Oil Palm Tree Detection and Health Assessment with a Machine Learning Model Using UAV Imagery

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Abstract

The oil palm industry is a vital contributor to Malaysia's economy but continues to face challenges in plantation monitoring and productivity management. Conventional approaches for tree counting and health assessment are labour-intensive, costly, and prone to errors. This study introduces a machine learning approach utilizing unmanned aerial vehicle (UAV) imagery to automate the detection and classification of oil palm tree health. UAV imagery was processed into a two-dimensional orthomosaic map, which was analysed with trained deep learning models capable of identifying individual trees and categorising their health status. The results achieved an overall F1-score of 0.84, with healthy trees classified most accurately. Tree counting accuracy exceeded 90%, and precision–recall analysis demonstrated that the model maintained high precision at strong confidence thresholds, though threshold adjustments are required to optimise recall. Overall, the proposed model can reduce manual effort, time, and cost, while improving consistency in plantation monitoring. These findings highlight the potential of UAV-based digital agriculture solutions to support sustainable and data-driven oil palm management in Malaysia.

Keywords: Unmanned Aerial Vehicles (UAVs), Machine Learning, Oil Palm Plantations, Tree Detection, Tree Health Assessment.

1. INTRODUCTION

Oil palm cultivation is a significant agricultural activity in Malaysia, contributing substantially to both the national economy and the global palm oil supply. The global palm oil production reached a staggering 77.56 million metric tons in the 2022–2023 marketing year, with Malaysia contributing approximately 24%, or nearly a quarter of the total global market (Ostfeld & Reiner, 2024). The demand for palm oil is driven by its versatile applications in the food industries as well as non-food industries such as cosmetics and biofuels Kadir et al. (2024). Beyond its economic impact, large-scale plantations also play a crucial role in environmental sustainability by serving as carbon sinks through extensive tree cover (Szulczyk, 2024). Given the scale and importance of this sector, effective plantation management is crucial to ensuring sustained productivity, long-term viability, and competitiveness in the global market.

However, traditional plantation management practices remain heavily dependent on manual monitoring, which is labour-intensive, costly, and prone to inaccuracies. Monitoring large plantations on the ground is particularly challenging, as issues such as pest infestations and diseases —recorded as one of the significant challenges in the oil palm industry (Murphy et al., 2021)—or nutrient deficiencies are often detected late, leading to yield loss and reduced efficiency. The lack of timely and precise information poses risks not only to plantation productivity but also to broader decision-making processes for stakeholders.

Recent advances in digital agriculture technologies, particularly unmanned aerial vehicles (UAVs) and machine learning, provide promising alternatives for addressing these challenges. UAVs enable efficient collection of high-resolution imagery over large plantation areas, while machine learning techniques can automate the detection and classification of oil palm trees, as well as assess their health conditions. By combining these technologies, plantations can be monitored more effectively and at lower cost, enabling faster response to emerging issues and reducing dependence on manual field inspections.

This study examines the application of UAV imagery and machine learning for the automated detection and health assessment of oil palm trees. Specifically, it develops and evaluates a model capable of identifying individual trees and classifying their health status. The outcomes are expected to enhance plantation monitoring practices and contribute to more sustainable and data-driven oil palm management in Malaysia.

Previous UAV-YOLO studies on oil palm have mostly focused on detection and counting on generic datasets, offer few or no expert-verified health labels specific to Malaysian cultivars, and frequently perform poorly on small palms because of tiling, scale, and occlusion problems. In order to fill these gaps, we (1) created a custom, manually annotated dataset that is specific to Malaysian oil palm species (2) implemented an orthomosaic-first mapping workflow that stitches overlapping flight strips into geo-referenced maps prior to analysis, allowing for estate-scale coverage and precise per-tree counting.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature. Section 3 presents the methodology, and Section 4 elaborates on the proposed solution for the problem. Section 5 evaluates the model, and finally, Section 6 summarises and concludes the paper.

2. LITERATURE REVIEW

The application of Unmanned Aerial Vehicles (UAVs) and deep learning in agriculture has gained significant attention within the last three years. Several object detection and classification techniques have been applied to enhance plantation monitoring, particularly for oil palm trees.

