		dataset l	-0.47	0.31	-1.53	0.59	1.000
		dataset m	-0.69	0.31	-1.75	0.37	1.000
	dataset j	dataset a	5.88*	0.31	4.82	6.94	<0.001*
		dataset b	0.16	0.31	-0.90	1.21	1.000
		dataset c	-0.25	0.31	-1.30	0.81	1.000
		dataset d	-0.50	0.31	-1.56	0.55	1.000
		dataset e	1.00	0.31	-0.06	2.06	0.099
		dataset f	0.32	0.31	-0.73	1.38	1.000
		dataset g	0.11	0.31	-0.94	1.17	1.000
		dataset h	0.82	0.31	-0.24	1.88	0.647
		dataset i	0.17	0.31	-0.89	1.22	1.000
		dataset k	0.35	0.31	-0.71	1.41	1.000
		dataset l	-0.30	0.31	-1.36	0.76	1.000
		dataset m	-0.52	0.31	-1.58	0.53	1.000
	dataset k	dataset a	5.53*	0.31	4.47	6.58	<0.001*
		dataset b	-0.20	0.31	-1.25	0.86	1.000
		dataset c	-0.60	0.31	-1.66	0.46	1.000
		dataset d	-0.86	0.31	-1.91	0.20	0.450
		dataset e	0.65	0.31	-0.41	1.70	1.000
		dataset f	-0.03	0.31	-1.09	1.03	1.000
		dataset g	-0.24	0.31	-1.29	0.82	1.000
		dataset h	0.47	0.31	-0.59	1.52	1.000
		dataset i	-0.18	0.31	-1.24	0.87	1.000
		dataset j	-0.35	0.31	-1.41	0.71	1.000
		dataset l	-0.65	0.31	-1.71	0.41	1.000
		dataset m	-0.87	0.31	-1.93	0.18	0.373
	dataset l	dataset a	6.18*	0.31	5.12	7.24	<0.001*
		dataset b	0.46	0.31	-0.60	1.51	1.000
		dataset c	0.05	0.31	-1.00	1.11	1.000
		dataset d	-0.20	0.31	-1.26	0.85	1.000
		dataset e	1.30*	0.31	0.24	2.36	0.002*
		dataset f	0.62	0.31	-0.43	1.68	1.000
		dataset g	0.41	0.31	-0.64	1.47	1.000
		dataset h	1.12*	0.31	0.06	2.18	0.024*
		dataset i	0.47	0.31	-0.59	1.53	1.000
		dataset j	0.30	0.31	-0.76	1.36	1.000
		dataset k	0.65	0.31	-0.41	1.71	1.000
		dataset m	-0.22	0.31	-1.28	0.84	1.000
	dataset m	dataset a	6.40*	0.31	5.34	7.46	<0.001*
		dataset b	0.68	0.31	-0.38	1.74	1.000
		dataset c	0.28	0.31	-0.78	1.33	1.000
		dataset d	0.02	0.31	-1.04	1.08	1.000
		dataset e	1.52*	0.31	0.46	2.58	<0.001*
		dataset f	0.85	0.31	-0.21	1.90	0.491
		dataset g	0.64	0.31	-0.42	1.69	1.000
		dataset h	1.34*	0.31	0.28	2.40	0.001*

Dependent Variable	(I) Dataset	(J) Dataset	Mean Difference (I-J)	Std. Error	95% Confidence Interval		p
		dataset i	0.69	0.31	-0.37	1.75	1.000
		dataset j	0.52	0.31	-0.53	1.58	1.000
		dataset k	0.87	0.31	-0.18	1.93	0.373
		dataset l	0.22	0.31	-0.84	1.28	1.000

Based on observed means.

The error term is Mean Square(Error) = 86.335.

* The mean difference is significant at the 0.05 level.

E.2.1 Mean of all parameters and datasets

Table E - 11 : Mean prediction error of all activation functions

Activation	Mean	N	Std. Deviation
ReLU	1602.44	7800	1497.03
TanH	1489.54	7800	1512.30
Sigmoid	1668.57	7800	1785.58
Total	1586.85	23400	1605.43

Table E - 12 : Mean prediction error of all window sizes

Window	Mean	N	Std. Deviation
w=21	241.68	5850	553.32
w=63	1270.07	5850	668.02
w=125	1286.89	5850	662.41
w=250	3548.76	5850	1808.25
Total	1586.85	23400	1605.43

Table E - 13 : Mean prediction error of all hidden

Hidden	Mean	N	Std. Deviation
h1	978.11	360	1413.37
h2	1134.61	360	1977.67
h4	1042.92	360	2020.29
h8	1022.04	360	1969.14
h16	1053.37	360	1990.47
Total	1046.21	1800	1886.97

Table E - 14 : Mean prediction error of all nodes

Node	Mean	N	Std. Deviation
n1	1748.61	4680	1852.09
n2	1678.59	4680	1732.69
n4	1602.42	4680	1603.83
n8	1494.43	4680	1434.68
n16	1410.18	4680	1323.44
Total	1586.85	23400	1605.43

Table E - 15 : Mean prediction error of all epochs

Epoch	Mean	N	Std. Deviation
10e	2241.41	3900	2339.32
20e	1844.77	3900	1734.86
50e	1452.37	3900	1352.17
100e	1336.78	3900	1220.34
150e	1328.31	3900	1221.75
200e	1317.44	3900	1208.30
Total	1586.85	23400	1605.43

Table E - 16 : Mean prediction error of all datasets

Dataset	Mean	N	Std. Deviation
dataset a	1046.21	1800	1886.97
dataset b	2001.00	1800	1807.62
dataset c	1679.63	1800	1592.77
dataset d	1756.89	1800	1839.26
dataset e	1383.93	1800	1445.53
dataset f	1758.44	1800	1552.05
dataset g	1779.04	1800	1681.91
dataset h	1837.89	1800	1510.03
dataset i	1230.83	1800	1236.99
dataset j	1233.26	1800	1296.90
dataset k	2067.24	1800	1729.22
dataset l	1443.76	1800	1399.64
dataset m	1410.89	1800	1341.65
Total	1586.85	23400	1605.43

Appendix F S&P 500 index companies' list

Table F - 1 : The companies change list of S&P 500 index between 2016 and 2020

Date	Added		Removed		Reason
	Ticker	Security	Ticker	Security	
2016-01-05	WLTW	Willis Towers Watson	FOSL	Fossil Group	WSH merges with TW (and renames to WLTW)
2016-01-19	EXR	Extra Space Storage	ACE	Chubb	EXR replaces ACE as ACE Ltd acquires Chubb and retains the CB ticker, giving up ACE
2016-02-01	CFG	Citizens	PCP	Precision Castparts Corporation	CFG replaces PCP
2016-02-01	FRT	Federal Realty Investment Trust	BRCM	Broadcom Corporation	FRT replaces BRCM
2016-02-22	CXO	Concho Resources	PCL	Plum Creek Timber	PCL taken over by WY
2016-03-04	AWK	American Water Works	CNX	Consol Energy	AWK replaces CNX
2016-03-07	UDR	UDR Inc	GMCR	Keurig Green Mountain	JAB Holding Company acquired Keurig Green Mountain
2016-03-30	HOLX	Hologic	POM	Pepco Holdings	Exelon acquired Pepco.
2016-03-30	CNC	Centene Corporation	ESV	Ensco	Centene acquired Health Net.
2016-04-04	FL	Foot Locker	CAM	Cameron International	Schlumberger acquired Cameron
2016-04-08	UA	Under Armour (Class C)			Under Armour distribution of second class of stock
2016-04-18	ULTA	Ulta Beauty	THC	Tenet Healthcare	Ulta replaces Tenet
2016-04-25	GPN	Global Payments	GME	GameStop	Global Payments is acquiring Heartland Payment Systems
2016-05-03	AYI	Acuity Brands	ADT	ADT	ADT acquired by APO
2016-05-13	ALK	Alaska Air Group	SNDK	SanDisk	SNDK acquired by WDC
2016-05-18	DLR	Digital Realty	TWC	Time Warner Cable	TWC acquired by CHTR
2016-05-23	LKQ	LKQ Corporation	ARG	Airgas	ARG acquired by Air Liquide
2016-05-31	AJG	Arthur J. Gallagher & Co.	CCE	Coca-Cola Enterprises	CCE merging with European bottlers
2016-06-03	TDG	TransDigm Group	BXLT	Baxalta	SHPG acquiring BXLT
2016-06-22	FBHS	Fortune Brands Home & Security	CVC	Cablevision Systems	CVC acquired by Altice NV
2016-07-01	LNT	Alliant Energy Corp	GAS	AGL Resources	GAS acquired by SO
2016-07-01	ALB	Albemarle Corporation	TE	TECO Energy	TE acquired by EMA
2016-07-05	FTV	Fortive Corp	CPGX	Columbia Pipeline Group	CPGX acquired by TRP
2016-08-06	MTD	Mfettler Toledo	TYC	Tyco International	TYC acquires JCI (and retains JCI ticker).

Appendix F S&P 500 index companies' list

Date	Added		Removed		Reason
	Ticker	Security	Ticker	Security	
2016-09-08	CHTR	Charter Communications	EMC	EMC Corporation	Dell acquires EMC
2016-09-22	COO	The Cooper Companies	HOT	Starwood	MAR acquires HOT
2016-09-30	COTY	Coty Inc	DO	Diamond Offshore Drilling	COTY replaces DO
2016-11-01	ARNC	Arconic Inc	AA	Alcoa Inc	AA spins off ARNC
2016-12-02	MAA	Mid-America Apartments	OI	Owens-Illinois	Market capitalization changes
2016-12-02	EVHC	Envision Healthcare	LM	Legg Mason	Market capitalization changes
2017-01-05	IDXX	Idexx Laboratories	STJ	St Jude Medical	S&P 100 & 500 constituent Abbott Laboratories (NYSE:ABT) acquired St. Jude Medical.
2017-02-28	INCY	Incyte	SE	Spectra Energy	SE acquired by ENB
2017-03-01	CBOE	Cboe Holdings	PBI	Pitney Bowes	CBOE acquires BATS
2017-03-02	REG	Regency Centers	ENDP	Endo International	REG acquires EQY
2017-03-13	DISH	Dish Network	LLTC	Linear Technology	S&P 500 constituent Analog Devices (NASD:ADI) acquired Linear Technology.
2017-03-16	SNPS	Synopsys	HAR	Harman International	Samsung Electronics acquired Harman International Industries.
2017-03-20	AMD	Advanced Micro Devices	URBN	Urban Outfitters	Market capitalization changes.
2017-03-20	RJF	Raymond James Financial	FTR	Frontier Communications	Market capitalization changes.
2017-03-20	ARE	Alexandria Real Estate Equities	FSLR	First Solar	Market capitalization changes.
2017-04-04	DXC	DXC Technology	SWN	Southwestern Energy	HPE spins off Everett, merged with CSC to form DXC
2017-04-05	IT	Gartner	DNB	Dun & Bradstreet	IT acquiring CEB
2017-06-02	INFO	IHS Markit	TGNA	Tegna	TGNA spins off Cars.com
2017-06-19	HLT	Hilton	YHOO	Yahoo!	VZ acquired YHOO operations; remainder of YHOO converted to closed-end company known as Altaba.
2017-06-19	ALGN	Align Technology	TDC	Teradata	Market capitalization changes.
2017-06-19	ANSS	Ansys	R	Ryder System	Market capitalization changes.
2017-06-19	RE	Everest Re	MJN	Mead Johnson	Reckitt Benckiser acquired Mead Johnson Nutrition.
2017-07-26	DRE	Duke Realty Corp	RIG	Transocean	Market capitalization change.
2017-07-26	AOS	A. O. Smith	BBBY	Bed Bath & Beyond	Market capitalization change.
2017-07-26	PKG	Packaging Corporation of America	MUR	Murphy Oil	Market capitalization change.

Appendix F S&P 500 index companies' list

Date	Added		Removed		Reason
	Ticker	Security	Ticker	Security	
2017-07-26	RMD	ResMed	MNK	Mallinckrodt	Market capitalization change.
2017-07-26	MGM	MGM Resorts International	RAI	Reynolds American	British American Tobacco (NYSE MKT:BTI) acquired Reynolds American.
2017-08-08	BHF	Brighthouse Financial	AN	AutoNation	BHF replaced AN,[72] MET spun off BHF
2017-08-29	Q	QuintilesIMS	WFM	Whole Foods Market	Amazon acquired Whole Foods Market.
2017-09-01	DWDP	DuPont	DOW	Dow Chemical Company	The Dow Chemical Company renamed to DowDuPont Inc. and ticker changed from DOW to DWDP after acquiring DuPont.
2017-09-01	SBAC	SBA Communications	DD	DuPont	The Dow Chemical Company acquired DuPont.
2017-09-18	CDNS	Cadence Design Systems	SPLS	Staples	Sycamore Partners acquired Staples.
2017-10-13	NCLH	Norwegian Cruise Line Holdings	LVL	Level 3 Communications	CenturyLink acquired LVL.
2018-01-03	HII	Huntington Ingalls Industries	BCR	CR Bard	Becton Dickinson acquired BCR.
2018-03-07	IPGP	IPG Photonics	SNI	Scripps Networks Interactive	Discovery Communications acquired SNI.
2018-03-19	TTWO	Take-Two Interactive	SIG	Signet Jewelers	Market capitalization change.
2018-03-19	SIVB	SVB Financial	PDCO	Patterson Companies	Market capitalization change.
2018-03-19	NKTR	Nektar Therapeutics	CHK	Chesapeake Energy	Market capitalization change.
2018-04-04	MSCI	MSCI	CSRA	CSRA	S&P 500 constituent General Dynamics (NYSE: GD) acquired CSRA.
2018-05-31	ABMD	Abiomed	WYN	Wyndham Worldwide	Wyndham Worldwide spun off Wyndham Hotels & Resorts (NYSE:WH).
2018-06-05	EVRG	Evergy	NAVI	Navient	Westar Energy (NYSE: WR) acquired Great Plains Energy (NYSE: GXP) and changed name to Evergy.
2018-06-07	TWTR	Twitter	MON	Monsanto	Bayer acquired Monsanto.
2018-06-18	BR	Broadridge Financial Solutions	RRC	Range Resources	Market capitalization change.
2018-06-18	HFC	HollyFrontier	AYI	Acuity Brands	Market capitalization change.
2018-06-20	FLT	FleetCor Technologies	TWX	Time Warner	AT&T acquired Time Warner.
2018-07-02	CPRT	Copart	DPS	Dr Pepper Snapple Group	DPS acquired by Keurig Green Mountain.
2018-08-28	ANET	Arista Networks	GGP	GGP	GGP acquired by Brookfield Property Partners.
2018-09-14	WCG	WellCare	XL	XL Group	XL acquired by AXA.
2018-10-01	ROL	Rollins Inc	ANDV	Andeavor	ANDV acquired by Marathon Petroleum.
2018-10-11	FTNT	Fortinet	EVHC	Envision Healthcare	EVHC acquired by KKR.
2018-11-06	KEYS	Keysight	CA	CA Technologies	CA acquired by Broadcom.

Appendix F S&P 500 index companies' list

Date	Added		Removed		Reason
	Ticker	Security	Ticker	Security	
2018-11-13	JKHY	Jack Henry & Associates	EQT	EQT	EQT spun off ETRN
2018-12-03	LW	Lamb Weston	COL	Rockwell Collins	UTX acquired COL
2018-12-03	MXIM	Maxim Integrated	AET	Aetna	CVS acquired Aetna
2018-12-03	FANG	Diamondback Energy	SRCL	Stericycle	Market Capitalization change
2018-12-24	CE	Celanese	ESRX	Express Scripts	S&P 500 constituent Cigna (NYSE: CI) acquired ESRX
2019-01-02	FRC	First Republic Bank	SCG	SCANA	Dominion Energy acquired SCANA Corporation
2019-01-18	TFX	Teleflex	PCG	Pacific Gas & Electric Company	PCG filed for bankruptcy
2019-02-15	ATO	Atmos Energy	NFX	Newfield Exploration	ECA acquired NFX
2019-02-27	WAB	Wabtec	GT	The Goodyear Tire & Rubber Company	WAB acquired GE transportation business
2019-04-02	DOW	Dow Inc	BHF	Brighthouse Financial	DOW spun off from DWDP
2019-06-03	DD	DuPont	DWDP	DuPont	DWDP changed to DD after spinning off Corteva.
2019-06-03	CTVA	Corteva	FLR	Fluor Corporation	CTVA spun off from DWDP (which then changed symbol to DD)
2019-06-07	AMCR	Amcor	MAT	Mattel	Bemis merged with Amcor; subsequently renamed to Amcor
2019-07-01	MKTX	MarketAxess	LLL	L3 Technologies	L3 purchased by Harris Corporation
2019-07-15	TMUS	T-Mobile US	RHT	Red Hat	S&P 500 & 100 constituent IBM acquired Red Hat.
2019-08-09	LDOS	Leidos	APC	Anadarko Petroleum	S&P 500 & 100 constituent Occidental Petroleum Corp. (NYSE:OXY) acquired Anadarko Petroleum.
2019-08-09	IEX	IDEX Corporation	FL	Foot Locker	Market capitalization change.
2019-09-23	CDW	CDW	TSS	TSYS	S&P 500 constituent Global Payments (NYSE: GPN) acquired TSS.
2019-09-26	NVR	NVR Inc	JEF	Jefferies Financial Group	JEF spun off SPB.
2019-10-03	LVS	Las Vegas Sands	NKTR	Nektar Therapeutics	Market capitalization change.
2019-12-05	WRB	W. R. Berkley Corporation	VIAB	Viacom	CBS acquired Viacom to form ViacomCBS.
2019-12-09	ODFL	Old Dominion Freight Line	STI	SunTrust Banks	BB&T acquired SunTrust to form Truist Financial.
2019-12-21	NOW	ServiceNow	CELG	Celgene	Bristol-Myers Squibb (NYSE:BMJ) acquired Celgene.
2019-12-23	LYV	Live Nation Entertainment	AMG	Affiliated Managers Group	Market capitalization change.
2019-12-23	ZBRA	Zebra Technologies	TRIP	TripAdvisor	Market capitalization change.
2019-12-23	STE	Steris	MAC	Macerich	Market capitalization change.

Appendix F S&P 500 index companies' list

Date	Added		Removed		Reason
	Ticker	Security	Ticker	Security	
2020-01-28	PAYC	Paycom	WCG	WellCare	S&P 500 constituent Centene Corp. (NYSE: CNC) acquired Wellcare Health Plans.
2020-03-02	IR	Ingersoll Rand	XEC	Cimarex Energy	Gardner Denver acquired Ingersoll Rand's industrial businesses then changed its name to the "new" Ingersoll Rand Inc.
2020-04-01	HWM	Howmet Aerospace	ARNC	Arconic	Arconic separated into 2 companies - Howmet remained on the index.
2020-04-03	OTIS	Otis Worldwide			United Technologies spun off Otis and Carrier and acquired Raytheon Company.
2020-04-03	CARR	Carrier			United Technologies spun off Otis and Carrier and acquired Raytheon Company.
2020-04-06			M	Macy's	Market capitalization change.
2020-04-06			RTN	Raytheon Company	United Technologies spun off Otis and Carrier and acquired Raytheon Company.
2020-05-12	DPZ	Domino's Pizza	CPRI	Capri Holdings	Market capitalization change.
2020-05-12	DXCM	Dexcom	AGN	Allergan	Allergan acquired by AbbVie.
2020-05-22	WST	West Pharmaceutical Services	HP	Helmerich & Payne	Market capitalization change.
2020-06-22	BIO	Bio-Rad Laboratories	ADS	Alliance Data Systems	Market capitalization change.
2020-06-22	TDY	Teledyne	HOG	Harley-Davidson	Market capitalization change.
2020-06-22	TYL	Tyler Technologies	JWN	Nordstrom	Market capitalization change.
2020-09-21	ETSY	Etsy	HRB	H&R Block	Market capitalization change.
2020-09-21	TER	Teradyne	COTY	Coty	Market capitalization change.
2020-09-21	CTLT	Catalent	KSS	Kohl's	Market capitalization change.
2020-10-07	POOL	Pool Corporation	ETFC	E-Trade	Morgan Stanley acquired E*Trade.
2020-10-09	VNT	Vontier			S&P 500 constituent Fortive spun off Vontier.
2020-10-12			NBL	Noble Energy	Chevron acquired Noble Energy.
2020-12-21	TSLA	Tesla Inc	AIV	Apartment Investment & Management	Apartment Investment and Management (Aimco) spun off Apartment Income REIT.

Table F - 2 : The companies listed on S&P 500 index in 2016

No.	Symbol	Security	Sector	Date first added	Date removed
1	MMM	3M	Industrials	1976-08-09	
2	ABT	Abbott Laboratories	Healthcare	1964-03-31	
3	ABBV	AbbVie	Healthcare	2012-12-31	
4	ACN	Accenture	Information Technology	2011-07-06	
5	ATVI	Activision Blizzard	Communication Services	2015-08-31	
6	AYI*	Acuity Brands	Industrials	2016-05-03	
7	ADM	ADM	Consumer Staples	1981-07-29	
8	ADBE	Adobe	Information Technology	1997-05-05	
9	ADT	ADT	Industrials	N/A	2016-05-03
10	AAP	Advance Auto Parts	Consumer Discretionary	2015-07-09	
11	AES	AES Corp	Utilities	1998-10-02	
12	AET	Aetna	Healthcare	N/A	
13	AMG	Affiliated Managers Group	Financials	N/A	
14	AFL	Aflac	Financials	1999-05-28	
15	A	Agilent Technologies	Healthcare	2000-06-05	
16	GAS	AGL Resources	Utilities	N/A	2016-07-01
17	APD	Air Products & Chemicals	Materials	1985-04-30	
18	ARG	Airgas	Materials	N/A	2016-05-23
19	AKAM	Akamai Technologies	Information Technology	2007-07-12	
20	ALK*	Alaska Air Group	Industrials	2016-05-13	
21	ALB*	Albemarle Corporation	Materials	2016-07-01	
22	AA	Alcoa Inc	Materials	N/A	2016-11-01
23	ALLE	Allegion	Industrials	2013-12-02	
24	AGN	Allergan	Healthcare	N/A	
25	ADS	Alliance Data Systems	Financials	N/A	
26	LNT*	Alliant Energy	Utilities	2016-07-01	
27	ALL	Allstate Corp	Financials	1995-07-13	
28	GOOGL	Alphabet (Class A)	Communication Services	2014-04-03	
29	GOOG	Alphabet (Class C)	Communication Services	2006-04-03	
30	MO	Altria Group	Consumer Staples	1957-03-04	
31	AMZN	Amazon	Consumer Discretionary	2005-11-18	
32	AEE	Ameren Corp	Utilities	1991-09-19	
33	AAL	American Airlines Group	Industrials	2015-03-23	
34	AEP	American Electric Power	Utilities	1957-03-04	
35	AXP	American Express	Financials	1976-06-30	
36	AIG	American International Group	Financials	1980-03-31	
37	AMT	American Tower	Real Estate	2007-11-19	
38	AWK*	American Water Works	Utilities	2016-03-04	
39	AMP	Ameriprise Financial	Financials	2005-10-03	
40	ABC	AmerisourceBergen	Healthcare	2001-08-30	
41	AME	Ametek	Industrials	2013-09-23	
42	AMGN	Amgen	Healthcare	1992-01-02	
43	APH	Amphenol Corp	Information Technology	2008-09-30	
44	APC	Anadarko Petroleum	Healthcare	N/A	

