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Drone-Based Surveillance of Palm Tress Ecosystems

Ya'akob Mansor[1,2,*], Sharudin Omar Baki[1], Zulhilmy Sahwee[3], Cheng Mengyue[4], Wu Yuanyuan[5]

1 Physics Unit, Centre of Foundation Studies in Science, Universiti Putra Malaysia (UPM),43400 Serdang, Malaysia
2 Institute of Plantation Studies, Universiti Putra Malaysia (UPM), 43400 Serdang, Malaysia
3 Universiti Kuala Lumpur, Malaysian Institute of Aviation Technology (MIAT), 43800, Dengkil, Selangor, Malaysia
4 Department of Computer and Communication, Faculty of Engineering, Universiti Putra Malaysia (UPM), 43400 Serdang, Malaysia
5 Faculty of Artificial Intelligence, Xiamen City University, Xiamen, 361008, China

Article Info

ABSTRACT

This paper presents a novel surveillance system designed to identify the health status of oil palm trees by leveraging MATLAB object detection and deep learning techniques. The study aims to improve the accuracy and efficiency of palm health detection by integrating MATLAB's initial object recognition with advanced deep learning algorithms. The initial phase of the research focuses on elucidating the challenges associated with detecting palm tree health issues using conventional image processing methods in MATLAB. Results indicate that traditional MATLAB object detection methods encounter difficulties in accurately identifying palm tree crowns and assessing their health status due to various factors such as the complexity of crown morphology, lighting variations, environmental conditions, limited feature discrimination, reliance on handcrafted features, and challenges in adaptation and generalization. Subsequently, the study proposes a second stage to enhance the accuracy and efficiency of palm tree health detection through the implementation of a deep learning approach using Faster R-CNN, addressing the limitations identified in the initial phase. Analysis of experimental results demonstrates a rapid increase in accuracy to nearly 100% early in the training process, indicating efficient learning and classification capabilities of the model. Moreover, a significant decrease in Root Mean Square Error (RMSE) at the outset of training signifies a reduction in prediction errors, followed by stabilization at a low level, suggesting that the model's predictions closely align with actual targets in the training data. Furthermore, the loss graph exhibits a similar trend to the RMSE graph, corroborating the effectiveness of RMSE as a common loss function for regression problems. Overall, this research contributes to the advancement of oil palm tree health detection systems, providing valuable insights for future developments in agricultural surveillance and monitoring technologies.

Keywords:

UAV; sensors; MATLAB; oil palm

1. Introduction

Oil palm has become one of the main sources of income for some countries, alongside rubber and rice cultivation. Its share exceeds 35%, and it also occupies a dominant position among global producers of soybean, rapeseed, sunflower seed and other vegetable oils. Malaysia and Indonesia

* *Corresponding author.*
E-mail address: yaakobms@upm.edu.my

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have become the world's leading palm oil producers [1]. In 2020, Malaysia will account for 25.8% of global palm oil production and 34.3% of global palm oil exports. Considering other oils and fats produced in the country, Malaysia accounted for 9.1% and 19.7% of global oils and fats production and exports, respectively, in the same year [2].

Traditionally, maintaining the health of palm trees in large plantations has been monitored through manual inspections. Although this method is simple, it can be more effective and accurate. It is labour-intensive, time-consuming, and prone to human error and subjectivity. Additionally, manual methods often delay the identification and resolution of tree health issues, negatively impacting plantation yields and productivity.

There has been a recent convergence of advanced technologies such as drones and deep learning, leading to revolution in many areas. The integration of unmanned aerial vehicles [3-6] with advanced image analysis technologies has led to precision agriculture [7]. An innovation that results from this technological blend is the provision of vast opportunities through which crop monitoring can be enhanced, as well as management efficiency and accuracy. UAVs equipped with high-resolution cameras capture detailed images from above agricultural fields while artificial intelligence revolutionizes data analysis and interpretation using pattern recognition [8]. Deep learning, as computational techniques, has shown capabilities in extracting intricate patterns from large datasets, particularly object detection tasks which are useful for plant health issues or anomalies since they enable automation in agriculture convolutional neural networks (CNNs) [9-15].

The study makes use of both drone technology and deep learning which are mutually inclusive to address the unique challenges of palm plantation management in this scenario. It brings together the nimbleness and information-gathering capacities of drones with MATLAB object detection and deep learning models, thus seeking to establish an all-round system for determining palm tree health.