A number of approaches for detecting and quantifying trees have been explored, including template matching and Object-Based Image Analysis (OBIA), which yielded accurate results in low-density plantations but struggled with occlusions and overlapping canopies, leading to misclassification Kalantar et al. (2017). To address these limitations, Chowdhury et al. (2021) suggested using Generalized Gradient Vector Flow (GGVF) in conjunction with YOLOv5, which achieved a precision of 69.8%. However, the incorporation of angle-based analysis introduced sensitivity to background noise, thereby reducing robustness in realistic scenarios.

The YOLO (You Only Look Once) family has been a leading solution to real-time object detection for plantation monitoring. Wibowo et al. (2022) compared different versions of YOLO and demonstrated that YOLOv4 and YOLOv5 outperformed YOLOv3 with F1-scores of 97.74% and 94.94%, respectively. There were still challenges in detecting small objects with limited feature extraction capabilities. Similarly, Nurhabib et al. (2022) highlighted the superior performance of YOLO compared to traditional models but noted that overlapping trees and varying lighting conditions still impacted detection accuracy.

Other deep learning-based approaches have also been explored for enhancing the detection and classification of oil palm trees. Kipli et al. (2023) fused Convolutional Neural Networks (CNNs), deep structured learning, and remote sensing, achieving over 90% accuracy in palm tree detection. The work observed the computational costliness of these approaches, though, making them less suitable for real-time applications. Ammar et al. (2021) fused geotagged aerial images with YOLOv4 and photogrammetry, achieving 99% mean average precision (mAP) at the cost of increased processing time and resource use. Similarly, Putra and Wijayanto (2023) compared image processing thresholding with YOLO-based deep learning, demonstrating YOLO's superiority while also highlighting challenges in palm tree detection under varying environmental conditions.

Building on these studies, oil palm detection and monitoring applications have also been expanded through the use of remote sensing techniques, ranging from traditional image analysis to UAV-based methods. Through remote sensing, including satellite and airborne imagery, data captured by unmanned aerial vehicles (UAV), and light detection and ranging (LiDAR), we can map the extent of oil palm plantations; delineate individual palm trees; assess their age; detect their health conditions, infestation, and disease attack; estimate carbon stock; identify biodiversity hotspots; and aid in risk assessment for ecosystems Kanniah and Yu (2024). In terms of data acquisition using drones, Hashim et al. (2020) have proposed an algorithm that includes Grey Level Co-Occurrence Matrix (GLCM), Haar, Biorthogonal Wavelet and Template Matching to provide a good assist in the accuracy of drone image data. Similarly, Yarak et al. (2021) achieved high accuracy in identifying both healthy and unhealthy trees by combining UAV imagery with deep learning models (Faster-RCNN, ResNet-50, and VGG-16) for oil palm tree detection and health classification. To achieve the best training outcome from the model, it is crucial to include all possible conditions of the oil palm trees, including age, surrounding vegetation, and background (Liu et al., 2021).

While advances in plantation monitoring with UAVs have been made, existing research still faces challenges in detecting small objects, dataset imbalance, and hyperparameter tuning. Most models lack robustness in detecting baby palm trees due to their small size and overlap in dense plantations, leading to misclassification and false alarms. In addition, unbalanced datasets where specific tree categories (e.g., young palms) have fewer examples adversely affect the model's capacity to generalise over various stages of growth.

This study addresses two major problems with earlier UAV oil-palm studies; small-object detection for younger palms and occlusion from overlapping canopies. Edge-detected polygon annotations were used instead of conventional bounding boxes to address occlusion, resulting in tighter crown outlines and minimizing overlap errors. A sliding-window (tiled) approach was used in conjunction with per-tile zooming for small-object detection, which enhances the visibility of tiny crowns.

3. METHODOLOGY

This study employed a systematic approach to ensure accurate detection and health assessment of oil palm trees from drone-based ortho-mosaic imagery. The methodology, illustrated in Figure 1, comprised five main phases: data pre-processing, model training and optimisation, detection module development, and evaluation.

