A generalised machine learning model based on multi-nomial logistic regression and frequency features for rolling bearing fault classification

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Abstract

Intelligent fault classification of rolling element bearings (REBs) using machine learning (ML) techniques increases the reliability of industrial assets. One of the main issues associated with ML model development is the lack of training data and most importantly the ability of models to be used for applications without specific training data, i.e., generalization capability of models. This study investigates the feasibility of using multinomial logistic regression (MLR) as generalised ML models for rolling element bearing fault classification without the requirement of training data for new bearing designs and varied machine operations. This has been achieved by using bearing characteristic frequencies (BCFs) as inputs to the MLR models extracted by a newly developed hybrid method. The new method combines cepstrum pre-whitening (CPW) and full-band enveloping , which can effectively identify the BCFs in vibration data from various machines. This paper presents the methods of the feature extraction and the development of generalised ML models for REBs based on data from EU Clean Sky2 I2BS project[1]. This model is then validated by data from Case Western Reserve University (CWRU) and US Society for Machinery Failure Prevention Technology (MFPT) available in the public domain without further training.

[1] An EU Clean Sky 2 project 'Integrated Intelligent Bearing Systems' collaborated between Schaeffler Technologies and the University of Southampton. Safran Aero Engines was the topic manager for this project.

Keywords: rolling element bearings, Intelligent fault classification, bearing characteristic frequencies, multinomial logistic regression, generalized machine learning model

1. Introduction

In modern rotating machinery, rolling element bearings (REBs) are one of the most critical components since they are often subjected to harsh operating conditions, such as high loads, high speeds, and high temperature in aero-engines. Over time, faults develop in bearings, leading to increased clearance, friction torque, overheating, etc. thus their performance drops [1]. Fault diagnosis plays a significant role in identifying faulty bearings and components in complex machinery as well as finding causes and relationships between monitoring data and the health of REBs. While engineers with vast knowledge and skills carry out majority of diagnosis on-site, health monitoring based on sensors and effective signal processing techniques can, not only reduce the dependence on engineers on-site measurements, but also significanly increase the diagnosis accuracy in real time, thus reduce maintenance cost and increase machine reliability and useful life. With the help of machine learning (ML) techniques and artificial intelligence (AI), fault diagnosis can be futher automated without relying on human intervention [2].

By employing suitable features extracted from signals, a ML method, such as artificial neural networks (ANNs), multi-nomial logistic regression (MLR), and support vector machines (SVMs) [3], can be used for fault diagnosis by conducting a pattern recognition task. The effectiveness of bearing fault diagnosis is found to be heavily influenced by the quality of features extracted from bearing vibration signals [4], [5]. For example, time-domain statistical features such as mean, root mean square (rms), kurtonsis and skewness data, are one of the mostly used input features for ML model development for bearing fault diagnosis. Since many factors such as changing in working conditions, noise in the surrounding environment, and unexpected compound failures in the machine can change the distribution of the features, thus significantly affect the effectiveness of fault diaganosis. It remains the biggest challenge to achieve high-accuracy bearing fault diagnosis in real industrial applications [6]. One of the challenges in bearing fault diagnosis using ML methods is the lack of training data from real engineering applications. Current ML based fault diagnosis approaches rely on data collected from same machine under same operating conditions for model training, validataion and testing [7], which sgnificantly limts the application of ML for bearing fault diagnosis in real-world applications. Developing ML models with generalisation funcationality, e.g. models trained by laboratory data can be directly used for real applications without further training, will make a revolutionary change in this field.

In an REB with a fault in one or more of its components, e.g. the outer race (OR), inner race (IR) or rolling elements, shocks are generated as a result of the localised fault, which excites high-frequency resonances of the entire structure containing the bearing including the vibration sensor. These shocks cause periodic impulsive features appearing in time-domain vibration signals, as well as the corresponding bearing characteristic frequencies (BCFs[1]) in their frequency spectra. While BCFs, if detected, are extremely powerful in fault diagnosis, they typically contain relatively low vibration energy comparing with other sources of vibrations in a machine, especially when the local fault

