OPPERTUNITIES FOR MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE IN A NATIONAL MAPPING AGENCY: A PERSPECTIVE ON ENHANCING ORDNANCE SURVEY WORKFLOW

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ABSTRACT:

National Mapping agencies (NMA) are tasked with providing highly accurate geospatial data for a range of customers. This challenge has traditionally been met by combining remote sensing data gathering, field work and manual interpretation and processing of the data. This is a significant logistical undertaking which requires novel approaches to improve potential feature extraction from the available data. Using research undertaken at Great Britain's NMA, Ordnance Survey (OS) as an example, this paper provides an overview of recent advances in the use of artificial intelligence (AI) to assist in improving feature classification from remotely sensed aerial imagery, describing research using high level neural network architecture to image classification that utilises convolutional neural network learning.

1. INTRODUCTION

National mapping agencies (NMA) of the world are typically tasked with producing geospatial data and topographic maps of their respective countries. Due to the enormity of the task coupled with the requirement to produce high quality data, many NMA utilise a combination of remote sensing data capture with field survey activities to capture an extensive range of real-world features and characteristics. The remote sensing activities are predominantly for the acquisition of highly detailed aerial imagery, for example at 25cm pixel resolution resulting in several thousand rows and columns per image (Sargent et al., 2019). Resultingly, these images contain greater levels of detail and information than it is possible for NMA's to extract and make available for their customers by using manual processing methods (Holland & Marshall, 2004, Cygan, 2019, Sargent et al., 2019)**.** Like many other NMA's, Great Britain's Ordnance Survey (OS) is embracing opportunities to move evermore towards automation, to enable the delivery of authoritative geospatial data and topographic mapping (Cygan, 2019). Typical for NMAs who also provide the geospatial infrastructure for their respective countries, OS provides mapping services for UK government, businesses and individual consumers and produces products and services that rely upon a data capture and processing workflow that costs tens of millions of pounds to operate. Until recently, the capture and maintenance of geospatial data was predominantly a manual process. However, OS research interests have turned to optimising the information flow from the source data and identifying the potential of artificial intelligence (AI) automation in the workflow for enhancing the product offerings to customers. Through using OS as an example NMA, this review briefly describes the development of past, present and future AI projects within an NMA.

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2. ISSUES OF LARGE-SCALE GEOSPATIAL DATA COLLECTION FOR AN NMA

Producing products for NMA customers is a massive undertaking. For example, OS captures aerial imagery covering approximately 80-90,000km^2 of the United Kingdom annually, resulting in a weekly workflow of 100,000 (change) updates, which are iterated over 650,000,000 features (Ordnance Survey, 2020). This task, therefore, presents the significant problem of how to manage the assessment and correction of such high numbers of features. In attempts to tackle this problem, OS undertook a sustained period of research into the automation of the change detection process (Holland, Gladstone et al., 2012). Subsequently, OS developed a rule-based automation process utilising eCognition (eCognition Essentials, Trimble, 2015) for improving efficiencies within the change detection workflow. These improvements detected change to a 92% correctness value (Holland, Gladstone et al., 2012). In addition, processing time savings were made, ~50% reduction when compared to the equivalent manual process (Holland, Gladstone et al., 2012). Other work producing robust automatic methods of extracting attribution such as building heights have been successfully added to the production pipelines (Sargent et al., 2015) and have expanded OS's product portfolio. These improvements highlight the potential of a more efficient processing strategy for an NMA, where service improvements can be made through time-based efficiency savings or facilitating more geospatial data being pushed through the workflow. These have direct benefits for both the business and the customer and have driven OS towards increasing the use of machine learning (ML) and AI within the operational workflow.