Drone imagery of the plantation was first collected and processed to produce a 2D ortho-mosaic map. Pre-processing steps included image enhancement, noise reduction, and normalisation to ensure consistent input quality. The dataset was then divided into training, validation, and testing subsets, which were used, respectively, for model learning, parameter optimization, and performance evaluation. The training phase enabled the model to identify distinctive image features of oil palm trees, while the validation data guided adjustments of key hyperparameters, such as the learning rate and batch size, to achieve optimal performance without underfitting or overfitting.

YOLOv8 was chosen for its state-of-the-art speed–accuracy trade-off on UAV imagery, given that comparative drone studies reported higher mAP and lower inference time than popular alternatives such as RetinaNet and Faster CNN. The experiments have found that the YOLOv8 variants outperform the other models by achieving larger mAP@50 values and lower inference times on both the original and augmented datasets Daraghmi et al. (2025) which motivated the implication of YOLOv8 for this research.

The model was trained on a Radeon Vega Mobile GFX GPU for a maximum of 1000 epochs, with early stopping at 100 epochs. Stochastic Gradient Descent (SGD) was used as the optimiser (initial learning rate = 0.01, momentum = 0.937, weight decay = 5e-4). Training was performed with an image size of 640, batch size of 16, and automatic mixed precision (AMP). The best weights were selected based on validation mAP50.

The detection module was then developed using the optimised model, with the specific objective of creating an advanced image recognition and classification framework capable of detecting oil palm trees and assessing their health status. Healthy and unhealthy differentiation was based on visual characteristics such as crown density, shape, and colour, and the categorisation was verified by an expert in the field. This ensured that the model could recognise variations linked to disease, nutritional deficiencies, or environmental stress and classify tree health effectively.

Finally, the optimised detection module was evaluated using the testing dataset. Performance was assessed through standard classification metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. These results provided a comprehensive evaluation of the model's robustness, generalisation ability, and suitability for large-scale plantation monitoring.

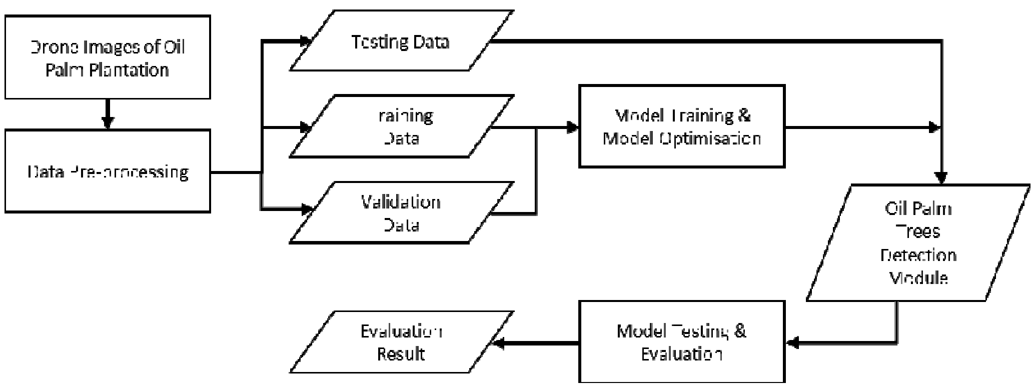


FIGURE 1: Methodology of the proposed approach.

4. PROPOSED APPROACH

The proposed model integrates Unmanned Aerial Vehicles (UAVs) and deep learning algorithms, specifically YOLOv8, for automating the detection and classification of oil palm trees. The model enhances tree counting accuracy and determines health conditions, offering an efficient solution for oil palm monitoring. The architecture consists of three main components: dataset preparation, model training, and tree detection and classification.

4.1 Dataset Preparation

The dataset for this project was meticulously collected using a MAVIC 3 Enterprise drone, specifically chosen for its advanced imaging capabilities. The data collection took place across several oil palm plantations located in the southern state of Malaysia. The images were representative of diverse plantation environments and were processed into 2D ortho-mosaic maps using DJI Terra software, ensuring spatial consistency and alignment.