[1] BCFs include ballpass frequency outer race (BPFO), ballpass frequency inner race (BPFI), ball spin frequency (BSF), and fundamental train frequency (FTF)

is at its early stage. High-Frequency Resonance Technique (HFRT), also known as envelope analysis, is one of the well-known techniques to detect BCFs [8]. However, HFRT has a fatal issue that limits its application as it requires accurately determining a suitable band filter around a resonance frequency. This is extremely challenging as the best suitable filter can change instantenously depending on machine operation [9]. To tackle this issue, several signal processing techniques have been developed, such as wavelet transforms (WTs), empirical mode decomposition (EMD), spectral kurtosis (SK), CPW, active noise cancelation (ANC) [10], [11], which all have some issues unfortunately [12]. In this study, the new developed hybrid technique based on the cepstrum pre-whitening (CPW) and full band envelope is used to extract BCFs from envelope spectra [12] as features for ML model development for REB fault classification.

In literature, many ML methods have been used for REB fault classification, and selecting an appropriate ML algorithm is also paramount. MLR as a statistical model can analyse a large number of samples based on their probability distribution that have been widely used to solve multiclass problems by evaluating the significance of each input feature. Moreover, it can achieve better accuracy than ANN and SVM without hyperparameter optimization or kernel function selection in similar situations [13], [14]. Therefore, MLR has been chosen for REB fault classification in this study.

Next section introduces the method of BCFs extraction, the mathematical concept of MLR and the architecture of the proposed model. Section 3. introduces the experimental datasets used for training and testing of the model for bearing fault classification. In section 4. , the proposed model is trained by experimental data obtained in I2BS subscale tests and then its generalisation capability is tested by CWRU and MFPT datasets in literature. The effectiveness of the input features using the novel hybrid method is compared with that using time-domain statistical features. Section 5. presents the conclusions of this study.

2. Methodology

2.1. Feature extraction

In this research, BCFs have been chosen as input features for the intelligent fault classification model. Actual values of BCFs usually differ from the theoretical values due to uncontrollable slipage occurring in rolling element bearings and minor shaft rotating speed fluctuations during machine operation [15]. To accuractely identify BCFs as inputs to MLP models, the following steps are taken [12]:

A. Obtaining shaft orders by dividing the frequency values by shaft rotating speed and ploting the bearing vibration amplitude vs order spectra. BCFs will appear as shaft orders instead of frequencies in Hz. This reduces the changes in BCFs due to potenatial shaft rotaing speed fluctuations.
B. Find the first harmonic of the actual BCFs based on their theoretical values. For instance, to find the actual value of the 1st harmonic of ball pass frequency of outer ring (BPFO), the first order of BPFO using theoretical formula is calculated. Then, peaks within the order band of (1±4%)×BPFO (the 4 % value is an empirical selection based on experience similar to other studies in literature [ref?]) are inspected and the maximum amplitude peak is identified as the actual value for the first order harmonic of the BPFO. Next, multiply the actual BPFO order by two and three as the ‘calculated’ second and third order harmonics of the BPFO

respectively to find the actual ones. For the second and third harmonics, peaks in the bands of (1±2 %) of the second and third calculated order harmonics are evaluated and the largest amplitudes are identified as the actual second and third order harmonics of BPFO.

C. For ball spin frequencys (BSFs), since they may only appear to have even harmonics (or both), up to six order harmonics of BSFs are identified following the same procedure described above. Then, sumations of adjacent two harmonics are conducted to produce three values that match the three array inputs to MLR.
D. For ball pass frequencies of inner ring (BPFIs), in addition to its three order harmonics, two pairs of its sidebands (SBs) for each of its order harmonics are also identified. Smilarly, two pairs of sidebands of BSFs are identified.
E. All values identified above are extracted features to be used in the input vector for the MLR model. As a result, 33 features are extracted from each vibration sample for the model development and fault classification.