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No.	Symbol	Security	Sector	Date first added	Date removed
45	ADI	Analog Devices	Information Technology	1999-10-12	
46	ANDV	Andeavor	Energy	N/A	
47	ANTM	Anthem	Healthcare	2002-07-25	
48	AON	Aon	Financials	1996-04-23	
49	APA	APA Corporation	Energy	1997-07-28	
50	AIV	Apartment Investment & Management	Real Estate	N/A	
51	AAPL	Apple	Information Technology	1982-11-30	
52	AMAT	Applied Materials	Information Technology	1995-03-16	
53	APTV	Aptiv	Consumer Discretionary	2012-12-24	
54	ARNC*	Arconic	Industrials	N/A	
55	AIG*	Arthur J. Gallagher & Co.	Financials	2016-05-31	
56	AIZ	Assurant	Financials	2007-04-10	
57	T	AT&T	Communication Services	1983-11-30 (1957-03-04)	
58	ADSK	Autodesk	Information Technology	1989-12-01	
59	ADP	Automatic Data Processing	Information Technology	1981-03-31	
60	AN	AutoNation	Consumer Cyclical	N/A	2017-08-08
61	AZO	AutoZone	Consumer Discretionary	1997-01-02	
62	AVB	AvalonBay Communities	Real Estate	2007-01-10	
63	AVY	Avery Dennison	Materials	1987-12-31	
64	BKR	Baker Hughes	Energy	2017-07-07	
65	BLL	Ball Corp	Materials	1984-10-31	
66	BAC	Bank of America	Financials	1976-06-30	
67	BBWI	Bath & Body Works, Inc.	Consumer Discretionary	1983-09-30	
68	BXLT	Baxalta	Healthcare	N/A	2016-06-03
69	BAX	Baxter International	Healthcare	1972-09-30	
70	BDX	Becton Dickinson	Healthcare	1972-09-30	
71	BBBY	Bed Bath & Beyond	Consumer Cyclical	N/A	2017-07-26
72	BRK.B	Berkshire Hathaway	Financials	2010-02-16	
73	BBY	Best Buy	Consumer Discretionary	1999-06-29	
74	BIIB	Biogen	Healthcare	2003-11-13	
75	TECH	Bio-Techne	Healthcare	2021-08-30	
76	BLK	BlackRock	Financials	2011-04-04	
77	BK	BNY Mellon	Financials	1995-03-31	
78	BA	Boeing Company	Industrials	1957-03-04	
79	BKNG	Booking Holdings	Consumer Discretionary	2009-11-06	
80	BWA	BorgWarner	Consumer Discretionary	2011-12-19	
81	BXP	Boston Properties	Real Estate	2006-04-03	
82	BSX	Boston Scientific	Healthcare	1995-02-24	
83	BMJ	Bristol-Myers Squibb	Healthcare	1957-03-04	
84	AVGO	Broadcom	Information Technology	2014-05-08	
85	BRCM	Broadcom Corporation	Information Technology	N/A	2016-02-01
86	BF.B	Brown–Forman	Consumer Staples	1982-10-31	
87	CHRW	C. H. Robinson	Industrials	2007-03-02	
88	CA	CA Technologies	Information Technology	N/A	
89	CVC	Cablevision Systems	Communication Services	N/A	2016-06-22
90	COG	Cabot Oil & Gas	Energy	2008-06-23	

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No.	Symbol	Security	Sector	Date first added	Date removed
91	CAM	Cameron International	Energy	N/A	2016-04-04
92	CPB	Campbell Soup	Consumer Staples	1957-03-04	
93	COF	Capital One Financial	Financials	1998-07-01	
94	CPRI	Capri Holdings	Consumer Cyclical	N/A	
95	CAH	Cardinal Health	Healthcare	1997-05-27	
96	KMX	CarMax	Consumer Discretionary	2010-06-28	
97	CCL	Carnival Corporation	Consumer Discretionary	1998-12-22	
98	CTLT	Catalent	Healthcare	2020-09-21	
99	CAT	Caterpillar	Industrials	1957-03-04	
100	CBRE	CBRE	Real Estate	2006-11-10	
101	CELG	Celgene	Healthcare	N/A	
102	CNC*	Centene Corporation	Healthcare	2016-03-30	
103	CNP	CenterPoint Energy	Utilities	1985-07-31	
104	CERN	Cerner	Healthcare	2010-04-30	
105	CF	CF Industries	Materials	2008-08-27	
106	SCHW	Charles Schwab Corporation	Financials	1997-06-02	
107	CHTR*	Charter Communications	Communication Services	2016-09-08	
108	CHK	Chesapeake Energy	Energy	N/A	
109	CVX	Chevron Corporation	Energy	1957-03-04	
110	CMG	Chipotle Mexican Grill	Consumer Discretionary	2011-04-28	
111	CB	Chubb	Financials	2010-07-15	
112	ACE	Chubb	Financials	N/A	2016-01-19
113	CHD	Church & Dwight	Consumer Staples	2015-12-29	
114	CI	Cigna	Healthcare	1976-06-30	
115	XEC	Cimarex Energy	Energy	N/A	
116	CINF	Cincinnati Financial	Financials	1997-12-18	
117	CTAS	Cintas Corporation	Industrials	2001-03-01	
118	CSCO	Cisco Systems	Information Technology	1993-12-01	
119	C	Citigroup	Financials	1988-05-31	
120	CFG*	Citizens Financial Group	Financials	2016-01-29	
121	CTXS	Citrix Systems	Information Technology	1999-12-01	
122	CLX	Clorox	Consumer Staples	1969-03-31	
123	CME	CME Group	Financials	2006-08-11	
124	CMS	CMS Energy	Utilities	1999-05-03	
125	KO	Coca-Cola Company	Consumer Staples	1957-03-04	
126	CCE	Coca-Cola Enterprises	Consumer Staples	N/A	2016-05-31
127	CTSH	Cognizant Technology Solutions	Information Technology	2006-11-17	
128	CL	Colgate-Palmolive	Consumer Staples	1957-03-04	
129	CPGX	Columbia Pipeline Group	Industrials	N/A	2016-07-05
130	CMCSA	Comcast	Communication Services	2002-11-19	
131	CMA	Comerica	Financials	1995-12-01	
132	CAG	Conagra Brands	Consumer Staples	1983-08-31	
133	CXO*	Concho Resources	Energy	2016-02-22	
134	COP	ConocoPhillips	Energy	1957-03-04	
135	CNX	Consol Energy	Energy	N/A	2016-03-04
136	ED	Consolidated Edison	Utilities	N/A	

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No.	Symbol	Security	Sector	Date first added	Date removed
137	STZ	Constellation Brands	Consumer Staples	2005-07-01	
138	GLW	Corning	Information Technology	N/A	
139	COST	Costco	Consumer Staples	1993-10-01	
140	COTY*	Coty	Consumer Defensive	2016-09-30	
141	BCR	CR Bard	Healthcare	N/A	
142	CCI	Crown Castle	Real Estate	2012-03-14	
143	CSRA	CSRA	Information Technology	N/A	
144	CSX	CSX	Industrials	1967-09-30	
145	CMI	Cummins	Industrials	1965-03-31	
146	CVS	CVS Health	Healthcare	1957-03-04	
147	DHI	D. R. Horton	Consumer Discretionary	2005-06-22	
148	DHR	Danaher Corporation	Healthcare	N/A	
149	DRI	Darden Restaurants	Consumer Discretionary	N/A	
150	DVA	DaVita	Healthcare	2008-07-31	
151	DE	Deere & Co.	Industrials	1957-03-04	
152	DAL	Delta Air Lines	Industrials	2013-09-11	
153	XRAY	Dentsply Sirona	Healthcare	2008-11-14	
154	DVN	Devon Energy	Energy	2000-08-30	
155	DO	Diamond Offshore Drilling	Energy	N/A	2016-09-30
156	DLR*	Digital Realty Trust	Real Estate	2016-05-18	
157	DFS	Discover Financial Services	Financials	2007-07-02	
158	DISCA	Discovery (Series A)	Communication Services	2010-03-01	
159	DISCK	Discovery (Series C)	Communication Services	2014-08-07	
160	DG	Dollar General	Consumer Discretionary	2012-12-03	
161	DLTR	Dollar Tree	Consumer Discretionary	2011-12-19	
162	D	Dominion Energy	Utilities	N/A	
163	DOV	Dover Corporation	Industrials	1985-10-31	
164	DOW	Dow Chemical Company	Materials	N/A	2017-09-01
165	DPS	Dr Pepper Snapple Group	Consumer Staples	N/A	
166	DTE	DTE Energy	Utilities	1957-03-04	
167	DUK	Duke Energy	Utilities	1976-06-30	
168	DNB	Dun & Bradstreet	Financials	N/A	2017-04-05
169	DD	DuPont	Materials	N/A	2017-09-01
170	EMN	Eastman Chemical	Materials	1994-01-01	
171	ETN	Eaton Corporation	Industrials	N/A	
172	EBAY	eBay	Consumer Discretionary	2002-07-22	
173	ECL	Ecolab	Materials	1989-01-31	
174	EIX	Edison International	Utilities	1957-03-04	
175	EW	Edwards Lifesciences	Healthcare	2011-04-01	
176	EA	Electronic Arts	Communication Services	2002-07-22	
177	LLY	Eli Lilly & Co	Healthcare	1970-12-31	
178	EMC	EMC Corporation	Information Technology	N/A	2016-09-08
179	EMR	Emerson Electric Company	Industrials	1965-03-31	
180	ENDP	Endo International	Healthcare	N/A	2017-03-02
181	ESV	Ensco	Energy	N/A	2016-03-30
182	ETR	Entergy	Utilities	1957-03-04	

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No.	Symbol	Security	Sector	Date first added	Date removed
183	EVHC*	Envision Healthcare	Healthcare	N/A	
184	EOG	EOG Resources	Energy	2000-11-02	
185	EQT	EQT	Energy	N/A	
186	EFX	Equifax	Industrials	1997-06-19	
187	EQIX	Equinix	Real Estate	2015-03-20	
188	EQR	Equity Residential	Real Estate	2001-12-03	
189	ESS	Essex Property Trust	Real Estate	2014-04-02	
190	EL	Estée Lauder Companies	Consumer Staples	2006-01-05	
191	ETFC	E-Trade	Financials	N/A	
192	ES	Eversource Energy	Utilities	N/A	
193	EXC	Exelon	Utilities	1957-03-04	
194	EXPE	Expedia Group	Consumer Discretionary	2007-10-02	
195	EXPD	Expeditors	Industrials	2007-10-10	
196	ESRX	Express Scripts	Healthcare	N/A	
197	EXR*	Extra Space Storage	Real Estate	2016-01-19	
198	XOM	ExxonMobil	Energy	1957-03-04	
199	FFIV	F5 Networks	Information Technology	2010-12-20	
200	FB	Facebook	Communication Services	2013-12-23	
201	FAST	Fastenal	Industrials	2008-09-15	
202	FRT*	Federal Realty Investment Trust	Real Estate	2016-02-01	
203	FDX	FedEx	Industrials	1980-12-31	
204	FIS	Fidelity National Information Services	Information Technology	2006-11-10	
205	FITB	Fifth Third Bancorp	Financials	N/A	
206	FSLR	First Solar	Information Technology	N/A	2017-03-20
207	FE	FirstEnergy	Utilities	N/A	
208	FISV	Fiserv	Information Technology	2001-04-02	
209	FLR	Fluor Corporation	Industrials	N/A	
210	FMC	FMC Corporation	Materials	2009-08-19	
211	FL*	Foot Locker	Consumer Cyclical	2016-04-04	
212	F	Ford	Consumer Discretionary	1957-03-04	
213	FTV*	Fortive	Industrials	2016-07-01	
214	FBHS*	Fortune Brands Home & Security	Industrials	2016-06-22	
215	FOSL	Fossil Group	Consumer Cyclical	N/A	2016-01-05
216	FOXA	Fox Corporation (Class A)	Communication Services	2013-07-01	
217	FOX	Fox Corporation (Class B)	Communication Services	2015-09-18	
218	BEN	Franklin Resources	Financials	N/A	
219	FCX	Freeport-McMoRan	Materials	N/A	
220	FTR	Frontier Communications	Communication Services	N/A	2017-03-20
221	GME	GameStop	Consumer Cyclical	N/A	2016-04-25
222	GPS	Gap	Consumer Discretionary	1986-08-31	
223	GRMN	Garmin	Consumer Discretionary	2012-12-12	
224	GD	General Dynamics	Industrials	1957-03-04	
225	GE	General Electric	Industrials	N/A	
226	GIS	General Mills	Consumer Staples	1969-03-31	
227	GM	General Motors	Consumer Discretionary	2013-06-06	
228	GPC	Genuine Parts	Consumer Discretionary	1973-12-31	

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No.	Symbol	Security	Sector	Date first added	Date removed
229	GGP	GGP	Materials	N/A	
230	GILD	Gilead Sciences	Healthcare	2004-07-01	
231	GPN*	Global Payments	Information Technology	2016-04-25	
232	GL	Globe Life	Financials	1989-04-30	
233	GS	Goldman Sachs	Financials	2002-07-22	
234	HRB	H&R Block	Consumer Cyclical	N/A	
235	HAL	Halliburton	Energy	1957-03-04	
236	HBI	Hanesbrands	Consumer Discretionary	2015-03-20	
237	HOG	Harley-Davidson	Consumer Cyclical	N/A	
238	HAR	Harman International	Information Technology	N/A	2017-03-16
239	HAS	Hasbro	Consumer Discretionary	1984-09-30	
240	HCA	HCA Healthcare	Healthcare	2015-01-27	
241	PEAK	Healthpeak Properties	Real Estate	2008-03-31	
242	HP	Helmerich & Payne	Energy	N/A	
243	HSIC	Henry Schein	Healthcare	2015-03-17	
244	HES	Hess Corporation	Energy	1984-05-31	
245	HPE	Hewlett Packard Enterprise	Information Technology	2015-11-02	
246	HOLX*	Hologic	Healthcare	2016-03-30	
247	HD	Home Depot	Consumer Discretionary	1988-03-31	
248	HON	Honeywell	Industrials	1964-03-31	
249	HRL	Hormel	Consumer Staples	2009-03-04	
250	HST	Host Hotels & Resorts	Real Estate	2007-03-20	
251	HWM	Howmet Aerospace	Industrials	1964-03-31	
252	HPQ	HP	Information Technology	1974-12-31	
253	HUM	Humana	Healthcare	N/A	
254	HBAN	Huntington Bancshares	Financials	N/A	
255	IBM	IBM	Information Technology	1957-03-04	
256	ITW	Illinois Tool Works	Industrials	1986-02-28	
257	ILMN	Illumina	Healthcare	2015-11-19	
258	INTC	Intel	Information Technology	1976-12-31	
259	ICE	Intercontinental Exchange	Financials	2007-09-26	
260	IFF	International Flavors & Fragrances	Materials	1976-03-31	
261	IP	International Paper	Materials	1957-03-04	
262	IPG	Interpublic Group	Communication Services	1992-10-01	
263	INTU	Intuit	Information Technology	2000-12-05	
264	ISRG	Intuitive Surgical	Healthcare	2008-06-02	
265	IVZ	Invesco	Financials	2008-08-21	
266	IQV	IQVIA	Healthcare	2017-08-29	
267	IRM	Iron Mountain	Real Estate	2009-01-06	
268	JBHT	J. B. Hunt	Industrials	2015-07-01	
269	J	Jacobs Engineering Group	Industrials	2007-10-26	
270	JEF	Jefferies Financial Group	Financials	N/A	
271	SJM	JM Smucker	Consumer Staples	2008-11-06	
272	JNJ	Johnson & Johnson	Healthcare	1973-06-30	
273	JCI	Johnson Controls	Industrials	2010-08-27	
274	JPM	JPMorgan Chase	Financials	1975-06-30	

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No.	Symbol	Security	Sector	Date first added	Date removed
275	JNPR	Juniper Networks	Information Technology	2006-06-02	
276	KSU	Kansas City Southern	Industrials	2013-05-24	
277	K	Kellogg's	Consumer Staples	1989-09-11	
278	GMCR	Keurig Green Mountain	Consumer Staples	N/A	2016-03-07
279	KEY	KeyCorp	Financials	1994-03-01	
280	KMB	Kimberly-Clark	Consumer Staples	1957-03-04	
281	KIM	Kimco Realty	Real Estate	2006-04-04	
282	KMI	Kinder Morgan	Energy	2012-05-25	
283	KLAC	KLA Corporation	Information Technology	N/A	
284	KSS	Kohl's	Consumer Cyclical	N/A	
285	KHC	Kraft Heinz	Consumer Staples	2015-07-06	
286	KR	Kroger	Consumer Staples	1957-03-04	
287	LLL	L3 Technologies	Information Technology	N/A	
288	LHX	L3Harris Technologies	Industrials	2008-09-22	
289	LH	LabCorp	Healthcare	2004-11-01	
290	LRCX	Lam Research	Information Technology	2012-06-29	
291	LM	Legg Mason	Financials	N/A	2016-12-02
292	LEG	Leggett & Platt	Consumer Discretionary	1999-10-14	
293	LEN	Lennar	Consumer Discretionary	2005-10-04	
294	LVT	Level 3 Communications	Communication Services	N/A	2017-10-13
295	LNC	Lincoln National	Financials	1976-06-30	
296	LIN	Linde	Materials	1992-07-01	
297	LLTC	Linear Technology	Information Technology	N/A	2017-03-13
298	LKQ*	LKQ Corporation	Consumer Discretionary	2016-05-23	
299	LMT	Lockheed Martin	Industrials	1984-07-31	
300	L	Loews Corporation	Financials	N/A	
301	LOW	Lowe's	Consumer Discretionary	1984-02-29	
302	LUMN	Lumen Technologies	Communication Services	1999-03-25	
303	LYB	LyondellBasell	Materials	2012-09-05	
304	MTB	M&T Bank	Financials	2004-02-23	
305	MAC	Macerich	Real Estate	N/A	
306	M	Macy's	Consumer Cyclical	N/A	
307	MNK	Mallinckrodt	Healthcare	N/A	2017-07-26
308	MRO	Marathon Oil	Energy	1991-05-01	
309	MPC	Marathon Petroleum	Energy	2011-07-01	
310	MAR	Marriott International	Consumer Discretionary	N/A	
311	MMC	Marsh & McLennan	Financials	1987-08-31	
312	MLM	Martin Marietta Materials	Materials	2014-07-02	
313	MAS	Masco	Industrials	1981-06-30	
314	MA	Mastercard	Information Technology	2008-07-18	
315	MAT	Mattel	Consumer Cyclical	N/A	
316	MKC	McCormick & Company	Consumer Staples	2003-03-20	
317	MCD	McDonald's	Consumer Discretionary	1970-06-30	
318	MCK	McKesson Corporation	Healthcare	N/A	
319	MJN	Mead Johnson	Consumer Staples	N/A	2017-06-19
320	MDT	Medtronic	Healthcare	1986-10-31	

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No.	Symbol	Security	Sector	Date first added	Date removed
321	MRK	Merck & Co.	Healthcare	1957-03-04	
322	MET	MetLife	Financials	N/A	
323	MTD*	Mettler Toledo	Healthcare	2016-09-06	
324	MCHP	Microchip Technology	Information Technology	2007-09-07	
325	MU	Micron Technology	Information Technology	1994-09-27	
326	MSFT	Microsoft	Information Technology	1994-06-01	
327	MAA*	Mid-America Apartments	Real Estate	2016-12-02	
328	MHK	Mohawk Industries	Consumer Discretionary	2013-12-23	
329	TAP	Molson Coors Beverage Company	Consumer Staples	1976-06-30	
330	MDLZ	Mondelez International	Consumer Staples	2012-10-02	
331	MON	Monsanto	Materials	N/A	
332	MNST	Monster Beverage	Consumer Staples	2012-06-28	
333	MCO	Moody's Corporation	Financials	N/A	
334	MS	Morgan Stanley	Financials	N/A	
335	MSI	Motorola Solutions	Information Technology	N/A	
336	MUR	Murphy Oil	Energy	N/A	2017-07-26
337	NDAQ	Nasdaq	Financials	2008-10-22	
338	NAVI	Navient	Financials	N/A	
339	NTAP	NetApp	Information Technology	1999-06-25	
340	NFLX	Netflix	Communication Services	2010-12-20	
341	NWL	Newell Brands	Consumer Discretionary	1989-04-30	
342	NFX	Newfield Exploration	Energy	N/A	
343	NEM	Newmont	Materials	1969-06-30	
344	NWSA	News Corp (Class A)	Communication Services	2013-08-01	
345	NWS	News Corp (Class B)	Communication Services	2015-09-18	
346	NEE	NextEra Energy	Utilities	1976-06-30	
347	NLSN	Nielsen Holdings	Industrials	2013-07-09	
348	NKE	Nike	Consumer Discretionary	1988-11-30	
349	NI	NiSource	Utilities	N/A	
350	NBL	Noble Energy	Energy	N/A	
351	JWN	Nordstrom	Consumer Cyclical	N/A	
352	NSC	Norfolk Southern	Industrials	1957-03-04	
353	NTRS	Northern Trust	Financials	N/A	
354	NOC	Northrop Grumman	Industrials	1985-06-30	
355	NLOK	NortonLifeLock	Information Technology	2003-03-25	
356	NOV	Nov	Energy	2005-03-14	
357	NRG	NRG Energy	Utilities	2010-01-29	
358	NUE	Nucor	Materials	1985-04-30	
359	NVDA	Nvidia	Information Technology	2001-11-30	
360	OXY	Occidental Petroleum	Energy	1982-12-31	
361	OMC	Omnicom Group	Communication Services	N/A	
362	OKE	Oneok	Energy	2010-03-15	
363	ORCL	Oracle	Information Technology	1989-08-31	
364	ORLY	O'Reilly Automotive	Consumer Discretionary	2009-03-27	
365	OI	Owens-Illinois	Energy	N/A	2016-12-02
366	PCAR	Paccar	Industrials	1980-12-31	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
367	PCG	Pacific Gas & Electric Company	Energy	N/A	
368	PH	Parker-Hannifin	Industrials	1985-11-30	
369	PDCO	Patterson Companies	Healthcare	N/A	
370	PAYX	Paychex	Information Technology	N/A	
371	PYPL	PayPal	Information Technology	2015-07-20	
372	PNR	Pentair	Industrials	2012-10-01	
373	PBCT	People's United Financial	Financials	2008-11-13	
374	POM	Pepco Holdings	Utilities	N/A	2016-03-30
375	PEP	PepsiCo	Consumer Staples	1957-03-04	
376	PKI	PerkinElmer	Healthcare	1985-05-31	
377	PRGO	Perrigo	Healthcare	2011-12-19	
378	PFE	Pfizer	Healthcare	1957-03-04	
379	PM	Philip Morris International	Consumer Staples	2008-03-31	
380	PSX	Phillips 66	Energy	2012-05-01	
381	PNW	Pinnacle West Capital	Utilities	N/A	
382	PXD	Pioneer Natural Resources	Energy	2008-09-24	
383	PBI	Pitney Bowes	Industrials	N/A	2017-03-01
384	PCL	Plum Creek Timber	Financials	N/A	2016-02-22
385	PNC	PNC Financial Services	Financials	1988-04-30	
386	PPG	PPG Industries	Materials	1957-03-04	
387	PPL	PPL	Utilities	N/A	
388	PCP	Precision Castparts Corporation	Materials	N/A	2016-02-01
389	PFG	Principal Financial Group	Financials	2002-07-22	
390	PG	Procter & Gamble	Consumer Staples	1957-03-04	
391	PGR	Progressive Corporation	Financials	1997-08-04	
392	PLD	Prologis	Real Estate	2003-07-17	
393	PRU	Prudential Financial	Financials	2002-07-22	
394	PEG	Public Service Enterprise Group	Utilities	1957-03-04	
395	PSA	Public Storage	Real Estate	2005-08-19	
396	PHM	PulteGroup	Consumer Discretionary	1984-04-30	
397	PVH	PVH	Consumer Discretionary	2013-02-15	
398	QRVO	Qorvo	Information Technology	2015-06-11	
399	QCOM	Qualcomm	Information Technology	N/A	
400	PWR	Quanta Services	Industrials	2009-07-01	
401	DGX	Quest Diagnostics	Healthcare	2002-12-12	
402	RL	Ralph Lauren Corporation	Consumer Discretionary	2007-02-02	
403	RRC	Range Resources	Energy	N/A	
404	RTN	Raytheon Company	Industrials	N/A	
405	RTX	Raytheon Technologies	Industrials	N/A	
406	O	Realty Income Corporation	Real Estate	2015-04-07	
407	RHT	Red Hat	Information Technology	N/A	
408	REGN	Regeneron Pharmaceuticals	Healthcare	2013-05-01	
409	RF	Regions Financial Corporation	Financials	1998-08-28	
410	RSG	Republic Services	Industrials	2008-12-05	
411	RAI	Reynolds American	Consumer Staple	N/A	2017-07-26
412	RHI	Robert Half International	Industrials	2000-12-05	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
413	ROK	Rockwell Automation	Industrials	N/A	
414	COL	Rockwell Collins	Industrials	N/A	
415	ROP	Roper Technologies	Industrials	2009-12-23	
416	ROST	Ross Stores	Consumer Discretionary	2009-12-21	
417	RCL	Royal Caribbean Group	Consumer Discretionary	2014-12-05	
418	R	Ryder System	Industrials	N/A	2017-06-19
419	SPGI	S&P Global	Financials	N/A	
420	CRM	Salesforce	Information Technology	2008-09-15	
421	SNDK	SanDisk	Information Technology	N/A	2016-05-13
422	SCG	SCANA	Industrials	N/A	
423	SLB	Schlumberger	Energy	1965-03-31	
424	SNI	Scripps Networks Interactive	Communication Services	N/A	
425	STX	Seagate Technology	Information Technology	2012-07-02	
426	SEE	Sealed Air	Materials	1957-03-04	
427	SRE	Sempra Energy	Utilities	N/A	
428	SHW	Sherwin-Williams	Materials	1964-06-30	
429	SIG	Signet Jewelers	Consumer Cyclical	N/A	
430	SPG	Simon Property Group	Real Estate	2002-06-26	
431	SWKS	Skyworks Solutions	Information Technology	2015-03-12	
432	SNA	Snap-on	Industrials	1982-09-30	
433	SO	Southern Company	Utilities	1957-03-04	
434	LUV	Southwest Airlines	Industrials	1994-07-01	
435	SWN	Southwestern Energy	Energy	N/A	2017-04-04
436	SE	Spectra Energy	Energy	N/A	2017-02-28
437	STJ	St Jude Medical	Healthcare	N/A	2017-01-05
438	SWK	Stanley Black & Decker	Industrials	1982-09-30	
439	SPLS	Staples	Consumer Discretionary	N/A	2017-09-18
440	SBUX	Starbucks	Consumer Discretionary	N/A	
441	HOT	Starwood	Consumer Discretionary	N/A	2016-09-22
442	STT	State Street Corporation	Financials	N/A	
443	SRCL	Stericycle	Industrials	N/A	
444	SYK	Stryker Corporation	Healthcare	2000-12-12	
445	STI	SunTrust Banks	Financials	N/A	
446	SYF	Synchrony Financial	Financials	2015-11-18	
447	SYY	Sysco	Consumer Staples	1986-12-31	
448	TROW	T. Rowe Price	Financials	N/A	
449	TPR	Tapestry	Consumer Discretionary	N/A	
450	TGT	Target Corporation	Consumer Discretionary	1976-12-31	
451	TEL	TE Connectivity	Information Technology	2011-10-17	
452	TE	TECO Energy	Energy	N/A	2016-07-01
453	TGNA	Tegna	Communication Services	N/A	2017-06-02
454	THC	Tenet Healthcare	Healthcare	N/A	2016-04-18
455	TDC	Teradata	Information Technology	N/A	2017-06-19
456	TXN	Texas Instruments	Information Technology	N/A	
457	TXT	Textron	Industrials	1978-12-31	
458	COO*	The Cooper Companies	Healthcare	2016-09-23	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
459	GT	The Goodyear Tire & Rubber Company	Consumer Cyclical	N/A	
460	HIG	The Hartford	Financials	1957-03-04	
461	HSY	The Hershey Company	Consumer Staples	1957-03-04	
462	MOS	The Mosaic Company	Materials	2011-09-26	
463	TRV	The Travelers Companies	Financials	2002-08-21	
464	DIS	The Walt Disney Company	Communication Services	1976-06-30	
465	TMO	Thermo Fisher Scientific	Healthcare	2004-08-03	
466	TWX	Time Warner	Communication Services	N/A	
467	TWC	Time Warner Cable	Communication Services	N/A	2016-05-18
468	TJX	TJX Companies	Consumer Discretionary	1985-09-30	
469	TSCO	Tractor Supply Company	Consumer Discretionary	2014-01-24	
470	TT	Trane Technologies	Industrials	2010-11-17	
471	TDG*	TransDigm Group	Industrials	2016-06-03	
472	RIG	Transocean	Energy	N/A	2017-07-26
473	TRIP	TripAdvisor	Consumer Cyclical	N/A	
474	TFC	Truist Financial	Financials	1997-12-04	
475	TSS	TSYS	Information Technology	N/A	
476	TYC	Tyco International	Industrials	N/A	2016-08-06
477	TSN	Tyson Foods	Consumer Staples	2005-08-10	
478	USB	U.S. Bancorp	Financials	N/A	
479	UDR*	UDR	Real Estate	2016-03-07	
480	ULTA*	Ulta Beauty	Consumer Discretionary	2016-04-18	
481	UAA	Under Armour (Class A)	Consumer Discretionary	2014-05-01	
482	UA*	Under Armour (Class C)	Consumer Discretionary	2016-04-08	
483	UNP	Union Pacific	Industrials	1957-03-04	
484	UAL	United Airlines	Industrials	2015-09-03	
485	UPS	United Parcel Service	Industrials	2002-07-22	
486	URI	United Rentals	Industrials	2014-09-20	
487	UNH	UnitedHealth Group	Healthcare	1994-07-01	
488	UHS	Universal Health Services	Healthcare	2014-09-20	
489	UNM	Unum Group	Financials	1994-03-01	
490	URBN	Urban Outfitters	Consumer Cyclical	N/A	2017-03-20
491	VLO	Valero Energy	Energy	N/A	
492	VTR	Ventas	Real Estate	2009-03-04	
493	VRSN	Verisign	Information Technology	2006-02-01	
494	VRSK	Verisk Analytics	Industrials	2015-10-08	
495	VZ	Verizon Communications	Communication Services	1983-11-30	
496	VRTX	Vertex Pharmaceuticals	Healthcare	2013-09-23	
497	VFC	VF Corporation	Consumer Discretionary	1979-06-30	
498	VIAB	Viacom	Consumer Services	N/A	
499	VIAC	ViacomCBS	Communication Services	N/A	
500	VTRS	Viatis	Healthcare	2004-04-23	
501	V	Visa	Information Technology	2009-12-21	
502	VNO	Vornado Realty Trust	Real Estate	N/A	
503	VMC	Vulcan Materials	Materials	1999-06-30	
504	GWW	W. W. Grainger	Industrials	1981-06-30	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
505	WBA	Walgreens Boots Alliance	Consumer Staples	1979-12-31	
506	WMT	Walmart	Consumer Staples	1982-08-31	
507	WM	Waste Management	Industrials	N/A	
508	WAT	Waters Corporation	Healthcare	N/A	
509	WEC	WEC Energy Group	Utilities	2008-10-31	
510	WFC	Wells Fargo	Financials	1976-06-30	
511	WELL	Welltower	Real Estate	2009-01-30	
512	WDC	Western Digital	Information Technology	2009-07-01	
513	WU	Western Union	Information Technology	2006-09-29	
514	WRK	WestRock	Materials	N/A	
515	WY	Weyerhaeuser	Real Estate	N/A	
516	WHR	Whirlpool Corporation	Consumer Discretionary	N/A	
517	WFM	Whole Foods Market	Consumer Staples	N/A	2017-08-29
518	WMB	Williams Companies	Energy	1975-03-31	
519	WLTW*	Willis Towers Watson	Financials	2016-01-05	
520	WYN	Wyndham Worldwide	Industrials	N/A	
521	WYNN	Wynn Resorts	Consumer Discretionary	2008-11-14	
522	XEL	Xcel Energy	Utilities	1957-03-04	
523	XLNX	Xilinx	Information Technology	1999-11-08	
524	XL	XL Group	Consumer Cyclical	N/A	
525	XYL	Xylem	Industrials	2011-11-01	
526	YHOO	Yahoo!	Communication Services	N/A	2017-06-19
527	YUM	Yum! Brands	Consumer Discretionary	1997-10-06	
528	ZBH	Zimmer Biomet	Healthcare	2001-08-07	
529	ZION	Zions Bancorp	Financials	2001-06-22	
530	ZTS	Zoetis	Healthcare	2013-06-21	

