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Classification of Coconut Trees Within Plantations from UAV Images Using Deep Learning with Faster R-CNN and Mask R-CNN

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Abstract

Agriculture currently serves as a crucial food source for the global population. However, coconut farming, in particular, demands extensive care and maintenance. This research aims to classify coconut trees across various plantation areas utilizing deep learning techniques, specifically through Faster R-CNN and Mask R-CNN models, based on unmanned aerial vehicle (UAV) imagery. The data collected by both types of RGB UAVs was used for the classification of coconut trees in experimental plots. For the analysis process, aerial photographs obtained from unmanned aerial vehicles, merged with the principles of aerial photography measurement, were analyzed. The research findings revealed that both Faster R-CNN and Mask R-CNN were capable of effectively classifying image data. Nevertheless, to achieve higher accuracy in results, it is essential that the characteristics of the test plots closely align with each other. This study points towards the adoption of a high-resolution tool, ensuring clearer images that facilitate more accurate classification of coconut trees across extensive areas. Consequently, this could lead to more efficient management and maintenance of coconut plantations. Thus, this approach can substantially enhance the efficiency of managing coconut plantations.

Keywords: Coconut; UAVs; Deep Learning; Mask R-CNN; Faster R-CNN.

1. Introduction

Presently, agriculture is a critical food source for the global population, fulfilling basic needs of human beings. However, the world's agricultural land is diminishing due to changes in land use and the impacts of global climate change. These shifts threaten agricultural productivity and directly jeopardize global food security. The coconut, particularly significant in tropical regions for its economic value [1], is in high demand in the international market. This global demand is projected to rise even further [2]. In 2019, Thailand's coconut cultivation spanned 1,347.046 sq.km., yielding 788,178 tons, with an average productivity of 1.643 kilograms per sq.km. By 2020, the country's coconut export value soared to over 8 billion baht, serving key markets in China, Hong Kong, Malaysia, Singapore, Taiwan, the United States, and the Netherlands [3].

However, coconut cultivation is an agricultural practice that demands substantial time and experience. Additionally, the market price is unpredictable, and the threat of diseases and pests can severely affect crop yields, prompting

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farmers to consider alternative crops. Moreover, the agricultural workforce is dwindling, as Thailand is entering an aging society phase. The decreasing population, alongside the expansion of urban areas and construction, has resulted in a shift in land use from coconut cultivation to other purposes. Coupled with challenges posed by diseases and pests, this change has compelled the Thai coconut farmers to switch to different crops [4].

Given the current situation, agricultural communities have increasingly embraced the integration of technology to enhance farming practices. The utilization of technology and local data for management purposes aims to ensure data accuracy and management precision, thereby leading to cost reductions and improved future predictions. Geoinformatics technology, in particular, has been widely adopted due to its constant development and its ability to describe data and spatial characteristics, especially in remote sensing applications that have been consistently utilized in agricultural monitoring. For example, Worachairungreung et al. (2023) conducted a study estimating oil palm production using Fuzzy principles and Machine Learning algorithms [5]. Terentev et al. (2022) studied the use of Hyperspectral Remote Sensing for early plant disease detection [6]. Noppon & Nipon (2019) explored the application of a stereo camera system in age classification of coconut trees [7]. Furthermore, even in coconut growth mapping, remote sensing and Geographic Information Systems have been employed [8]. With technological advancements, the use of unmanned aerial vehicles (UAVs) in agriculture has also significantly increased, such as in predicting oil palm production [9].

In addition to Geoinformatics technology, developments have been made in machine learning and deep learning, which serve as crucial tools for conducting precise and accurate data analysis. These methodologies are commonly utilized in agricultural settings and for predicting agricultural yields. For instance, Gibril et al. (2021) conducted research on the application of Deep Convolutional Neural Networks (CNN) in mapping oil palm plantations using unmanned aerial vehicles (UAVs) [10]. Similarly, Erdem et al. (2023) explored the use of UAVs for detecting apricot trees through deep learning algorithms, resulting in highly accurate outcomes and expedited processing [11].

The previous studies mentioned above illustrate the application of Geoinformatics technology in agricultural research, particularly in the context of agricultural yields, with a notable emphasis on crops such as coconut and oil palm. However, due to the distinct characteristics of coconut leaves compared to other types of crops, for example, studies on how to classify vegetation in photographs, Islam et al. (2024) studied the detection and segmentation of lettuce seedlings from seedling tray images using an improved R-CNN mask. The results of the study showed that the improved Mask R-CNN can detect lettuce seedlings in the tray background and can also extract the leaf area of the specified lettuce seedlings [12]. Manoharan et al. (2023) used a hybrid fuzzy support vector machine (SVM) approach for coconut tree classification using image measurements. The results showed that architecture gives better performance than state-of-the-art classifiers, with an accuracy of 88.86% [13]. Palananda and Kimpan's study (2022) was conducted on the classification of contaminant particles in coconut oil using a deep learning approach using a CNN model. The experiment's results indicated that the MobileNetV2 architecture performed the best [14]. Furthermore, there have been studies on the use of remote sensing technology for surveying plants such as coconut and palm trees. For example, Gibril et al. (2024) used UAV and remote sensing to assess date palm plantations [15]. Kavithamani & UmaMaheswari (2023) have studied a Deep Convolutional Neural Network (DCNN) method to identify whiteflies in coconut leaves. Results of the study found that the deep learning model can detect problems such as root bleeding, blade pollution, and insect infestation using segmented areas [16]. The benefits of this study could lead to the monitoring of plant growth and timely pest management. From related research, it was found that this method can be used in the study and management of coconut plantations, thereby using remote sensing that gives accurate results. This study will lead to guidelines that will help increase the efficiency of coconut plantation management more effectively.

Thus, the objective of this study is to specifically classify coconut trees in diverse plantation areas by employing deep learning techniques, namely Faster R-CNN and Mask R-CNN, and utilizing imagery captured by unmanned aerial vehicles (UAVs). These methodologies constitute essential components of the high-resolution remote sensing process further leading to efficient plantation management.

