# ECM2427: Literature Review on Aerial Imaging & AI for Object Identification

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## I. Introduction

In this Literature Review, I will discuss recent literature publications documenting how Aerial Imaging and Artificial Intelligence (AI) tools are being utilised for application in Object Identification problems.

Aerial Imaging will cover the scope of both low altitude imaging, such as drone surveying, whilst also covering high altitude techniques like satellite imaging; the merits of both will be discussed and evaluated against one another.

A range of goal objects will be discussed also, this includes both the presence of things for example shipwrecks and tropical cyclones, but also the properties surrounding an object such as if a crop is ready for harvest or the type of crop. By exploring a range of identifiable objects and features, I will be able to fairly evaluate the techniques used and the appropriateness of technique for the goal.

When referring to Artificial Intelligence tools, this is predominantly referring to computer vision and the use of Deep Learning (DL) to identify objects in images. This literature review will discuss popular Deep Learning techniques, once again evaluating the appropriacy of each approach with respect to the goal outcomes. Common Deep Learning techniques conform to the nature-inspired ”Neural Network” architecture, where models are built to replicate the way Neurons in the human brain pass information in order to make conclusions from sensory observations [1]. A neuron can be characterised by having multiple input ”nodes” and one or more output ”nodes” [1]; a sum of these neurons come together in a layered structure to make one large decision making network: a Neural Network. When testing a neural network, a validation data set is passed through the model and the performance is measured by numerical metrics. Accuracy is the calculated as the percentage of correct classifications [2]; whilst this is an effective metric, it does not take into account the consequence of false positive and false negative classification. For this reason, Recall and Precision are preferred measures [2], being calculated by considering false results in the metric.

The following Literature Review will begin by outlining the range of aerial imaging techniques that are employed; then going on to explain the architecture of AI and DL tools with reference to computer vision and image processing. The adjacent subsection will discuss object identification applications, making comment on the different techniques used for different types of aerial imaging. Finally a conclusion will summarise the reviewed literature and discuss the future of research in this field, commenting on where application of the reviewed research could be wholly appropriate.

Sources will be selected by finding well respected, peer reviewed examples of articles, journals and research reports in the relevant sector. Tools such as Google Scholar, ResearchGate and the University of Exeter internal library will be harnessed to ensure high quality sources: solidifying the reliability of the findings of the following report.

## II. Review

The following literature review is ordered Thematically; the subsections build literature from each of the constituent parts of the topic and then tie them together by reviewing literature where all relevant parts unite. Each subsection will be ordered logically and comment will be made on prevalent challenges, where appropriate.

### A. Aerial Imaging Techniques

This section aims to critique relevant literature on aerial imaging techniques.

*1) Low Altitude Imaging:* One of the first accounts of low altitude aerial imaging was documented in 1865, when astronomer James Glaisher took pictures of London from his hot air balloon [3]. Since then technology has advanced; with Unmanned Air Vehicles (UAVs) being the preferred method. In the paper by Henri Eisenbeiss, from the year 2004, a ”Mini UAV” is described [4]. This particular paper was published under what is now the world renowned university, ETH Zurich; giving me confidence in the validity of his findings. Eisenbeiss describes applications in ”rice paddy remote sensing”, eluding to the potential agricultural applications of drone based imaging, giving specific examples of technology. He made use of the 2002 Yamaha RMAX helicopter, shown in Figure 1, to survey land at test sites in Sweden, before going on to deploy the technology in Peru. The main criticism of this source is it’s age: with camera technology being far less advanced than the modern age. At this stage in time, imaging results were also still reviewed manually.

Fig. 1. Yamaha RMAX UAV

*2) High Altitude Imaging:* Under the University of Hanover, K.Jacobsen published a paper on the overview of "High Resolution Satellite Imaging Systems" [5]. Reliability of this paper is validated by the prestige of the publishing University, as well as it's peer-reviewed status. The 2005 paper outlines the upward trend in availability and quality of high resolution satellite technology, the initial purpose of which was tailored toward military reconnaissance and mapping. The military applications are strongly supported by the 2014 "Military reconnaissance application of high-resolution optical satellite remote sensing" [6]. Figure 2, taken from the aforementioned paper [6], demonstrates how a high resolution satellite can be used for reconnaissance purposes. The use of high quality satellite imaging raises obvious privacy concerns, as highlighted by Megan M. Coffer [7], in a peer-reviewed paper published under the well respected American Chemical Society. She states that "between 1980 and 2016, average spatial resolution improved nearly 20-fold, from pixel sizes of roughly 500 to 25m", thus showing the significance of the imaging improvements over time. This calls attention to the sudden stripping of land privacy, especially when considering how publicly available these images are as highlighted by Jacobsen [5].