Table F - 3 : The companies listed on S&P 500 index in 2017

No.	Symbol	Security	Sector	Date first added	Date removed
1	MMM	3M	Industrials	1976-08-09	
2	AOS*	A. O. Smith	Industrials	2017-07-26	
3	ABT	Abbott Laboratories	Healthcare	1964-03-31	
4	ABBV	AbbVie	Healthcare	2012-12-31	
5	ACN	Accenture	Information Technology	2011-07-06	
6	ATVI	Activision Blizzard	Communication Services	2015-08-31	
7	AYI	Acuity Brands	Industrials	2016-05-03	
8	ADM	ADM	Consumer Staples	1981-07-29	
9	ADBE	Adobe	Information Technology	1997-05-05	
10	AAP	Advance Auto Parts	Consumer Discretionary	2015-07-09	
11	AMD*	Advanced Micro Devices	Information Technology	N/A	
12	AES	AES Corp	Utilities	1998-10-02	
13	AET	Aetna	Healthcare	N/A	
14	AMG	Affiliated Managers Group	Financials	N/A	
15	AFL	Aflac	Financials	1999-05-28	
16	A	Agilent Technologies	Healthcare	2000-06-05	
17	APD	Air Products & Chemicals	Materials	1985-04-30	
18	AKAM	Akamai Technologies	Information Technology	2007-07-12	
19	ALK	Alaska Air Group	Industrials	2016-05-13	
20	ALB	Albemarle Corporation	Materials	2016-07-01	
21	ARE*	Alexandria Real Estate Equities	Real Estate	2017-03-20	
22	ALGN*	Align Technology	Healthcare	2017-06-19	
23	ALLE	Allegion	Industrials	2013-12-02	
24	AGN	Allergan	Healthcare	N/A	
25	ADS	Alliance Data Systems	Financials	N/A	
26	LNT	Alliant Energy	Utilities	2016-07-01	
27	ALL	Allstate Corp	Financials	1995-07-13	
28	GOOGL	Alphabet (Class A)	Communication Services	2014-04-03	
29	GOOG	Alphabet (Class C)	Communication Services	2006-04-03	
30	MO	Altria Group	Consumer Staples	1957-03-04	
31	AMZN	Amazon	Consumer Discretionary	2005-11-18	
32	AEE	Ameren Corp	Utilities	1991-09-19	
33	AAL	American Airlines Group	Industrials	2015-03-23	
34	AEP	American Electric Power	Utilities	1957-03-04	
35	AXP	American Express	Financials	1976-06-30	
36	AIG	American International Group	Financials	1980-03-31	
37	AMT	American Tower	Real Estate	2007-11-19	
38	AWK	American Water Works	Utilities	2016-03-04	
39	AMP	Ameriprise Financial	Financials	2005-10-03	
40	ABC	AmerisourceBergen	Healthcare	2001-08-30	
41	AME	Ametek	Industrials	2013-09-23	
42	AMGN	Amgen	Healthcare	1992-01-02	
43	APH	Amphenol Corp	Information Technology	2008-09-30	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
44	APC	Anadarko Petroleum	Healthcare	N/A	
45	ADI	Analog Devices	Information Technology	1999-10-12	
46	ANDV	Andeavor	Energy	N/A	
47	ANSS*	Ansys	Information Technology	2017-06-19	
48	ANTM	Anthem	Healthcare	2002-07-25	
49	AON	Aon	Financials	1996-04-23	
50	APA	APA Corporation	Energy	1997-07-28	
51	AIV	Apartment Investment & Management	Real Estate	N/A	
52	AAPL	Apple	Information Technology	1982-11-30	
53	AMAT	Applied Materials	Information Technology	1995-03-16	
54	APTV	Aptiv	Consumer Discretionary	2012-12-24	
55	ARNC	Arconic	Industrials	N/A	
56	AJG	Arthur J. Gallagher & Co.	Financials	2016-05-31	
57	AIZ	Assurant	Financials	2007-04-10	
58	T	AT&T	Communication Services	1983-11-30 (1957-03-04)	
59	ADSK	Autodesk	Information Technology	1989-12-01	
60	ADP	Automatic Data Processing	Information Technology	1981-03-31	
61	AN	AutoNation	Consumer Cyclical	N/A	2017-08-08
62	AZO	AutoZone	Consumer Discretionary	1997-01-02	
63	AVB	AvalonBay Communities	Real Estate	2007-01-10	
64	AVY	Avery Dennison	Materials	1987-12-31	
65	BKR	Baker Hughes	Energy	2017-07-07	
66	BLL	Ball Corp	Materials	1984-10-31	
67	BAC	Bank of America	Financials	1976-06-30	
68	BBWI	Bath & Body Works, Inc.	Consumer Discretionary	1983-09-30	
69	BAX	Baxter International	Healthcare	1972-09-30	
70	BDX	Becton Dickinson	Healthcare	1972-09-30	
71	BBBY	Bed Bath & Beyond	Consumer Cyclical	N/A	2017-07-26
72	BRK.B	Berkshire Hathaway	Financials	2010-02-16	
73	BBY	Best Buy	Consumer Discretionary	1999-06-29	
74	BIIB	Biogen	Healthcare	2003-11-13	
75	TECH	Bio-Techne	Healthcare	2021-08-30	
76	BLK	BlackRock	Financials	2011-04-04	
77	BK	BNY Mellon	Financials	1995-03-31	
78	BA	Boeing Company	Industrials	1957-03-04	
79	BKNG	Booking Holdings	Consumer Discretionary	2009-11-06	
80	BWA	BorgWarner	Consumer Discretionary	2011-12-19	
81	BXP	Boston Properties	Real Estate	2006-04-03	
82	BSX	Boston Scientific	Healthcare	1995-02-24	
83	BHF*	Brighthouse Financial	Financials	N/A	
84	BMJ	Bristol-Myers Squibb	Healthcare	1957-03-04	
85	AVGO	Broadcom	Information Technology	2014-05-08	
86	BF.B	Brown–Forman	Consumer Staples	1982-10-31	
87	CHRW	C. H. Robinson	Industrials	2007-03-02	
88	CA	CA Technologies	Information Technology	N/A	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
89	COG	Cabot Oil & Gas	Energy	2008-06-23	
90	CDNS*	Cadence Design Systems	Information Technology	2017-09-18	
91	CPB	Campbell Soup	Consumer Staples	1957-03-04	
92	COF	Capital One Financial	Financials	1998-07-01	
93	CPRI	Capri Holdings	Consumer Cyclical	N/A	
94	CAH	Cardinal Health	Healthcare	1997-05-27	
95	KMX	CarMax	Consumer Discretionary	2010-06-28	
96	CCL	Carnival Corporation	Consumer Discretionary	1998-12-22	
97	CTLT	Catalent	Healthcare	2020-09-21	
98	CAT	Caterpillar	Industrials	1957-03-04	
99	CBOE*	Cboe Global Markets	Financials	2017-03-01	
100	CBRE	CBRE	Real Estate	2006-11-10	
101	CELG	Celgene	Healthcare	N/A	
102	CNC	Centene Corporation	Healthcare	2016-03-30	
103	CNP	CenterPoint Energy	Utilities	1985-07-31	
104	CERN	Cerner	Healthcare	2010-04-30	
105	CF	CF Industries	Materials	2008-08-27	
106	SCHW	Charles Schwab Corporation	Financials	1997-06-02	
107	CHTR	Charter Communications	Communication Services	2016-09-08	
108	CHK	Chesapeake Energy	Energy	N/A	
109	CVX	Chevron Corporation	Energy	1957-03-04	
110	CMG	Chipotle Mexican Grill	Consumer Discretionary	2011-04-28	
111	CB	Chubb	Financials	2010-07-15	
112	CHD	Church & Dwight	Consumer Staples	2015-12-29	
113	CI	Cigna	Healthcare	1976-06-30	
114	XEC	Cimarex Energy	Energy	N/A	
115	CINF	Cincinnati Financial	Financials	1997-12-18	
116	CTAS	Cintas Corporation	Industrials	2001-03-01	
117	CSCO	Cisco Systems	Information Technology	1993-12-01	
118	C	Citigroup	Financials	1988-05-31	
119	CFG	Citizens Financial Group	Financials	2016-01-29	
120	CTXS	Citrix Systems	Information Technology	1999-12-01	
121	CLX	Clorox	Consumer Staples	1969-03-31	
122	CME	CME Group	Financials	2006-08-11	
123	CMS	CMS Energy	Utilities	1999-05-03	
124	KO	Coca-Cola Company	Consumer Staples	1957-03-04	
125	CTSH	Cognizant Technology Solutions	Information Technology	2006-11-17	
126	CL	Colgate-Palmolive	Consumer Staples	1957-03-04	
127	CMCSA	Comcast	Communication Services	2002-11-19	
128	CMA	Comerica	Financials	1995-12-01	
129	CAG	Conagra Brands	Consumer Staples	1983-08-31	
130	COP	ConocoPhillips	Energy	1957-03-04	
131	ED	Consolidated Edison	Utilities	N/A	
132	STZ	Constellation Brands	Consumer Staples	2005-07-01	
133	GLW	Corning	Information Technology	N/A	
134	COST	Costco	Consumer Staples	1993-10-01	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
135	COTY	Coty	Consumer Defensive	2016-09-30	
136	BCR	CR Bard	Healthcare	N/A	
137	CCI	Crown Castle	Real Estate	2012-03-14	
138	CSRA	CSRA	Information Technology	N/A	
139	CSX	CSX	Industrials	1967-09-30	
140	CMI	Cummins	Industrials	1965-03-31	
141	CVS	CVS Health	Healthcare	1957-03-04	
142	DHI	D. R. Horton	Consumer Discretionary	2005-06-22	
143	DHR	Danaher Corporation	Healthcare	N/A	
144	DRI	Darden Restaurants	Consumer Discretionary	N/A	
145	DVA	DaVita	Healthcare	2008-07-31	
146	DE	Deere & Co.	Industrials	1957-03-04	
147	DAL	Delta Air Lines	Industrials	2013-09-11	
148	XRAY	Dentsply Sirona	Healthcare	2008-11-14	
149	DVN	Devon Energy	Energy	2000-08-30	
150	DLR	Digital Realty Trust	Real Estate	2016-05-18	
151	DFS	Discover Financial Services	Financials	2007-07-02	
152	DISCA	Discovery (Series A)	Communication Services	2010-03-01	
153	DISCK	Discovery (Series C)	Communication Services	2014-08-07	
154	DISH*	Dish Network	Communication Services	2017-03-13	
155	DG	Dollar General	Consumer Discretionary	2012-12-03	
156	DLTR	Dollar Tree	Consumer Discretionary	2011-12-19	
157	D	Dominion Energy	Utilities	N/A	
158	DOV	Dover Corporation	Industrials	1985-10-31	
159	DOW	Dow Chemical Company	Materials	N/A	2017-09-01
160	DPS	Dr Pepper Snapple Group	Consumer Staples	N/A	
161	DTE	DTE Energy	Utilities	1957-03-04	
162	DUK	Duke Energy	Utilities	1976-06-30	
163	DRE*	Duke Realty Corp	Real Estate	2017-07-26	
164	DNB	Dun & Bradstreet	Financials	N/A	2017-04-05
165	DWDP*	DuPont	Industrials	N/A	
166	DD	DuPont	Materials	N/A	2017-09-01
167	DXC*	DXC Technology	Information Technology	2017-04-04	
168	EMN	Eastman Chemical	Materials	1994-01-01	
169	ETN	Eaton Corporation	Industrials	N/A	
170	EBAY	eBay	Consumer Discretionary	2002-07-22	
171	ECL	Ecolab	Materials	1989-01-31	
172	EIX	Edison International	Utilities	1957-03-04	
173	EW	Edwards Lifesciences	Healthcare	2011-04-01	
174	EA	Electronic Arts	Communication Services	2002-07-22	
175	LLY	Eli Lilly & Co	Healthcare	1970-12-31	
176	EMR	Emerson Electric Company	Industrials	1965-03-31	
177	ENDP	Endo International	Healthcare	N/A	2017-03-02
178	ETR	Entergy	Utilities	1957-03-04	
179	EVHC	Envision Healthcare	Healthcare	N/A	
180	EOG	EOG Resources	Energy	2000-11-02	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
181	EQT	EQT	Energy	N/A	
182	EFX	Equifax	Industrials	1997-06-19	
183	EQIX	Equinix	Real Estate	2015-03-20	
184	EQR	Equity Residential	Real Estate	2001-12-03	
185	ESS	Essex Property Trust	Real Estate	2014-04-02	
186	EL	Estée Lauder Companies	Consumer Staples	2006-01-05	
187	ETFC	E-Trade	Financials	N/A	
188	RE*	Everest Re	Financials	2017-06-19	
189	ES	Eversource Energy	Utilities	N/A	
190	EXC	Exelon	Utilities	1957-03-04	
191	EXPE	Expedia Group	Consumer Discretionary	2007-10-02	
192	EXPD	Expeditors	Industrials	2007-10-10	
193	ESRX	Express Scripts	Healthcare	N/A	
194	EXR	Extra Space Storage	Real Estate	2016-01-19	
195	XOM	ExxonMobil	Energy	1957-03-04	
196	FFIV	F5 Networks	Information Technology	2010-12-20	
197	FB	Facebook	Communication Services	2013-12-23	
198	FAST	Fastenal	Industrials	2008-09-15	
199	FRT	Federal Realty Investment Trust	Real Estate	2016-02-01	
200	FDX	FedEx	Industrials	1980-12-31	
201	FIS	Fidelity National Information Services	Information Technology	2006-11-10	
202	FITB	Fifth Third Bancorp	Financials	N/A	
203	FSLR	First Solar	Information Technology	N/A	2017-03-20
204	FE	FirstEnergy	Utilities	N/A	
205	FISV	Fiserv	Information Technology	2001-04-02	
206	FLR	Fluor Corporation	Industrials	N/A	
207	FMC	FMC Corporation	Materials	2009-08-19	
208	FL	Foot Locker	Consumer Cyclical	2016-04-04	
209	F	Ford	Consumer Discretionary	1957-03-04	
210	FTV	Fortive	Industrials	2016-07-01	
211	FBHS	Fortune Brands Home & Security	Industrials	2016-06-22	
212	FOXA	Fox Corporation (Class A)	Communication Services	2013-07-01	
213	FOX	Fox Corporation (Class B)	Communication Services	2015-09-18	
214	BEN	Franklin Resources	Financials	N/A	
215	FCX	Freeport-McMoRan	Materials	N/A	
216	FTR	Frontier Communications	Communication Services	N/A	2017-03-20
217	GPS	Gap	Consumer Discretionary	1986-08-31	
218	GRMN	Garmin	Consumer Discretionary	2012-12-12	
219	IT*	Gartner	Information Technology	2017-04-05	
220	GD	General Dynamics	Industrials	1957-03-04	
221	GE	General Electric	Industrials	N/A	
222	GIS	General Mills	Consumer Staples	1969-03-31	
223	GM	General Motors	Consumer Discretionary	2013-06-06	
224	GPC	Genuine Parts	Consumer Discretionary	1973-12-31	
225	GGP	GGP	Materials	N/A	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
226	GILD	Gilead Sciences	Healthcare	2004-07-01	
227	GPN	Global Payments	Information Technology	2016-04-25	
228	GL	Globe Life	Financials	1989-04-30	
229	GS	Goldman Sachs	Financials	2002-07-22	
230	HRB	H&R Block	Consumer Cyclical	N/A	
231	HAL	Halliburton	Energy	1957-03-04	
232	HBI	Hanesbrands	Consumer Discretionary	2015-03-20	
233	HOG	Harley-Davidson	Consumer Cyclical	N/A	
234	HAR	Harman International	Information Technology	N/A	2017-03-16
235	HAS	Hasbro	Consumer Discretionary	1984-09-30	
236	HCA	HCA Healthcare	Healthcare	2015-01-27	
237	PEAK	Healthpeak Properties	Real Estate	2008-03-31	
238	HP	Helmerich & Payne	Energy	N/A	
239	HSIC	Henry Schein	Healthcare	2015-03-17	
240	HES	Hess Corporation	Energy	1984-05-31	
241	HPE	Hewlett Packard Enterprise	Information Technology	2015-11-02	
242	HLT*	Hilton Worldwide	Consumer Discretionary	2017-06-19	
243	HOLX	Hologic	Healthcare	2016-03-30	
244	HD	Home Depot	Consumer Discretionary	1988-03-31	
245	HON	Honeywell	Industrials	1964-03-31	
246	HRL	Hormel	Consumer Staples	2009-03-04	
247	HST	Host Hotels & Resorts	Real Estate	2007-03-20	
248	HWM	Howmet Aerospace	Industrials	1964-03-31	
249	HPQ	HP	Information Technology	1974-12-31	
250	HUM	Humana	Healthcare	N/A	
251	HBAN	Huntington Bancshares	Financials	N/A	
252	IBM	IBM	Information Technology	1957-03-04	
253	IDXX*	Idexx Laboratories	Healthcare	2017-01-05	
254	INFO*	IHS Markit	Industrials	2017-06-02	
255	ITW	Illinois Tool Works	Industrials	1986-02-28	
256	ILMN	Illumina	Healthcare	2015-11-19	
257	INCY*	Incyte	Healthcare	2017-02-28	
258	INTC	Intel	Information Technology	1976-12-31	
259	ICE	Intercontinental Exchange	Financials	2007-09-26	
260	IFF	International Flavors & Fragrances	Materials	1976-03-31	
261	IP	International Paper	Materials	1957-03-04	
262	IPG	Interpublic Group	Communication Services	1992-10-01	
263	INTU	Intuit	Information Technology	2000-12-05	
264	ISRG	Intuitive Surgical	Healthcare	2008-06-02	
265	IVZ	Invesco	Financials	2008-08-21	
266	IQV	IQVIA	Healthcare	2017-08-29	
267	IRM	Iron Mountain	Real Estate	2009-01-06	
268	JBHT	J. B. Hunt	Industrials	2015-07-01	
269	J	Jacobs Engineering Group	Industrials	2007-10-26	
270	JEF	Jefferies Financial Group	Financials	N/A	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
271	SJM	JM Smucker	Consumer Staples	2008-11-06	
272	JNJ	Johnson & Johnson	Healthcare	1973-06-30	
273	JCI	Johnson Controls	Industrials	2010-08-27	
274	JPM	JPMorgan Chase	Financials	1975-06-30	
275	JNPR	Juniper Networks	Information Technology	2006-06-02	
276	KSU	Kansas City Southern	Industrials	2013-05-24	
277	K	Kellogg's	Consumer Staples	1989-09-11	
278	KEY	KeyCorp	Financials	1994-03-01	
279	KMB	Kimberly-Clark	Consumer Staples	1957-03-04	
280	KIM	Kimco Realty	Real Estate	2006-04-04	
281	KMI	Kinder Morgan	Energy	2012-05-25	
282	KLAC	KLA Corporation	Information Technology	N/A	
283	KSS	Kohl's	Consumer Cyclical	N/A	
284	KHC	Kraft Heinz	Consumer Staples	2015-07-06	
285	KR	Kroger	Consumer Staples	1957-03-04	
286	LLL	L3 Technologies	Information Technology	N/A	
287	LHX	L3Harris Technologies	Industrials	2008-09-22	
288	LH	LabCorp	Healthcare	2004-11-01	
289	LRCX	Lam Research	Information Technology	2012-06-29	
290	LEG	Leggett & Platt	Consumer Discretionary	1999-10-14	
291	LEN	Lennar	Consumer Discretionary	2005-10-04	
292	LVT	Level 3 Communications	Communication Services	N/A	2017-10-13
293	LNC	Lincoln National	Financials	1976-06-30	
294	LIN	Linde	Materials	1992-07-01	
295	LLTC	Linear Technology	Information Technology	N/A	2017-03-13
296	LKQ	LKQ Corporation	Consumer Discretionary	2016-05-23	
297	LMT	Lockheed Martin	Industrials	1984-07-31	
298	L	Loews Corporation	Financials	N/A	
299	LOW	Lowe's	Consumer Discretionary	1984-02-29	
300	LUMN	Lumen Technologies	Communication Services	1999-03-25	
301	LYB	LyondellBasell	Materials	2012-09-05	
302	MTB	M&T Bank	Financials	2004-02-23	
303	MAC	Macerich	Real Estate	N/A	
304	M	Macy's	Consumer Cyclical	N/A	
305	MNK	Mallinckrodt	Healthcare	N/A	2017-07-26
306	MRO	Marathon Oil	Energy	1991-05-01	
307	MPC	Marathon Petroleum	Energy	2011-07-01	
308	MAR	Marriott International	Consumer Discretionary	N/A	
309	MMC	Marsh & McLennan	Financials	1987-08-31	
310	MLM	Martin Marietta Materials	Materials	2014-07-02	
311	MAS	Masco	Industrials	1981-06-30	
312	MA	Mastercard	Information Technology	2008-07-18	
313	MAT	Mattel	Consumer Cyclical	N/A	
314	MKC	McCormick & Company	Consumer Staples	2003-03-20	
315	MCD	McDonald's	Consumer Discretionary	1970-06-30	
316	MCK	McKesson Corporation	Healthcare	N/A	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
317	MJN	Mead Johnson	Consumer Staples	N/A	2017-06-19
318	MDT	Medtronic	Healthcare	1986-10-31	
319	MRK	Merck & Co.	Healthcare	1957-03-04	
320	MET	MetLife	Financials	N/A	
321	MTD	Mettler Toledo	Healthcare	2016-09-06	
322	MGM*	MGM Resorts International	Consumer Discretionary	2017-07-26	
323	MCHP	Microchip Technology	Information Technology	2007-09-07	
324	MU	Micron Technology	Information Technology	1994-09-27	
325	MSFT	Microsoft	Information Technology	1994-06-01	
326	MAA	Mid-America Apartments	Real Estate	2016-12-02	
327	MHK	Mohawk Industries	Consumer Discretionary	2013-12-23	
328	TAP	Molson Coors Beverage Company	Consumer Staples	1976-06-30	
329	MDLZ	Mondelez International	Consumer Staples	2012-10-02	
330	MON	Monsanto	Materials	N/A	
331	MNST	Monster Beverage	Consumer Staples	2012-06-28	
332	MCO	Moody's Corporation	Financials	N/A	
333	MS	Morgan Stanley	Financials	N/A	
334	MSI	Motorola Solutions	Information Technology	N/A	
335	MUR	Murphy Oil	Energy	N/A	2017-07-26
336	NDAQ	Nasdaq	Financials	2008-10-22	
337	NAVI	Navient	Financials	N/A	
338	NTAP	NetApp	Information Technology	1999-06-25	
339	NFLX	Netflix	Communication Services	2010-12-20	
340	NWL	Newell Brands	Consumer Discretionary	1989-04-30	
341	NFX	Newfield Exploration	Energy	N/A	
342	NEM	Newmont	Materials	1969-06-30	
343	NWSA	News Corp (Class A)	Communication Services	2013-08-01	
344	NWS	News Corp (Class B)	Communication Services	2015-09-18	
345	NEE	NextEra Energy	Utilities	1976-06-30	
346	NLSN	Nielsen Holdings	Industrials	2013-07-09	
347	NKE	Nike	Consumer Discretionary	1988-11-30	
348	NI	NiSource	Utilities	N/A	
349	NBL	Noble Energy	Energy	N/A	
350	JWN	Nordstrom	Consumer Cyclical	N/A	
351	NSC	Norfolk Southern	Industrials	1957-03-04	
352	NTRS	Northern Trust	Financials	N/A	
353	NOC	Northrop Grumman	Industrials	1985-06-30	
354	NLOK	NortonLifeLock	Information Technology	2003-03-25	
355	NCLH*	Norwegian Cruise Line Holdings	Consumer Discretionary	2017-10-13	
356	NOV	Nov	Energy	2005-03-14	
357	NRG	NRG Energy	Utilities	2010-01-29	
358	NUE	Nucor	Materials	1985-04-30	
359	NVDA	Nvidia	Information Technology	2001-11-30	
360	OXY	Occidental Petroleum	Energy	1982-12-31	
361	OMC	Omnicom Group	Communication Services	N/A	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
362	OKE	Oneok	Energy	2010-03-15	
363	ORCL	Oracle	Information Technology	1989-08-31	
364	ORLY	O'Reilly Automotive	Consumer Discretionary	2009-03-27	
365	PCAR	Paccar	Industrials	1980-12-31	
366	PCG	Pacific Gas & Electric Company	Energy	N/A	
367	PKG*	Packaging Corporation of America	Materials	2017-07-26	
368	PH	Parker-Hannifin	Industrials	1985-11-30	
369	PDCO	Patterson Companies	Healthcare	N/A	
370	PAYX	Paychex	Information Technology	N/A	
371	PYPL	PayPal	Information Technology	2015-07-20	
372	PNR	Pentair	Industrials	2012-10-01	
373	PBCT	People's United Financial	Financials	2008-11-13	
374	PEP	PepsiCo	Consumer Staples	1957-03-04	
375	PKI	PerkinElmer	Healthcare	1985-05-31	
376	PRGO	Perrigo	Healthcare	2011-12-19	
377	PFE	Pfizer	Healthcare	1957-03-04	
378	PM	Philip Morris International	Consumer Staples	2008-03-31	
379	PSX	Phillips 66	Energy	2012-05-01	
380	PNW	Pinnacle West Capital	Utilities	N/A	
381	PXD	Pioneer Natural Resources	Energy	2008-09-24	
382	PBI	Pitney Bowes	Industrials	N/A	2017-03-01
383	PNC	PNC Financial Services	Financials	1988-04-30	
384	PPG	PPG Industries	Materials	1957-03-04	
385	PPL	PPL	Utilities	N/A	
386	PFG	Principal Financial Group	Financials	2002-07-22	
387	PG	Procter & Gamble	Consumer Staples	1957-03-04	
388	PGR	Progressive Corporation	Financials	1997-08-04	
389	PLD	Prologis	Real Estate	2003-07-17	
390	PRU	Prudential Financial	Financials	2002-07-22	
391	PEG	Public Service Enterprise Group	Utilities	1957-03-04	
392	PSA	Public Storage	Real Estate	2005-08-19	
393	PHM	PulteGroup	Consumer Discretionary	1984-04-30	
394	PVH	PVH	Consumer Discretionary	2013-02-15	
395	QRVO	Qorvo	Information Technology	2015-06-11	
396	QCOM	Qualcomm	Information Technology	N/A	
397	PWR	Quanta Services	Industrials	2009-07-01	
398	DGX	Quest Diagnostics	Healthcare	2002-12-12	
399	Q*	QuintilesIMS	Healthcare	2017-08-29	
400	RL	Ralph Lauren Corporation	Consumer Discretionary	2007-02-02	
401	RRC	Range Resources	Energy	N/A	
402	RJF*	Raymond James Financial	Financials	2017-03-20	
403	RTN	Raytheon Company	Industrials	N/A	
404	RTX	Raytheon Technologies	Industrials	N/A	
405	O	Realty Income Corporation	Real Estate	2015-04-07	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
406	RHT	Red Hat	Information Technology	N/A	
407	REG*	Regency Centers	Real Estate	2017-03-02	
408	REGN	Regeneron Pharmaceuticals	Healthcare	2013-05-01	
409	RF	Regions Financial Corporation	Financials	1998-08-28	
410	RSG	Republic Services	Industrials	2008-12-05	
411	RMD*	ResMed	Healthcare	2017-07-26	
412	RAI	Reynolds American	Consumer Staple	N/A	2017-07-26
413	RHI	Robert Half International	Industrials	2000-12-05	
414	ROK	Rockwell Automation	Industrials	N/A	
415	COL	Rockwell Collins	Industrials	N/A	
416	ROP	Roper Technologies	Industrials	2009-12-23	
417	ROST	Ross Stores	Consumer Discretionary	2009-12-21	
418	RCL	Royal Caribbean Group	Consumer Discretionary	2014-12-05	
419	R	Ryder System	Industrials	N/A	2017-06-19
420	SPGI	S&P Global	Financials	N/A	
421	CRM	Salesforce	Information Technology	2008-09-15	
422	SBAC*	SBA Communications	Real Estate	2017-09-01	
423	SCG	SCANA	Industrials	N/A	
424	SLB	Schlumberger	Energy	1965-03-31	
425	SNI	Scripps Networks Interactive	Communication Services	N/A	
426	STX	Seagate Technology	Information Technology	2012-07-02	
427	SEE	Sealed Air	Materials	1957-03-04	
428	SRE	Sempra Energy	Utilities	N/A	
429	SHW	Sherwin-Williams	Materials	1964-06-30	
430	SIG	Signet Jewelers	Consumer Cyclical	N/A	
431	SPG	Simon Property Group	Real Estate	2002-06-26	
432	SWKS	Skyworks Solutions	Information Technology	2015-03-12	
433	SNA	Snap-on	Industrials	1982-09-30	
434	SO	Southern Company	Utilities	1957-03-04	
435	LUV	Southwest Airlines	Industrials	1994-07-01	
436	SWN	Southwestern Energy	Energy	N/A	2017-04-04
437	SE	Spectra Energy	Energy	N/A	2017-02-28
438	STJ	St Jude Medical	Healthcare	N/A	2017-01-05
439	SWK	Stanley Black & Decker	Industrials	1982-09-30	
440	SPLS	Staples	Consumer Discretionary	N/A	2017-09-18
441	SBUX	Starbucks	Consumer Discretionary	N/A	
442	STT	State Street Corporation	Financials	N/A	
443	SRCL	Stericycle	Industrials	N/A	
444	SYK	Stryker Corporation	Healthcare	2000-12-12	
445	STI	SunTrust Banks	Financials	N/A	
446	SYF	Synchrony Financial	Financials	2015-11-18	
447	SNPS*	Synopsys	Information Technology	2017-03-16	
448	SYY	Sysco	Consumer Staples	1986-12-31	
449	TROW	T. Rowe Price	Financials	N/A	
450	TPR	Tapestry	Consumer Discretionary	N/A	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
451	TGT	Target Corporation	Consumer Discretionary	1976-12-31	
452	TEL	TE Connectivity	Information Technology	2011-10-17	
453	TGNA	Tegna	Communication Services	N/A	2017-06-02
454	TDC	Teradata	Information Technology	N/A	2017-06-19
455	TXN	Texas Instruments	Information Technology	N/A	
456	TXT	Textron	Industrials	1978-12-31	
457	COO	The Cooper Companies	Healthcare	2016-09-23	
458	GT	The Goodyear Tire & Rubber Company	Consumer Cyclical	N/A	
459	HIG	The Hartford	Financials	1957-03-04	
460	HSY	The Hershey Company	Consumer Staples	1957-03-04	
461	MOS	The Mosaic Company	Materials	2011-09-26	
462	TRV	The Travelers Companies	Financials	2002-08-21	
463	DIS	The Walt Disney Company	Communication Services	1976-06-30	
464	TMO	Thermo Fisher Scientific	Healthcare	2004-08-03	
465	TWX	Time Warner	Communication Services	N/A	
466	TJX	TJX Companies	Consumer Discretionary	1985-09-30	
467	TSCO	Tractor Supply Company	Consumer Discretionary	2014-01-24	
468	TT	Trane Technologies	Industrials	2010-11-17	
469	TDG	TransDigm Group	Industrials	2016-06-03	
470	RIG	Transocean	Energy	N/A	2017-07-26
471	TRIP	TripAdvisor	Consumer Cyclical	N/A	
472	TFC	Truist Financial	Financials	1997-12-04	
473	TSS	TSYS	Information Technology	N/A	
474	TSN	Tyson Foods	Consumer Staples	2005-08-10	
475	USB	U.S. Bancorp	Financials	N/A	
476	UDR	UDR	Real Estate	2016-03-07	
477	ULTA	Ulta Beauty	Consumer Discretionary	2016-04-18	
478	UAA	Under Armour (Class A)	Consumer Discretionary	2014-05-01	
479	UA	Under Armour (Class C)	Consumer Discretionary	2016-04-08	
480	UNP	Union Pacific	Industrials	1957-03-04	
481	UAL	United Airlines	Industrials	2015-09-03	
482	UPS	United Parcel Service	Industrials	2002-07-22	
483	URI	United Rentals	Industrials	2014-09-20	
484	UNH	UnitedHealth Group	Healthcare	1994-07-01	
485	UHS	Universal Health Services	Healthcare	2014-09-20	
486	UNM	Unum Group	Financials	1994-03-01	
487	URBN	Urban Outfitters	Consumer Cyclical	N/A	2017-03-20
488	VLO	Valero Energy	Energy	N/A	
489	VTR	Ventas	Real Estate	2009-03-04	
490	VRSN	Verisign	Information Technology	2006-02-01	
491	VRSK	Verisk Analytics	Industrials	2015-10-08	
492	VZ	Verizon Communications	Communication Services	1983-11-30	
493	VRTX	Vertex Pharmaceuticals	Healthcare	2013-09-23	
494	VFC	VF Corporation	Consumer Discretionary	1979-06-30	
495	VIAB	Viacom	Consumer Services	N/A	
496	VIAC	ViacomCBS	Communication Services	N/A	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
497	VTRS	Viatis	Healthcare	2004-04-23	
498	V	Visa	Information Technology	2009-12-21	
499	VNO	Vornado Realty Trust	Real Estate	N/A	
500	VMC	Vulcan Materials	Materials	1999-06-30	
501	GWW	W. W. Grainger	Industrials	1981-06-30	
502	WBA	Walgreens Boots Alliance	Consumer Staples	1979-12-31	
503	WMT	Walmart	Consumer Staples	1982-08-31	
504	WM	Waste Management	Industrials	N/A	
505	WAT	Waters Corporation	Healthcare	N/A	
506	WEC	WEC Energy Group	Utilities	2008-10-31	
507	WFC	Wells Fargo	Financials	1976-06-30	
508	WELL	Welltower	Real Estate	2009-01-30	
509	WDC	Western Digital	Information Technology	2009-07-01	
510	WU	Western Union	Information Technology	2006-09-29	
511	WRK	WestRock	Materials	N/A	
512	WY	Weyerhaeuser	Real Estate	N/A	
513	WHR	Whirlpool Corporation	Consumer Discretionary	N/A	
514	WFM	Whole Foods Market	Consumer Staples	N/A	2017-08-29
515	WMB	Williams Companies	Energy	1975-03-31	
516	WLTW	Willis Towers Watson	Financials	2016-01-05	
517	WYN	Wyndham Worldwide	Industrials	N/A	
518	WYNN	Wynn Resorts	Consumer Discretionary	2008-11-14	
519	XEL	Xcel Energy	Utilities	1957-03-04	
520	XLNX	Xilinx	Information Technology	1999-11-08	
521	XL	XL Group	Consumer Cyclical	N/A	
522	XYL	Xylem	Industrials	2011-11-01	
523	YHOO	Yahoo!	Communication Services	N/A	2017-06-19
524	YUM	Yum! Brands	Consumer Discretionary	1997-10-06	
525	ZBH	Zimmer Biomet	Healthcare	2001-08-07	
526	ZION	Zions Bancorp	Financials	2001-06-22	
527	ZTS	Zoetis	Healthcare	2013-06-21	