2.2. Theoretical background of MLR

Logistic regression (LR) model is a generalized linear model that uses logistic curve modelling to fit the probabilistic occurrence of an event. In this case, the probability p of a binary outcome event is related to a set of explanatory variables in the form of Equation 1.

$$logit(p) = ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n = \beta_0 + \sum_{i=1}^{n} \beta_i x_i \quad \text{Equation 1}$$

where β_0 is the intercept and $\beta_1, \beta_2, \beta_3, \ldots, \beta_n$ are the coefficients corresponding to the explanatory variables $x_1, x_2, x_3, \ldots, x_n$ (i.e. the vibration features in this study) respectively [16]. In MLR, with a slight modification for multi-class problems, if there are n variables with k categories or classes, all logits are constructed based on one category as the base level. The base level can be taken from any available category. So,the k^{th} class will be used as the base level. Since there is no order, any category may be labelled as k. To find the relationship between an observation's probability to fall into the j^{th} relative to k^{th} category, the MLR model could be written as Equation 2 or Equation 3.

$$log\left[\frac{p_j}{p_k}\right] = \beta_{j0} + \beta_{j1} x_1 + \beta_{j2} x_2 + \cdots + \beta_{jn} x_n \quad \text{Equation 2}$$

$$p_j = p_k * exp\,(\beta_{j0} + \beta_{j1} x_1 + \beta_{j2} x_2 + \cdots + \beta_{jn} x_n) \quad \text{Equation 3}$$

Moreover, as shown in Equation 4, the sum of all categories' probabilities equals one.

$$p_1 + p_2 + \cdots + p_j + \cdots + p_k = 1 \quad \text{Equation 4}$$

Deriving Equation 3 for all of the categories and combining with Equation 4, the probability of the category k could be obtained using Equation 5.

$$p_k = \frac{1}{1 + \sum_{j=1}^{k-1} \exp\,(\beta_{j0} + \beta_{j1} x_1 + \beta_{j2} x_2 + \cdots + \beta_{jn} x_n)} \quad \text{Equation 5}$$

Using Equation 3 and Equation 5, the probability of each category such as category j, could be written as Equation 6. For training MLR models, maximum likelihood technique is used to choose the appropriate β parameters for the model [17], with the probability for the j^{th} category.

$$p_j = \frac{exp\ (\beta_{j0}+\beta_{j1}x_1+\beta_{j2}x_2+\cdots+\beta_{jn}x_n)}{1+\sum_{j=1}^{k-1} exp\ (\beta_{j0}+\beta_{j1}x_1+\beta_{j2}x_2+\cdots+\beta_{jn}x_n)}\ ;\ j = 1,2,\ldots,k-1 \qquad \text{Equation 6}$$

2.3. MLR model development for REB fault classification

To develop an MLR model for REB fault classification, vibration data from I2BS project [18] has been used to train and validate the model. Once a satisfactory prediction is achieved, the model is then tested by data from literature (CWRU [19] and MFPT [20]) to check if it can classify faults in different bearing designs under completely different test conditions, i.e. its generalisation capability. The model development procedure is illustrated in Figure 1.

During MLR training, the coefficient of each feature is analysed by statistical inference to determine its significance. Effective features for the model are selected based on their probability value (p_value). The lower the p_value, the more significance the feature is for the model.

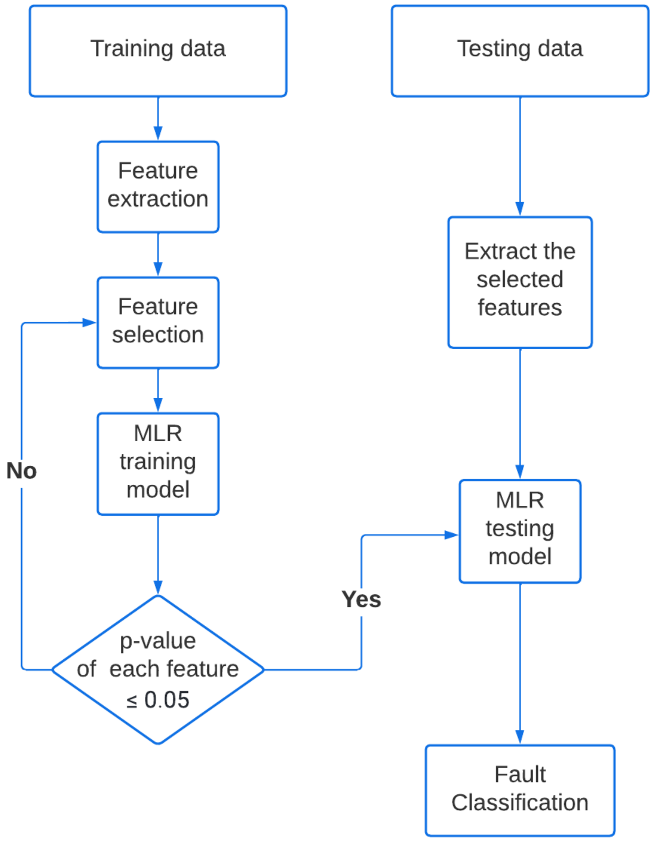

Figure 1: The procedure of the MLR model development.