Fig. 2. A mobile missile base: Novosibirsk, Russia

## B. Architecture of AI

This section will highlight relevant literature covering typical Neural Network architectures for computer vision tasks; namely image decomposition and object recognition.

Together, Albawi and Mohammed published the 2017 paper "Understanding of a Convolutional Neural Network" [8], being a peer reviewed paper from the Istanbul Kemerburgaz University, it is extremely reliable and very relevant to the literature review being conducted. The paper presents findings as to how CNNs can be implemented for image classification problems. The pair conducted primary research by implementing an example on the commonly used CIFAR-10 dataset of images, showing how CNNs can decompose images to constituent parts, whilst still keeping contextual location intact. A popular pre-configured architecture is the 1998 proposed LeNet [9]; being a renowned and well documented architecture the source is deemed an extremely reliable example of a CNN in practice.

## C. Object Detection Applications

Now that relevant literature has been presented as to how each component can be structured, it is prudent to elaborate upon the application of these technologies; providing literature so as to support how and why the technology was a viable solution for the problem.

*1) Agricultural Surveying:* In the published paper "A CNN approach to simultaneously count plants and detect plantation-rows from UAV imagery" [10], primary research was conducted on the implementation of a CNN to process images collected by a low altitude UAV in order to count plants and detect the location of plantation rows. Being primary research supports the reliability of the details presented in the report; a CNN was implemented to analyse imagery provided by a UAV over Brazilian citrus orchards and corn farms, as a result the CNN yielded precision and recall scores of 0.922 and 0.911 respectively on a citrus-tree test dataset, demonstrated visually in Figure 3. It is important to note that the report advises this is reliable to "assist in precision farming practices" and is not intended to entirely replace manual inspection, generally due to the accuracy of the network. Application of this research in a real-world agricultural practice would help improve efficiency whilst simultaneously acting as another layer of validation for farmers. Issues arise due to the scalability of UAV surveying, due to the associated fees and skills required to pilot such a drone, as highlighted in an IEEE published article titled "Recognizing User Proficiency in Piloting Small Unmanned Aerial Vehicles (UAVs)" [11] - deemed a reliable source due to the prestige of IEEE publications.

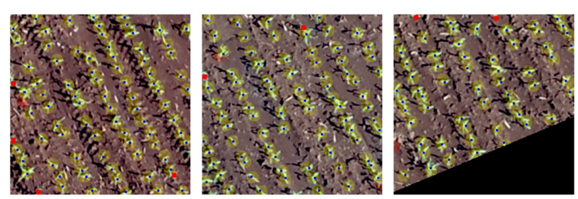

Fig. 3. Visual results showing plants as dots and tree-canopies as circles [10]

*2) Black Reef Shipwreck Site Detection:* "Identification of Black Reef Shipwreck Sites Using AI and Satellite Multispectral Imagery" [12] - an article championed by professors at the University of Southampton - highlights the applications of AI for analysing high altitude satellite imagery to identify Shipwrecks. The reliable, peer-reviewed report outlines how a CNN was implemented first hand by the researchers, with results demonstrated in Figure 4. One standout issue with this research was the lack of open source labelled shipwreck data, this presented the issue of optimisation, which researchers mitigated the consequences of by reducing the number of CNN layers; thus improving the complexity of the search space. Satellite images are deemed appropriate for this application due to the availability: saving the costs and resources associated with travelling. Overall, the article concludes that the implementation of AI tools for detecting Black Reef Shipwrecks is crucial for identifying chemical threats to both marine ecosystems and human health; currently the lack of available labelled data is a bottleneck for the research but, once overcome, a reliable detection system can be implemented.