Table F - 4 : The companies listed on S&P 500 index in 2018

No.	Symbol	Security	Sector	Date first added	Date removed
1	MMM	3M	Industrials	1976-08-09	
2	AOS	A. O. Smith	Industrials	2017-07-26	
3	ABT	Abbott Laboratories	Healthcare	1964-03-31	
4	ABBV	AbbVie	Healthcare	2012-12-31	
5	ABMD*	Abiomed	Healthcare	2018-05-31	
6	ACN	Accenture	Information Technology	2011-07-06	
7	ATVI	Activision Blizzard	Communication Services	2015-08-31	
8	AYI	Acuity Brands	Industrials	2016-05-03	2018-06-18
9	ADM	ADM	Consumer Staples	1981-07-29	
10	ADBE	Adobe	Information Technology	1997-05-05	
11	AAP	Advance Auto Parts	Consumer Discretionary	2015-07-09	
12	AMD	Advanced Micro Devices	Information Technology	N/A	
13	AES	AES Corp	Utilities	1998-10-02	
14	AET	Aetna	Healthcare	N/A	2018-12-03
15	AMG	Affiliated Managers Group	Financials	N/A	
16	AFL	Aflac	Financials	1999-05-28	
17	A	Agilent Technologies	Healthcare	2000-06-05	
18	APD	Air Products & Chemicals	Materials	1985-04-30	
19	AKAM	Akamai Technologies	Information Technology	2007-07-12	
20	ALK	Alaska Air Group	Industrials	2016-05-13	
21	ALB	Albemarle Corporation	Materials	2016-07-01	
22	ARE	Alexandria Real Estate Equities	Real Estate	2017-03-20	
23	ALGN	Align Technology	Healthcare	2017-06-19	
24	ALLE	Allegion	Industrials	2013-12-02	
25	AGN	Allergan	Healthcare	N/A	
26	ADS	Alliance Data Systems	Financials	N/A	
27	LNT	Alliant Energy	Utilities	2016-07-01	
28	ALL	Allstate Corp	Financials	1995-07-13	
29	GOOGL	Alphabet (Class A)	Communication Services	2014-04-03	
30	GOOG	Alphabet (Class C)	Communication Services	2006-04-03	
31	MO	Altria Group	Consumer Staples	1957-03-04	
32	AMZN	Amazon	Consumer Discretionary	2005-11-18	
33	AEE	Ameren Corp	Utilities	1991-09-19	
34	AAL	American Airlines Group	Industrials	2015-03-23	
35	AEP	American Electric Power	Utilities	1957-03-04	
36	AXP	American Express	Financials	1976-06-30	
37	AIG	American International Group	Financials	1980-03-31	
38	AMT	American Tower	Real Estate	2007-11-19	
39	AWK	American Water Works	Utilities	2016-03-04	
40	AMP	Ameriprise Financial	Financials	2005-10-03	
41	ABC	AmerisourceBergen	Healthcare	2001-08-30	
42	AME	Ametek	Industrials	2013-09-23	
43	AMGN	Amgen	Healthcare	1992-01-02	
44	APH	Amphenol Corp	Information Technology	2008-09-30	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
45	APC	Anadarko Petroleum	Healthcare	N/A	
46	ADI	Analog Devices	Information Technology	1999-10-12	
47	ANDV	Andeavor	Energy	N/A	2018-10-01
48	ANSS	Ansys	Information Technology	2017-06-19	
49	ANTM	Anthem	Healthcare	2002-07-25	
50	AON	Aon	Financials	1996-04-23	
51	APA	APA Corporation	Energy	1997-07-28	
52	AIV	Apartment Investment & Management	Real Estate	N/A	
53	AAPL	Apple	Information Technology	1982-11-30	
54	AMAT	Applied Materials	Information Technology	1995-03-16	
55	APTV	Aptiv	Consumer Discretionary	2012-12-24	
56	ARNC	Arconic	Industrials	N/A	
57	ANET*	Arista Networks	Information Technology	2018-08-28	
58	AJG	Arthur J. Gallagher & Co.	Financials	2016-05-31	
59	AIZ	Assurant	Financials	2007-04-10	
60	T	AT&T	Communication Services	1983-11-30 (1957-03-04)	
61	ADSK	Autodesk	Information Technology	1989-12-01	
62	ADP	Automatic Data Processing	Information Technology	1981-03-31	
63	AZO	AutoZone	Consumer Discretionary	1997-01-02	
64	AVB	AvalonBay Communities	Real Estate	2007-01-10	
65	AVY	Avery Dennison	Materials	1987-12-31	
66	BKR	Baker Hughes	Energy	2017-07-07	
67	BLL	Ball Corp	Materials	1984-10-31	
68	BAC	Bank of America	Financials	1976-06-30	
69	BBWI	Bath & Body Works, Inc.	Consumer Discretionary	1983-09-30	
70	BAX	Baxter International	Healthcare	1972-09-30	
71	BDX	Becton Dickinson	Healthcare	1972-09-30	
72	BRK.B	Berkshire Hathaway	Financials	2010-02-16	
73	BBY	Best Buy	Consumer Discretionary	1999-06-29	
74	BIIB	Biogen	Healthcare	2003-11-13	
75	TECH	Bio-Techne	Healthcare	2021-08-30	
76	BLK	BlackRock	Financials	2011-04-04	
77	BK	BNY Mellon	Financials	1995-03-31	
78	BA	Boeing Company	Industrials	1957-03-04	
79	BKNG	Booking Holdings	Consumer Discretionary	2009-11-06	
80	BWA	BorgWarner	Consumer Discretionary	2011-12-19	
81	BXP	Boston Properties	Real Estate	2006-04-03	
82	BSX	Boston Scientific	Healthcare	1995-02-24	
83	BHF	Brighthouse Financial	Financials	N/A	
84	BMJ	Bristol-Myers Squibb	Healthcare	1957-03-04	
85	AVGO	Broadcom	Information Technology	2014-05-08	
86	BR*	Broadridge Financial Solutions	Information Technology	2018-06-18	
87	BF.B	Brown–Forman	Consumer Staples	1982-10-31	
88	CHRW	C. H. Robinson	Industrials	2007-03-02	
89	CA	CA Technologies	Information Technology	N/A	2018-11-06