In addition to the individual images, four 2D ortho mosaic maps were generated to provide comprehensive aerial views of the plantations. Each image was then manually annotated using Roboflow, a widely used open-source annotation tool, ensuring precise labelling of the data as illustrated in Figure 2. Following annotation, the dataset underwent formatting and resizing to standardise the image dimensions and ensure compatibility with machine learning models.

FIGURE 2: Manual annotation of the image using Roboflow.

Baby trees were labelled as small trees with zero canopy cover, while premature trees were labelled as young trees with immature leaves that had not reached maturity. Healthy mature trees had full, green crowns, while unhealthy mature trees had thin, diseased, or discoloured crowns.

The healthy and unhealthy differentiation of oil palm trees was based on the main visual characteristics, including crown density, shape, and colour. The healthy trees displayed dense and well-spaced fronds that were dark green in colour, an indication of ideal growth conditions. The unhealthy trees, in contrast, exhibited abnormal crown shapes, discoloured or yellow leaves, and reduced frond density, which typically indicated disease, nutritional deficiency, or environmental stress. The classification criteria were validated by two plantation supervisors, each with over 15 years of practical experience in oil palm cultivation, harvesting, and plantation management.These variations played a significant role in classification, enabling the model to recognise and assess tree health effectively.Table 1 shows an example of images for healthy and unhealthy oil palm.

	Crown Density	**Tree Shape**	**Tree Colour**
Healthy			
Unhealthy			

TABLE 1: Comparison of Healthy and Unhealthy Oil Palm.

Index	Training Dataset	Validation Dataset	Testing Dataset
Healthy Trees	1108	240	103
Unhealthy Trees	1380	297	29
Premature Trees	2045	318	49
Baby Trees	693	96	47
Total	5226	951	228

TABLE 2: Number of images for each category.

To summarise, for data preparation, 450 high-resolution images were labelled, and four orthomosaic maps were developed to be utilized for large-scale plantation analysis. The dataset was divided into 80% training, 15% validation, and 5% testing to maintain a balanced ratio across different tree classes. Data augmentation techniques, such as rotation, brightness adjustment, and contrast enhancement, were employed to further improve the model. The aforementioned pre-processing steps made the model more generalizable and robust against diverse environmental scenarios, resulting in the accurate detection and classification of oil palm trees in real-world scenes. Table 2 shows the number of images for each category for the training, validation, and testing datasets.

4.2 Model Development for Detection Module

There are two key modules: Oil Palm Tree Detection and Oil Palm Health Classification. Both modules utilize the YOLOv8 model as their backbone. YOLOv8 model was used because of its quick detection rate and accuracy, appropriate for the detection of oil palm trees from UAV images. It consists of three major components: Backbone, Neck, and Head, with each being critical for feature extraction, processing, and tree category prediction. The Backbone obtains critical features from the UAV images via Feature Pyramid Networks (FPN), which support multi-scale feature representation. This ensures the proper detection of both large and small objects in complex plantation scenes. Neck also enhances object detection with up-sampling and feature map concatenation, ensuring that the model is better capable of detecting overlapping crowns of trees. The head subsequently processes enhanced feature maps and generates bounding boxes, classifying the detected trees into their respective categories: baby, premature, healthy mature, and unhealthy mature trees.

To improve the model's performance, training and optimisation methods were employed. The YOLOv8 model was trained on a preprocessed dataset, incorporating various enhancements to achieve maximum detection accuracy. Hyperparameter tuning was done, modifying the learning rate, batch size, and confidence threshold to enhance training convergence and reduce false detections. Custom anchor boxes were implemented to improve the detection of small oil palm trees, which are challenging to identify due to overlapping canopies. Bounding box regression optimisation was added to enhance localisation accuracy, facilitating precise tree detection in dense plantation environments.

During the training stage, object confidence loss functions, classification loss functions, and bounding box prediction loss functions were minimised to fine-tune the model's accuracy. Training of the model was accomplished in multiple passes of epoch cycles, continuously building up its capability to recognise and classify oil palm trees across various lighting conditions and spatial arrangements. The overall training was designed to optimise generalisation in the model, enabling it to effectively scrutinise new, unseen UAV imagery with great precision.