2. Material and Methods

2.1. Study Area

Samut Songkhram Province was selected as the research setting in this study because it is one of the most fertile provinces in the Mae Klong River basin group, located in the central plains of Thailand. Covering approximately 413.8 square kilometers, it lies at latitude 13° 26' 45" North and longitude 100° 01' 55" East. Samut Songkhram Province also features three types of water bodies: freshwater from the Mae Klong River, saline water from the Gulf of

Thailand, and brackish water at the estuary of the Mae Klong River, contributing to its fertility [17]. This makes it suitable for cultivating coconut palms, as coconuts can tolerate both saline soil and water, resulting in sweet-tasting coconut water.

The analysis of land use data from the fiscal year of 2019 showed that the majority of the area has been used for agriculture, with coconut cultivation covering up to 130,574.4 square kilometers, accounting for 27.09% of the province's total area [18]. Coconut production amounted to 230,673 tons, comprising 147,184 tons of mature coconuts, 65,880 tons of semi-mature coconuts, and 17,609 tons of young coconuts [19]. This data underscores the province's significant potential for coconut farming.

The test plots in this study involved coconut cultivation areas with varying land uses and diverse coconut tree ages. There were 4 test plots in total, located in Bang Khon Thi District, Samut Songkhram Province, as depicted in Figure 1.

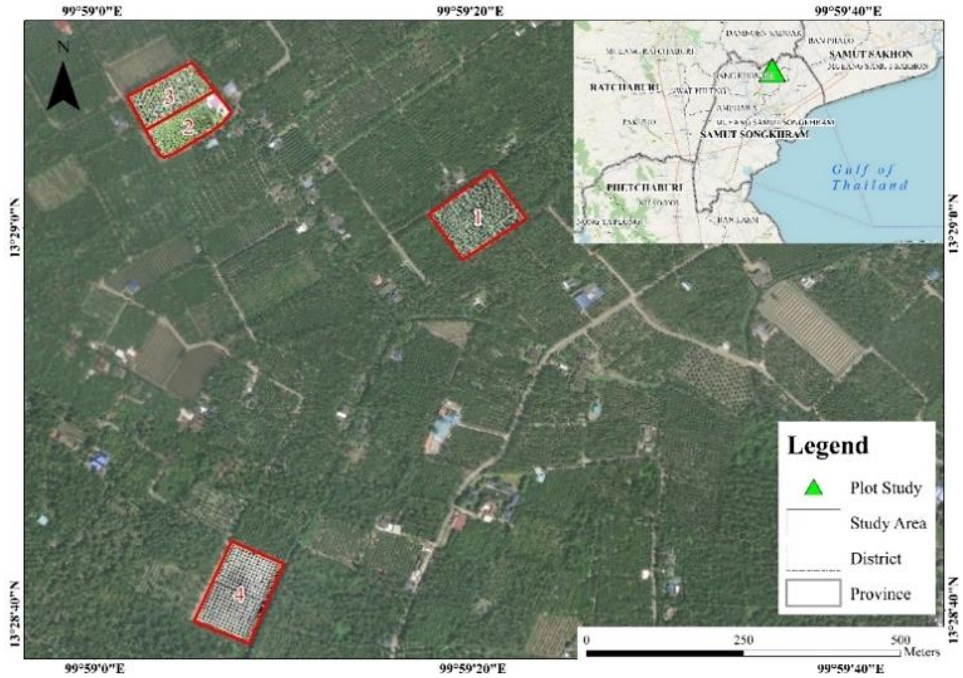


Figure 1. Map of the study area

2.2. Data Collection

In this study, data was obtained from four different test plots, as described. Plot 1 covered an area of 11,056.525 square meters, hosting coconut trees of various ages, predominantly under 10 years old. Plot 2, spanning 7,148.529 square meters, featured coconut trees primarily aged over 15 years. Plot 3, covering 6,773.243 square meters, contained coconut trees with mixed ages, mostly under 10 years old. Plot 4, which encompassed 12,840.431 square meters, housed coconut trees aged approximately 2 years old dispersing across the study area.

Subsequently, data collection was conducted using a DJI Phantom 4 Pro V 2.0 multi-rotor unmanned aerial vehicle (UAV), equipped with essential components such as a global positioning system (GPS)/global navigation satellite system (GLONASS) for ground positioning. It boasted a maximum flight range of 7 kilometers, a maximum flight altitude of 500 meters, and the ability to withstand wind speeds of up to 36 kilometers per hour. Operating frequency ranged from 2.40 to 5.85 GHz. The camera featured a 1-inch CMOS sensor (12.80×9.60 mm) with a static image resolution of 20 megapixels (MP). The lens had an 84-degree field of view (FOV) and an aperture size ranging from f/2.8 to f/11, with a focus distance of 1 meter and beyond. Additionally, it featured three-axis gimbal stabilization for pitch, roll, and pan. Moreover, it supported ground positioning systems via satellite positioning systems like GPS and GLONASS [20, 21].

The aerial photography technique employed by the DJI Phantom 4 Pro V 2.0 utilized a double grid flight pattern, with the flight altitude set at 80 meters. Image overlap was configured at 70% for side lap and 80% for overlap, resulting in a ground sample distance of 2.32 centimeters per pixel. Additionally, ground control points were strategically placed around the four corners and four edges of the plot, totaling eight positions. An illustrative example of the survey flight is depicted in Figure 2.

Figure 2. Data collection using UAV

2.3. Methods

During the object detection process for coconut trees within the test plots, this study utilized the Faster R-CNN method, which is a part of Convolutional Neural Network (CNN) techniques. The approach involved simulating small-scale areas in images and conducting incremental training, which then passed through the Region Proposal Network (RPN). The RPN was responsible for generating multiple proposals from different parts of the image to inspect objects within the input image. It also selected objects from various regions of the image with different sizes, classifying the detected objects, and exporting them with specified boundaries [22]. Application of the Faster R-CNN model was expected to diminish human errors and provide precise and dependable data, which would be advantageous for comprehensive agricultural management [23].

For the analysis process, aerial photographs obtained from unmanned aerial vehicles, merged with the principles of aerial photography measurement, were analyzed. This involved orthorectification of the images using specialized software to enhance accuracy, in line with photogrammetry principles. Subsequently, object classification from images within each test plot was conducted, one by one. This process involved the following stages [24]:

Stage 1 Input Image: The input image was processed.