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No.	Symbol	Security	Sector	Date first added	Date removed
90	COG	Cabot Oil & Gas	Energy	2008-06-23	
91	CDNS	Cadence Design Systems	Information Technology	2017-09-18	
92	CPB	Campbell Soup	Consumer Staples	1957-03-04	
93	COF	Capital One Financial	Financials	1998-07-01	
94	CPRI	Capri Holdings	Consumer Cyclical	N/A	
95	CAH	Cardinal Health	Healthcare	1997-05-27	
96	KMX	CarMax	Consumer Discretionary	2010-06-28	
97	CCL	Carnival Corporation	Consumer Discretionary	1998-12-22	
98	CTLT	Catalent	Healthcare	2020-09-21	
99	CAT	Caterpillar	Industrials	1957-03-04	
100	CBOE	Cboe Global Markets	Financials	2017-03-01	
101	CBRE	CBRE	Real Estate	2006-11-10	
102	CE*	Celanese	Materials	2018-12-24	
103	CELG	Celgene	Healthcare	N/A	
104	CNC	Centene Corporation	Healthcare	2016-03-30	
105	CNP	CenterPoint Energy	Utilities	1985-07-31	
106	CERN	Cerner	Healthcare	2010-04-30	
107	CF	CF Industries	Materials	2008-08-27	
108	SCHW	Charles Schwab Corporation	Financials	1997-06-02	
109	CHTR	Charter Communications	Communication Services	2016-09-08	
110	CHK	Chesapeake Energy	Energy	N/A	2018-03-19
111	CVX	Chevron Corporation	Energy	1957-03-04	
112	CMG	Chipotle Mexican Grill	Consumer Discretionary	2011-04-28	
113	CB	Chubb	Financials	2010-07-15	
114	CHD	Church & Dwight	Consumer Staples	2015-12-29	
115	CI	Cigna	Healthcare	1976-06-30	
116	XEC	Cimarex Energy	Energy	N/A	
117	CINF	Cincinnati Financial	Financials	1997-12-18	
118	CTAS	Cintas Corporation	Industrials	2001-03-01	
119	CSCO	Cisco Systems	Information Technology	1993-12-01	
120	C	Citigroup	Financials	1988-05-31	
121	CFG	Citizens Financial Group	Financials	2016-01-29	
122	CTXS	Citrix Systems	Information Technology	1999-12-01	
123	CLX	Clorox	Consumer Staples	1969-03-31	
124	CME	CME Group	Financials	2006-08-11	
125	CMS	CMS Energy	Utilities	1999-05-03	
126	KO	Coca-Cola Company	Consumer Staples	1957-03-04	
127	CTSH	Cognizant Technology Solutions	Information Technology	2006-11-17	
128	CL	Colgate-Palmolive	Consumer Staples	1957-03-04	
129	CMCSA	Comcast	Communication Services	2002-11-19	
130	CMA	Comerica	Financials	1995-12-01	
131	CAG	Conagra Brands	Consumer Staples	1983-08-31	
132	COP	ConocoPhillips	Energy	1957-03-04	
133	ED	Consolidated Edison	Utilities	N/A	
134	STZ	Constellation Brands	Consumer Staples	2005-07-01	
135	CPRT*	Copart	Industrials	2018-07-02	

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No.	Symbol	Security	Sector	Date first added	Date removed
136	GLW	Corning	Information Technology	N/A	
137	COST	Costco	Consumer Staples	1993-10-01	
138	COTY	Coty	Consumer Defensive	2016-09-30	
139	BCR	CR Bard	Healthcare	N/A	2018-01-03
140	CCI	Crown Castle	Real Estate	2012-03-14	
141	CSRA	CSRA	Information Technology	N/A	2018-04-04
142	CSX	CSX	Industrials	1967-09-30	
143	CMI	Cummins	Industrials	1965-03-31	
144	CVS	CVS Health	Healthcare	1957-03-04	
145	DHI	D. R. Horton	Consumer Discretionary	2005-06-22	
146	DHR	Danaher Corporation	Healthcare	N/A	
147	DRI	Darden Restaurants	Consumer Discretionary	N/A	
148	DVA	DaVita	Healthcare	2008-07-31	
149	DE	Deere & Co.	Industrials	1957-03-04	
150	DAL	Delta Air Lines	Industrials	2013-09-11	
151	XRAY	Dentsply Sirona	Healthcare	2008-11-14	
152	DVN	Devon Energy	Energy	2000-08-30	
153	FANG*	Diamondback Energy	Energy	2018-12-03	
154	DLR	Digital Realty Trust	Real Estate	2016-05-18	
155	DFS	Discover Financial Services	Financials	2007-07-02	
156	DISCA	Discovery (Series A)	Communication Services	2010-03-01	
157	DISCK	Discovery (Series C)	Communication Services	2014-08-07	
158	DISH	Dish Network	Communication Services	2017-03-13	
159	DG	Dollar General	Consumer Discretionary	2012-12-03	
160	DLTR	Dollar Tree	Consumer Discretionary	2011-12-19	
161	D	Dominion Energy	Utilities	N/A	
162	DOV	Dover Corporation	Industrials	1985-10-31	
163	DPS	Dr Pepper Snapple Group	Consumer Staples	N/A	2018-07-02
164	DTE	DTE Energy	Utilities	1957-03-04	
165	DUK	Duke Energy	Utilities	1976-06-30	
166	DRE	Duke Realty Corp	Real Estate	2017-07-26	
167	DWDP	DuPont	Industrials	N/A	
168	DXC	DXC Technology	Information Technology	2017-04-04	
169	EMN	Eastman Chemical	Materials	1994-01-01	
170	ETN	Eaton Corporation	Industrials	N/A	
171	EBAY	eBay	Consumer Discretionary	2002-07-22	
172	ECL	Ecolab	Materials	1989-01-31	
173	EIX	Edison International	Utilities	1957-03-04	
174	EW	Edwards Lifesciences	Healthcare	2011-04-01	
175	EA	Electronic Arts	Communication Services	2002-07-22	
176	LLY	Eli Lilly & Co	Healthcare	1970-12-31	
177	EMR	Emerson Electric Company	Industrials	1965-03-31	
178	ETR	Entergy	Utilities	1957-03-04	
179	EVHC	Envision Healthcare	Healthcare	N/A	2018-10-11
180	EOG	EOG Resources	Energy	2000-11-02	
181	EQT	EQT	Energy	N/A	2018-11-13

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No.	Symbol	Security	Sector	Date first added	Date removed
182	EFX	Equifax	Industrials	1997-06-19	
183	EQIX	Equinix	Real Estate	2015-03-20	
184	EQR	Equity Residential	Real Estate	2001-12-03	
185	ESS	Essex Property Trust	Real Estate	2014-04-02	
186	EL	Estée Lauder Companies	Consumer Staples	2006-01-05	
187	ETFC	E-Trade	Financials	N/A	
188	RE	Everest Re	Financials	2017-06-19	
189	EVERG*	Eversource Energy	Utilities	2018-06-05	
190	ES	Eversource Energy	Utilities	N/A	
191	EXC	Exelon	Utilities	1957-03-04	
192	EXPE	Expedia Group	Consumer Discretionary	2007-10-02	
193	EXPD	Expeditors	Industrials	2007-10-10	
194	ESRX	Express Scripts	Healthcare	N/A	2018-12-24
195	EXR	Extra Space Storage	Real Estate	2016-01-19	
196	XOM	ExxonMobil	Energy	1957-03-04	
197	FFIV	F5 Networks	Information Technology	2010-12-20	
198	FB	Facebook	Communication Services	2013-12-23	
199	FAST	Fastenal	Industrials	2008-09-15	
200	FRT	Federal Realty Investment Trust	Real Estate	2016-02-01	
201	FDX	FedEx	Industrials	1980-12-31	
202	FIS	Fidelity National Information Services	Information Technology	2006-11-10	
203	FITB	Fifth Third Bancorp	Financials	N/A	
204	FE	FirstEnergy	Utilities	N/A	
205	FISV	Fiserv	Information Technology	2001-04-02	
206	FLT*	Fleetcor	Information Technology	2018-06-20	
207	FLR	Fluor Corporation	Industrials	N/A	
208	FMC	FMC Corporation	Materials	2009-08-19	
209	FL	Foot Locker	Consumer Cyclical	2016-04-04	
210	F	Ford	Consumer Discretionary	1957-03-04	
211	FTNT*	Fortinet	Information Technology	2018-10-11	
212	FTV	Fortive	Industrials	2016-07-01	
213	FBHS	Fortune Brands Home & Security	Industrials	2016-06-22	
214	FOXA	Fox Corporation (Class A)	Communication Services	2013-07-01	
215	FOX	Fox Corporation (Class B)	Communication Services	2015-09-18	
216	BEN	Franklin Resources	Financials	N/A	
217	FCX	Freeport-McMoRan	Materials	N/A	
218	GPS	Gap	Consumer Discretionary	1986-08-31	
219	GRMN	Garmin	Consumer Discretionary	2012-12-12	
220	IT	Gartner	Information Technology	2017-04-05	
221	GD	General Dynamics	Industrials	1957-03-04	
222	GE	General Electric	Industrials	N/A	
223	GIS	General Mills	Consumer Staples	1969-03-31	
224	GM	General Motors	Consumer Discretionary	2013-06-06	
225	GPC	Genuine Parts	Consumer Discretionary	1973-12-31	
226	GGP	GGP	Materials	N/A	2018-08-28

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No.	Symbol	Security	Sector	Date first added	Date removed
227	GILD	Gilead Sciences	Healthcare	2004-07-01	
228	GPN	Global Payments	Information Technology	2016-04-25	
229	GL	Globe Life	Financials	1989-04-30	
230	GS	Goldman Sachs	Financials	2002-07-22	
231	HRB	H&R Block	Consumer Cyclical	N/A	
232	HAL	Halliburton	Energy	1957-03-04	
233	HBI	Hanesbrands	Consumer Discretionary	2015-03-20	
234	HOG	Harley-Davidson	Consumer Cyclical	N/A	
235	HAS	Hasbro	Consumer Discretionary	1984-09-30	
236	HCA	HCA Healthcare	Healthcare	2015-01-27	
237	PEAK	Healthpeak Properties	Real Estate	2008-03-31	
238	HP	Helmerich & Payne	Energy	N/A	
239	HSIC	Henry Schein	Healthcare	2015-03-17	
240	HES	Hess Corporation	Energy	1984-05-31	
241	HPE	Hewlett Packard Enterprise	Information Technology	2015-11-02	
242	HLT	Hilton Worldwide	Consumer Discretionary	2017-06-19	
243	HOLX	Hologic	Healthcare	2016-03-30	
244	HD	Home Depot	Consumer Discretionary	1988-03-31	
245	HON	Honeywell	Industrials	1964-03-31	
246	HRL	Hormel	Consumer Staples	2009-03-04	
247	HST	Host Hotels & Resorts	Real Estate	2007-03-20	
248	HWM	Howmet Aerospace	Industrials	1964-03-31	
249	HPQ	HP	Information Technology	1974-12-31	
250	HUM	Humana	Healthcare	N/A	
251	HBAN	Huntington Bancshares	Financials	N/A	
252	HII*	Huntington Ingalls Industries	Industrials	2018-01-03	
253	IBM	IBM	Information Technology	1957-03-04	
254	IDXX	Idexx Laboratories	Healthcare	2017-01-05	
255	INFO	IHS Markit	Industrials	2017-06-02	
256	ITW	Illinois Tool Works	Industrials	1986-02-28	
257	ILMN	Illumina	Healthcare	2015-11-19	
258	INCY	Incyte	Healthcare	2017-02-28	
259	INTC	Intel	Information Technology	1976-12-31	
260	ICE	Intercontinental Exchange	Financials	2007-09-26	
261	IFF	International Flavors & Fragrances	Materials	1976-03-31	
262	IP	International Paper	Materials	1957-03-04	
263	IPG	Interpublic Group	Communication Services	1992-10-01	
264	INTU	Intuit	Information Technology	2000-12-05	
265	ISRG	Intuitive Surgical	Healthcare	2008-06-02	
266	IVZ	Invesco	Financials	2008-08-21	
267	IPGP*	IPG Photonics	Information Technology	2018-03-07	
268	IQV	IQVIA	Healthcare	2017-08-29	
269	IRM	Iron Mountain	Real Estate	2009-01-06	
270	JBHT	J. B. Hunt	Industrials	2015-07-01	
271	JKHY*	Jack Henry & Associates	Information Technology	2018-11-13	
272	J	Jacobs Engineering Group	Industrials	2007-10-26	

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No.	Symbol	Security	Sector	Date first added	Date removed
273	JEF	Jefferies Financial Group	Financials	N/A	
274	SJM	JM Smucker	Consumer Staples	2008-11-06	
275	JNJ	Johnson & Johnson	Healthcare	1973-06-30	
276	JCI	Johnson Controls	Industrials	2010-08-27	
277	JPM	JPMorgan Chase	Financials	1975-06-30	
278	JNPR	Juniper Networks	Information Technology	2006-06-02	
279	KSU	Kansas City Southern	Industrials	2013-05-24	
280	K	Kellogg's	Consumer Staples	1989-09-11	
281	KEY	KeyCorp	Financials	1994-03-01	
282	KEYS*	Keysight Technologies	Information Technology	2018-11-06	
283	KMB	Kimberly-Clark	Consumer Staples	1957-03-04	
284	KIM	Kimco Realty	Real Estate	2006-04-04	
285	KMI	Kinder Morgan	Energy	2012-05-25	
286	KLAC	KLA Corporation	Information Technology	N/A	
287	KSS	Kohl's	Consumer Cyclical	N/A	
288	KHC	Kraft Heinz	Consumer Staples	2015-07-06	
289	KR	Kroger	Consumer Staples	1957-03-04	
290	LLL	L3 Technologies	Information Technology	N/A	
291	LHX	L3Harris Technologies	Industrials	2008-09-22	
292	LH	LabCorp	Healthcare	2004-11-01	
293	LRCX	Lam Research	Information Technology	2012-06-29	
294	LW*	Lamb Weston	Consumer Staples	2018-12-03	
295	LEG	Leggett & Platt	Consumer Discretionary	1999-10-14	
296	LEN	Lennar	Consumer Discretionary	2005-10-04	
297	LNC	Lincoln National	Financials	1976-06-30	
298	LIN	Linde	Materials	1992-07-01	
299	LKQ	LKQ Corporation	Consumer Discretionary	2016-05-23	
300	LMT	Lockheed Martin	Industrials	1984-07-31	
301	L	Loews Corporation	Financials	N/A	
302	LOW	Lowe's	Consumer Discretionary	1984-02-29	
303	LUMN	Lumen Technologies	Communication Services	1999-03-25	
304	LYB	LyondellBasell	Materials	2012-09-05	
305	MTB	M&T Bank	Financials	2004-02-23	
306	MAC	Macerich	Real Estate	N/A	
307	M	Macy's	Consumer Cyclical	N/A	
308	MRO	Marathon Oil	Energy	1991-05-01	
309	MPC	Marathon Petroleum	Energy	2011-07-01	
310	MAR	Marriott International	Consumer Discretionary	N/A	
311	MMC	Marsh & McLennan	Financials	1987-08-31	
312	MLM	Martin Marietta Materials	Materials	2014-07-02	
313	MAS	Masco	Industrials	1981-06-30	
314	MA	Mastercard	Information Technology	2008-07-18	
315	MAT	Mattel	Consumer Cyclical	N/A	
316	MKC	McCormick & Company	Consumer Staples	2003-03-20	
317	MCD	McDonald's	Consumer Discretionary	1970-06-30	
318	MCK	McKesson Corporation	Healthcare	N/A	

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No.	Symbol	Security	Sector	Date first added	Date removed
319	MDT	Medtronic	Healthcare	1986-10-31	
320	MRK	Merck & Co.	Healthcare	1957-03-04	
321	MET	MetLife	Financials	N/A	
322	MTD	Mettler Toledo	Healthcare	2016-09-06	
323	MGM	MGM Resorts International	Consumer Discretionary	2017-07-26	
324	MCHP	Microchip Technology	Information Technology	2007-09-07	
325	MU	Micron Technology	Information Technology	1994-09-27	
326	MSFT	Microsoft	Information Technology	1994-06-01	
327	MAA	Mid-America Apartments	Real Estate	2016-12-02	
328	MHK	Mohawk Industries	Consumer Discretionary	2013-12-23	
329	TAP	Molson Coors Beverage Company	Consumer Staples	1976-06-30	
330	MDLZ	Mondelez International	Consumer Staples	2012-10-02	
331	MON	Monsanto	Materials	N/A	2018-06-07
332	MNST	Monster Beverage	Consumer Staples	2012-06-28	
333	MCO	Moody's Corporation	Financials	N/A	
334	MS	Morgan Stanley	Financials	N/A	
335	MSI	Motorola Solutions	Information Technology	N/A	
336	MSCI*	MSCI	Financials	2018-04-04	
337	NDAQ	Nasdaq	Financials	2008-10-22	
338	NAVI	Navient	Financials	N/A	2018-06-05
339	NKTR*	Nektar Therapeutics	Healthcare	N/A	
340	NTAP	NetApp	Information Technology	1999-06-25	
341	NFLX	Netflix	Communication Services	2010-12-20	
342	NWL	Newell Brands	Consumer Discretionary	1989-04-30	
343	NFX	Newfield Exploration	Energy	N/A	
344	NEM	Newmont	Materials	1969-06-30	
345	NWSA	News Corp (Class A)	Communication Services	2013-08-01	
346	NWS	News Corp (Class B)	Communication Services	2015-09-18	
347	NEE	NextEra Energy	Utilities	1976-06-30	
348	NLSN	Nielsen Holdings	Industrials	2013-07-09	
349	NKE	Nike	Consumer Discretionary	1988-11-30	
350	NI	NiSource	Utilities	N/A	
351	NBL	Noble Energy	Energy	N/A	
352	JWN	Nordstrom	Consumer Cyclical	N/A	
353	NSC	Norfolk Southern	Industrials	1957-03-04	
354	NTRS	Northern Trust	Financials	N/A	
355	NOC	Northrop Grumman	Industrials	1985-06-30	
356	NLOK	NortonLifeLock	Information Technology	2003-03-25	
357	NCLH	Norwegian Cruise Line Holdings	Consumer Discretionary	2017-10-13	
358	NOV	Nov	Energy	2005-03-14	
359	NRG	NRG Energy	Utilities	2010-01-29	
360	NUE	Nucor	Materials	1985-04-30	
361	NVDA	Nvidia	Information Technology	2001-11-30	
362	OXY	Occidental Petroleum	Energy	1982-12-31	
363	OMC	Omnicom Group	Communication Services	N/A	
364	OKE	Oneok	Energy	2010-03-15	

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No.	Symbol	Security	Sector	Date first added	Date removed
365	ORCL	Oracle	Information Technology	1989-08-31	
366	ORLY	O'Reilly Automotive	Consumer Discretionary	2009-03-27	
367	PCAR	Paccar	Industrials	1980-12-31	
368	PCG	Pacific Gas & Electric Company	Energy	N/A	
369	PKG	Packaging Corporation of America	Materials	2017-07-26	
370	PH	Parker-Hannifin	Industrials	1985-11-30	
371	PDCO	Patterson Companies	Healthcare	N/A	2018-03-19
372	PAYX	Paychex	Information Technology	N/A	
373	PYPL	PayPal	Information Technology	2015-07-20	
374	PNR	Pentair	Industrials	2012-10-01	
375	PBCT	People's United Financial	Financials	2008-11-13	
376	PEP	PepsiCo	Consumer Staples	1957-03-04	
377	PKI	PerkinElmer	Healthcare	1985-05-31	
378	PRGO	Perrigo	Healthcare	2011-12-19	
379	PFE	Pfizer	Healthcare	1957-03-04	
380	PM	Philip Morris International	Consumer Staples	2008-03-31	
381	PSX	Phillips 66	Energy	2012-05-01	
382	PNW	Pinnacle West Capital	Utilities	N/A	
383	PXD	Pioneer Natural Resources	Energy	2008-09-24	
384	PNC	PNC Financial Services	Financials	1988-04-30	
385	PPG	PPG Industries	Materials	1957-03-04	
386	PPL	PPL	Utilities	N/A	
387	PFG	Principal Financial Group	Financials	2002-07-22	
388	PG	Procter & Gamble	Consumer Staples	1957-03-04	
389	PGR	Progressive Corporation	Financials	1997-08-04	
390	PLD	Prologis	Real Estate	2003-07-17	
391	PRU	Prudential Financial	Financials	2002-07-22	
392	PEG	Public Service Enterprise Group	Utilities	1957-03-04	
393	PSA	Public Storage	Real Estate	2005-08-19	
394	PHM	PulteGroup	Consumer Discretionary	1984-04-30	
395	PVH	PVH	Consumer Discretionary	2013-02-15	
396	QRVO	Qorvo	Information Technology	2015-06-11	
397	QCOM	Qualcomm	Information Technology	N/A	
398	PWR	Quanta Services	Industrials	2009-07-01	
399	DGX	Quest Diagnostics	Healthcare	2002-12-12	
400	RL	Ralph Lauren Corporation	Consumer Discretionary	2007-02-02	
401	RRC	Range Resources	Energy	N/A	2018-06-18
402	RJF	Raymond James Financial	Financials	2017-03-20	
403	RTN	Raytheon Company	Industrials	N/A	
404	RTX	Raytheon Technologies	Industrials	N/A	
405	O	Realty Income Corporation	Real Estate	2015-04-07	
406	RHT	Red Hat	Information Technology	N/A	
407	REG	Regency Centers	Real Estate	2017-03-02	
408	REGN	Regeneron Pharmaceuticals	Healthcare	2013-05-01	
409	RF	Regions Financial Corporation	Financials	1998-08-28	

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No.	Symbol	Security	Sector	Date first added	Date removed
410	RSG	Republic Services	Industrials	2008-12-05	
411	RMD	ResMed	Healthcare	2017-07-26	
412	RHI	Robert Half International	Industrials	2000-12-05	
413	ROK	Rockwell Automation	Industrials	N/A	
414	COL	Rockwell Collins	Industrials	N/A	2018-12-03
415	ROL*	Rollins	Industrials	2018-10-01	
416	ROP	Roper Technologies	Industrials	2009-12-23	
417	ROST	Ross Stores	Consumer Discretionary	2009-12-21	
418	RCL	Royal Caribbean Group	Consumer Discretionary	2014-12-05	
419	SPGI	S&P Global	Financials	N/A	
420	CRM	Salesforce	Information Technology	2008-09-15	
421	SBAC	SBA Communications	Real Estate	2017-09-01	
422	SCG	SCANA	Industrials	N/A	
423	SLB	Schlumberger	Energy	1965-03-31	
424	SNI	Scripps Networks Interactive	Communication Services	N/A	2018-03-07
425	STX	Seagate Technology	Information Technology	2012-07-02	
426	SEE	Sealed Air	Materials	1957-03-04	
427	SRE	Sempra Energy	Utilities	N/A	
428	SHW	Sherwin-Williams	Materials	1964-06-30	
429	SIG	Signet Jewelers	Consumer Cyclical	N/A	2018-03-19
430	SPG	Simon Property Group	Real Estate	2002-06-26	
431	SWKS	Skyworks Solutions	Information Technology	2015-03-12	
432	SNA	Snap-on	Industrials	1982-09-30	
433	SO	Southern Company	Utilities	1957-03-04	
434	LUV	Southwest Airlines	Industrials	1994-07-01	
435	SWK	Stanley Black & Decker	Industrials	1982-09-30	
436	SBUX	Starbucks	Consumer Discretionary	N/A	
437	STT	State Street Corporation	Financials	N/A	
438	SRCL	Stericycle	Industrials	N/A	2018-12-03
439	SYK	Stryker Corporation	Healthcare	2000-12-12	
440	STI	SunTrust Banks	Financials	N/A	
441	SIVB*	SVB Financial	Financials	2018-03-19	
442	SYF	Synchrony Financial	Financials	2015-11-18	
443	SNPS	Synopsys	Information Technology	2017-03-16	
444	SYY	Sysco	Consumer Staples	1986-12-31	
445	TROW	T. Rowe Price	Financials	N/A	
446	TTWO*	Take-Two Interactive	Communication Services	2018-03-19	
447	TPR	Tapestry	Consumer Discretionary	N/A	
448	TGT	Target Corporation	Consumer Discretionary	1976-12-31	
449	TEL	TE Connectivity	Information Technology	2011-10-17	
450	TXN	Texas Instruments	Information Technology	N/A	
451	TXT	Textron	Industrials	1978-12-31	
452	COO	The Cooper Companies	Healthcare	2016-09-23	
453	GT	The Goodyear Tire & Rubber Company	Consumer Cyclical	N/A	
454	HIG	The Hartford	Financials	1957-03-04	
455	HSY	The Hershey Company	Consumer Staples	1957-03-04	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
456	MOS	The Mosaic Company	Materials	2011-09-26	
457	TRV	The Travelers Companies	Financials	2002-08-21	
458	DIS	The Walt Disney Company	Communication Services	1976-06-30	
459	TMO	Thermo Fisher Scientific	Healthcare	2004-08-03	
460	TWX	Time Warner	Communication Services	N/A	2018-06-20
461	TJX	TJX Companies	Consumer Discretionary	1985-09-30	
462	TSCO	Tractor Supply Company	Consumer Discretionary	2014-01-24	
463	TT	Trane Technologies	Industrials	2010-11-17	
464	TDG	TransDigm Group	Industrials	2016-06-03	
465	TRIP	TripAdvisor	Consumer Cyclical	N/A	
466	TFC	Truist Financial	Financials	1997-12-04	
467	TSS	TSYS	Information Technology	N/A	
468	TWTR*	Twitter	Communication Services	2018-06-07	
469	TSN	Tyson Foods	Consumer Staples	2005-08-10	
470	USB	U.S. Bancorp	Financials	N/A	
471	UDR	UDR	Real Estate	2016-03-07	
472	ULTA	Ulta Beauty	Consumer Discretionary	2016-04-18	
473	UAA	Under Armour (Class A)	Consumer Discretionary	2014-05-01	
474	UA	Under Armour (Class C)	Consumer Discretionary	2016-04-08	
475	UNP	Union Pacific	Industrials	1957-03-04	
476	UAL	United Airlines	Industrials	2015-09-03	
477	UPS	United Parcel Service	Industrials	2002-07-22	
478	URI	United Rentals	Industrials	2014-09-20	
479	UNH	UnitedHealth Group	Healthcare	1994-07-01	
480	UHS	Universal Health Services	Healthcare	2014-09-20	
481	UNM	Unum Group	Financials	1994-03-01	
482	VLO	Valero Energy	Energy	N/A	
483	VTR	Ventas	Real Estate	2009-03-04	
484	VRSN	Verisign	Information Technology	2006-02-01	
485	VRSK	Verisk Analytics	Industrials	2015-10-08	
486	VZ	Verizon Communications	Communication Services	1983-11-30	
487	VRTX	Vertex Pharmaceuticals	Healthcare	2013-09-23	
488	VFC	VF Corporation	Consumer Discretionary	1979-06-30	
489	VIAB	Viacom	Consumer Services	N/A	
490	VIAC	ViacomCBS	Communication Services	N/A	
491	VTRS	Viatis	Healthcare	2004-04-23	
492	V	Visa	Information Technology	2009-12-21	
493	VNO	Vornado Realty Trust	Real Estate	N/A	
494	VMC	Vulcan Materials	Materials	1999-06-30	
495	GWW	W. W. Grainger	Industrials	1981-06-30	
496	WBA	Walgreens Boots Alliance	Consumer Staples	1979-12-31	
497	WMT	Walmart	Consumer Staples	1982-08-31	
498	WM	Waste Management	Industrials	N/A	
499	WAT	Waters Corporation	Healthcare	N/A	
500	WEC	WEC Energy Group	Utilities	2008-10-31	
501	WCG*	WellCare	Healthcare	N/A	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
502	WFC	Wells Fargo	Financials	1976-06-30	
503	WELL	Welltower	Real Estate	2009-01-30	
504	WDC	Western Digital	Information Technology	2009-07-01	
505	WU	Western Union	Information Technology	2006-09-29	
506	WRK	WestRock	Materials	N/A	
507	WY	Weyerhaeuser	Real Estate	N/A	
508	WHR	Whirlpool Corporation	Consumer Discretionary	N/A	
509	WMB	Williams Companies	Energy	1975-03-31	
510	WLTW	Willis Towers Watson	Financials	2016-01-05	
511	WYN	Wyndham Worldwide	Industrials	N/A	2018-05-31
512	WYNN	Wynn Resorts	Consumer Discretionary	2008-11-14	
513	XEL	Xcel Energy	Utilities	1957-03-04	
514	XLNX	Xilinx	Information Technology	1999-11-08	
515	XL	XL Group	Consumer Cyclical	N/A	2018-09-14
516	XYL	Xylem	Industrials	2011-11-01	
517	YUM	Yum! Brands	Consumer Discretionary	1997-10-06	
518	ZBH	Zimmer Biomet	Healthcare	2001-08-07	
519	ZION	Zions Bancorp	Financials	2001-06-22	
520	ZTS	Zoetis	Healthcare	2013-06-21	

