Calculating Leaf Area Index Using Neural Network and WorldView 3 Multispectral Imagery

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Abstract – **Leaf Area Index (LAI) holds significant importance as a specific characteristic of Leaf Areas in the field of smart agriculture. This study explores the estimation of LAI using a multi-spectral image from WorldView 3 satellite. The image combines 8 VNIR bands and has a spatial resolution of 1.24m. To overcome the limited amount of available data, the image was split into smaller subsets called paxels, resulting in 500 paxels for training and testing. For enhancing machine learning models' performance, the standardisation of a dataset is made, after that, a Multilayer Perceptron with a specific architecture aimed to predict LAI from the multiple bands is trained. The achieved results showed promising performance in LAI prediction. Overall, the study demonstrates the potential of using satellite imagery and machine learning algorithms to improve our understanding of crop health and productivity.**

Keywords – **remote sensing, machine learning, image processing, smart agriculture.**

I. Introduction

Over the past few decades, advancements in satellite technology and machine learning techniques have revolutionised the way we monitor and manage agricultural land. The ability to collect and analyse vast amounts of data using satellite imagery and machine learning algorithms has opened new avenues for improving crop yields, managing resources, and ensuring food safety [1][2]. In recent years, researchers have focused on using image processing techniques to analyse remote sensing data and extract key indicators related to crop health, such as Leaf Area Index (LAI) and Normalised Difference Vegetation Index (NDVI). The resulting models are robust, efficient, and trustworthy, providing farmers with valuable insights into crop health and productivity. With further research and development, this technology has the potential to revolutionise the agricultural industry [3], increasing efficiency and sustainability while ensuring the safety and security of the food supply.

This paper aims to explore the use of satellite imagery and machine learning algorithms for smart agriculture and food safety, with a focus on the estimation of LAI as a key biophysical indicator using WorldView 3, a proprietary satellite probe.

II. Literature Review

Leaf Area Index (LAI) and Normalised Difference Vegetation Index (NDVI) are pivotal indicators for assessing plant growth and nutrient status. LAI characterises the canopy structure of crops and is intricately linked to vital plant processes such as photosynthesis, respiration, and transpiration [4]. Traditional methods for acquiring LAI and NDVI data, predominantly field sampling and manual measurements, are often labour-intensive and inefficient for large-scale applications.

In recent years, remote sensing technologies, especially satellite and Unmanned Aerial Vehicle (UAV) multispectral imaging, have emerged as a potent tool in precision agriculture, enabling detailed quantitative assessments of LAI, NDVI, and other plant physicochemical parameters [5][6]. Compared to satellite remote sensing and hyperspectral instruments, UAV multispectral remote sensing stands out for its cost-effectiveness, flexibility, spatial resolution, and specific spectral bands that are instrumental in monitoring agronomic parameters [7][8].

On the other side, the development of machine learning techniques has been successfully combined with remote sensing data to extract essential insights to aid smart agriculture. For instance, in a study focusing on estimation of LAI and aboveground biomass of C. camphora dwarf forests based on UAV multispectral remote sensing data, algorithms such as Extreme Gradient Boosting (XGBoost), Gradient Boosting Decision Tree (GBDT), Random Forest (RF), Radial Basis Function Neural Network (RBFNN), and Support Vector Regression (SVR) were employed [9]. These models, particularly XGBoost, demonstrated high accuracy in estimating LAI and Aboveground Biomass (AGB), outperforming traditional methods.

The integration of machine learning algorithms with WorldView 3 multispectral imaging, however, presents a novel approach to estimating LAI and NDVI.

In that research, a significant correlation was observed between the reflectance of specific bands (blue, green, red, red edge, and near-infrared) and LAI and AGB of C. camphora,

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with the highest correlation noted for the red edge band. This suggests the critical role of specific spectral bands in accurately determining certain biophysical properties. The study highlighted that a combination of multiple band reflectances, were more effective as independent variables for LAI and AGB estimation in models like XGBoost, GBDT, and RF. Furthermore, [10] investigated the influence of different soil reflectance sources and extraction schemes and suggested that such influence was larger on the retrieval of LAI than other biophysical property indices. Such findings underscore the effectiveness of combining machine learning algorithms with multispectral imaging for enhancing precision in LAI and NDVI estimation.

In conclusion, the utilisation of multispectral technology with high spatial resolution, in tandem with advanced machine learning models, offers a promising pathway for rapid, non-destructive, and accurate monitoring of LAI and NDVI [11][12][13]. This advancement not only aids in precision agriculture but also contributes significantly to the broader field of remote sensing and plant health assessment. Studies [14] and [15] conclude that machine learning algorithms are a robust and fast approach for predicting biodiversity variables from remote sensing data, hence in this paper we look into implementing a neural network capable of estimating LAI using WorldView 3 imagery.

In this article, we propose an innovative method that utilizes satellite data and Machine Learning to optimize the process for acquiring LAI data. Using high-resolution satellite imagery and sophisticated machine learning algorithms, we can effectively calculate vegetation indices over extensive regions, enhancing precision and scalability.