Stage 2 Extract Region Proposals: The model detected coconut tree features predefined for detection. However, some areas overlapped or had shapes not covered during training, resulting in warped regions.

Stage 3-4 Faster R-CNN Model: The CNN features were computed, and regions were classified using the Faster R-CNN model.

Expected outcomes of this study include the classification of coconut trees to facilitate the tree counting of future plantation areas, as illustrated in Figure 3.

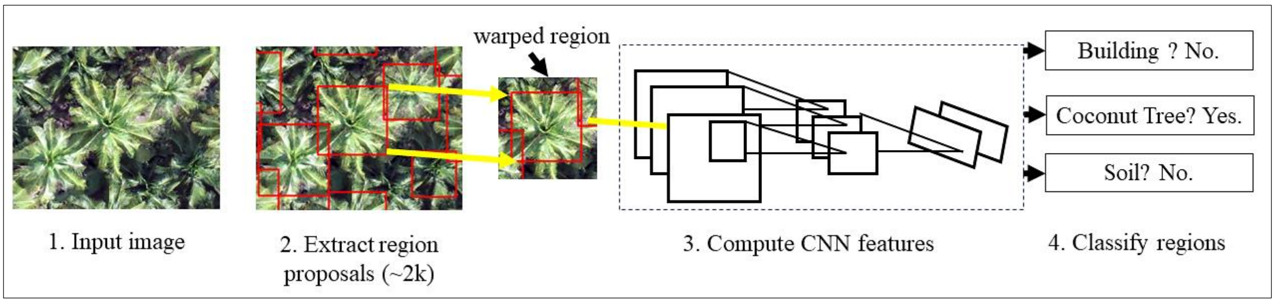


Figure 3. Object detection by deep learning imagery using Faster R-CNN Model

In addition to Faster R-CNN, which had been employed to study coconut trees within test plots, another widely used deep learning model, Mask R-CNN, was also applied. This model, derived from Faster R-CNN, applies the principle of grouping samples by linking them with all three elements: class labels, bounding boxes, and segmentation masks, which collaborate in tandem. Initially, the original tree photographs were input into the main axis of the CNN system to analyze their characteristics, including image colors, object edges, and object surfaces, as well as other categories or data present in the original images. Subsequently, the system processed the images and segmented them based on the regions of interest (ROIs) within the images of interest. Following this, the ROIs extracted various features according to the objectives of the images through the ROI data layers and produced the output, with the mask effect aligning with the highest value, categorized at the pixel level [25, 26]. Therefore, it can be concluded that Mask R-CNN evolved from Faster R-CNN. Its capability to delineate object boundaries (instance segmentation) was enhanced and went beyond mere object detection. This functionality is demonstrated in Figure 4.

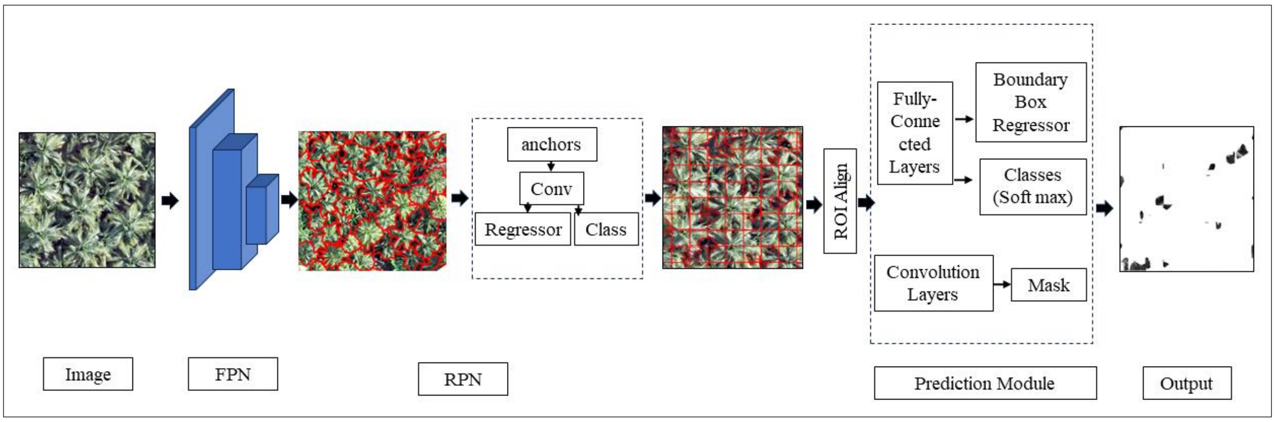


Figure 4. Object Detection by Deep Learning Imagery Using Mask R-CNN Model

In this study, the Mask R-CNN model collected data from the test plots. The model was divided into an 80% training set and a 20% testing set. The model underwent 20 iterations to obtain the best test results. For the data set selection method, the selection was made from the coconut tree data in the sample plot area. Then, the training set boundary in the sample plot area was created according to the characteristics of the coconut tree canopy. As for the test data, another 3 sample plots were used for validation. Then, the model's performance was evaluated using the Confusion Matrix principle.

Evaluation of the detection accuracy in this study involved using F1 score, Precision, Recall, and IoU as criteria for assessing correctness. These matrices are described by Equations 1 to 3, with the details provided below.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{1}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{2}$$

$$\text{F1score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

The evaluation conducted in this manner involved assessing the results obtained from object detection. F1 score, precision, and recall were computed as criteria for evaluating accuracy in object detection. That means that when generating a mask, if it overlapped with the actual area by more than half, it would be considered a true positive; otherwise, it would be classified as a false positive. Precision represented the ratio of correctly predicted instances to all instances predicted as positive, while recall was the ratio of correctly predicted positive instances to all actual positive instances. The F1 score was the weighted average of precision and recall [27].

All these calculations were derived from the Confusion Matrix, which included the following details: True Positive represented the number of correctly predicted instances, meaning objects that were accurately detected. In this study, these instances must be predicted as coconut trees, and the model's output must match coconut trees. False Positive denoted the number of incorrect positive predictions, indicating instances where the model predicted coconut trees but the actual outcome from the image was different. False Negative was the count of incorrect negative predictions, meaning instances where the model predicted no coconut trees, but the actual outcome showed otherwise. Lastly, True Negative signified the number of correctly predicted negative instances, implying cases where objects were correctly identified as not being present. These instances indicated other objects that were not coconut trees, and the model's prediction was accurate. These results are demonstrated in Table 1.