Table F - 5 : The companies listed on S&P 500 index in 2019

No.	Symbol	Security	Sector	Date first added	Date removed
1	MMM	3M	Industrials	1976-08-09	
2	AOS	A. O. Smith	Industrials	2017-07-26	
3	ABT	Abbott Laboratories	Healthcare	1964-03-31	
4	ABBV	AbbVie	Healthcare	2012-12-31	
5	ABMD	Abiomed	Healthcare	2018-05-31	
6	ACN	Accenture	Information Technology	2011-07-06	
7	ATVI	Activision Blizzard	Communication Services	2015-08-31	
8	ADM	ADM	Consumer Staples	1981-07-29	
9	ADBE	Adobe	Information Technology	1997-05-05	
10	AAP	Advance Auto Parts	Consumer Discretionary	2015-07-09	
11	AMD	Advanced Micro Devices	Information Technology	N/A	
12	AES	AES Corp	Utilities	1998-10-02	
13	AMG	Affiliated Managers Group	Financials	N/A	2019-12-23
14	AFL	Aflac	Financials	1999-05-28	
15	A	Agilent Technologies	Healthcare	2000-06-05	
16	APD	Air Products & Chemicals	Materials	1985-04-30	
17	AKAM	Akamai Technologies	Information Technology	2007-07-12	
18	ALK	Alaska Air Group	Industrials	2016-05-13	
19	ALB	Albemarle Corporation	Materials	2016-07-01	
20	ARE	Alexandria Real Estate Equities	Real Estate	2017-03-20	
21	ALGN	Align Technology	Healthcare	2017-06-19	
22	ALLE	Allegion	Industrials	2013-12-02	
23	AGN	Allergan	Healthcare	N/A	
24	ADS	Alliance Data Systems	Financials	N/A	
25	LNT	Alliant Energy	Utilities	2016-07-01	
26	ALL	Allstate Corp	Financials	1995-07-13	
27	GOOGL	Alphabet (Class A)	Communication Services	2014-04-03	
28	GOOG	Alphabet (Class C)	Communication Services	2006-04-03	
29	MO	Altria Group	Consumer Staples	1957-03-04	
30	AMZN	Amazon	Consumer Discretionary	2005-11-18	
31	AMCR*	Amcor	Materials	2019-06-07	
32	AEE	Ameren Corp	Utilities	1991-09-19	
33	AAL	American Airlines Group	Industrials	2015-03-23	
34	AEP	American Electric Power	Utilities	1957-03-04	
35	AXP	American Express	Financials	1976-06-30	
36	AIG	American International Group	Financials	1980-03-31	
37	AMT	American Tower	Real Estate	2007-11-19	
38	AWK	American Water Works	Utilities	2016-03-04	
39	AMP	Ameriprise Financial	Financials	2005-10-03	
40	ABC	AmerisourceBergen	Healthcare	2001-08-30	
41	AME	Ametek	Industrials	2013-09-23	
42	AMGN	Amgen	Healthcare	1992-01-02	
43	APH	Amphenol Corp	Information Technology	2008-09-30	
44	APC	Anadarko Petroleum	Healthcare	N/A	2019-08-09

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
45	ADI	Analog Devices	Information Technology	1999-10-12	
46	ANSS	Ansys	Information Technology	2017-06-19	
47	ANTM	Anthem	Healthcare	2002-07-25	
48	AON	Aon	Financials	1996-04-23	
49	APA	APA Corporation	Energy	1997-07-28	
50	AIV	Apartment Investment & Management	Real Estate	N/A	
51	AAPL	Apple	Information Technology	1982-11-30	
52	AMAT	Applied Materials	Information Technology	1995-03-16	
53	APTV	Aptiv	Consumer Discretionary	2012-12-24	
54	ARNC	Arconic	Industrials	N/A	
55	ANET	Arista Networks	Information Technology	2018-08-28	
56	AJG	Arthur J. Gallagher & Co.	Financials	2016-05-31	
57	AIZ	Assurant	Financials	2007-04-10	
58	T	AT&T	Communication Services	1983-11-30 (1957-03-04)	
59	ATO*	Atmos Energy	Utilities	2019-02-15	
60	ADSK	Autodesk	Information Technology	1989-12-01	
61	ADP	Automatic Data Processing	Information Technology	1981-03-31	
62	AZO	AutoZone	Consumer Discretionary	1997-01-02	
63	AVB	AvalonBay Communities	Real Estate	2007-01-10	
64	AVY	Avery Dennison	Materials	1987-12-31	
65	BKR	Baker Hughes	Energy	2017-07-07	
66	BLL	Ball Corp	Materials	1984-10-31	
67	BAC	Bank of America	Financials	1976-06-30	
68	BBWI	Bath & Body Works, Inc.	Consumer Discretionary	1983-09-30	
69	BAX	Baxter International	Healthcare	1972-09-30	
70	BDX	Becton Dickinson	Healthcare	1972-09-30	
71	BRK.B	Berkshire Hathaway	Financials	2010-02-16	
72	BBY	Best Buy	Consumer Discretionary	1999-06-29	
73	BIIB	Biogen	Healthcare	2003-11-13	
74	TECH	Bio-Techne	Healthcare	2021-08-30	
75	BLK	BlackRock	Financials	2011-04-04	
76	BK	BNY Mellon	Financials	1995-03-31	
77	BA	Boeing Company	Industrials	1957-03-04	
78	BKNG	Booking Holdings	Consumer Discretionary	2009-11-06	
79	BWA	BorgWarner	Consumer Discretionary	2011-12-19	
80	BXP	Boston Properties	Real Estate	2006-04-03	
81	BSX	Boston Scientific	Healthcare	1995-02-24	
82	BHF	Brighthouse Financial	Financials	N/A	2019-04-02
83	BMJ	Bristol-Myers Squibb	Healthcare	1957-03-04	
84	AVGO	Broadcom	Information Technology	2014-05-08	
85	BR	Broadridge Financial Solutions	Information Technology	2018-06-18	
86	BF.B	Brown–Forman	Consumer Staples	1982-10-31	
87	CHRW	C. H. Robinson	Industrials	2007-03-02	
88	COG	Cabot Oil & Gas	Energy	2008-06-23	
89	CDNS	Cadence Design Systems	Information Technology	2017-09-18	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
90	CPB	Campbell Soup	Consumer Staples	1957-03-04	
91	COF	Capital One Financial	Financials	1998-07-01	
92	CPRI	Capri Holdings	Consumer Cyclical	N/A	
93	CAH	Cardinal Health	Healthcare	1997-05-27	
94	KMX	CarMax	Consumer Discretionary	2010-06-28	
95	CCL	Carnival Corporation	Consumer Discretionary	1998-12-22	
96	CTLT	Catalent	Healthcare	2020-09-21	
97	CAT	Caterpillar	Industrials	1957-03-04	
98	CBOE	Cboe Global Markets	Financials	2017-03-01	
99	CBRE	CBRE	Real Estate	2006-11-10	
100	CDW*	CDW	Information Technology	2019-09-23	
101	CE	Celanese	Materials	2018-12-24	
102	CELG	Celgene	Healthcare	N/A	2019-12-21
103	CNC	Centene Corporation	Healthcare	2016-03-30	
104	CNP	CenterPoint Energy	Utilities	1985-07-31	
105	CERN	Cerner	Healthcare	2010-04-30	
106	CF	CF Industries	Materials	2008-08-27	
107	SCHW	Charles Schwab Corporation	Financials	1997-06-02	
108	CHTR	Charter Communications	Communication Services	2016-09-08	
109	CVX	Chevron Corporation	Energy	1957-03-04	
110	CMG	Chipotle Mexican Grill	Consumer Discretionary	2011-04-28	
111	CB	Chubb	Financials	2010-07-15	
112	CHD	Church & Dwight	Consumer Staples	2015-12-29	
113	CI	Cigna	Healthcare	1976-06-30	
114	XEC	Cimarex Energy	Energy	N/A	
115	CINF	Cincinnati Financial	Financials	1997-12-18	
116	CTAS	Cintas Corporation	Industrials	2001-03-01	
117	CSCO	Cisco Systems	Information Technology	1993-12-01	
118	C	Citigroup	Financials	1988-05-31	
119	CFG	Citizens Financial Group	Financials	2016-01-29	
120	CTXS	Citrix Systems	Information Technology	1999-12-01	
121	CLX	Clorox	Consumer Staples	1969-03-31	
122	CME	CME Group	Financials	2006-08-11	
123	CMS	CMS Energy	Utilities	1999-05-03	
124	KO	Coca-Cola Company	Consumer Staples	1957-03-04	
125	CTSH	Cognizant Technology Solutions	Information Technology	2006-11-17	
126	CL	Colgate-Palmolive	Consumer Staples	1957-03-04	
127	CMCSA	Comcast	Communication Services	2002-11-19	
128	CMA	Comerica	Financials	1995-12-01	
129	CAG	Conagra Brands	Consumer Staples	1983-08-31	
130	COP	ConocoPhillips	Energy	1957-03-04	
131	ED	Consolidated Edison	Utilities	N/A	
132	STZ	Constellation Brands	Consumer Staples	2005-07-01	
133	CPRT	Copart	Industrials	2018-07-02	
134	GLW	Corning	Information Technology	N/A	
135	CTVA*	Corteva	Materials	2019-06-03	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
136	COST	Costco	Consumer Staples	1993-10-01	
137	COTY	Coty	Consumer Defensive	2016-09-30	
138	CCI	Crown Castle	Real Estate	2012-03-14	
139	CSX	CSX	Industrials	1967-09-30	
140	CMI	Cummins	Industrials	1965-03-31	
141	CVS	CVS Health	Healthcare	1957-03-04	
142	DHI	D. R. Horton	Consumer Discretionary	2005-06-22	
143	DHR	Danaher Corporation	Healthcare	N/A	
144	DRI	Darden Restaurants	Consumer Discretionary	N/A	
145	DVA	DaVita	Healthcare	2008-07-31	
146	DE	Deere & Co.	Industrials	1957-03-04	
147	DAL	Delta Air Lines	Industrials	2013-09-11	
148	XRAY	Dentsply Sirona	Healthcare	2008-11-14	
149	DVN	Devon Energy	Energy	2000-08-30	
150	FANG	Diamondback Energy	Energy	2018-12-03	
151	DLR	Digital Realty Trust	Real Estate	2016-05-18	
152	DFS	Discover Financial Services	Financials	2007-07-02	
153	DISCA	Discovery (Series A)	Communication Services	2010-03-01	
154	DISCK	Discovery (Series C)	Communication Services	2014-08-07	
155	DISH	Dish Network	Communication Services	2017-03-13	
156	DG	Dollar General	Consumer Discretionary	2012-12-03	
157	DLTR	Dollar Tree	Consumer Discretionary	2011-12-19	
158	D	Dominion Energy	Utilities	N/A	
159	DOV	Dover Corporation	Industrials	1985-10-31	
160	DOW*	Dow	Materials	2019-04-01	
161	DTE	DTE Energy	Utilities	1957-03-04	
162	DUK	Duke Energy	Utilities	1976-06-30	
163	DRE	Duke Realty Corp	Real Estate	2017-07-26	
164	DD*	DuPont	Materials	2019-04-02	
165	DWDP	DuPont	Industrials	N/A	2019-06-03
166	DXC	DXC Technology	Information Technology	2017-04-04	
167	EMN	Eastman Chemical	Materials	1994-01-01	
168	ETN	Eaton Corporation	Industrials	N/A	
169	EBAY	eBay	Consumer Discretionary	2002-07-22	
170	ECL	Ecolab	Materials	1989-01-31	
171	EIX	Edison International	Utilities	1957-03-04	
172	EW	Edwards Lifesciences	Healthcare	2011-04-01	
173	EA	Electronic Arts	Communication Services	2002-07-22	
174	LLY	Eli Lilly & Co	Healthcare	1970-12-31	
175	EMR	Emerson Electric Company	Industrials	1965-03-31	
176	ETR	Entergy	Utilities	1957-03-04	
177	EOG	EOG Resources	Energy	2000-11-02	
178	EFX	Equifax	Industrials	1997-06-19	
179	EQIX	Equinix	Real Estate	2015-03-20	
180	EQR	Equity Residential	Real Estate	2001-12-03	
181	ESS	Essex Property Trust	Real Estate	2014-04-02	

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No.	Symbol	Security	Sector	Date first added	Date removed
182	EL	Estée Lauder Companies	Consumer Staples	2006-01-05	
183	ETFC	E-Trade	Financials	N/A	
184	RE	Everest Re	Financials	2017-06-19	
185	EVRG	Eversource Energy	Utilities	2018-06-05	
186	ES	Eversource Energy	Utilities	N/A	
187	EXC	Exelon	Utilities	1957-03-04	
188	EXPE	Expedia Group	Consumer Discretionary	2007-10-02	
189	EXPD	Expeditors	Industrials	2007-10-10	
190	EXR	Extra Space Storage	Real Estate	2016-01-19	
191	XOM	ExxonMobil	Energy	1957-03-04	
192	FFIV	F5 Networks	Information Technology	2010-12-20	
193	FB	Facebook	Communication Services	2013-12-23	
194	FAST	Fastenal	Industrials	2008-09-15	
195	FRT	Federal Realty Investment Trust	Real Estate	2016-02-01	
196	FDX	FedEx	Industrials	1980-12-31	
197	FIS	Fidelity National Information Services	Information Technology	2006-11-10	
198	FITB	Fifth Third Bancorp	Financials	N/A	
199	FRC*	First Republic Bank	Financials	2019-01-02	
200	FE	FirstEnergy	Utilities	N/A	
201	FISV	Fiserv	Information Technology	2001-04-02	
202	FLT	Fleetcor	Information Technology	2018-06-20	
203	FLR	Fluor Corporation	Industrials	N/A	2019-06-03
204	FMC	FMC Corporation	Materials	2009-08-19	
205	FL	Foot Locker	Consumer Cyclical	2016-04-04	2019-08-09
206	F	Ford	Consumer Discretionary	1957-03-04	
207	FTNT	Fortinet	Information Technology	2018-10-11	
208	FTV	Fortive	Industrials	2016-07-01	
209	FBHS	Fortune Brands Home & Security	Industrials	2016-06-22	
210	FOXA	Fox Corporation (Class A)	Communication Services	2013-07-01	
211	FOX	Fox Corporation (Class B)	Communication Services	2015-09-18	
212	BEN	Franklin Resources	Financials	N/A	
213	FCX	Freeport-McMoRan	Materials	N/A	
214	GPS	Gap	Consumer Discretionary	1986-08-31	
215	GRMN	Garmin	Consumer Discretionary	2012-12-12	
216	IT	Gartner	Information Technology	2017-04-05	
217	GD	General Dynamics	Industrials	1957-03-04	
218	GE	General Electric	Industrials	N/A	
219	GIS	General Mills	Consumer Staples	1969-03-31	
220	GM	General Motors	Consumer Discretionary	2013-06-06	
221	GPC	Genuine Parts	Consumer Discretionary	1973-12-31	
222	GILD	Gilead Sciences	Healthcare	2004-07-01	
223	GPN	Global Payments	Information Technology	2016-04-25	
224	GL	Globe Life	Financials	1989-04-30	
225	GS	Goldman Sachs	Financials	2002-07-22	
226	HRB	H&R Block	Consumer Cyclical	N/A	