3. The datasets

Developing an MLR model that can classify faults in completely different REBs under different operating conditions requires training and evaluating datasets as well as testing datasets. In this study, three datasets from three completely different studies with different REB sizes being tested under different load and speed conditions on different machines. The model training used dataset from I2BS sub-scale testing, where defects have been seeded on bearing components and tested under a wide range of conditions [12], [21], [22]. The CWRU dataset in the public domain, which has been widely used for REB fault classification in many studies [19], has been used to test the MLR without further training. Similarly, the generalisation capability of the MLR model is tested by a third set of data from MFPT database [23]. Details of these datasets are given in the sections below.

3.1. I2BS sub-scale dataset

I2BS experiments were conducted on bearing test data from an EU Clean Sky 2 Joint Undertaking under the European Union's Horizon 2020 research and innovation programme. A sub-scale test rig was used to test smart bearings which are 3-point contact ball bearings with multiple sensors under simulated aero-engine REB working conditions to develop intelligent condition monitoring for REBs [22]. There are 387 vibration signals for outer ring (OR) fault, 361 signals for inner ring (IR) fault, and 189 signals for ball fault with a sampling rate of 100 kHz in these tests. Table 1 shows the details of the bearings, defects and corresponding test conditions selected for this study.

Table 1: I2BS sub-scale bearing information[1] and data details for training

$\mathbf{D_{pitch}}$, mm	$\mathbf{D_{ball}}$, mm	**Z**	$\emptyset$, deg	$\mathbf{f_{shaft}}$, rpm	**Axial load**, kN	**Defect diameter**, mm
75	9.525	20	15	5000, 10000, 14000	1, 2.5, 9	0.4

3.2. CWRU dataset

The CWRU vibration data were collected from a test rig that includes a 1.5 kW electrical motor, torque meter, and dynamometer. Drive-end vibration samples of the bearing data centre of CWRU have been used to test the MLR bearing fault classification model. The bearings used in the motor are deep groove ball bearings. There are 140 signals for OR fault, 64 signals for OR fault, and 64 signals for ball fault that were sampled at 12 kHz and 48 kHz in this experiment [19]. Details of the bearings and the test conditions are given in Table 2.

Table 2: Bearing dimensions and test conditions of CWRU dataset

$\mathbf{D_{pitch}}$, mm	$\mathbf{D_{ball}}$, mm	**Z**	$\emptyset$, deg	$\mathbf{f_{shaft}}$ rpm	**Defect diameter**, mm
44	8.2	9	0	1720 – 1797	0.177, 0.355, 0.533

3.3. MFPT dataset

The MFPT dataset was obtained from bearing tests on deep groove bearings with defects on the IR and OR under various loads from 0 to 1.34 kN. In this dataset, there are 39 vibration samples for the OR fault and 21 vibration samples for the IR fault with a

[1] $\mathrm{D_{pitch}}$: Pitch diameter, $\mathrm{D_{ball}}$: Ball diameter, Z: Number of the ball, $\emptyset$: Contact angle

sampling rate of 48.828 kHz and 97.656 kHz [23]. The details of the bearings and test conditions are shown in Table 3.