3. EARLY EXPLORATION OF AI CAPABILITIES AT OS

OS research into the AI field began in 2015, where the research focus was on understanding the capabilities of the techniques. At the time, advances in machine learning had predominantly been achieved using limited, specialised datasets e.g. ImageNet (Deng et al., 2009), therefore, OS explored how representational learning could be applied to NMA dataset (Sargent, 2019). Early research applying machine learning techniques focussed on unsupervised approaches to categorising roof shapes from digital surface models (Sargent et al., 2015). Some simple roof shapes and building shapes were identified, as well as artefacts such as overhanging vegetation which are useful to identify to reduce the instances of label misclassification. This initial research provided a series of opportunities that would inform the AI research direction of the OS from this point forward.

4. ENHANCING FEATURE RECOGNITION WITH AI

In order to further the potential of AI use for feature recognition, a protype two-phase DL algorithm, trained using aerial imagery and OS topographical data, has been developed at OS to enable the extraction of attribute information from the remotely sensed data. The first phase creates a general-purpose model for pre-processing imagery. The outputs from this phase are subsequently used as inputs to intuitively model the required product, for example, building attributes (Sargent et al., 2019). This method, TopoNet, is a deep neural network which identifies characteristic, repeated patterns from large scale aerial imagery (Sargent et al., 2019). Similar to other classification works that utilise computer vision and DL (Branson et al., 2018, Griffiths & Boehm 2019), TopoNet utilises a deep convolutional neural network (DCNN) to act as a feature extractor, where multiple layers of convolutional filters are learned using back-propagation using a Keras framework (Chollet, 2018). This approach to the processing of aerial imagery permits the fluid manipulation of pre-constructed network architecture. Initially the 13 layer AlexNet (Krizhevsky 2012) was tested, and when the architecture was exploited to its maximum, ResNet-50 was utilised, which, as the name suggests provides a 50-layer network which also has the ability to use 'skip connection' instead of simply stacking convolution layers one after another (He et al., 2015).

The secondary phases of TopoNet uses the techniques of 'inference' and 'discovery', where inference utilises shallow machine learning approaches to response to bespoke requests from customers and discovery is an investigation ways of better understanding the landscape (Sargent et al., 2017). This two-phase approach means that deep learning can be performed less frequently than customer requests are typically received. By performing discovery as well as inference, it is hoped that deeper and more meaning landscape understanding can be obtained to address longer-term customer requirements (Sargent et al., 2017). The various phases of the TopoNet approach are identified at Figure 1.