Table 1. Example of Accuracy Assessment Table using Confusion Matrix

	Predicted Positive	**Predicted Negative**	
Actual Positive	True Positive (TP)	False Negative (FN)	**Sensitivity**
Actual Negative	False Positive (FP)	True Negative (TN)	**Specificity**
	Precision	**Negative Predictive**	**Accuracy**

Furthermore, the Mean Average Precision (mAP) model was utilized to assess the performance of the Mask R-CNN model by considering the Intersection over Union (IoU) value. IoU was employed to evaluate object detection performance by comparing the ground truth bounding box with the predicted bounding box. The IoU principle was to determine the intersection area of the overlapping regions divided by the union area between the captured image and the predicted mask [28]. The IoU value ranged from 0 to 1, with higher values indicating better alignment or overlap between the predicted and ground truth bounding boxes, while lower values suggested discrepancies. This detection or bounding box drawing is explained in Equation 4:

$$\text{IoU} = \frac{\text{Area of Intersection}}{\text{Area of Union}} \tag{4}$$

In this study, surveys were conducted in the research setting to gather data from all four test plots. The Faster R-CNN method was employed to detect coconut trees within these plots, facilitating tree counting from the photographs. In addition, the Mask R-CNN operated by detecting objects based on predefined annotations, allowing for efficient classification of various objects. The research methodology of this study is illustrated step by step in Figure 5.