2. Methodology

2.1 Data Acquisitions

The study area is located at Universiti Putra Malaysia palm oil plantations, Serdang, Selangor, Malaysia. The area located within latitudes 2^{o} 59’19 N and longitudes 101^{o} 43’31E (Degree, Decimal, Minutes). DJI M300 RTK drone with Zenmuse L1 Lidar and RGB sensor were used for data acquisitions where the study area covers approximately 60,824.96 m^2 of land plantation and 80-meter drone aerial height.

2.2 Stage 1: Traditional MATLAB Object Detection

During its initial phase, the initiative will rely on conventional MATLAB object detection approaches that consider diverse parameters related to oil palm tree health by processing high-resolution aerial drone images. While significant emphasis lies on singling out the diseased trees based on visual aspects like colour and texture due to numerous impediments that come with image interpretation using plain image processing, such as varying backgrounds or lighting conditions, it does not limit itself to these traditional boundaries.

The first procedure is colour thresholding which detects areas of possible tree abnormalities by identifying spots of high variance in canopy colour [16]. Generally, healthy palm trees have a uniform green colour while an unhealthy tree may show yellow or brown colours within the green leaves. This helps in the quick determination of the areas requiring more attention.

Another technique that enhances the precision of localizing palm trees is using edge detection to outline individual tree boundaries [17]. Distinguishing tree outlines from complex plantation backgrounds plays a significant role in singling out each tree for detailed analysis. Gabor filters and co-occurrence matrices are applied for texture analysis after edge detection [18]. The unique textures of palm tree canopies offer distinct visual cues on their health; by obtaining these features, additional information to distinguish between healthy and unhealthy palms. MATLAB Object Detection design for this project is summarized in Figure 1.

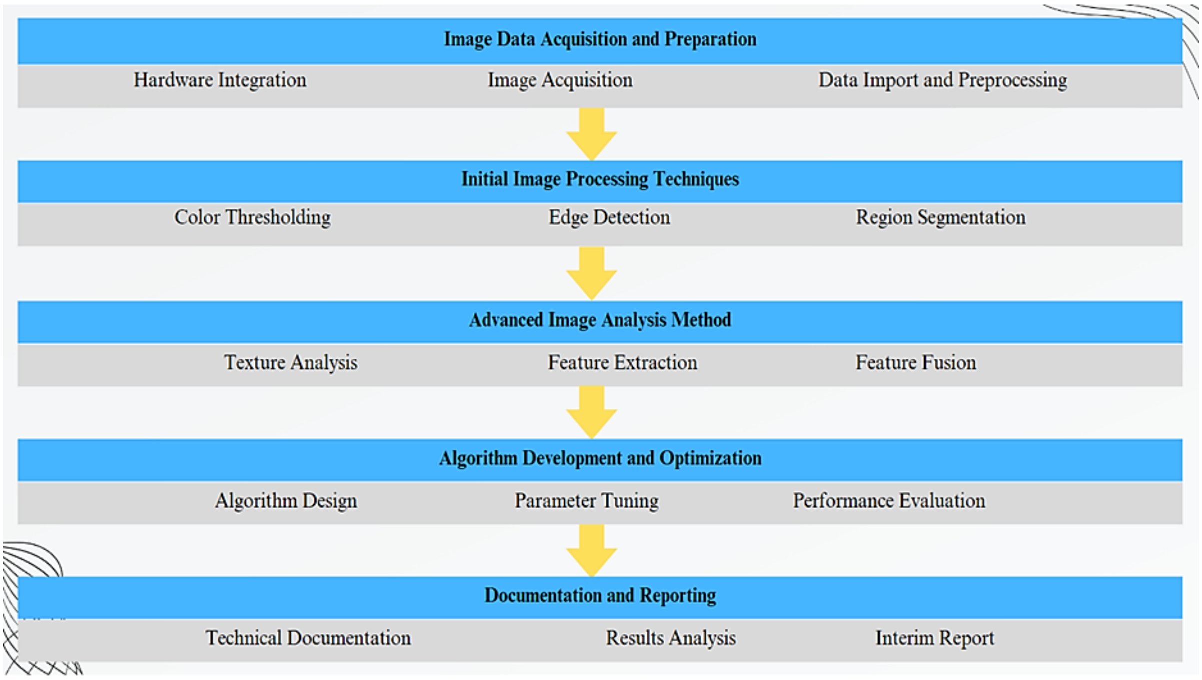

Fig. 1. Design of the stage 1 of the project

2.3 Stage 2: Deep Learning with Faster R-CNN

In the second phase of the project, a more advanced approach to monitoring oil palm health by applying deep learning techniques, specifically the Faster R-CNN (region-based convolutional neural network) algorithm. The goal of this phase is to overcome the limitations encountered in the first phase by leveraging deep learning to improve the accuracy and efficiency of detecting unhealthy palm trees from aerial drone imagery.