Upon successful training, the model was applied to make predictions on test images to ensure its performance on oil palm tree detection and classification. The model operated on UAV-generated images, categorising the predicted total number of trees based on their health statuses. The output provided bounding boxes around the identified trees to facilitate accurate identification. The identification includes class labels indicating whether a tree belonged to the baby, premature, healthy mature, or unhealthy mature class. Each prediction was also accompanied by a confidence score that reflected the model's confidence in the classification, allowing for the reliable identification of trees under varying plantation conditions.

To validate the accuracy of the trained model, it was cross-tested on a previously unseen test dataset (5%), providing an objective evaluation of its generalisation ability. The model's accuracy was also evaluated using significant performance metrics, including precision, recall, F1-score, and confusion matrix analysis. This is to provide a thorough assessment of both detection capability and classification authenticity. High-precision values demonstrated a good ability to accurately label oil palm trees with minimal false positives, and a high recall ensured that the model selected most trees in the plantation zone with high accuracy. The F1-score provided the average of precision and recall, while the confusion matrix presented the numbers of correct and incorrect classifications between the classes of trees.

5. RESULT AND DISCUSSION

The YOLOv8 deep learning model was utilised to detect and classify oil palm trees based on UAV images. This section provides an analysis of the model's performance, with a focus on tree detection, health classification, and overall accuracy.

5.1 Performance of the Model

The YOLOv8 model was trained on a custom dataset of oil palm trees, which was manually annotated for high-quality learning. The dataset was divided into 80% training, 15% validation, and 5% testing. The training utilised convolutional layers for feature extraction, and the model learned parameters through multiple epochs.

The loss function trends (bounding box, classification, and segmentation loss) indicated a steady decrease, as shown in Figure 3, which is an indicator of successful model learning without overfitting. The F1-score curve in Figure 4 determined an overall F1-score of 0.84, which supports a good precision-recall trade-off. However, the "baby trees" category had lower accuracy, indicating data imbalance.

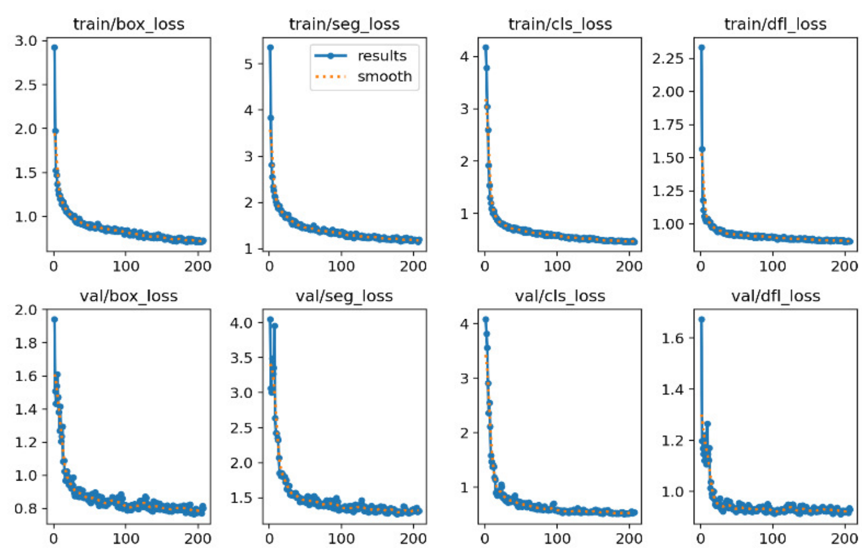


FIGURE 3: Loss curves illustrating model optimisation across epochs.

5.2 Evaluation of Tree Detection and Health Classification

Single trees in UAV images were effectively detected by the tree detection module using bounding box prediction. Classification performance is illustrated in Figure 5, which highlights that healthy trees were classified most accurately, while baby trees had the highest rates of false positives and false negatives.

Further scrutiny of the Precision-Confidence Curve in Figure 6 indicates that the model possessed high precision (1.00) at a high confidence level (0.966). This would mean that the model is extremely confident about its predictions but might be rejecting low-confidence detections, thus missing detections under adverse conditions.