Table 3: Bearing dimensions and test condition of the MFPT experiments

$\mathbf{D_{pitch}}$, mm	$\mathbf{D_{ball}}$, mm	**Z**	$\emptyset$, deg	$\mathbf{f_{shaft}}$, rpm	**load**, kN
31.62	5.97	8	0	1500	0.22, 0.44, 0.66, 0.88, 1.11, 1.33

4. REB fault classification using a generalised MLR model

4.1. Model training

The I2BS sub-scale dataset has been used to find the optimum coefficients for an MLR model using maximum likelihood estimation through training. In this step, feature vectors have been analysed by p_values of the corresponding coefficients. Considering $p\_values \leq 0.05$ (i.e., 95 % of confidence level), three harmonics and a pair of SB for all three BCFs are found to be significant features for the fault classification. The training results are shown by a confusion matrix in Table 4. As it is seen, all training samples have been classified correctly. In other words, the training accuracy is 100 %.

Table 4: Confusion matrix of the training data by I2BS sub-scale dataset

	OR	IR	Ball
OR	387	0	0
IR	0	361	0
Ball	0	0	189

4.2. The generalisation capability of the MLR model

4.2.1. Tested by CWRU dataset

To analyse the generalistion capability of the MLR trained by I2BS dataset, it is firstly tested by the CWRU dataset. In comparison to the training dataset, CWRU used a different REB type and size under completely different working conditions (see details in Tables 1&2). The test results are summarised in Table 5. It can be seen that some samples have been classified inaccurately and the overall classification accuracy is 82.8%. Among the three classes of defects, ball fault samples have more misclassifications, where 23 samples of ball faults were classified as OR or IR faults.

In a comprehensive study on bearing fault classification by Randall et al. using the same datasets with different signal processing techniques as well as manually analyses of the spectra [24], many of the samples were identified as 'not diagnosable' due to problems related to the test rig. The CWRU samples were then put into three categories, including diagnoseable, partial diagnoseable, and not diagnoseable samples.

To evaluate the fault diagnosis effectiveness of the MLR model, the results from Randall's study are compared with that achieved in this study. Randall's study showed that 61.1% and 73.5% of the samples are diagnoseable and both diagnosable and partial diagnoseable respectively, while the MLR model is able to correctly classify faults of 82.8% of the samples. Furthermore, when choosing the 'diagnoseable samples' identified by Randall's work, a 100% accuracy is achieved using the MLR model as shown in Table 6.

Table 5: Confusion matrix of test results by all of the samples of CWRU dataset.

	OR	IR	Ball
OR	127	3	10
IR	4	54	6
Ball	13	10	41

Table 6: Confusion matrix of test results by diagnoseable samples of CWRU dataset.

	OR	IR	Ball
OR	117	0	0
IR	0	45	0
Ball	0	0	5

4.2.2. MFPT

To further test the MLR model, the MFPT dataset is fed to the model. Despite the differences between the operating conditions and REB size of this dataset with the training data (details are shown in Tables 1&3), all cases have been accurately classified ($Accuracy = 100\%$). The confusion matrix of the test results is illustrated in Table 7.

Table 7: Confusion matrix of test results of the samples of MFPT dataset.

	OR	IR	Ball
OR	39	0	0
IR	0	21	0

Ball	0	0	0

4.3. A comparison with using statistical time-domain features

In order to further evaluate the effectiveness and robustness of the new method, especially the BCF features extracted using the novel hybrid method, similar study is conducted by using time-domain statistical features as the inputs for MLR training and testing . The input vector contains RMS, shape factor, crest factor, impulse factor, margin factor, kurtosis, peak to peak, skewness, and rectified skewness [25], [26] similar to many other studies. To analyse the effect of operating conditions, shaft speed is added to the statistical feature vectors. Analysis of p_value is performed following the same process described in 4.1 to determine the most effective features and datasets from CWRU and MFPT have then been used to test the model. Table 8 summarises the results. As it is clearly shown, while the training accuracy using the statistical features of 98.71 is close to that of the BCFs and SBs, the testing accuracties are significantlty lower when using the time-domain features.

Table 8: A comparison of the model accuracies when using the frequency features (BCFs and SBs) and statistical time-domain features

	Statistical features	BCFs and SBs
Training by I2BS sub-scale	98.71	100
Testing by all CWRU samples	31.34	82.8
Testing by diagnoseable CWRU samples	34.13	100
Testing MFPT samples	68.33	100

5. Conclusion

An MLR model based on BCFs and SBs features, extracted by a novel hybrid method, has been developed for REB fault classification. While the model has been trained using the I2BS test data, it can also successfully classify bearing faults in other datasets obtained from completely different studies. This is for the first time that an ML based model with generalisation capabilities has been developed.