Faster R-CNN, proposed by Shaoqing Ren, Kaiming He, Ross B. Girshick, and Jian Sun in 2015 [19], is a state-of-the-art object detection architecture. The main goal of Faster R-CNN is to create a unified architecture that can not only detect objects in images but also accurately localize them. It combines the advantages of deep learning, convolutional neural networks (CNN), and region proposal networks (RPN) into a tightly coupled system, significantly improving speed and accuracy [20]. As shown in Figure 2. Faster R-CNN architecture consists of two components: Region Proposal Network (RPN) and Fast R-CNN detector.

A convolutional neural network (CNN) backbone like VGG16 is the first component of the Faster R-CNN architecture and is responsible for extracting feature maps from the input image. These feature maps capture different levels of visual information and are used by Region Proposal Network (RPN) and Fast R-CNN detectors. The main function of CNN is to extract relevant features and capture a hierarchical representation of the input image by applying multiple convolutional layers with different convolutional kernels. Initial CNN layers detect low-level features such as edges and texture, while deeper layers identify higher-level semantic features such as object parts and shapes.

Leveraging these multi-layer features, RPN and Fast R-CNN detectors significantly reduce computational time and memory consumption by sharing computational resources.

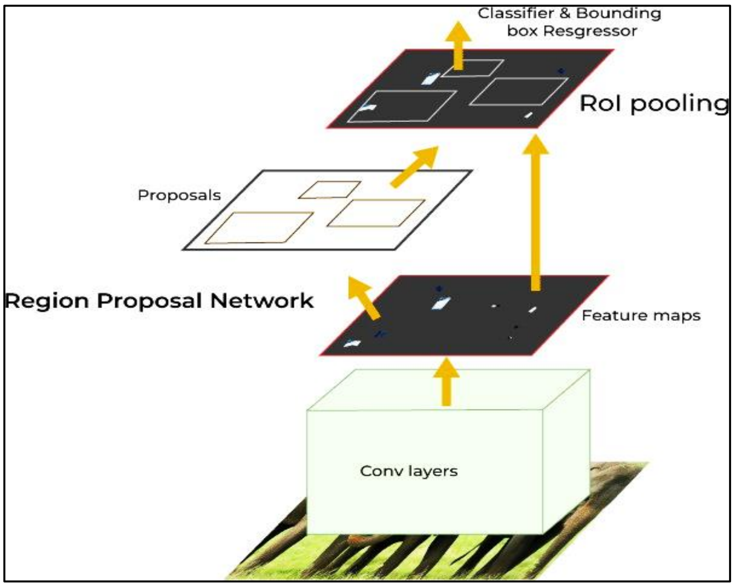

Fig. 2. Faster R-CNN architecture

The Region Proposal Network (RPN) is integral to Faster R-CNN, generating areas of interest in images that may contain objects [21]. It uses the attention mechanism in neural networks to guide the Fast R-CNN detectors in locating objects within images. The main components of the RPN are as follows:

i. Anchor box: Anchors generate regional recommendations in the Faster R-CNN model. It uses a set of predefined anchor boxes that have various proportions and aspect ratios. These anchor frames are placed at different locations on the feature map.
ii. Sliding window method: RPN operates as a sliding window mechanism on the feature map obtained from the CNN backbone. It uses a small convolutional network (typically a 3×3 convolutional layer) to process features within the acceptance domain of the sliding window. This convolution operation produces a score that represents the likelihood that the object exists and a regression value that is used to adjust the anchor box.
iii. Object score: The object score represents the probability that a given anchor box contains objects of interest rather than background objects. In Faster R-CNN, the RPN predicts each anchor's score. The objectivity score reflects the degree of confidence that the anchor corresponds to a meaningful object region. This score is used to classify the anchor as positive (object) or negative (background) during training.
iv. IoU (Intersection over Union): IoU is a metric that measures the overlap between two bounding boxes. It calculates the ratio of the overlapping area between two boxes to their union area.

$$IoU = \frac{Area\ of\ Intersection}{Area\ of\ Union} \tag{1}$$

v. Non-Maximum Suppression (NMS): According to the objective score of overlapping proposals, redundancy is removed, the most accurate proposals are selected, only the proposals with the highest score are retained, and other proposals are suppressed.