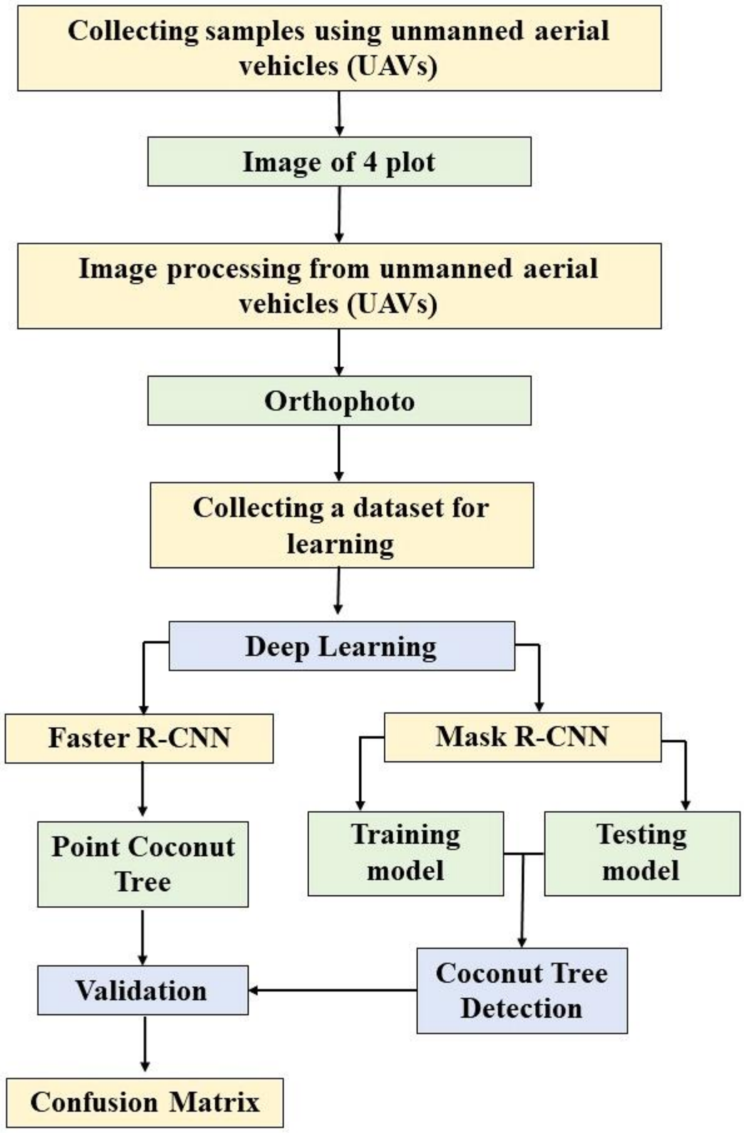


Figure 5. Conceptual Framework

3. Results

3.1. Classification of Coconut Trees Based on Aerial Images Taken by UAVs using Faster R-CNN Model

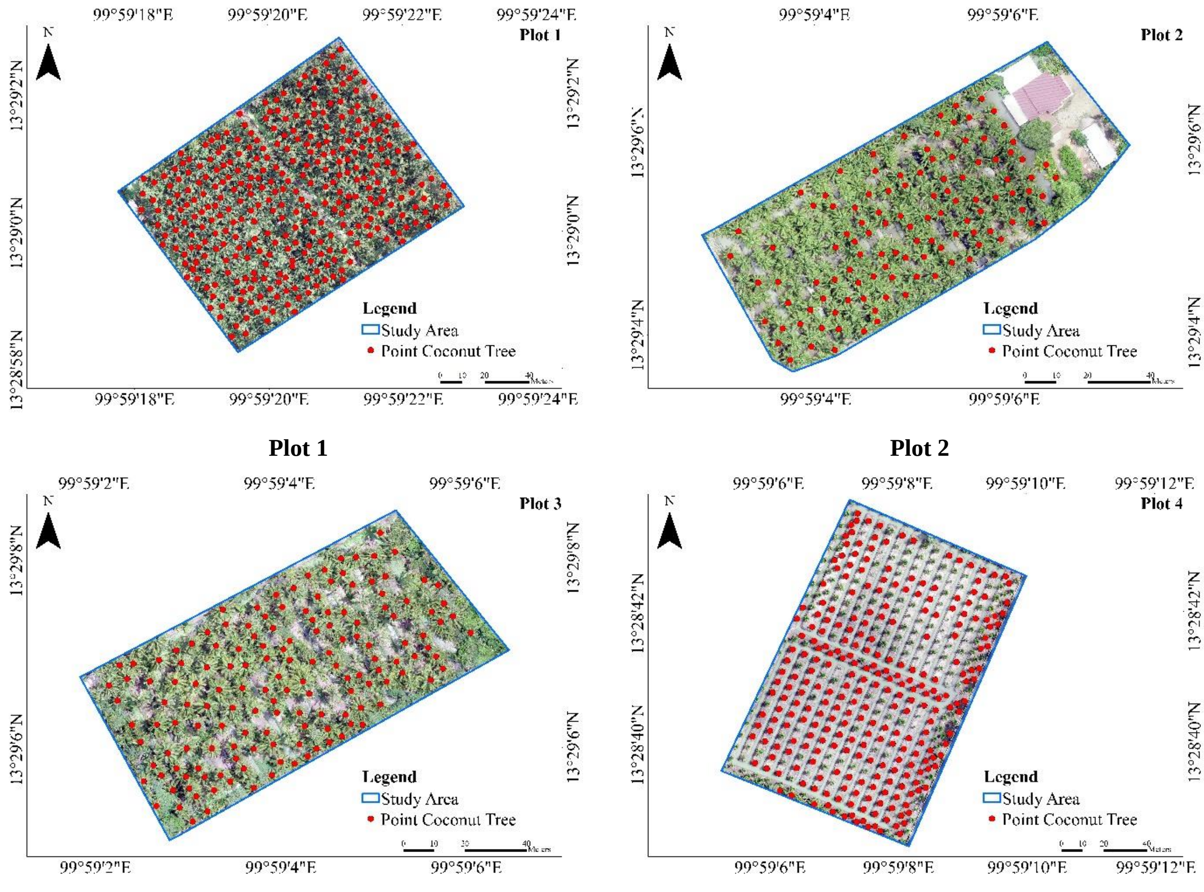
In this study, coconut trees were classified by deep learning techniques combined with the Faster R-CNN model. Details of the four test plots are described below, followed by an illustration of the findings in Figure 6.

Plot 1 covered an area of 11,056.525 square meters. The coconut trees in this plot varied in age, with most being less than 10 years old. Upon counting the number of coconut trees within the plot, 306 trees were found. However, when classified using the Fast-R-CNN model, the count was 328 trees, exceeding the actual count by 22 trees. This resulted in an accuracy rate of 93%.

Plot 2 spanned an area of 7,148.529 square meters. The coconut trees in this plot had mixed ages, with none being less than 15 years old. Upon counting, there were 248 trees, but the Fast-R-CNN model classified only 112 trees, indicating a shortfall of 136 trees. Consequently, the accuracy rate was only 45%.

Plot 3 encompassed an area of 6,773.243 square meters. The coconut trees here represented various age groups, with most being less than 10 years old. Counting revealed 207 trees, but the Fast-R-CNN model counted only 151 trees, indicating a shortfall of 56 trees. The accuracy rate in this plot was 72%.

Plot 4 spanned 12,840.431 square meters, and the coconut trees were predominantly 2 years old. Counting showed 450 trees, but the Fast-R-CNN model counted only 269 trees, resulting in an accuracy rate of 59%.



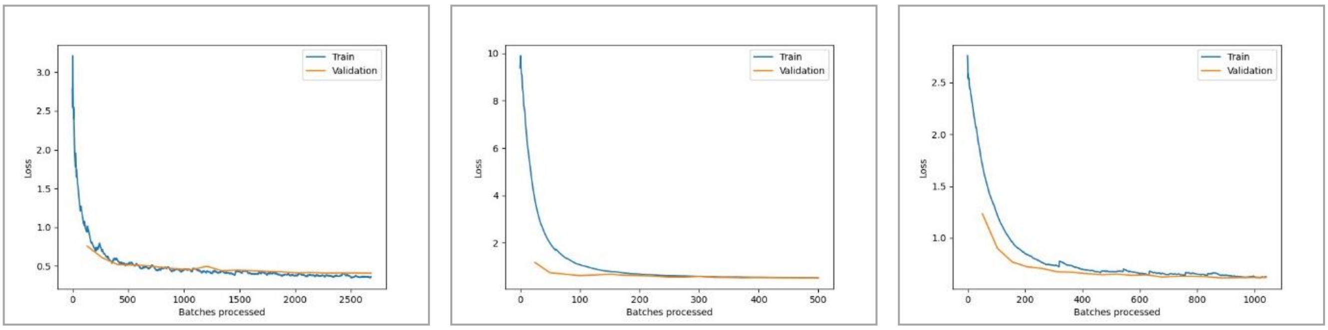
Plot 1 Plot 2

Plot 3 Plot 4

Figure 6. Coconut tree classification results using the Faster R-CNN Model

3.2. Object Detection by Boundary Delineation Using the Mask R-CNN Model

For the detection of coconut tree features using the Mask R-CNN model, the initial step requires the identification of the characteristics of coconut trees based on the data from each test plot. This process entails generating masks specific to each test plot to predict outcomes accurately. In this study, the data was partitioned into two segments: 80% for training and 20% for validation, utilizing self-learning iterations of no fewer than 20 rounds. Subsequently, the analysis revealed that the first test plot achieved a maximum accuracy level of 96.2% using the Mask R-CNN model. Following closely, the second test plot attained a maximum accuracy level of 76%, while the third plot demonstrated an accuracy level of 65%. These findings are depicted in Figure 7. In Figure 7, the data demonstrated the learning outcomes obtained from the image set. The images on the left depict the training sample group, whereas those on the right showcase the results of learning with Mask R-CNN. Figure 8 illustrates the findings using a sample image set for training with the Mask R-CNN model.