Ininially, BCFs and SBs are identified from the frequency spectra extracted by a new hybrid method based on the CPW and full-band envelope methods. They then are used as inputs to train MLR models for REB fault classification. While the model training has been conducted using the I2BS test data, and 100% training accuracy is achieved, its high generalisation capability has been demonstrated by using two completely different datasets from literature, i.e. CWRU and MFPT. Without further training being required, the MLR model has achieved 82.8% and 100% classification accuracies for the CWRU and MFPT data respectively, which are much higher than those achieved by other studies. Comparing with using time-domain statistical input features, the BCFs and SBs extracted by the noval hybrid method can achieve far better accuracies for both training and testing, i.e. higher generalisation capability of the MLR model.

The newly developed MLR model presents a powerful tool that has the potential to be used for general REB fault diagnosis without further training, i.e. being used in real industrial applications without the requirments for training data. During the development of this model, vibration signals have been collected at relatively high sampling rates to enable to spectral analysis, which might limit the application of the MLR model developed. Further study is being carried out to evaluate the optimum sampling rates for bearing fault detection as well as using other ML models for intelligent bearing fault detection and diagnosis.

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References

[1] J. Singh, A. K. Darpe, and S. P. Singh, "Rolling element bearing fault diagnosis based on Over-Complete rational dilation wavelet transform and auto-correlation of analytic energy operator," *Mech. Syst. Signal Process.*, vol. 100, pp. 662–693, 2018, doi: 10.1016/j.ymssp.2017.06.040.

[2] A. Stetco *et al.*, "Machine learning methods for wind turbine condition monitoring: A review," *Renew. Energy*, vol. 133, pp. 620–635, 2019, doi: 10.1016/j.renene.2018.10.047.

[3] A. M. Abdelrhman *et al.*, "Diagnosis model for bearing faults in rotating machinery by using vibration signals and binary logistic regression," *AIP Conference Proceedings*, vol. 2262. 2020, doi: 10.1063/5.0017221.

[4] B. Zhao, X. Zhang, H. Li, and Z. Yang, "Intelligent fault diagnosis of rolling bearings based on normalized CNN considering data imbalance and variable working conditions," *Knowledge-Based Syst.*, vol. 199, p. 105971, 2020, doi: 10.1016/j.knosys.2020.105971.

[5] Z. Yuan, L. Zhang, L. Duan, and T. Li, "Intelligent Fault Diagnosis of Rolling Element Bearings Based on HHT and CNN," *Proc. - 2018 Progn. Syst. Heal. Manag. Conf. PHM-Chongqing 2018*, pp. 292–296, 2019, doi: 10.1109/PHM-Chongqing.2018.00056.

[6] P. Liang, C. Deng, J. Wu, and Z. Yang, "Intelligent fault diagnosis of rotating machinery via wavelet transform, generative adversarial nets and convolutional neural network," *Meas. J. Int. Meas. Confed.*, vol. 159, p. 107768, 2020, doi: 10.1016/j.measurement.2020.107768.

[7] P. Gangsar and R. Tiwari, "Signal based condition monitoring techniques for fault detection and diagnosis of induction motors: A state-of-the-art review," *Mech. Syst. Signal Process.*, vol. 144, p. 106908, 2020, doi: 10.1016/j.ymssp.2020.106908.

[8] R. B. Randall and J. Antoni, "Rolling element bearing diagnostics-A tutorial," *Mechanical Systems and Signal Processing*, vol. 25, no. 2. Academic Press, pp. 485–520, Feb. 01, 2011, doi: 10.1016/j.ymssp.2010.07.017.

[9] W. Su, F. Wang, H. Zhu, Z. Zhang, and Z. Guo, "Rolling element bearing faults diagnosis based on optimal Morlet wavelet filter and autocorrelation enhancement," *Mech. Syst. Signal Process.*, vol. 24, no. 5, pp. 1458–1472, 2010, doi: 10.1016/j.ymssp.2009.11.011.

[10] Y. Wei, Y. Li, M. Xu, and W. Huang, "A Review of Early Fault Diagnosis Approaches and Their Applications in Rotating Machinery," no. I, 2019.