As shown in Figure 3, the regional suggestion network (RPN) uses the feature mapping of the CNN backbone network to identify potential target locations using the anchor frame sliding window method of different sizes and shapes. During training, the RPN modified these anchor boxes to better align with the position and size of the actual object. The RPN is responsible for generating the anchor points and it predicts two parameters for each anchor point: whether the anchor contains the object or not and adjusting the position of the anchor window to better fit over the actual object shape [22]. Since many such proposals can have significant overlap, non-maximum suppression is employed to whittle down these candidates.

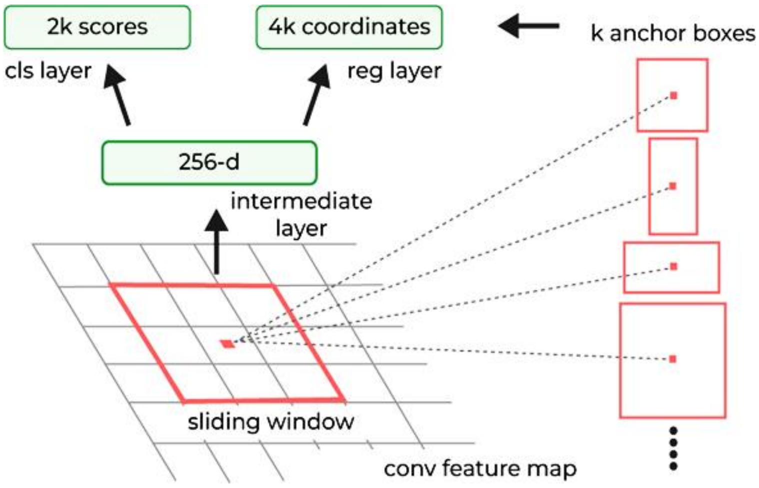

Fig. 3. Region Proposal Network (RPN)

The implementation begins with running aerial images through shared convolutional layers which are pre-trained on large datasets as part of the Fast R-CNN process. These layers work in unison to extract informative features that would help in detecting palm trees from other background objects and further assessing their health details. Then, RPN slides conv feature map seeking interesting regions hence proposal generation. The use of anchors reference boxes covering different sizes and shapes intended to match variations of palm appearances among images based on scale and aspect ratio.

The Fast R-CNN model in Figure 4, after proposal generation, extracts fixed-size feature maps from each proposal through ROI pooling. This step plays a significant role in extracting essential features. It helps the model to distinguish relevant information for palm tree classification. The features go through the box classification and regression via fully connected layers: an object score is assigned by the box classification layer to indicate likelihood while the box regression layer ensures precise positioning of palm trees within proposals.

To carry out non-maximum suppression (NMS) eliminating redundant detections and retaining confident ones marks the end of the detection process. Its implementation guarantees only relevant and accurate detections are kept it reduces redundancy keeping only those with higher confidence levels. Reducing the likelihood of false positives, thus improving the reliability of model output, due to being based on multiple comparisons made by different features' analysis at varied stages before reaching NMS decision or not having fewer but more meaningful detections passed through NMS. Ultimately, the Fast R-CNN approach provides a scalable and effective solution for monitoring palm health in oil palm plantations.