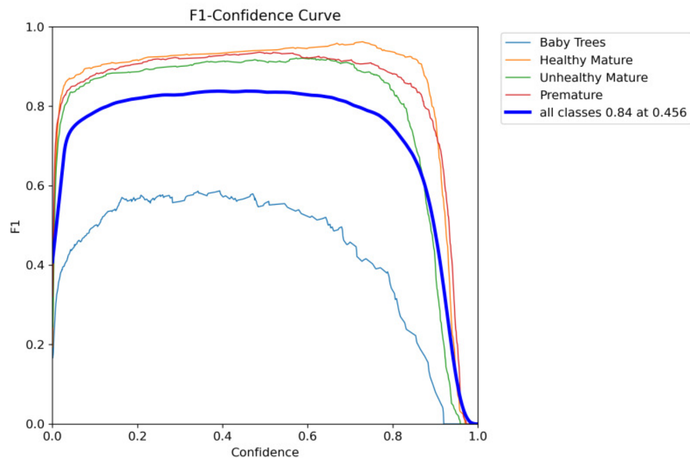


FIGURE 4: F1-score curve illustrating classification performance.

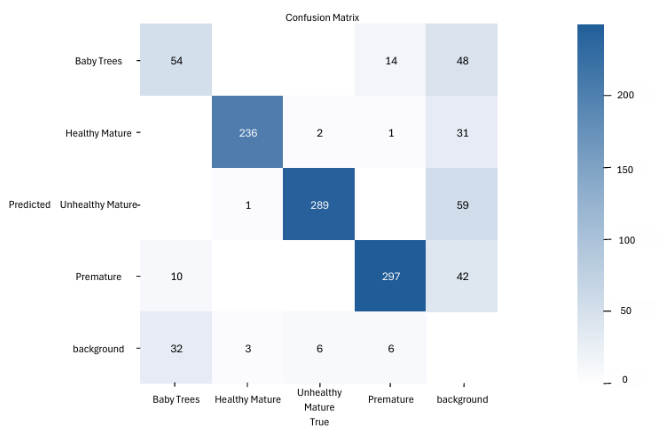


FIGURE 5: Confusion matrix illustrating classification accuracy.

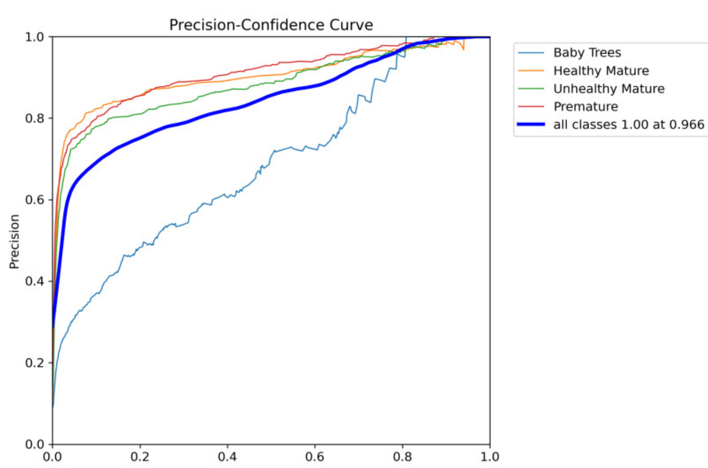


FIGURE 6: Precision-Confidence Curve for the model's precision performance.

The Recall-Confidence Curve in Figure 7 shows that the model identified the majority of true positives at low confidence levels, but also generated false positives, indicating that the detection thresholds required additional adjustments.