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No.	Symbol	Security	Sector	Date first added	Date removed
227	HAL	Halliburton	Energy	1957-03-04	
228	HBI	Hanesbrands	Consumer Discretionary	2015-03-20	
229	HOG	Harley-Davidson	Consumer Cyclical	N/A	
230	HAS	Hasbro	Consumer Discretionary	1984-09-30	
231	HCA	HCA Healthcare	Healthcare	2015-01-27	
232	PEAK	Healthpeak Properties	Real Estate	2008-03-31	
233	HP	Helmerich & Payne	Energy	N/A	
234	HSIC	Henry Schein	Healthcare	2015-03-17	
235	HES	Hess Corporation	Energy	1984-05-31	
236	HPE	Hewlett Packard Enterprise	Information Technology	2015-11-02	
237	HLT	Hilton Worldwide	Consumer Discretionary	2017-06-19	
238	HOLX	Hologic	Healthcare	2016-03-30	
239	HD	Home Depot	Consumer Discretionary	1988-03-31	
240	HON	Honeywell	Industrials	1964-03-31	
241	HRL	Hormel	Consumer Staples	2009-03-04	
242	HST	Host Hotels & Resorts	Real Estate	2007-03-20	
243	HWM	Howmet Aerospace	Industrials	1964-03-31	
244	HPQ	HP	Information Technology	1974-12-31	
245	HUM	Humana	Healthcare	N/A	
246	HBAN	Huntington Bancshares	Financials	N/A	
247	HII	Huntington Ingalls Industries	Industrials	2018-01-03	
248	IBM	IBM	Information Technology	1957-03-04	
249	IEX*	IDEX Corporation	Industrials	2019-08-09	
250	IDXX	Idexx Laboratories	Healthcare	2017-01-05	
251	INFO	IHS Markit	Industrials	2017-06-02	
252	ITW	Illinois Tool Works	Industrials	1986-02-28	
253	ILMN	Illumina	Healthcare	2015-11-19	
254	INCY	Incyte	Healthcare	2017-02-28	
255	INTC	Intel	Information Technology	1976-12-31	
256	ICE	Intercontinental Exchange	Financials	2007-09-26	
257	IFF	International Flavors & Fragrances	Materials	1976-03-31	
258	IP	International Paper	Materials	1957-03-04	
259	IPG	Interpublic Group	Communication Services	1992-10-01	
260	INTU	Intuit	Information Technology	2000-12-05	
261	ISRG	Intuitive Surgical	Healthcare	2008-06-02	
262	IVZ	Invesco	Financials	2008-08-21	
263	IPGP	IPG Photonics	Information Technology	2018-03-07	
264	IQV	IQVIA	Healthcare	2017-08-29	
265	IRM	Iron Mountain	Real Estate	2009-01-06	
266	JBHT	J. B. Hunt	Industrials	2015-07-01	
267	JKHY	Jack Henry & Associates	Information Technology	2018-11-13	
268	J	Jacobs Engineering Group	Industrials	2007-10-26	
269	JEF	Jefferies Financial Group	Financials	N/A	2019-09-26
270	SJM	JM Smucker	Consumer Staples	2008-11-06	
271	JNJ	Johnson & Johnson	Healthcare	1973-06-30	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
272	JCI	Johnson Controls	Industrials	2010-08-27	
273	JPM	JPMorgan Chase	Financials	1975-06-30	
274	JNPR	Juniper Networks	Information Technology	2006-06-02	
275	KSU	Kansas City Southern	Industrials	2013-05-24	
276	K	Kellogg's	Consumer Staples	1989-09-11	
277	KEY	KeyCorp	Financials	1994-03-01	
278	KEYS	Keysight Technologies	Information Technology	2018-11-06	
279	KMB	Kimberly-Clark	Consumer Staples	1957-03-04	
280	KIM	Kimco Realty	Real Estate	2006-04-04	
281	KMI	Kinder Morgan	Energy	2012-05-25	
282	KLAC	KLA Corporation	Information Technology	N/A	
283	KSS	Kohl's	Consumer Cyclical	N/A	
284	KHC	Kraft Heinz	Consumer Staples	2015-07-06	
285	KR	Kroger	Consumer Staples	1957-03-04	
286	LLL	L3 Technologies	Information Technology	N/A	2019-07-01
287	LHX	L3Harris Technologies	Industrials	2008-09-22	
288	LH	LabCorp	Healthcare	2004-11-01	
289	LRCX	Lam Research	Information Technology	2012-06-29	
290	LW	Lamb Weston	Consumer Staples	2018-12-03	
291	LVS*	Las Vegas Sands	Consumer Discretionary	2019-10-03	
292	LEG	Leggett & Platt	Consumer Discretionary	1999-10-14	
293	LDOS*	Leidos	Industrials	2019-08-09	
294	LEN	Lennar	Consumer Discretionary	2005-10-04	
295	LNC	Lincoln National	Financials	1976-06-30	
296	LIN	Linde	Materials	1992-07-01	
297	LYV*	Live Nation Entertainment	Communication Services	2019-12-23	
298	LKQ	LKQ Corporation	Consumer Discretionary	2016-05-23	
299	LMT	Lockheed Martin	Industrials	1984-07-31	
300	L	Loews Corporation	Financials	N/A	
301	LOW	Lowe's	Consumer Discretionary	1984-02-29	
302	LUMN	Lumen Technologies	Communication Services	1999-03-25	
303	LYB	LyondellBasell	Materials	2012-09-05	
304	MTB	M&T Bank	Financials	2004-02-23	
305	MAC	Macerich	Real Estate	N/A	2019-12-23
306	M	Macy's	Consumer Cyclical	N/A	
307	MRO	Marathon Oil	Energy	1991-05-01	
308	MPC	Marathon Petroleum	Energy	2011-07-01	
309	MKTX*	MarketAxess	Financials	2019-07-01	
310	MAR	Marriott International	Consumer Discretionary	N/A	
311	MMC	Marsh & McLennan	Financials	1987-08-31	
312	MLM	Martin Marietta Materials	Materials	2014-07-02	
313	MAS	Masco	Industrials	1981-06-30	
314	MA	Mastercard	Information Technology	2008-07-18	
315	MAT	Mattel	Consumer Cyclical	N/A	2019-06-07
316	MKC	McCormick & Company	Consumer Staples	2003-03-20	
317	MCD	McDonald's	Consumer Discretionary	1970-06-30	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
318	MCK	McKesson Corporation	Healthcare	N/A	
319	MDT	Medtronic	Healthcare	1986-10-31	
320	MRK	Merck & Co.	Healthcare	1957-03-04	
321	MET	MetLife	Financials	N/A	321
322	MTD	Mettler Toledo	Healthcare	2016-09-06	322
323	MGM	MGM Resorts International	Consumer Discretionary	2017-07-26	323
324	MCHP	Microchip Technology	Information Technology	2007-09-07	324
325	MU	Micron Technology	Information Technology	1994-09-27	
326	MSFT	Microsoft	Information Technology	1994-06-01	
327	MAA	Mid-America Apartments	Real Estate	2016-12-02	
328	MHK	Mohawk Industries	Consumer Discretionary	2013-12-23	
329	TAP	Molson Coors Beverage Company	Consumer Staples	1976-06-30	
330	MDLZ	Mondelez International	Consumer Staples	2012-10-02	
331	MNST	Monster Beverage	Consumer Staples	2012-06-28	
332	MCO	Moody's Corporation	Financials	N/A	
333	MS	Morgan Stanley	Financials	N/A	
334	MSI	Motorola Solutions	Information Technology	N/A	
335	MSCI	MSCI	Financials	2018-04-04	
336	NDAQ	Nasdaq	Financials	2008-10-22	
337	NKTR	Nektar Therapeutics	Healthcare	N/A	2019-10-03
338	NTAP	NetApp	Information Technology	1999-06-25	
339	NFLX	Netflix	Communication Services	2010-12-20	
340	NWL	Newell Brands	Consumer Discretionary	1989-04-30	
341	NFX	Newfield Exploration	Energy	N/A	2019-02-15
342	NEM	Newmont	Materials	1969-06-30	
343	NWSA	News Corp (Class A)	Communication Services	2013-08-01	
344	NWS	News Corp (Class B)	Communication Services	2015-09-18	
345	NEE	NextEra Energy	Utilities	1976-06-30	
346	NLSN	Nielsen Holdings	Industrials	2013-07-09	
347	NKE	Nike	Consumer Discretionary	1988-11-30	
348	NI	NiSource	Utilities	N/A	
349	NBL	Noble Energy	Energy	N/A	
350	JWN	Nordstrom	Consumer Cyclical	N/A	
351	NSC	Norfolk Southern	Industrials	1957-03-04	
352	NTRS	Northern Trust	Financials	N/A	
353	NOC	Northrop Grumman	Industrials	1985-06-30	
354	NLOK	NortonLifeLock	Information Technology	2003-03-25	
355	NCLH	Norwegian Cruise Line Holdings	Consumer Discretionary	2017-10-13	
356	NOV	Nov	Energy	2005-03-14	
357	NRG	NRG Energy	Utilities	2010-01-29	
358	NUE	Nucor	Materials	1985-04-30	
359	NVDA	Nvidia	Information Technology	2001-11-30	
360	NVR*	NVR	Consumer Discretionary	2019-09-26	
361	OXY	Occidental Petroleum	Energy	1982-12-31	
362	ODFL*	Old Dominion Freight Line	Industrials	2019-12-09	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
363	OMC	Omnicom Group	Communication Services	N/A	
364	OKE	Oneok	Energy	2010-03-15	
365	ORCL	Oracle	Information Technology	1989-08-31	
366	ORLY	O'Reilly Automotive	Consumer Discretionary	2009-03-27	
367	PCAR	Paccar	Industrials	1980-12-31	
368	PCG	Pacific Gas & Electric Company	Energy	N/A	2019-01-18
369	PKG	Packaging Corporation of America	Materials	2017-07-26	
370	PH	Parker-Hannifin	Industrials	1985-11-30	
371	PAYX	Paychex	Information Technology	N/A	
372	PYPL	PayPal	Information Technology	2015-07-20	
373	PNR	Pentair	Industrials	2012-10-01	
374	PBCT	People's United Financial	Financials	2008-11-13	
375	PEP	PepsiCo	Consumer Staples	1957-03-04	
376	PKI	PerkinElmer	Healthcare	1985-05-31	
377	PRGO	Perrigo	Healthcare	2011-12-19	
378	PFE	Pfizer	Healthcare	1957-03-04	
379	PM	Philip Morris International	Consumer Staples	2008-03-31	
380	PSX	Phillips 66	Energy	2012-05-01	
381	PNW	Pinnacle West Capital	Utilities	N/A	
382	PXD	Pioneer Natural Resources	Energy	2008-09-24	
383	PNC	PNC Financial Services	Financials	1988-04-30	
384	PPG	PPG Industries	Materials	1957-03-04	
385	PPL	PPL	Utilities	N/A	
386	PFG	Principal Financial Group	Financials	2002-07-22	
387	PG	Procter & Gamble	Consumer Staples	1957-03-04	
388	PGR	Progressive Corporation	Financials	1997-08-04	
389	PLD	Prologis	Real Estate	2003-07-17	
390	PRU	Prudential Financial	Financials	2002-07-22	
391	PEG	Public Service Enterprise Group	Utilities	1957-03-04	
392	PSA	Public Storage	Real Estate	2005-08-19	
393	PHM	PulteGroup	Consumer Discretionary	1984-04-30	
394	PVH	PVH	Consumer Discretionary	2013-02-15	
395	QRVO	Qorvo	Information Technology	2015-06-11	
396	QCOM	Qualcomm	Information Technology	N/A	
397	PWR	Quanta Services	Industrials	2009-07-01	
398	DGX	Quest Diagnostics	Healthcare	2002-12-12	
399	RL	Ralph Lauren Corporation	Consumer Discretionary	2007-02-02	
400	RJF	Raymond James Financial	Financials	2017-03-20	
401	RTN	Raytheon Company	Industrials	N/A	
402	RTX	Raytheon Technologies	Industrials	N/A	
403	O	Realty Income Corporation	Real Estate	2015-04-07	
404	RHT	Red Hat	Information Technology	N/A	2019-07-15
405	REG	Regency Centers	Real Estate	2017-03-02	
406	REGN	Regeneron Pharmaceuticals	Healthcare	2013-05-01	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
407	RF	Regions Financial Corporation	Financials	1998-08-28	
408	RSG	Republic Services	Industrials	2008-12-05	
409	RMD	ResMed	Healthcare	2017-07-26	
410	RHI	Robert Half International	Industrials	2000-12-05	
411	ROK	Rockwell Automation	Industrials	N/A	
412	ROL	Rollins	Industrials	2018-10-01	
413	ROP	Roper Technologies	Industrials	2009-12-23	
414	ROST	Ross Stores	Consumer Discretionary	2009-12-21	
415	RCL	Royal Caribbean Group	Consumer Discretionary	2014-12-05	
416	SPGI	S&P Global	Financials	N/A	
417	CRM	Salesforce	Information Technology	2008-09-15	
418	SBAC	SBA Communications	Real Estate	2017-09-01	
419	SCG	SCANA	Industrials	N/A	2019-01-02
420	SLB	Schlumberger	Energy	1965-03-31	
421	STX	Seagate Technology	Information Technology	2012-07-02	
422	SEE	Sealed Air	Materials	1957-03-04	
423	SRE	Sempra Energy	Utilities	N/A	
424	NOW*	ServiceNow	Information Technology	2019-11-21	
425	SHW	Sherwin-Williams	Materials	1964-06-30	
426	SPG	Simon Property Group	Real Estate	2002-06-26	
427	SWKS	Skyworks Solutions	Information Technology	2015-03-12	
428	SNA	Snap-on	Industrials	1982-09-30	
429	SO	Southern Company	Utilities	1957-03-04	
430	LUV	Southwest Airlines	Industrials	1994-07-01	
431	SWK	Stanley Black & Decker	Industrials	1982-09-30	
432	SBUX	Starbucks	Consumer Discretionary	N/A	
433	STT	State Street Corporation	Financials	N/A	
434	STE*	Steris	Healthcare	2019-12-23	
435	SYK	Stryker Corporation	Healthcare	2000-12-12	
436	STI	SunTrust Banks	Financials	N/A	2019-12-09
437	SIVB	SVB Financial	Financials	2018-03-19	
438	SYF	Synchrony Financial	Financials	2015-11-18	
439	SNPS	Synopsys	Information Technology	2017-03-16	
440	SYY	Sysco	Consumer Staples	1986-12-31	
441	TROW	T. Rowe Price	Financials	N/A	
442	TTWO	Take-Two Interactive	Communication Services	2018-03-19	
443	TPR	Tapestry	Consumer Discretionary	N/A	
444	TGT	Target Corporation	Consumer Discretionary	1976-12-31	
445	TEL	TE Connectivity	Information Technology	2011-10-17	
446	TFX*	Teleflex	Healthcare	2019-01-18	
447	TXN	Texas Instruments	Information Technology	N/A	
448	TXT	Textron	Industrials	1978-12-31	
449	COO	The Cooper Companies	Healthcare	2016-09-23	
450	GT	The Goodyear Tire & Rubber Company	Consumer Cyclical	N/A	2019-02-27
451	HIG	The Hartford	Financials	1957-03-04	
452	HSY	The Hershey Company	Consumer Staples	1957-03-04	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
453	MOS	The Mosaic Company	Materials	2011-09-26	
454	TRV	The Travelers Companies	Financials	2002-08-21	
455	DIS	The Walt Disney Company	Communication Services	1976-06-30	
456	TMO	Thermo Fisher Scientific	Healthcare	2004-08-03	
457	TJX	TJX Companies	Consumer Discretionary	1985-09-30	
458	TMUS*	T-Mobile US	Communication Services	2019-07-15	
459	TSCO	Tractor Supply Company	Consumer Discretionary	2014-01-24	
460	TT	Trane Technologies	Industrials	2010-11-17	
461	TDG	TransDigm Group	Industrials	2016-06-03	
462	TRIP	TripAdvisor	Consumer Cyclical	N/A	2019-12-23
463	TFC	Truist Financial	Financials	1997-12-04	
464	TSS	TSYS	Information Technology	N/A	2019-09-23
465	TWTR	Twitter	Communication Services	2018-06-07	
466	TSN	Tyson Foods	Consumer Staples	2005-08-10	
467	USB	U.S. Bancorp	Financials	N/A	
468	UDR	UDR	Real Estate	2016-03-07	
469	ULTA	Ulta Beauty	Consumer Discretionary	2016-04-18	
470	UAA	Under Armour (Class A)	Consumer Discretionary	2014-05-01	
471	UA	Under Armour (Class C)	Consumer Discretionary	2016-04-08	
472	UNP	Union Pacific	Industrials	1957-03-04	
473	UAL	United Airlines	Industrials	2015-09-03	
474	UPS	United Parcel Service	Industrials	2002-07-22	
475	URI	United Rentals	Industrials	2014-09-20	
476	UNH	UnitedHealth Group	Healthcare	1994-07-01	
477	UHS	Universal Health Services	Healthcare	2014-09-20	
478	UNM	Unum Group	Financials	1994-03-01	
479	VLO	Valero Energy	Energy	N/A	
480	VTR	Ventas	Real Estate	2009-03-04	
481	VRSN	Verisign	Information Technology	2006-02-01	
482	VRSK	Verisk Analytics	Industrials	2015-10-08	
483	VZ	Verizon Communications	Communication Services	1983-11-30	
484	VRTX	Vertex Pharmaceuticals	Healthcare	2013-09-23	
485	VFC	VF Corporation	Consumer Discretionary	1979-06-30	
486	VIAB	Viacom	Consumer Services	N/A	2019-12-05
487	VIAC	ViacomCBS	Communication Services	N/A	
488	VTRS	Viatis	Healthcare	2004-04-23	
489	V	Visa	Information Technology	2009-12-21	
490	VNO	Vornado Realty Trust	Real Estate	N/A	
491	VMC	Vulcan Materials	Materials	1999-06-30	
492	WRB*	W. R. Berkley Corporation	Financials	2019-12-05	
493	GWV	W. W. Grainger	Industrials	1981-06-30	
494	WAB*	Wabtec	Industrials	2019-02-27	
495	WBA	Walgreens Boots Alliance	Consumer Staples	1979-12-31	
496	WMT	Walmart	Consumer Staples	1982-08-31	
497	WM	Waste Management	Industrials	N/A	
498	WAT	Waters Corporation	Healthcare	N/A	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
499	WEC	WEC Energy Group	Utilities	2008-10-31	
500	WCG	WellCare	Healthcare	N/A	
501	WFC	Wells Fargo	Financials	1976-06-30	
502	WELL	Welltower	Real Estate	2009-01-30	
503	WDC	Western Digital	Information Technology	2009-07-01	
504	WU	Western Union	Information Technology	2006-09-29	
505	WRK	WestRock	Materials	N/A	
506	WY	Weyerhaeuser	Real Estate	N/A	
507	WHR	Whirlpool Corporation	Consumer Discretionary	N/A	
508	WMB	Williams Companies	Energy	1975-03-31	
509	WLTW	Willis Towers Watson	Financials	2016-01-05	
510	WYNN	Wynn Resorts	Consumer Discretionary	2008-11-14	
511	XEL	Xcel Energy	Utilities	1957-03-04	
512	XLNX	Xilinx	Information Technology	1999-11-08	

Table F - 6 : The companies listed on S&P 500 index in 2020

No.	Symbol	Security	Sector	Date first added	Date removed
1	MMM	3M	Industrials	1976-08-09	
2	AOS	A. O. Smith	Industrials	2017-07-26	
3	ABT	Abbott Laboratories	Health Care	1964-03-31	
4	ABBV	AbbVie	Health Care	2012-12-31	
5	ABMD	Abiomed	Health Care	2018-05-31	
6	ACN	Accenture	Information Technology	2011-07-06	
7	ATVI	Activision Blizzard	Communication Services	2015-08-31	
8	ADM	ADM	Consumer Staples	1981-07-29	
9	ADBE	Adobe	Information Technology	1997-05-05	
10	AAP	Advance Auto Parts	Consumer Discretionary	2015-07-09	
11	AMD	Advanced Micro Devices	Information Technology	N/A	
12	AES	AES Corp	Utilities	1998-10-02	
13	AFL	Aflac	Financials	1999-05-28	
14	A	Agilent Technologies	Health Care	2000-06-05	
15	APD	Air Products & Chemicals	Materials	1985-04-30	
16	AKAM	Akamai Technologies	Information Technology	2007-07-12	
17	ALK	Alaska Air Group	Industrials	2016-05-13	
18	ALB	Albemarle Corporation	Materials	2016-07-01	
19	ARE	Alexandria Real Estate Equities	Real Estate	2017-03-20	
20	ALGN	Align Technology	Health Care	2017-06-19	
21	ALLE	Allegion	Industrials	2013-12-02	
22	AGN	Allergan	Health Care	N/A	2020-05-12
23	ADS	Alliance Data Systems	Financials	N/A	2020-06-22
24	LNT	Alliant Energy	Utilities	2016-07-01	
25	ALL	Allstate Corp	Financials	1995-07-13	
26	GOOGL	Alphabet (Class A)	Communication Services	2014-04-03	
27	GOOG	Alphabet (Class C)	Communication Services	2006-04-03	
28	MO	Altria Group	Consumer Staples	1957-03-04	
29	AMZN	Amazon	Consumer Discretionary	2005-11-18	
30	AMCR	Amcort	Materials	2019-06-07	
31	AEE	Ameren Corp	Utilities	1991-09-19	
32	AAL	American Airlines Group	Industrials	2015-03-23	
33	AEP	American Electric Power	Utilities	1957-03-04	
34	AXP	American Express	Financials	1976-06-30	
35	AIG	American International Group	Financials	1980-03-31	
36	AMT	American Tower	Real Estate	2007-11-19	
37	AWK	American Water Works	Utilities	2016-03-04	
38	AMP	Ameriprise Financial	Financials	2005-10-03	
39	ABC	AmerisourceBergen	Health Care	2001-08-30	
40	AME	Ametek	Industrials	2013-09-23	
41	AMGN	Amgen	Health Care	1992-01-02	
42	APH	Amphenol Corp	Information Technology	2008-09-30	
43	ADI	Analog Devices	Information Technology	1999-10-12	
44	ANSS	Ansys	Information Technology	2017-06-19	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
45	ANTM	Anthem	Health Care	2002-07-25	
46	AON	Aon	Financials	1996-04-23	
47	APA	APA Corporation	Energy	1997-07-28	
48	AIV	Apartment Investment & Management	Real Estate	N/A	2020-12-21
49	AAPL	Apple	Information Technology	1982-11-30	
50	AMAT	Applied Materials	Information Technology	1995-03-16	
51	APTV	Aptiv	Consumer Discretionary	2012-12-24	
52	ARNC	Arconic	Industrials	N/A	2020-04-01
53	ANET	Arista Networks	Information Technology	2018-08-28	
54	AJG	Arthur J. Gallagher & Co.	Financials	2016-05-31	
55	AIZ	Assurant	Financials	2007-04-10	
56	T	AT&T	Communication Services	1983-11-30 (1957-03-04)	
57	ATO	Atmos Energy	Utilities	2019-02-15	
58	ADSK	Autodesk	Information Technology	1989-12-01	
59	ADP	Automatic Data Processing	Information Technology	1981-03-31	
60	AZO	AutoZone	Consumer Discretionary	1997-01-02	
61	AVB	AvalonBay Communities	Real Estate	2007-01-10	
62	AVY	Avery Dennison	Materials	1987-12-31	
63	BKR	Baker Hughes	Energy	2017-07-07	
64	BLL	Ball Corp	Materials	1984-10-31	
65	BAC	Bank of America	Financials	1976-06-30	
66	BBWI	Bath & Body Works, Inc.	Consumer Discretionary	1983-09-30	
67	BAX	Baxter International	Health Care	1972-09-30	
68	BDX	Becton Dickinson	Health Care	1972-09-30	
69	BRK.B	Berkshire Hathaway	Financials	2010-02-16	
70	BBY	Best Buy	Consumer Discretionary	1999-06-29	
71	BIIB	Biogen	Health Care	2003-11-13	
72	BIO*	Bio-Rad Laboratories	Health Care	2020-06-22	
73	TECH	Bio-Techne	Health Care	2021-08-30	
74	BLK	BlackRock	Financials	2011-04-04	
75	BK	BNY Mellon	Financials	1995-03-31	
76	BA	Boeing Company	Industrials	1957-03-04	
77	BKNG	Booking Holdings	Consumer Discretionary	2009-11-06	
78	BWA	BorgWarner	Consumer Discretionary	2011-12-19	
79	BXP	Boston Properties	Real Estate	2006-04-03	
80	BSX	Boston Scientific	Health Care	1995-02-24	
81	BMJ	Bristol-Myers Squibb	Health Care	1957-03-04	
82	AVGO	Broadcom	Information Technology	2014-05-08	
83	BR	Broadridge Financial Solutions	Information Technology	2018-06-18	
84	BF.B	Brown–Forman	Consumer Staples	1982-10-31	
85	CHRW	C. H. Robinson	Industrials	2007-03-02	
86	COG	Cabot Oil & Gas	Energy	2008-06-23	
87	CDNS	Cadence Design Systems	Information Technology	2017-09-18	
88	CPB	Campbell Soup	Consumer Staples	1957-03-04	
89	COF	Capital One Financial	Financials	1998-07-01	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
90	CPRI	Capri Holdings	Consumer Cyclical	N/A	2020-05-12
91	CAH	Cardinal Health	Health Care	1997-05-27	
92	KMX	CarMax	Consumer Discretionary	2010-06-28	
93	CCL	Carnival Corporation	Consumer Discretionary	1998-12-22	
94	CARR*	Carrier Global	Industrials	2020-04-03	
95	CTLT	Catalent	Health Care	2020-09-21	
96	CAT	Caterpillar	Industrials	1957-03-04	
97	CBOE	Cboe Global Markets	Financials	2017-03-01	
98	CBRE	CBRE	Real Estate	2006-11-10	
99	CDW	CDW	Information Technology	2019-09-23	
100	CE	Celanese	Materials	2018-12-24	
101	CNC	Centene Corporation	Health Care	2016-03-30	
102	CNP	CenterPoint Energy	Utilities	1985-07-31	
103	CERN	Cerner	Health Care	2010-04-30	
104	CF	CF Industries	Materials	2008-08-27	
105	SCHW	Charles Schwab Corporation	Financials	1997-06-02	
106	CHTR	Charter Communications	Communication Services	2016-09-08	
107	CVX	Chevron Corporation	Energy	1957-03-04	
108	CMG	Chipotle Mexican Grill	Consumer Discretionary	2011-04-28	
109	CB	Chubb	Financials	2010-07-15	
110	CHD	Church & Dwight	Consumer Staples	2015-12-29	
111	CI	Cigna	Health Care	1976-06-30	
112	XEC	Cimarex Energy	Energy	N/A	2020-03-02
113	CINF	Cincinnati Financial	Financials	1997-12-18	
114	CTAS	Cintas Corporation	Industrials	2001-03-01	
115	CSCO	Cisco Systems	Information Technology	1993-12-01	
116	C	Citigroup	Financials	1988-05-31	
117	CFG	Citizens Financial Group	Financials	2016-01-29	
118	CTXS	Citrix Systems	Information Technology	1999-12-01	
119	CLX	Clorox	Consumer Staples	1969-03-31	
120	CME	CME Group	Financials	2006-08-11	
121	CMS	CMS Energy	Utilities	1999-05-03	
122	KO	Coca-Cola Company	Consumer Staples	1957-03-04	
123	CTSH	Cognizant Technology Solutions	Information Technology	2006-11-17	
124	CL	Colgate-Palmolive	Consumer Staples	1957-03-04	
125	CMCSA	Comcast	Communication Services	2002-11-19	
126	CMA	Comerica	Financials	1995-12-01	
127	CAG	Conagra Brands	Consumer Staples	1983-08-31	
128	COP	ConocoPhillips	Energy	1957-03-04	
129	ED	Consolidated Edison	Utilities	N/A	
130	STZ	Constellation Brands	Consumer Staples	2005-07-01	
131	CPRT	Copart	Industrials	2018-07-02	
132	GLW	Corning	Information Technology	N/A	
133	CTVA	Corteva	Materials	2019-06-03	
134	COST	Costco	Consumer Staples	1993-10-01	
135	COTY	Coty	Consumer Defensive	2016-09-30	2020-09-21

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
136	CCI	Crown Castle	Real Estate	2012-03-14	
137	CSX	CSX	Industrials	1967-09-30	
138	CMI	Cummins	Industrials	1965-03-31	
139	CVS	CVS Health	Health Care	1957-03-04	
140	DHI	D. R. Horton	Consumer Discretionary	2005-06-22	
141	DHR	Danaher Corporation	Health Care	N/A	
142	DRI	Darden Restaurants	Consumer Discretionary	N/A	
143	DVA	DaVita	Health Care	2008-07-31	
144	DE	Deere & Co.	Industrials	1957-03-04	
145	DAL	Delta Air Lines	Industrials	2013-09-11	
146	XRAY	Dentsply Sirona	Health Care	2008-11-14	
147	DVN	Devon Energy	Energy	2000-08-30	
148	DXCM*	DexCom	Health Care	2020-05-12	
149	FANG	Diamondback Energy	Energy	2018-12-03	
150	DLR	Digital Realty Trust	Real Estate	2016-05-18	
151	DFS	Discover Financial Services	Financials	2007-07-02	
152	DISCA	Discovery (Series A)	Communication Services	2010-03-01	
153	DISCK	Discovery (Series C)	Communication Services	2014-08-07	
154	DISH	Dish Network	Communication Services	2017-03-13	
155	DG	Dollar General	Consumer Discretionary	2012-12-03	
156	DLTR	Dollar Tree	Consumer Discretionary	2011-12-19	
157	D	Dominion Energy	Utilities	N/A	
158	DPZ*	Domino's Pizza	Consumer Discretionary	2020-05-12	
159	DOV	Dover Corporation	Industrials	1985-10-31	
160	DOW	Dow	Materials	2019-04-01	
161	DTE	DTE Energy	Utilities	1957-03-04	
162	DUK	Duke Energy	Utilities	1976-06-30	
163	DRE	Duke Realty Corp	Real Estate	2017-07-26	
164	DD	DuPont	Materials	2019-04-02	
165	DXC	DXC Technology	Information Technology	2017-04-04	
166	EMN	Eastman Chemical	Materials	1994-01-01	
167	ETN	Eaton Corporation	Industrials	N/A	
168	EBAY	eBay	Consumer Discretionary	2002-07-22	
169	ECL	Ecolab	Materials	1989-01-31	
170	EIX	Edison International	Utilities	1957-03-04	
171	EW	Edwards Lifesciences	Health Care	2011-04-01	
172	EA	Electronic Arts	Communication Services	2002-07-22	
173	LLY	Eli Lilly & Co	Health Care	1970-12-31	
174	EMR	Emerson Electric Company	Industrials	1965-03-31	
175	ETR	Entergy	Utilities	1957-03-04	
176	EOG	EOG Resources	Energy	2000-11-02	
177	EFX	Equifax	Industrials	1997-06-19	
178	EQIX	Equinix	Real Estate	2015-03-20	
179	EQR	Equity Residential	Real Estate	2001-12-03	
180	ESS	Essex Property Trust	Real Estate	2014-04-02	
181	EL	Estée Lauder Companies	Consumer Staples	2006-01-05	