Plot 1 **Plot 2** **Plot 3**

Figure 7. Graphs depicting accuracy evaluation results of the Mask R-CNN Model

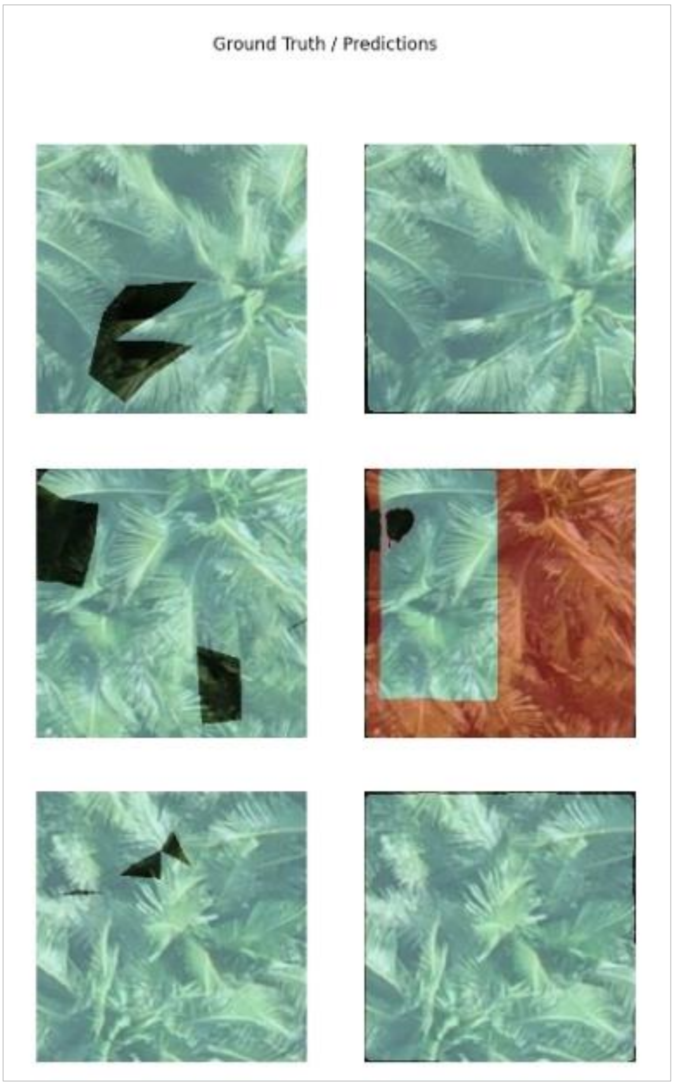
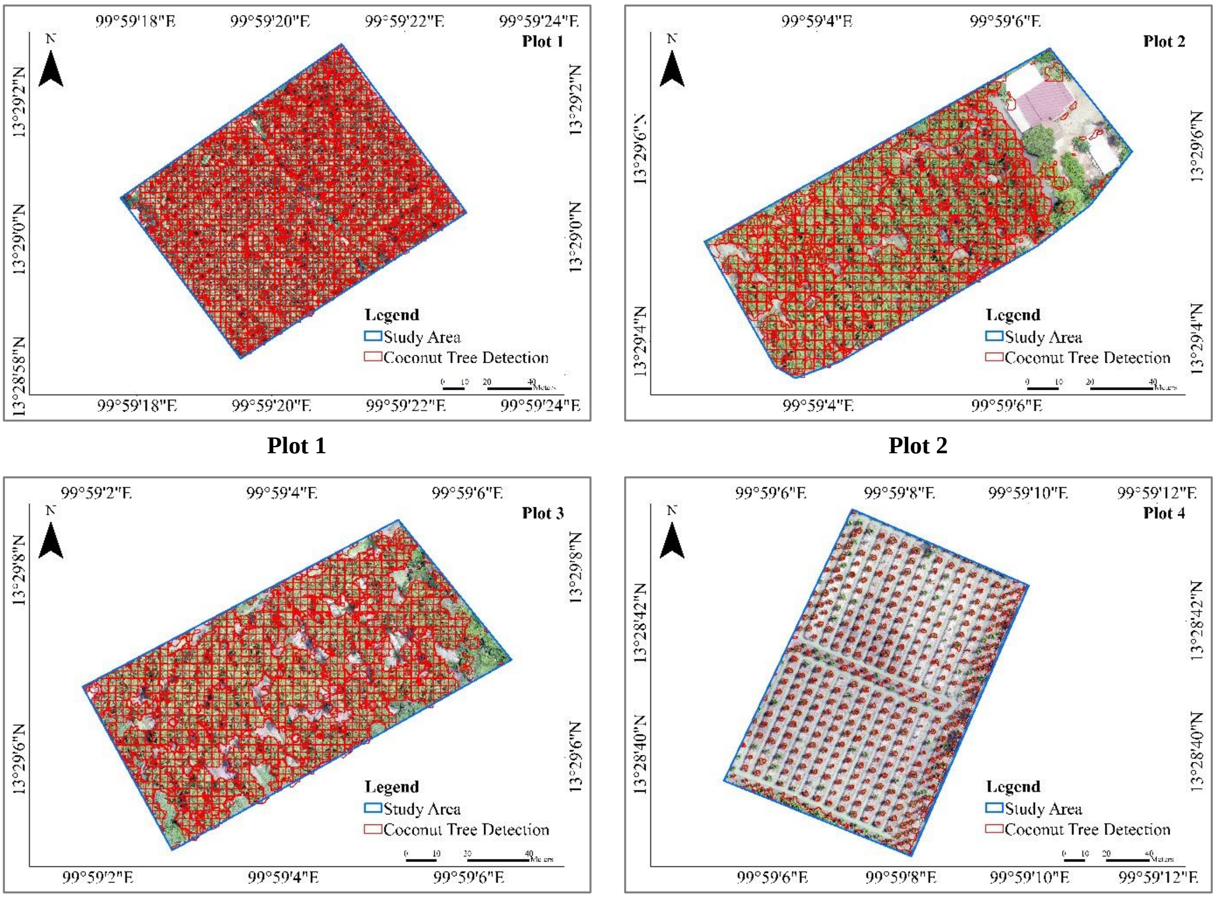


Figure 8. Sample image set of training with Mask R-CNN

Then, the Mask model of Plot 1, which exhibited the highest accuracy, was tested against all four test plots to derive the image classification outcomes of coconut trees from aerial drone imagery across the four plots. Following this, the tabular data was aggregated to illustrate the findings, as shown in Figure 9.



Plot 1 **Plot 2**

Plot 3 **Plot 4**

Figure 9. Maps of Test Plots Derived from Calculations using the Mask R-CNN Model

Then, the obtained results were validated for accuracy using the Confusion Matrix principles. It was observed that Plot 1, tested with self-trained learning, achieved an accuracy rate of 0.994, as shown in Table 2.