III. Data Preparation

III.1. Data Source

The WorldView 3 satellite, operating at an altitude of 617 km, represents a significant advancement in remote sensing technology. It is equipped with sophisticated imaging capabilities, notably a panchromatic resolution of approximately 0.31 meters, which facilitates highly detailed black-and-white imagery. Additionally, its multi-spectral imaging capabilities are noteworthy, with a resolution of 1.24 meters across eight spectral bands, listed in Table 1.

Table 1: Band distribution and spectral characteristics for WorldView3 [10].

Spectral Range	Band Name	Spectral Band
Multispectral Bands in VNIR (Visible Near Infrared)	Coastal Blue	400 - 450 nm
	Blue	450 - 510 nm
	Green	510 - 580 nm
	Yellow	585 - 625 nm
	Red	630 - 690 nm
	Red edge	705 - 745 nm
	Near-IR1	770 - 895 nm
	Near-IR2	860 - 1040 nm

These characteristics allow the collection of a sufficient amount of qualitative data to conduct comprehensive analysis across various parts of the electromagnetic spectrum, offering detailed insights that extend beyond the visible range, as shown in Figure 1. Furthermore, WorldView 3 boasts a short-wave infrared resolution of 3.7 meters across eight bands, enhancing its utility in geological and vegetation studies. Complementing these features are the 12 bands of the Clouds, Aerosols, Vapours, Ice, and Snow (CAVIS) system, which provide atmospheric data with a resolution of 30 meters, essential for environmental monitoring and atmospheric correction. For this study, we mainly focused on the eight multispectral bands.

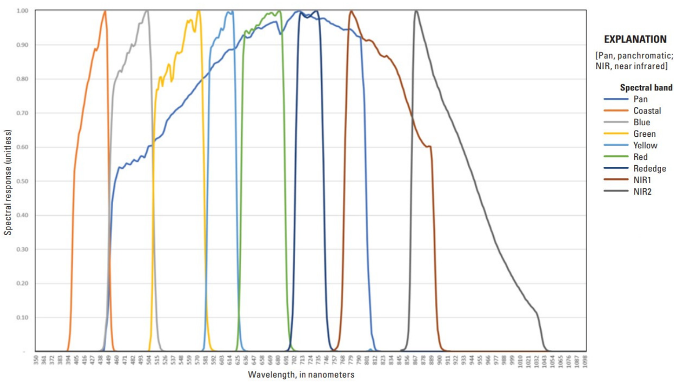

Figure 1: WorldView 3 visible and near-infrared relative spectral response [16].

III.2. Dependant Variable and Data Segmentation

In this study, the first step towards creating the training dataset for predicting LAI from multi-spectral imagery captured by the WorldView 3 satellite probe involved a manual calculation of LAI, which was then used as the dependent variable or 'y' in the data as shown in Figure 2. Various open-source software packages are available for calculating LAI, each using different coefficients. For this study, we utilised a widely accepted formula to calculate LAI, which allowed for accurate and reliable comparison with other studies in the field.

$$LAI = (3.618 \times EVI) - 0.118$$

where

$$EVI = 2.5 \times \frac{NIR - RED}{NIR + 6 \times RED^2 - 7.5 \times BLUE + 1}$$

The above formula is given as a standard for calculating LAI [17]. However, as discussed previously WorldView3 contains two Near Infra-Red (NIR) bands and, for this study, just the first one was taken into account together with both Red and Blue bands.

The manual calculation of LAI for each pixel in the multispectral image provided a basis for further analysis and identification of Leaf Areas with specific characteristics, intending to enhance the accuracy and efficiency of smart agriculture applications. To overcome the challenge of limited data availability, we adopted a strategy of splitting the original WorldView 3 image into multiple smaller subsets, or paxels, of a certain size. This resulted in a total of approximately 500 paxels, which were then used for training and testing the machine learning model. By utilising this approach, we were able to make the most out of the available data and improve the accuracy and robustness of our results. This method of data preparation has been widely used in other studies that deal with remote sensing data and machine learning, as it allows for more efficient and effective analysis of large datasets.

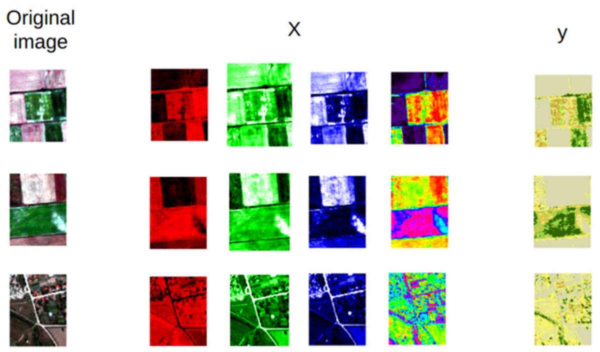

Figure 2: Data set example displaying a sub-set of the inputs together with the target variable.