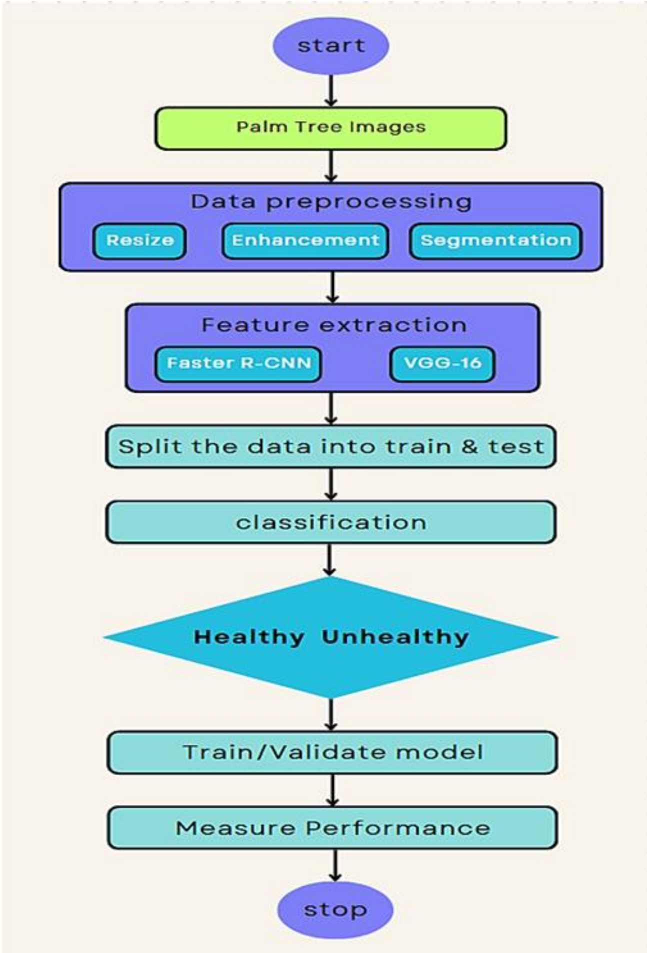

Fig. 4. Flow chart for fast R-CNN model

2.4 Visual Geometry Group 16-Layer Network (VGG-16)

In the second phase of the work, VGG-16 is adopted as the basic structure for the Fast R-CNN model which has an important function in realizing target detection efficiency through feature extraction. The VGG-16 is a pre-trained convolutional neural network with sixteen layers: 13 layers are convolutional and capture low-level features while the remaining layers capture high-level semantic features. These extracted features play a vital role in identifying & classifying oil palm health from aerial images, allowing dual usage between RPN and Fast R-CNN detector for the features obtained by VGG-16, thus lowering computational cost significantly [23].

The feature maps derived from VGG-16 are inputted into the RPN, which employs these maps to generate proposals for areas and predict potential target locations by moving a small network over the feature map. These ideas are subject to the Region of Interest (ROI) method, which pools the proposed areas into one standardized representation. The features that are pooled are then evaluated, and regression via fully connected layers is employed. The box regression layer estimates the probability of each region having objects and labels them as appropriate. Conversely, the box regression layer reduces the size of the bounding box to better fit the detected objects. Through the utilization of the powerful feature extraction ability of VGG-16, the Fast R-CNN model is capable of effectively and accurately surveying the health of oil palm trees. This information is of value in the management of plantations.

2.5 Image Labeller

In the project's second phase, labelling data to train the Fast R-CNN model begins with preparing and inputting aerial images of oil palm plantations. MATLAB's image datastore function is utilized to manage these images, aiding in processing extensive collections of photos. Each image is tagged to indicate whether the depicted palm is healthy or unhealthy, a process facilitated by MATLAB's Image Labeler application, providing a graphical interface for drawing bounding boxes around the tree and assigning labels.

Once the images are labelled, the labels are stored using the *boxLabelDatastore* function, organizing the labelled bounding box and corresponding labels into a format suitable for training the model. This step ensures that each image accurately labels the location and health of the palm tree, which is crucial for the training process as it provides the underlying truth data from which the Fast R-CNN model learns.

VGG16 is selected because of its depth and effectiveness in feature extraction, this process converts images into feature maps. The Region Proposal Network (RPN) employs these feature maps to produce area proposals and potential boxes that would indicate where objects (palm trees) could be located. The RPN moves a small network over the feature map, this network predicts the probability that each region contains objects, if the network is too large, it will be reduced.

After creating suggestions for regions, the ROI method averts this information into a consistent representation of the feature map for processing. These aggregation features are then passed through the entire network for final classification and regression on boundaries. The classification layer gives a label (healthy or unhealthy) to each region, while the regression layer focuses on the detection of smaller objects to accurately enclose the identified objects. The training model is evaluated using a separate validation set to measure its performance, ensuring it can accurately detect and classify palm trees in new aerial images.

Labelling the data used to train the Fast R-CNN model involves distinguishing between healthy and unhealthy palm trees based on various visual indicators, as depicted in Figure 5. Crown of the tree is what determines the classification. Healthy palms present with a bright green colour which is uniform and demonstrates good photosynthetic activity plus high levels of chlorophyll. On the other hand, when palm trees are unhealthy, they will show signs such as yellowing or browning that indicate a possible lack of enough nutrients, scarcity of water, pest infestation or disease attack.