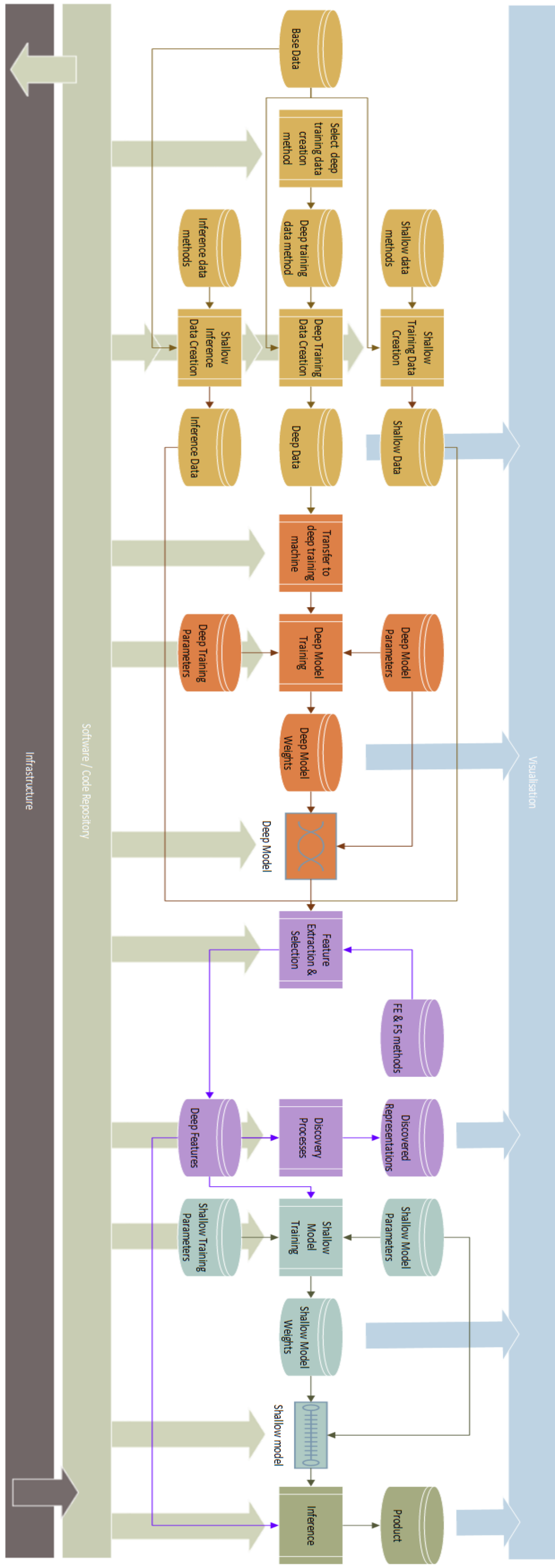

Figure 1. A model of the core components for the TopoNet deep learning method used at Ordnance Survey, UK.

TopoNet was developed using a process where the error of prediction was tested and forward propagated through to the final layer that predict the image label. Throughout an iterative process, the error was adjusted with network weightings, therefore, promoting increased classification accuracies in detecting building features (Figure 2). As the initial network architecture was based on ImageNet, the weightings were developed and used on the ResNet-50 architecture to enable a comparison. This approach provided an opportunity for a two-phase comparison, where in one approach the ResNet-50 was fine-tuned from the initial ImageNet weighting (Fine Tuned Weights), and secondly ResNet-50 weightings were defined from scratch (ScratchTrained Weights) (Figure 2). This provided the opportunity to utilise methods to interrogate the decision process within the neural network, and subsequently make improvements to the network that resulted in the accuracy improvements visualised as TopoNet V2 and V3 (Figure 2).

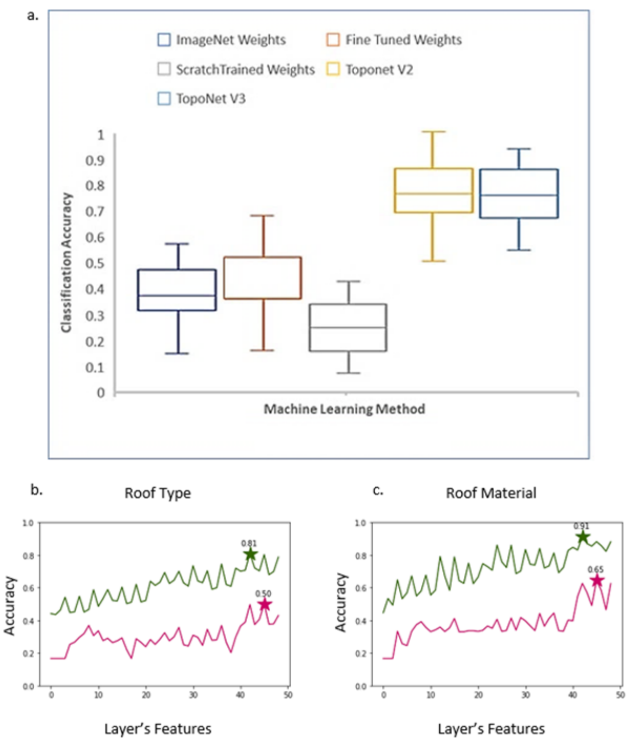

Figure 2. Comparison of classification accuracy from features extracted by the deep neural network, TopoNet. a. overall classification accuracy of TopoNet (orange and blue) when compared against other common deep learning networks. b. accuracy for inference of roof types, and c. accuracy for inference of roof material, comparing both ImageNet and TopoNet methods. Legend (b & c): Pink line: ImageNet features, Green line: TopoNet features