[11] A. B. Ming, W. Zhang, Z. Y. Qin, and F. L. Chu, "Envelope calculation of the multi-component signal and its application to the deterministic component cancellation in bearing fault diagnosis," *Mech. Syst. Signal Process.*, vol. 50–51, pp. 70–100, 2015, doi: 10.1016/j.ymssp.2014.05.033.

[12] A. Kiakojouri, Z. Lu, P. Mirring, H. Powrie, and L. Wang, "A novel hybrid technique combining improved cepstrum pre-whitening and high-pass filtering for effective bearing fault detection," *Under reviewing*, 2022.

[13] D. H. Pandya, S. H. Upadhyay, and S. P. Harsha, "Fault diagnosis of rolling element bearing by using multinomial logistic regression and wavelet packet transform," *Soft Comput.*, vol. 18, no. 2, pp. 255–266, 2014, doi: 10.1007/s00500-013-1055-1.

[14] S. Dreiseitl and L. Ohno-Machado, "Logistic regression and artificial neural network classification models: A methodology review," *J. Biomed. Inform.*, vol. 35, no. 5–6, pp. 352–359, 2002, doi: 10.1016/S1532-0464(03)00034-0.

[15] H. Wang, H. Liu, T. Qing, W. Liu, and T. He, "An automatic fault diagnosis method for aerospace rolling bearings based on ensemble empirical mode decomposition," *2017 8th Int. Conf. Mech. Aerosp. Eng. ICMAE 2017*, pp. 502–506, 2017, doi: 10.1109/ICMAE.2017.8038697.

[16] S. Shalev-Shwartz and S. Ben-David, *Understanding machine learning: From theory to algorithms*, vol. 9781107057. 2013.

[17] S. Le Cessie and J. C. Van Houwelingen, "Ridge Estimators in Logistic Regression," *Appl. Stat.*, vol. 41, no. 1, p. 191, 1992, doi: 10.2307/2347628.

[18] I. Bashir, B. Zaghari, T. J. Harvey, A. S. Weddell, N. M. White, and L. Wang, "Design and Testing of a Sensing System for Aero-Engine Smart Bearings," *Proceedings*, vol. 2, no. 13, p. 1005, Jan. 2019, doi: 10.3390/proceedings2131005.

[19] "Case Western Reserve University bearing data center, 2009. Available from:" https://engineering.case.edu/bearingdatacenter (accessed Jan. 06, 2022).

[20] "Fault Data Sets - Society For Machinery Failure Prevention Technology." https://www.mfpt.org/fault-data-sets/ (accessed Apr. 12, 2022).

[21] I. Bashir, L. Wang, T. J. Harvey, B. Zaghari, A. S. Weddell, and N. M. White, "Integrated smart bearings for next generation aero-engines Part 1: Development of a sensor suite for automatic bearing health monitoring."

[22] B. Zaghari, A. Weddell, N. White, I. Bashir, T. J. Harvey, and L. Wang, "Integrated smart bearings for next generation aero-engines. Part II: Energy harvesting and wireless communication Development," *WCCM 2017 - 1st World Congr. Cond. Monit. 2017*, no. Cm, 2017.

[23] "Fault Data Sets - Society For Machinery Failure Prevention Technology." https://www.mfpt.org/fault-data-sets/ (accessed Mar. 11, 2022).

[24] W. A. Smith and R. B. Randall, "Rolling element bearing diagnostics using the Case Western Reserve University data: A benchmark study," *Mech. Syst. Signal Process.*, vol. 64–65, pp. 100–131, 2015, doi: 10.1016/j.ymssp.2015.04.021.

[25] F. Honarvar and H. R. Martin, "New statistical moments for diagnostics of rolling element bearings," *J. Manuf. Sci. Eng. Trans. ASME*, vol. 119, no. 3, pp. 425–432, 1997, doi: 10.1115/1.2831123.

[26] R. Liu, B. Yang, E. Zio, and X. Chen, "Artificial intelligence for fault diagnosis of rotating machinery: A review," *Mech. Syst. Signal Process.*, vol. 108, pp. 33–47, 2018, doi: 10.1016/j.ymssp.2018.02.016.