(a)

(b)

Fig. 5. Oil palm trees condition (a) Healthy (b) Unhealthy [24]

Canopy density and uniformity are crucial factors in determining palm tree health. For healthy palm trees, leaves are evenly distributed and are plenty to form a complete symmetrical crown showing vigorous growth; this is not the case for unhealthy palm trees whose leaves are sparse or unevenly distributed with gaps or thinning areas due to physical injury, disease or poor growth conditions. The state of the leaves themselves also tells a lot: healthy leaves are whole and strong without any visible signs like wilting or tearing unlike unhealthy ones which appear damaged in different ways including being wilted or broken as well as showing signs of pest damage or disease infection [25].

Furthermore, the presence of disease symptoms and overall tree structure were considered. Healthy palms typically show no apparent signs of disease or pest infestation, maintain a straight, upright posture, and have a balanced and evenly shaped crown. However, an unhealthy palm may exhibit symptoms such as fungal infections, bacterial spots, or viral patterns. Due to uneven or damaged growth, it may have a slanted or tilted trunk and a deformed or unbalanced canopy.

3. Results

The proposed detection method's performance was evaluated using the dataset over 1229 images. The train-test ratio used in these experiments is 80:20 for the training and testing. All experiments were conducted using MathWorks MATLAB R2022b on a workstation with an Intel Core i7-14700HX (5.5 GHz) CPU and 32 GB of RAM.

The complexity and heterogeneity of palm plantations pose significant challenges, and many non-tree-related factors (e.g., shade, soil, and understory vegetation) may affect accurate canopy delineation. Traditional image processing methods have difficulty distinguishing these elements from the actual tree canopy. This problem is particularly obvious in areas where the contrast between the tree crown and the background is low, making it difficult for the algorithm to detect tree lines, as shown in Figure 6.

Fig. 6. Results of traditional detection methods

Changes in canopy shape, size and density make monitoring palm health more difficult. The appearance of palm trees varies greatly at different stages of growth or under different types of stress. Traditional methods that rely heavily on fixed thresholds and edge detection techniques cannot adapt to this change, resulting in inconsistent detection performance. For example, small trees with smaller canopies are often missed, while older trees with larger or overlapping canopies are sometimes counted multiple times.

Variations in lighting conditions across growing areas and times of day can significantly affect the colour and texture characteristics used for detection. Shadows, overexposed areas, and fluctuations in sunlight intensity can cause image inconsistencies, making it difficult to accurately identify unhealthy palms. Traditional methods require greater robustness to adapt to these changes, resulting in inaccurate health assessments. For example, shadows or highlights may alter the perceived colour and texture and cause healthy trees to be misinterpreted as unhealthy.

Therefore, advanced technologies such as deep learning are needed to overcome these limitations and improve the accuracy of palm health assessment. As shown in Figure 7, palm trees in the row of the picture are marked by the Image Labeler function in MATLAB. Palm trees in healthy states are marked with green boxes, and those in unhealthy states are marked with blue boxes.