IV. Modelling

IV.1. Standardisation

Standardisation, sometimes referred to as data normalisation, is a machine learning preprocessing technique that scales a dataset's characteristics to have a unit variance and zero mean. Usually, to do this, each feature's mean is subtracted from each data point, and the result is divided by the feature's standard deviation. Because standardisation can enhance machine learning models' performance, it is beneficial. The size of the input characteristics affects the performance of some algorithms, including support vector machines and neural networks. The model may perform poorly if certain features dominate the learning process and have a considerably wider range of values than others. By standardising the data, we make sure that every feature makes an equal contribution to the learning process, which can increase the model's resilience and effectiveness. Additionally, by placing all features on a uniform scale, standardisation can facilitate data visualisation and interpretation. Hence, in this study, we employ a standardisation technique to guarantee consistency among the paxels used for training the deep learning model.

IV.2. Training

To enhance the reliability and credibility of our model, we followed a standard practice of splitting the data set into training and testing sets. This was achieved by a random split of 70% for training, 20% for testing, and 10% for validating before feeding the data into the neural network. Such practice is crucial in ensuring the robustness and validity of the model.

Furthermore, such a technique prevents overfitting and helps with model generalisation. This generalisation is important for the model's ability to perform well on new, unseen data, reflecting its true predictive power and applicability to real-world scenarios.

IV.3. Model Architecture

The multi-layer perceptron (MLP) is a foundational model widely recognised within the domain of machine learning. Despite its simplicity relative to more advanced architectures such as convolutional or recurrent neural networks, it remains a powerful tool. Because of this in our study, we implemented an MLP algorithm for our machine learning framework.

Estimation of LAI is approached as a pixel regression task. The input bands are 164×128 dimensional paxels, focusing on 8 bands from the VNIR spectre of WorldView3. The output is the value of LAI for each pixel.

We implemented an MLP algorithm featuring three hidden layers for our machine learning model. Rectified Linear Unit (ReLU) activation function was employed for each hidden layer, whilst the sigmoid function was used for the output layer given the regression-oriented nature of the problem. The optimiser used was Adam with a learning rate of 0.01, and the Root Mean Square Error (RMSE) was chosen as the loss function. RMSE quantifies the model's prediction errors by computing the square root of the mean of the squared differences between the predicted and observed values.

V. Results

Correctness of our results is estimated by RMSE, which is a widely accepted metric in the field of predictive analytics. Our model demonstrated an RMSE value of 0.9525, which signifies substantial potential.

For simplifying and enhancing the verification of our model's potential we present a comparative visualisation of the original, actual, and predicted data, thereby fostering a more intuitive understanding. Some examples, for both urban and rural areas, are given in Figures 3 and 4. As is seen, our model shows good recognition of LAI regions but needs improvement in the direction of obtaining a smoother representation of LAI values.

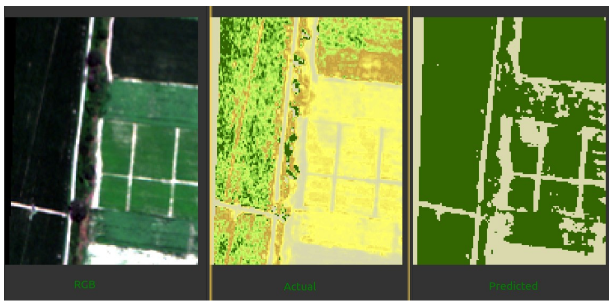

Figure 3: Rural area. Left-Input image (RGB); Center - y; Right - $\hat{y}$.

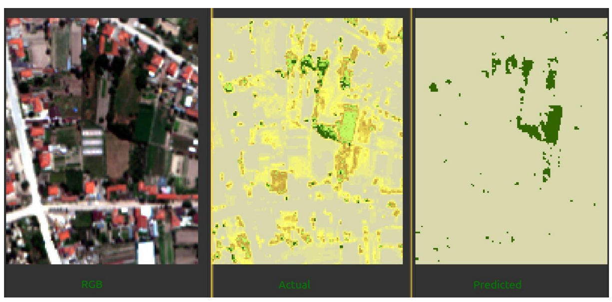

Figure 4: Urban area. Left-Input image (RGB); Center - y; Right - $\hat{y}$.

By combining quantitative analysis with these visual interpretations, we provide a comprehensive overview of the model's performance, offering both statistical and visual evidence of its effectiveness and potential applications.

VI. Improvements and Future Work

Verifying results using in-situ data is a critical step in ensuring the accuracy and reliability of our findings. We have already gathered and analysed some data, and we are going to validate the results acquired as part of this study. In addition to that, we plan to experiment with various reflectance models to gain insights into their respective strengths and weaknesses.

As previously noted, the spatial resolution of WorldView 3 multi-spectral images at 1.24 meters stands out significantly. However, we aim to explore an image fusion algorithm called pan-sharpening to improve this even further. The goal is to derive a comprehensive and quantitative analysis of whether spatial resolution has any impact on the performance of the proposed algorithm.

Furthermore, for achieving better smoothness of the LAI values we plan to extend our exploration beyond the current framework by experimenting with a variety of other machine learning models.

VII. Conclusion

Our study presents a framework encompassing data preparation, modelling, and training of a neural network specifically designed for estimating Leaf Area Index (LAI) using WorldView 3 multi-spectral imagery. The Root Mean Square Error (RMSE) metric quantifies the encouraging outcomes we achieved, which emphasises the usefulness and the great potential of this approach.

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