5. THE FUTURE OF AI IN AN NMA

OS has also undertaken several exploratory experiments assessing whether the trained deep network has learned meaningful representations of the landscape. In these experiments, there is an appearance that broad land use and land cover categories are separated (e.g. industrial, residential, water, grassland), and OS are currently validating this by establishing if the separation is based on less semantic details, such as object colour or texture. It is believed that AI can identify repeated patterns in the landscape with clear visual signatures and is seen a key research area for the future recognition of broad land-use categories. In addition, OS has initiated a collaboration with the National Physical Laboratories and Science and Technology Facilities Council, in efforts to gain better understanding of landscape representations that are learned by deep networks using remotely sensed imagery. It is envisaged that using the TopoNet approach, OS and other NMAs will be able to learn new ways to discover features within the landscape (Sargent et al., 2019).

This perspective has enabled OS to contribute to novel projects for exploiting geospatial data to its maximum potential. A new concept of utilising object-based convolutional neural network (OCNN) has been developed in partnership with Lancaster University. The OCNN approach has achieved classification accuracies at ~90% overall accuracy, which is a significant improvement over other established classification methods (Zhang, Sargent et al., 2018) (Table 1).

Class	**MRF**	**OBIA -SVM**	**Pixel-wise CNN**	**OCNN 48***	**OCNN 128**	**OCNN 128+48***
Commercial	70.09	72.87	73.26	76.4	81.13	**82.46**
Highway	77.23	78.04	76.12	78.17	74.35	**79.69**
Industrial	67.28	69.01	71.23	78.24	83.87	**84.75**
High-density Residential	81.52	80.59	80.05	81.75	85.35	**86.43**
Medium density Residential	82.54	84.42	85.27	87.28	90.34	**90.59**
Parks and Recreation	91.05	93.14	92.34	92.59	96.41	**97.09**
Parking	80.09	83.17	84.76	86.02	85.59	**88.83**
Railway	88.07	90.65	86.57	89.51	87.28	**91.92**
Redeveloped Area	89.13	90.02	89.26	89.71	94.57	**94.69**
Harbour and Sea	97.39	98.43	98.54	98.62	98.75	**98.95**
Overall Accuracy (OA)	78.67%	79.54%	81.62%	84.23%	87.31%	**89.52%**
Kappa Coefficient (k)	0.76	0.78	0.8	0.82	0.86	**0.88**

Table 1. Classification accuracy comparison amongst MRF, OBIA-SVM, Pixel-wise CNN, OCNN48*, OCNN128, and the proposed OCNN128+48*. Overall accuracy (OA) and Kappa coefficient (k) are stated with 'bold' highlighting the greatest classification accuracy per method

Furthermore, OCNN has recently been used within a novel Joint Deep Learning (JDL) approach that utilises Markov iteration, that updates between land cover (LC) and land use (LU) classifications. Initial research shows that this approach results in further classification accuracies and has the potential to enhance the generalised processing workflows of NMAs at a range of data levels or topographic scales (Zhang et al., 2019). It is suggested that a key advantage of the JDL method is the move away from a 2-part classification process, specifically the utilisation of both LC and LU data, and provides opportunities for a move towards a unified representation of geographical space (Zhang et al., 2019), which could achieve higher classification accuracies and improved workflows for NMAs.

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6. CONCLUDING REMARKS

It is understood that to maximise the potential for AI use in NMAs, that robust systems of network training and interrogation will need to be developed in order to understand where AI supported discoveries are meaningful and to what end these could be applied in an operational sense (Sargent et al., 2019). It is understood that there is value in utilising AI and ML in the operational workflows of NMAs, and this can lead to significant business efficiencies, greater product consistency and an enhanced series of products available for the customer. Throughout their exploration of developing AI use within the workflow, OS has taken the opportunity to learn the unique requirements of a suitable computational infrastructure which will enable the handling of the AI data flow and permits the robust development of workflow automation. These initial forays into AI automation have provided great insights into the potential application of AI for a NMA and therefore, OS plans to further maximise the benefits of developing AI capabilities in the near future, which it is envisaged will lead to greater uptake and application of AI use within the NMA sector.

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