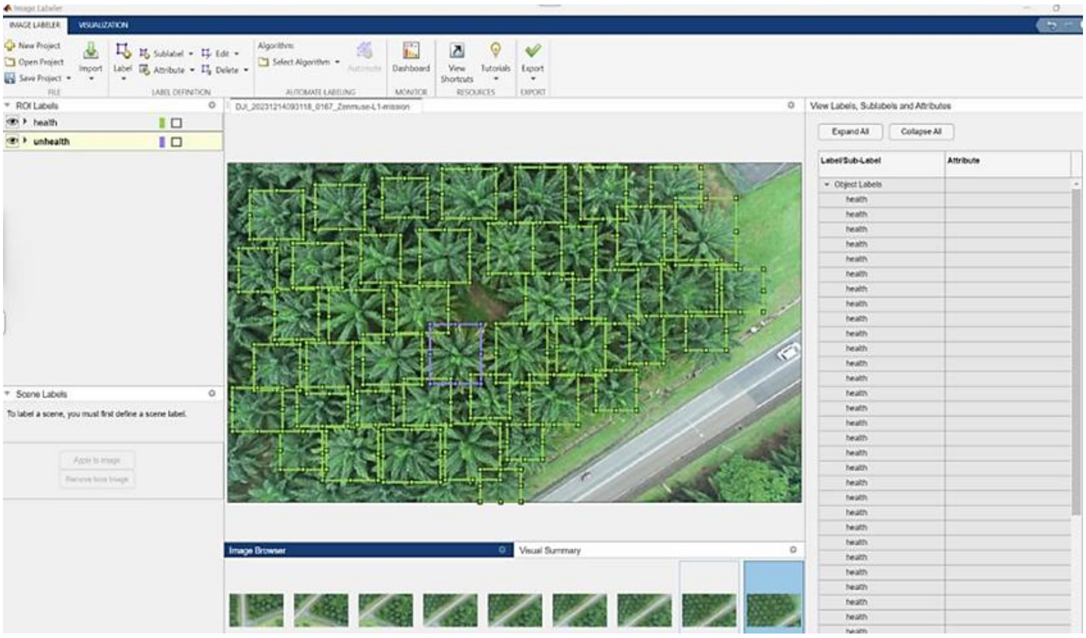

Fig. 7. Annotate the data set

After the annotation of the data set is completed, the Fast R-CNN model is trained, and the training result shown in Figure 8 below can be obtained. The results display the training progress of a deep learning model, with three graphs showing different metrics over iterations, Accuracy, RMSE (Root Mean Square Error) and Loss. The accuracy graph tracks the accuracy of the model during training and validation. The RMSE graph tracks the RMSE of the model during training and validation and the Loss graph tracks the loss function value during training and validation.

The development process of this model is marked by some interesting characteristics. Firstly, the accuracy map sharply rises to almost perfect levels at the start of training and then settles into a stable state. While this fast attainment of high accuracy levels indicates efficient learning, the absence of validation metrics in the later plateau phase raises doubts about overfitting. Secondly, the root mean square error (RMSE) demonstrates a significant drop initially which later tapers off implying that retracing back through more iterations is not beneficial. This trend is also echoed in the loss plot: it steadily descends before levelling off, showcasing successful convergence and optimization efforts.

The choice of training configurations (such as using a single GPU and segmented learning rate plans) allows fine control over the learning dynamics but be aware that conducting 500 epochs and 20,000 iterations to train may lead towards overfitting due to lack of stopping criteria along with validation sets. The presentation or visualization results for individual samples (e.g., accuracy, RMSE or loss) would facilitate an easier inspection of whether specific areas have learned well without such information being masked by overall performance indices like mean values typically computed over all samples within a dataset.