Table 2. Accuracy validation using the Mask R-CNN Learning Method for Test Plot 1

Plot 1	Predicted Positive	Predicted Negative	
Actual Positive	True Positive 9,919.576	False Negative 3.824	Sensitivity 0.999
Actual Negative	False Positive 62.208	True Negative 1,136.950	Specificity 0.948
	Precision 0.993	Negative Predictive 0.996	Accuracy 0.994

After obtaining the outcomes of model learning in Plot ١, which involved learning from data acquired through self-training within the plot, the research team proceeded to assess the trained data on Plot ٢. The testing revealed an accuracy of ٠.٩٨٢. Similarly, for Plot ٣, the testing indicated an accuracy of ٠.٩٩, and for Plot ٤, the results showed an accuracy of ٠.٩٦٢. The study's findings are elaborated on in Tables 3 to 5.

Table 3. Accuracy validation using the Mask R-CNN Learning Method in Test Plot 2

Plot 2	Predicted Positive	Predicted Negative	
Actual Positive	True Positive 4,826.39	False Negative 78.263	Sensitivity 0.984
Actual Negative	False Positive 40.069	True Negative 1,946.850	Specificity 0.979
	Precision 0.991	Negative Predictive 0.961	Accuracy 0.982

Table 4. Accuracy validation using the Mask R-CNN Learning Method in Test Plot 3

Plot 3	Predicted Positive	Predicted Negative	
Actual Positive	True Positive 5,387.030	False Negative 27.587	Sensitivity 0.994
Actual Negative	False Positive 13.258	True Negative 1,761.500	Specificity 0.990
	Precision 0.997	Negative Predictive 0.984	Accuracy 0.990

Table 5. Accuracy validation using the Mask R-CNN Learning Method in Test Plot 4

Plot 4	Predicted Positive	Predicted Negative	
Actual Positive	True Positive 1,281.334	False Negative 481.595	Sensitivity 0.726
Actual Negative	False Positive 13.607	True Negative 11,559.100	Specificity 1.000
	Precision 0.989	Negative Predictive 0.960	Accuracy 0.962

Next, the accuracy of the model was validated using Intersection over Union (IoU), a metric employed to assess detection performance by comparing the overlap between actual and predicted boundaries. Among the plots, Plot 1, utilized for training and learning assessment, exhibited the highest IoU score at 0.897, indicating the most precise delineation. Furthermore, Plot 2 and Plot 3 yielded IoU scores of 0.712 and 0.753, respectively. However, Plot 4 recorded the lowest IoU score, nearly reaching 0, at 0.099. This suggests discrepancies between the predicted and actual boundaries during the detection process, likely due to the small size of the coconut crowns in the early growth stage, since the coconut trees in Plot 4 were still in their first two years of planting. These findings, showcasing the test results of each test plot, are illustrated in Figure 10.