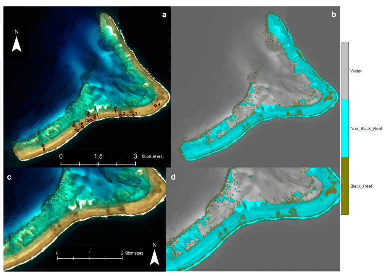

Fig. 4. "Vision-1 satellite image of Kenn reef with the location of the 11 known shipwrecks (red dots), (b) the resulting segmented image after the application of the trained algorithm, (c) zoomed part of the Google Earth image and (d) the corresponding zoomed part of the segmented image" [12]

*3) Cyclone Track Forecasting:* In 2020, primary research was conducted so as to forecast the movement direction of tropical cyclones [13]. The researchers used satellite data from the Himawari-8 real time satellite database, taking 2250 images containing 97 typhoons in order to train a CNN to predict the movement angle of a cyclone. It is stated in the article that, in regular scenarios, data is numerically analysed to predict the movement of cyclones. This takes a significant amount of, not only time, but also computational resources; by moving toward a CNN classification approach, a substantial amount of time can be saved as neural network results take just a few seconds to process. Research conducted by this paper is deemed reliable due to the primary nature of the implementation. The article gives strong argument as to how and why CNNs can be used to analyse satellite images for storm tracking, however, it does also highlight the key issues that researchers must overcome in order for meaningful implementation of CNNs on satellite imagery. Mainly, there is a lack of labelled typhoon images for training; of the 2250 images a mere 4.3% were of typhoons which shows a large imbalance, thus more data would help significantly improve model accuracy.

### *D. Technique Comparison*

In the review titled "Deep Learning Models for the Classification of Crops in Aerial Imagery" [14] a direct comparison is made between the use of satellite and UAV imaging for a crop classification problem. The review contains detail of the CNN architecture in addition to detail of the merits of both imaging technologies and their appropriacy for the problem being tackled. Satellite images are noted as being widely available and free; ensuring the ability to collect samples easily. On the other hand, satellite data is vast and expansive: covering the entire globe, hence finding labelled samples of ideal outcomes is time consuming. UAVs on the other hand need to be manually flown by a trained pilot, which has associated overhead costs involved, as well as a restriction on how and when data can be collected due to weather systems, as supported by the article "The Unmanned Aerial Vehicle (UAV): Its Impact and Challenges" [15]. UAVs cannot be flown at higher altitudes and as such they are wholly inappropriate for problems, for instance the weather mapping example discussed previously.

## III. Conclusion

In summary, it is clear that (from the reviewed literature) both satellite imaging and Unmanned Aerial Vehicles have their own place in collecting data for a deep learning approach to object classification. UAVs being suited to low altitude data collection where circumstances are known and high resolution over a small geographical area is important. Satellite images however can be found openly and freely online; commonly used for collecting data on large area effects that can be seen from space, for example weather systems or Black Reef shipwrecks.

The application of Deep Learning approaches, namely Convolutional Neural Networks, for feature detection and pattern analysis in images is clearly applicable and appropriate. Other methods, such as Long Short Term Memory neural networks were mentioned in papers, but CNNs are the industry favoured approach. Whilst a CNN can yield strong accuracy, none of the reviewed sources advise the sole use of these for observation automation and instead advise human, manual verification steps. There is a large deficit of labelled training data for a majority of the problem topics mentioned; leading to a neural network with perhaps sub-optimal accuracy scores. Many papers made comment on how, once more labelled data is openly available, the conducted research would be more deployable.

Overall, it can be clearly demonstrated that Artificial Intelligence and Aerial Imaging tools can be an optimal combination for applications in feature recognition on geographical problems; by doing so confidence in a judgement and efficiency in coming to such a judgement is bolstered. More data collection and labelling must take place on aforementioned applications before a reliable model can be used on a wide scale.

## Acknowledgement

With thanks to Dr. David Moffat for his talk on "A Career in Data Science"; introducing his research at the Plymouth Marine Laboratory into using drones and AI to detect Pacific Oysters, as well as inspecting satellite imagery for analysing plankton populations.

Generative AI was not used in the writing of this literature report.

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