Appendix F S&P 500 index companies' list

No.	Symbol	Security	Sector	Date first added	Date removed
182	ETFC	E-Trade	Financials	N/A	2020-10-07
183	ETSY*	Etsy	Consumer Discretionary	2020-09-21	
184	RE	Everest Re	Financials	2017-06-19	
185	EVRG	Eversource Energy	Utilities	2018-06-05	
186	ES	Eversource Energy	Utilities	N/A	
187	EXC	Exelon	Utilities	1957-03-04	
188	EXPE	Expedia Group	Consumer Discretionary	2007-10-02	
189	EXPD	Expeditors	Industrials	2007-10-10	
190	EXR	Extra Space Storage	Real Estate	2016-01-19	
191	XOM	ExxonMobil	Energy	1957-03-04	
192	FFIV	F5 Networks	Information Technology	2010-12-20	
193	FB	Facebook	Communication Services	2013-12-23	
194	FAST	Fastenal	Industrials	2008-09-15	
195	FRT	Federal Realty Investment Trust	Real Estate	2016-02-01	
196	FDX	FedEx	Industrials	1980-12-31	
197	FIS	Fidelity National Information Services	Information Technology	2006-11-10	
198	FITB	Fifth Third Bancorp	Financials	N/A	
199	FRC	First Republic Bank	Financials	2019-01-02	
200	FE	FirstEnergy	Utilities	N/A	
201	FISV	Fiserv	Information Technology	2001-04-02	
202	FLT	Fleetcor	Information Technology	2018-06-20	
203	FMC	FMC Corporation	Materials	2009-08-19	
204	F	Ford	Consumer Discretionary	1957-03-04	
205	FTNT	Fortinet	Information Technology	2018-10-11	
206	FTV	Fortive	Industrials	2016-07-01	
207	FBHS	Fortune Brands Home & Security	Industrials	2016-06-22	
208	FOXA	Fox Corporation (Class A)	Communication Services	2013-07-01	
209	FOX	Fox Corporation (Class B)	Communication Services	2015-09-18	
210	BEN	Franklin Resources	Financials	N/A	
211	FCX	Freeport-McMoRan	Materials	N/A	
212	GPS	Gap	Consumer Discretionary	1986-08-31	
213	GRMN	Garmin	Consumer Discretionary	2012-12-12	
214	IT	Gartner	Information Technology	2017-04-05	
215	GD	General Dynamics	Industrials	1957-03-04	
216	GE	General Electric	Industrials	N/A	
217	GIS	General Mills	Consumer Staples	1969-03-31	
218	GM	General Motors	Consumer Discretionary	2013-06-06	
219	GPC	Genuine Parts	Consumer Discretionary	1973-12-31	
220	GILD	Gilead Sciences	Health Care	2004-07-01	
221	GPN	Global Payments	Information Technology	2016-04-25	
222	GL	Globe Life	Financials	1989-04-30	
223	GS	Goldman Sachs	Financials	2002-07-22	
224	HRB	H&R Block	Consumer Cyclical	N/A	2020-09-21
225	HAL	Halliburton	Energy	1957-03-04	
226	HBI	Hanesbrands	Consumer Discretionary	2015-03-20	

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No.	Symbol	Security	Sector	Date first added	Date removed
227	HOG	Harley-Davidson	Consumer Cyclical	N/A	2020-06-22
228	HAS	Hasbro	Consumer Discretionary	1984-09-30	
229	HCA	HCA Healthcare	Health Care	2015-01-27	
230	PEAK	Healthpeak Properties	Real Estate	2008-03-31	
231	HP	Helmerich & Payne	Energy	N/A	2020-05-22
232	HSIC	Henry Schein	Health Care	2015-03-17	
233	HES	Hess Corporation	Energy	1984-05-31	
234	HPE	Hewlett Packard Enterprise	Information Technology	2015-11-02	
235	HLT	Hilton Worldwide	Consumer Discretionary	2017-06-19	
236	HOLX	Hologic	Health Care	2016-03-30	
237	HD	Home Depot	Consumer Discretionary	1988-03-31	
238	HON	Honeywell	Industrials	1964-03-31	
239	HRL	Hormel	Consumer Staples	2009-03-04	
240	HST	Host Hotels & Resorts	Real Estate	2007-03-20	
241	HWM	Howmet Aerospace	Industrials	1964-03-31	
242	HPQ	HP	Information Technology	1974-12-31	
243	HUM	Humana	Health Care	N/A	
244	HBAN	Huntington Bancshares	Financials	N/A	
245	HII	Huntington Ingalls Industries	Industrials	2018-01-03	
246	IBM	IBM	Information Technology	1957-03-04	
247	IEX	IDEX Corporation	Industrials	2019-08-09	
248	IDXX	Idexx Laboratories	Health Care	2017-01-05	
249	INFO	IHS Markit	Industrials	2017-06-02	
250	ITW	Illinois Tool Works	Industrials	1986-02-28	
251	ILMN	Illumina	Health Care	2015-11-19	
252	INCY	Incyte	Health Care	2017-02-28	
253	IR*	Ingersoll Rand	Industrials	2020-03-03	
254	INTC	Intel	Information Technology	1976-12-31	
255	ICE	Intercontinental Exchange	Financials	2007-09-26	
256	IFF	International Flavors & Fragrances	Materials	1976-03-31	
257	IP	International Paper	Materials	1957-03-04	
258	IPG	Interpublic Group	Communication Services	1992-10-01	
259	INTU	Intuit	Information Technology	2000-12-05	
260	ISRG	Intuitive Surgical	Health Care	2008-06-02	
261	IVZ	Invesco	Financials	2008-08-21	
262	IPGP	IPG Photonics	Information Technology	2018-03-07	
263	IQV	IQVIA	Health Care	2017-08-29	
264	IRM	Iron Mountain	Real Estate	2009-01-06	
265	JBHT	J. B. Hunt	Industrials	2015-07-01	
266	JKHY	Jack Henry & Associates	Information Technology	2018-11-13	
267	J	Jacobs Engineering Group	Industrials	2007-10-26	
268	SJM	JM Smucker	Consumer Staples	2008-11-06	
269	JNJ	Johnson & Johnson	Health Care	1973-06-30	
270	JCI	Johnson Controls	Industrials	2010-08-27	
271	JPM	JPMorgan Chase	Financials	1975-06-30	

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No.	Symbol	Security	Sector	Date first added	Date removed
272	JNPR	Juniper Networks	Information Technology	2006-06-02	
273	KSU	Kansas City Southern	Industrials	2013-05-24	
274	K	Kellogg's	Consumer Staples	1989-09-11	
275	KEY	KeyCorp	Financials	1994-03-01	
276	KEYS	Keysight Technologies	Information Technology	2018-11-06	
277	KMB	Kimberly-Clark	Consumer Staples	1957-03-04	
278	KIM	Kimco Realty	Real Estate	2006-04-04	
279	KMI	Kinder Morgan	Energy	2012-05-25	
280	KLAC	KLA Corporation	Information Technology	N/A	
281	KSS	Kohl's	Consumer Cyclical	N/A	2020-09-21
282	KHC	Kraft Heinz	Consumer Staples	2015-07-06	
283	KR	Kroger	Consumer Staples	1957-03-04	
284	LHX	L3Harris Technologies	Industrials	2008-09-22	
285	LH	LabCorp	Health Care	2004-11-01	
286	LRCX	Lam Research	Information Technology	2012-06-29	
287	LW	Lamb Weston	Consumer Staples	2018-12-03	
288	LVS	Las Vegas Sands	Consumer Discretionary	2019-10-03	
289	LEG	Leggett & Platt	Consumer Discretionary	1999-10-14	
290	LDOS	Leidos	Industrials	2019-08-09	
291	LEN	Lennar	Consumer Discretionary	2005-10-04	
292	LNC	Lincoln National	Financials	1976-06-30	
293	LIN	Linde	Materials	1992-07-01	
294	LYV	Live Nation Entertainment	Communication Services	2019-12-23	
295	LKQ	LKQ Corporation	Consumer Discretionary	2016-05-23	
296	LMT	Lockheed Martin	Industrials	1984-07-31	
297	L	Loews Corporation	Financials	N/A	
298	LOW	Lowe's	Consumer Discretionary	1984-02-29	
299	LUMN	Lumen Technologies	Communication Services	1999-03-25	
300	LYB	LyondellBasell	Materials	2012-09-05	
301	MTB	M&T Bank	Financials	2004-02-23	
302	M	Macy's	Consumer Cyclical	N/A	2020-04-06
303	MRO	Marathon Oil	Energy	1991-05-01	
304	MPC	Marathon Petroleum	Energy	2011-07-01	
305	MKTX	MarketAxess	Financials	2019-07-01	
306	MAR	Marriott International	Consumer Discretionary	N/A	
307	MMC	Marsh & McLennan	Financials	1987-08-31	
308	MLM	Martin Marietta Materials	Materials	2014-07-02	
309	MAS	Masco	Industrials	1981-06-30	
310	MA	Mastercard	Information Technology	2008-07-18	
311	MKC	McCormick & Company	Consumer Staples	2003-03-20	
312	MCD	McDonald's	Consumer Discretionary	1970-06-30	
313	MCK	McKesson Corporation	Health Care	N/A	
314	MDT	Medtronic	Health Care	1986-10-31	
315	MRK	Merck & Co.	Health Care	1957-03-04	
316	MET	MetLife	Financials	N/A	
317	MTD	Mettler Toledo	Health Care	2016-09-06	

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No.	Symbol	Security	Sector	Date first added	Date removed
318	MGM	MGM Resorts International	Consumer Discretionary	2017-07-26	
319	MCHP	Microchip Technology	Information Technology	2007-09-07	
320	MU	Micron Technology	Information Technology	1994-09-27	
321	MSFT	Microsoft	Information Technology	1994-06-01	
322	MAA	Mid-America Apartments	Real Estate	2016-12-02	
323	MHK	Mohawk Industries	Consumer Discretionary	2013-12-23	
324	TAP	Molson Coors Beverage Company	Consumer Staples	1976-06-30	
325	MDLZ	Mondelez International	Consumer Staples	2012-10-02	
326	MNST	Monster Beverage	Consumer Staples	2012-06-28	
327	MCO	Moody's Corporation	Financials	N/A	
328	MS	Morgan Stanley	Financials	N/A	
329	MSI	Motorola Solutions	Information Technology	N/A	
330	MSCI	MSCI	Financials	2018-04-04	
331	NDAQ	Nasdaq	Financials	2008-10-22	
332	NTAP	NetApp	Information Technology	1999-06-25	
333	NFLX	Netflix	Communication Services	2010-12-20	
334	NWL	Newell Brands	Consumer Discretionary	1989-04-30	
335	NEM	Newmont	Materials	1969-06-30	
336	NWSA	News Corp (Class A)	Communication Services	2013-08-01	
337	NWS	News Corp (Class B)	Communication Services	2015-09-18	
338	NEE	NextEra Energy	Utilities	1976-06-30	
339	NLSN	Nielsen Holdings	Industrials	2013-07-09	
340	NKE	Nike	Consumer Discretionary	1988-11-30	
341	NI	NiSource	Utilities	N/A	
342	NBL	Noble Energy	Energy	N/A	2020-10-12
343	JWN	Nordstrom	Consumer Cyclical	N/A	2020-06-22
344	NSC	Norfolk Southern	Industrials	1957-03-04	
345	NTRS	Northern Trust	Financials	N/A	
346	NOC	Northrop Grumman	Industrials	1985-06-30	
347	NLOK	NortonLifeLock	Information Technology	2003-03-25	
348	NCLH	Norwegian Cruise Line Holdings	Consumer Discretionary	2017-10-13	
349	NOV	Nov	Energy	2005-03-14	
350	NRG	NRG Energy	Utilities	2010-01-29	
351	NUE	Nucor	Materials	1985-04-30	
352	NVDA	Nvidia	Information Technology	2001-11-30	
353	NVR	NVR	Consumer Discretionary	2019-09-26	
354	OXY	Occidental Petroleum	Energy	1982-12-31	
355	ODFL	Old Dominion Freight Line	Industrials	2019-12-09	
356	OMC	Omnicom Group	Communication Services	N/A	
357	OKE	Oneok	Energy	2010-03-15	
358	ORCL	Oracle	Information Technology	1989-08-31	
359	ORLY	O'Reilly Automotive	Consumer Discretionary	2009-03-27	
360	OTIS*	Otis Worldwide	Industrials	2020-04-03	
361	PCAR	Paccar	Industrials	1980-12-31	
362	PKG	Packaging Corporation of America	Materials	2017-07-26	

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No.	Symbol	Security	Sector	Date first added	Date removed
363	PH	Parker-Hannifin	Industrials	1985-11-30	
364	PAYX	Paychex	Information Technology	N/A	
365	PAYC*	Paycom	Information Technology	2020-01-28	
366	PYPL	PayPal	Information Technology	2015-07-20	
367	PNR	Pentair	Industrials	2012-10-01	
368	PBCT	People's United Financial	Financials	2008-11-13	
369	PEP	PepsiCo	Consumer Staples	1957-03-04	
370	PKI	PerkinElmer	Health Care	1985-05-31	
371	PRGO	Perrigo	Health Care	2011-12-19	
372	PFE	Pfizer	Health Care	1957-03-04	
373	PM	Philip Morris International	Consumer Staples	2008-03-31	
374	PSX	Phillips 66	Energy	2012-05-01	
375	PNW	Pinnacle West Capital	Utilities	N/A	
376	PXD	Pioneer Natural Resources	Energy	2008-09-24	
377	PNC	PNC Financial Services	Financials	1988-04-30	
378	POOL*	Pool Corporation	Consumer Discretionary	2020-10-07	
379	PPG	PPG Industries	Materials	1957-03-04	
380	PPL	PPL	Utilities	N/A	
381	PFG	Principal Financial Group	Financials	2002-07-22	
382	PG	Procter & Gamble	Consumer Staples	1957-03-04	
383	PGR	Progressive Corporation	Financials	1997-08-04	
384	PLD	Prologis	Real Estate	2003-07-17	
385	PRU	Prudential Financial	Financials	2002-07-22	
386	PEG	Public Service Enterprise Group	Utilities	1957-03-04	
387	PSA	Public Storage	Real Estate	2005-08-19	
388	PHM	PulteGroup	Consumer Discretionary	1984-04-30	
389	PVH	PVH	Consumer Discretionary	2013-02-15	
390	QRVO	Qorvo	Information Technology	2015-06-11	
391	QCOM	Qualcomm	Information Technology	N/A	
392	PWR	Quanta Services	Industrials	2009-07-01	
393	DGX	Quest Diagnostics	Health Care	2002-12-12	
394	RL	Ralph Lauren Corporation	Consumer Discretionary	2007-02-02	
395	RJF	Raymond James Financial	Financials	2017-03-20	
396	RTN	Raytheon Company	Industrials	N/A	2020-04-06
397	RTX	Raytheon Technologies	Industrials	N/A	
398	O	Realty Income Corporation	Real Estate	2015-04-07	
399	REG	Regency Centers	Real Estate	2017-03-02	
400	REGN	Regeneron Pharmaceuticals	Health Care	2013-05-01	
401	RF	Regions Financial Corporation	Financials	1998-08-28	
402	RSG	Republic Services	Industrials	2008-12-05	
403	RMD	ResMed	Health Care	2017-07-26	
404	RHI	Robert Half International	Industrials	2000-12-05	
405	ROK	Rockwell Automation	Industrials	N/A	
406	ROL	Rollins	Industrials	2018-10-01	
407	ROP	Roper Technologies	Industrials	2009-12-23	

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No.	Symbol	Security	Sector	Date first added	Date removed
408	ROST	Ross Stores	Consumer Discretionary	2009-12-21	
409	RCL	Royal Caribbean Group	Consumer Discretionary	2014-12-05	
410	SPGI	S&P Global	Financials	N/A	
411	CRM	Salesforce	Information Technology	2008-09-15	
412	SBAC	SBA Communications	Real Estate	2017-09-01	
413	SLB	Schlumberger	Energy	1965-03-31	
414	STX	Seagate Technology	Information Technology	2012-07-02	
415	SEE	Sealed Air	Materials	1957-03-04	
416	SRE	Sempra Energy	Utilities	N/A	
417	NOW	ServiceNow	Information Technology	2019-11-21	
418	SHW	Sherwin-Williams	Materials	1964-06-30	
419	SPG	Simon Property Group	Real Estate	2002-06-26	
420	SWKS	Skyworks Solutions	Information Technology	2015-03-12	
421	SNA	Snap-on	Industrials	1982-09-30	
422	SO	Southern Company	Utilities	1957-03-04	
423	LUV	Southwest Airlines	Industrials	1994-07-01	
424	SWK	Stanley Black & Decker	Industrials	1982-09-30	
425	SBUX	Starbucks	Consumer Discretionary	N/A	
426	STT	State Street Corporation	Financials	N/A	
427	STE	Steris	Health Care	2019-12-23	
428	SYK	Stryker Corporation	Health Care	2000-12-12	
429	SIVB	SVB Financial	Financials	2018-03-19	
430	SYF	Synchrony Financial	Financials	2015-11-18	
431	SNPS	Synopsys	Information Technology	2017-03-16	
432	SYF	Sysco	Consumer Staples	1986-12-31	
433	TROW	T. Rowe Price	Financials	N/A	
434	TTWO	Take-Two Interactive	Communication Services	2018-03-19	
435	TPR	Tapestry	Consumer Discretionary	N/A	
436	TGT	Target Corporation	Consumer Discretionary	1976-12-31	
437	TEL	TE Connectivity	Information Technology	2011-10-17	
438	TDY*	Teledyne Technologies	Industrials	2020-06-22	
439	TFX	Teleflex	Health Care	2019-01-18	
440	TER*	Teradyne	Information Technology	2020-09-21	
441	TSLA*	Tesla	Consumer Discretionary	2020-12-21	
442	TXN	Texas Instruments	Information Technology	N/A	
443	TXT	Textron	Industrials	1978-12-31	
444	COO	The Cooper Companies	Health Care	2016-09-23	
445	HIG	The Hartford	Financials	1957-03-04	
446	HSY	The Hershey Company	Consumer Staples	1957-03-04	
447	MOS	The Mosaic Company	Materials	2011-09-26	
448	TRV	The Travelers Companies	Financials	2002-08-21	
449	DIS	The Walt Disney Company	Communication Services	1976-06-30	
450	TMO	Thermo Fisher Scientific	Health Care	2004-08-03	
451	TJX	TJX Companies	Consumer Discretionary	1985-09-30	
452	TMUS	T-Mobile US	Communication Services	2019-07-15	
453	TSCO	Tractor Supply Company	Consumer Discretionary	2014-01-24	

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No.	Symbol	Security	Sector	Date first added	Date removed
454	TT	Trane Technologies	Industrials	2010-11-17	
455	TDG	TransDigm Group	Industrials	2016-06-03	
456	TFC	Truist Financial	Financials	1997-12-04	
457	TWTR	Twitter	Communication Services	2018-06-07	
458	TYL*	Tyler Technologies	Information Technology	2020-06-22	
459	TSN	Tyson Foods	Consumer Staples	2005-08-10	
460	USB	U.S. Bancorp	Financials	N/A	
461	UDR	UDR	Real Estate	2016-03-07	
462	ULTA	Ulta Beauty	Consumer Discretionary	2016-04-18	
463	UAA	Under Armour (Class A)	Consumer Discretionary	2014-05-01	
464	UA	Under Armour (Class C)	Consumer Discretionary	2016-04-08	
465	UNP	Union Pacific	Industrials	1957-03-04	
466	UAL	United Airlines	Industrials	2015-09-03	
467	UPS	United Parcel Service	Industrials	2002-07-22	
468	URI	United Rentals	Industrials	2014-09-20	
469	UNH	UnitedHealth Group	Health Care	1994-07-01	
470	UHS	Universal Health Services	Health Care	2014-09-20	
471	UNM	Unum Group	Financials	1994-03-01	
472	VLO	Valero Energy	Energy	N/A	
473	VTR	Ventas	Real Estate	2009-03-04	
474	VRSN	Verisign	Information Technology	2006-02-01	
475	VRSK	Verisk Analytics	Industrials	2015-10-08	
476	VZ	Verizon Communications	Communication Services	1983-11-30	
477	VRTX	Vertex Pharmaceuticals	Health Care	2013-09-23	
478	VFC	VF Corporation	Consumer Discretionary	1979-06-30	
479	VIAC	ViacomCBS	Communication Services	N/A	
480	VTRS	Viatis	Health Care	2004-04-23	
481	V	Visa	Information Technology	2009-12-21	
482	VNT*	Vontier	Industrials	2020-10-20	
483	VNO	Vornado Realty Trust	Real Estate	N/A	
484	VMC	Vulcan Materials	Materials	1999-06-30	
485	WRB	W. R. Berkley Corporation	Financials	2019-12-05	
486	GWW	W. W. Grainger	Industrials	1981-06-30	
487	WAB	Wabtec	Industrials	2019-02-27	
488	WBA	Walgreens Boots Alliance	Consumer Staples	1979-12-31	
489	WMT	Walmart	Consumer Staples	1982-08-31	
490	WM	Waste Management	Industrials	N/A	
491	WAT	Waters Corporation	Health Care	N/A	
492	WEC	WEC Energy Group	Utilities	2008-10-31	
493	WCG	WellCare	Health Care	N/A	2020-01-28
494	WFC	Wells Fargo	Financials	1976-06-30	
495	WELL	Welltower	Real Estate	2009-01-30	
496	WST*	West Pharmaceutical Services	Health Care	2020-05-22	
497	WDC	Western Digital	Information Technology	2009-07-01	
498	WU	Western Union	Information Technology	2006-09-29	
499	WRK	WestRock	Materials	N/A	

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No.	Symbol	Security	Sector	Date first added	Date removed
500	WY	Weyerhaeuser	Real Estate	N/A	
501	WHR	Whirlpool Corporation	Consumer Discretionary	N/A	
502	WMB	Williams Companies	Energy	1975-03-31	
503	WLTW	Willis Towers Watson	Financials	2016-01-05	
504	WYNN	Wynn Resorts	Consumer Discretionary	2008-11-14	
505	XEL	Xcel Energy	Utilities	1957-03-04	
506	XLNX	Xilinx	Information Technology	1999-11-08	
507	XYL	Xylem	Industrials	2011-11-01	
508	YUM	Yum! Brands	Consumer Discretionary	1997-10-06	
509	ZBRA	Zebra Technologies	Information Technology	2019-12-23	
510	ZBH	Zimmer Biomet	Health Care	2001-08-07	
511	ZION	Zions Bancorp	Financials	2001-06-22	
512	ZTS	Zoetis	Health Care	2013-06-21	

Glossary of Terms

Bond rating	A letter grade defined to bonds to indicates their credit quality (Chen, 2019a).
Credit risk	The general risk that the counterparty will default and not honour the contract (Cuthbertson and Nitzsche, 2008).
Credit rating.....	A quantified assessment of the creditworthiness of a borrower in general terms or with respect to a particular debt or financial obligation (Kagan, 2019).
Cryptocurrency.....	A type of digital currency in which encryption techniques to secure and anti-counterfeiting measures, operating independently of a central bank (Bakar, Rosbi and Uzaki, 2017).
Default probability	The likelihood that a borrower will not be able to settle its debt obligations over a particular time horizon (Kenton, 2018).
Exchange rates	The price of a unit of one country's currency in terms of another country's currency (Bodie, Kane and Marcus, 2018).
Hedging.....	Investing in an asset or derivative security to offset a specific source of risk (Bodie, Kane and Marcus, 2018)
Options	The contract which gives the purchaser the right, but not the obligation, to buy (a 'call' option), or to sell (a 'put' option), a specified amount of a commodity or financial asset at a specified price, by or on a specified date (Cuthbertson and Nitzsche, 2008).
Pricing:.....	The method of defining the value that a producer will receive in the exchange of products and services (Maxwell and Estelami, 2005).
Value at risk (VaR)	The measurement of downside risk. The loss that will be incurred in the event of an extreme adverse price change with some given, typically low, probability (Bodie, Kane and Marcus, 2011).
Volatility:	The measurement of the variability in asset prices (Cuthbertson and Nitzsche, 2008).

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