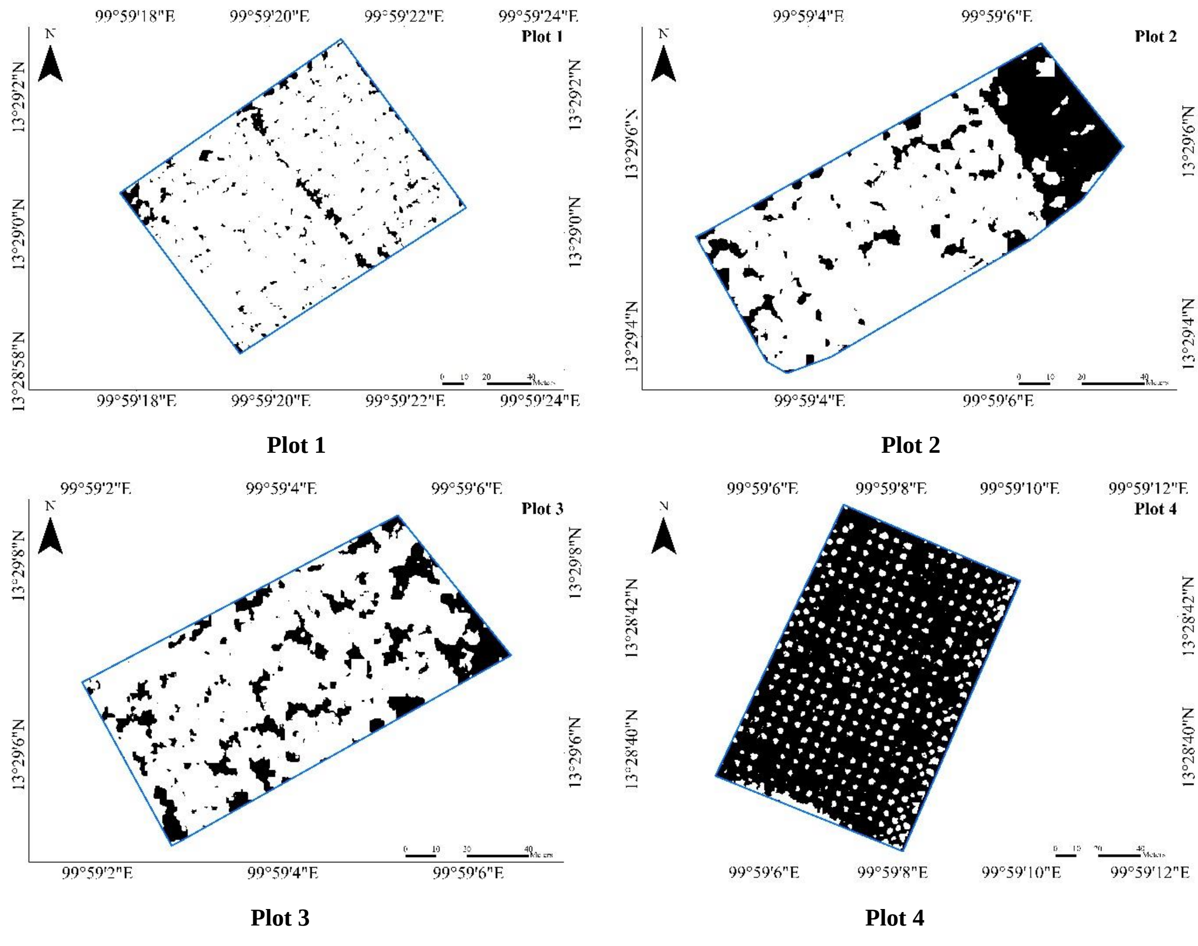


Figure 10. Test results obtained from the Mask R-CNN Model

4. Discussion

In modern agriculture, the integration of deep learning technologies is crucial for enhancing data analysis and the monitoring of agricultural outputs. This is particularly evident in the extensive use of unmanned aerial vehicle (UAV) imagery [29, 30]. This study is an application of object classification principles from drone images, which aims to classify the characteristics of coconut trees, which are important economic areas, using Faster R-CNN and Mask R-CNN models. Both models are part of the process of Deep learning, where Faster R-CNN will detect objects in images by learning from the given image data to predict all areas of the image, while Mask R-CNN will be trained by data from the user's object detection characteristics in the image. Therefore, both models have different advantages. The Faster R-CNN model is a model that uses high-precision data to train and detect data quickly. However, if the data is very complex, especially the characteristics of coconut trees, it is easy to make data errors. Therefore, it can only detect the number of coconut trees. On the other hand, if the Mask R-CNN model is used, which the user himself teaches using the characteristics of objects from the image, it has a higher chance of detecting objects from the image correctly.

Coconut farming, however, demands considerable care from the initial planting stage through a span of about 10 to 20 years. Adverse conditions can lead to the death of the coconut trees and severely affect the farmers. Therefore, this study underscores the importance of gathering a substantial sample collection for training the Mask R-CNN model. This approach could significantly improve the precision of the model's learning outcomes and its efficacy in other areas [31]. Moreover, the unique forked canopy shape of coconut trees [16] enables precise boundary definition, facilitating their distinction from other plant species and objects within the plantation.

Nonetheless, due to limitations in space, the study was only able to distinguish between two age categories of coconut plantations: those in the harvest stage of 10 to 15 years and those that were newly planted, around 2 years old. Incorporating a wider range of tree ages would introduce more diversity, especially in structured plantations. This study suggests that the model could perform better in a well-organized plantation with trees of uniform age.

This research also found that UAV imagery is an applicable instrument for exploring coconut plantation areas because the high resolution of the images is suited to areas with moderate size [32]; this also enabled a detailed assessment of the health of each coconut tree [33]. Moreover, this method can also be applied to examine the characteristics of trees in forest areas, as in a study by Hoi & Dung [34]. In addition, there has been a study of object classification that uses a method of taking pictures with a camera and then classifying objects from the images with the R-CNN model. However, this study has applied photos from unmanned aerial vehicles to help in the study. This makes it possible to monitor plants that are already growing and able to produce yield. However, there has also been a study on the measurement and classification of coconut trees using a hybrid fuzzy support vector machine (SVM) method, which has high reliability results, but in exchange requires collecting a large number of samples. The method of this study uses a smaller number of training groups than the previous studies.

This study is useful for coconut farmers, as they can apply the study methods to monitor coconut yield and diseases or pests that destroy coconut plantations in their own areas, and it can be used in all seasons by flying to survey the plantations by the farmers themselves. Regarding the rapid development of UAV technology, if images from multispectral cameras or thermal cameras are combined with deep learning modeling methods, the results can be even more efficient, leading to more efficient use and production by farmers.

5. Conclusion

This study utilized aerial imagery captured by unmanned aerial vehicles to analyze the canopy area of coconut trees using deep learning models like Faster R-CNN. Two sample plots with similar age characteristics were selected for analysis, along with an additional plot differing in age. The study revealed that employing Faster R-CNN for counting coconut trees in Plot 1 resulted in an excess count of 22 trees (328 counted versus 306 actual), representing an accuracy of 93%. In Plot 2, there was an undercount of 136 trees (112 counted versus 248 actual), with an accuracy of 45%. Plot 3 showed an undercount of 56 trees (151 counted versus 207 actual), with an accuracy of 72%. Plot 4, initially reported to have 450 trees, was assessed to have 269 trees using the Faster R-CNN model, representing an accuracy of 59%. However, the use of the R-CNN model also allows for the application of the Mask R-CNN method, a deep learning approach using aerial imagery from unmanned aerial vehicles, trained with masking techniques. For this study, the training was conducted with 80% of the data, while testing comprised 20%, with the tests repeated 20 times to ensure the most reliable results possible. The accuracy was then evaluated using a Confusion Matrix and the Intersection over Union (IoU) method. Accordingly, this study found that Plot 1 had an accuracy of 0.994 and an IoU score of 0.897, indicating that the model's testing performance for this plot was excellent. For Plot 2, the accuracy was 0.982 and the IoU score was 0.712. Similarly, Plot 3 exhibited an accuracy of 0.99 with an IoU score of 0.753. This shows that the model's performance for both plots was acceptable. However, Plot 4 had an accuracy of 0.962 but an IoU score of only 0.099, indicating that while the model's accuracy for this plot was high, the predicted or delineated boundaries did not align well with the actual boundaries in detection.

Therefore, the use of Faster R-CNN and Mask R-CNN to classify objects from images, especially for coconut trees, requires management of the plantation area to be orderly and the pruning of coconut trees to leave gaps for sunlight to reach the ground in the plantation area, which will make the classification of objects from images more efficient. Especially at the beginning of planting, there is a gap between coconut trees that have been reserved for growth and can lead to the analysis of coconut tree diseases from the leaf expression, which will directly affect the amount of production and survival of coconut trees in the plot.

6. Declarations

6.1. Author Contributions

Conceptualization, M.W., N.K., and K.T.; methodology, M.W. and N.K.; software, P.S., N.K., and K.A.; validation, M.W., N.K., and K.A.; formal analysis, M.W., N.K., and P.S.; investigation, N.K. and K.A.; resources, M.W., N.K., and P.S.; data curation, N.K. and K.A.; writing—original draft preparation, M.W. and N.K.; writing—review and editing, M.W., N.K., and K.T.; visualization, K.A.; supervision, P.H.; project administration, M.W. and N.K.; funding acquisition, N.K. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that there are no conflicts of interest concerning the publication of this manuscript. Furthermore, all ethical considerations, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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