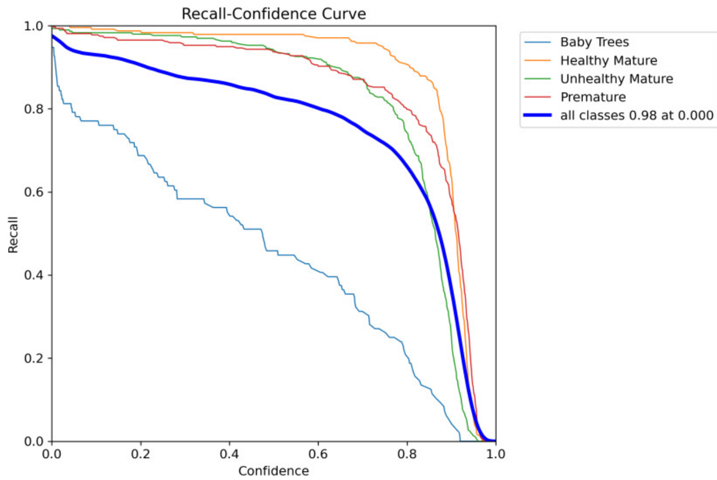


FIGURE 7: Recall-Confidence Curve for the model's recall performance.

Next, a series of tests was conducted to evaluate the accuracy of the Tree Counting Module. It involved manually counting the number of oil palm trees in an image and then uploading the same image to the website for comparison. This test was repeated three times with different images to ensure the consistency and reliability of the results. In addition, the manual counts were verified by two experts mentioned in the previous section. It can be concluded that the accuracy of the tree counting module is high, exceeding 90%.Table 3 shows the images with their results

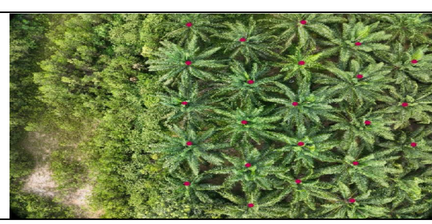
Image 1		Manual count: 39 Model's count:41 Accuracy: 95%
Image 2		Manual count: 103 Model's count:107 Accuracy: 96%
Image 3		Manual count: 23 Model's count:25 Accuracy: 91%

TABLE 3: Comparison of manual and model's counts.

Although the YOLOv8 model performed very well in detecting and classifying oil palm trees, certain limitations were encountered. Data imbalance was one of the main issues, particularly in the "baby trees" class, where there were fewer samples than in the other classes. This resulted in lower accuracy during classification because the model had fewer examples to learn from. Subsequent research needs to address this issue by incorporating data augmentation techniques or expanding the dataset to ensure better generalisation across all tree classes.

To summarise, the model could classify and detect oil palm trees from UAV images with high accuracy for mature trees, but with comparatively lower accuracy for young trees. Future research can involve expanding the dataset, refining detection parameters, and integrating expert small-object detection approaches to enhance performance in real-world plantation scenarios.

6. CONCLUSION AND FUTURE WORK

This study demonstrates that UAV imagery, combined with machine learning, can effectively detect, classify, and count oil palm trees, while also providing an assessment of their health status. The model achieved an overall F1-score of 0.84, reflecting a good precision–recall balance, and the tree counting module reached an accuracy exceeding 90%. These results confirm that the proposed system is capable of meeting its primary objectives. The use of a hand-annotated dataset specific to Malaysian oil palm plantations further enhanced detection accuracy, ensuring outcomes that are well aligned with regional plantation characteristics.

Nevertheless, the findings also highlight some limitations. In particular, the “baby trees” category exhibited reduced accuracy, characterized by higher false positives and false negatives, primarily due to dataset imbalance. Precision–confidence and recall–confidence analyses revealed that the model was highly confident in its predictions at higher thresholds but tended to miss detections in adverse conditions. These challenges underscore the need for improved data representation and refined detection thresholds.

Future work should therefore prioritize expanding and diversifying the dataset to address class imbalance and improve generalization. Increasing the number of annotated samples per class (ideally 5,000–7,000 images) would support more robust model training and reduce bias toward dominant categories. Additionally, incorporating a crown size–based age classification module could provide finer-grained insights by moving beyond broad categories such as “baby” or “premature” trees toward precise age estimation. Integrating these enhancements would further improve the reliability, scalability, and practical applicability of the system for large-scale plantation monitoring.In addition, the broader implications of this work lie in supporting the wider adoption of digital agriculture in Malaysia, enabling cost reduction, more efficient monitoring, and laying the foundation for future integration into real-time plantation management systems.

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