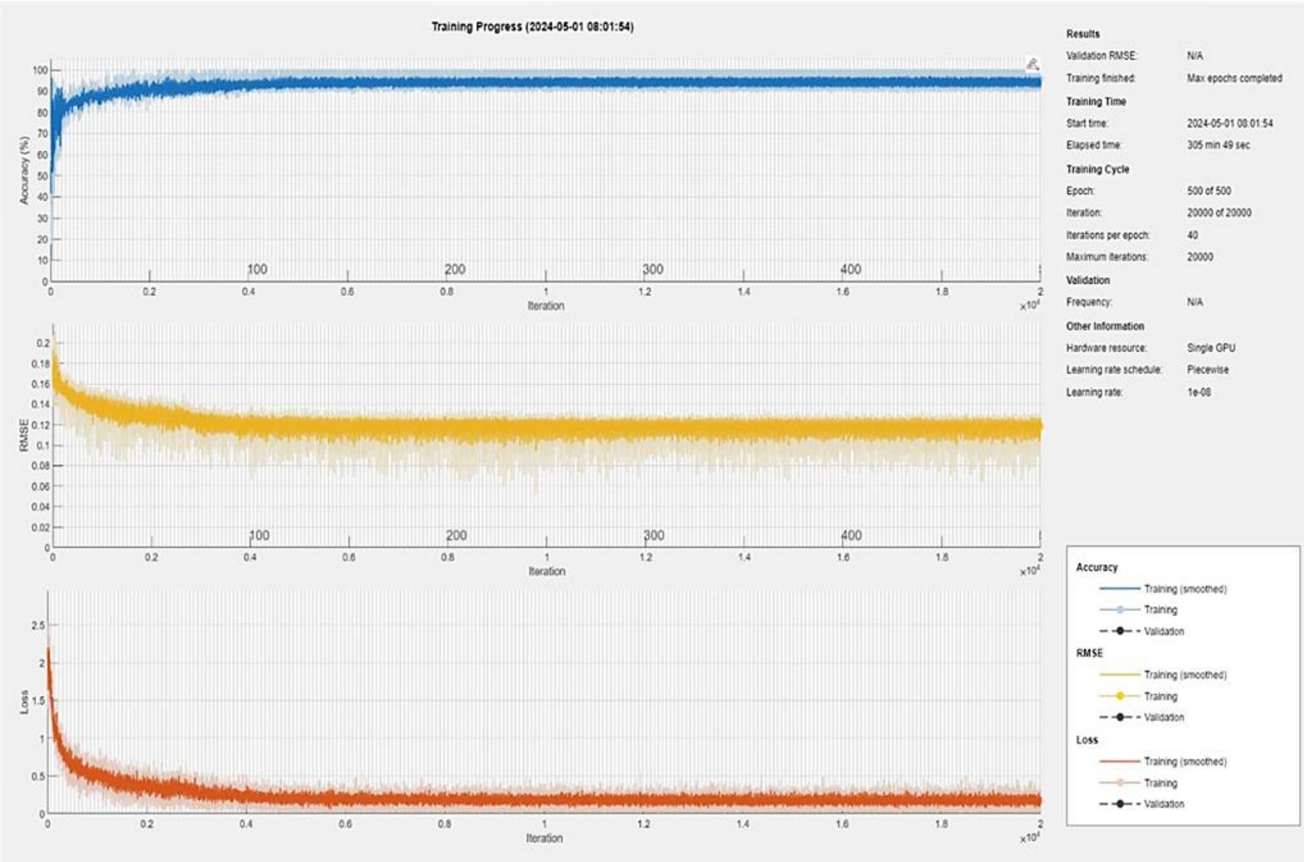

Fig. 8. Model training result

Upon completion of the training, aerial images of palm trees can be imported for detection. An individual confidence or probability score is associated with each detected object, typically ranging between 0 and 1, whereby higher scores reflect a stronger belief in the outcome. These scores are essential in providing information on prediction reliability and guiding the assessment of detection accuracy and dependability.

When some palms are highlighted using a red boundary while their infected counterparts are delineated using yellow boundaries, as depicted in Figure 9, decisions based on detections can be prioritized or filtered based on the confidence level indicated by the accompanying score. Table 1 compares the effectiveness of these two detection methods and Faster R-CNN overcomes the limitations of traditional monitoring methods to improve detection accuracy and contribute to sustainable agricultural practices.

Fig. 9. Model detection result

Table 1
Compare the detection methods

Feature	Faster R-CNN	Traditional Detection
Architecture	Two-stage: Region Proposal Network (RPN) + Fast R-CNN.	Various (edge detection, texture analysis, color thresholding).
Speed (inference time)	Slower (due to two-stage process).	Generally fast, but less accurate.
Accuracy	High.	Low to moderate.
Localization	More accurate bounding box predictions.	Poor, often unable to precisely localize objects.
Training time	Longer (complex training process).	Not applicable (rule-based, not trainable).
Model complexity	More complex (RPN + detection network).	Simple algorithms.
Implementation ease	More challenging (requires careful tuning).	Generally easy, but can be difficult to fine-tune.
Use cases	Applications requiring high precision.	Basic detection tasks, preliminary analysis.
Backbone networks	Typically uses ResNet, VGG, or similar networks.	No specific backbone (uses image processing techniques).
Frameworks	TensorFlow, PyTorch.	OpenCV, MATLAB.

4. Conclusions

In summary, this study has established the successful application of UAV technology in conjunction with Faster R-CNN deep learning models to increase oil palm tree health monitoring. The traditional approaches, which are reliant on human experts' subjective estimations and image processing, are rendered less effective compared to the new and innovative method, which shows a substantial improvement in detection rate and operational efficiency. The use of the Faster R-CNN model, particularly when the VGG-16 backbone was used, proved capable of distinguishing between unhealthy and healthy oil palms, accommodating the environmental variability, and speeding up the data processing. The accuracy model for both training and validation improves quickly at first and then plateaus, indicating that the model is learning well and approaching its maximum performance.

The RMSE model decreases over time, which is expected as the model learns and the error between predicted and actual values reduces. The trend shows a good learning process as the RMSE stabilizes at a lower value. Finally, the loss model decreases significantly during the early iterations and then levels off, indicating that the model is converging. A lower loss indicates better model performance. With the potential for scalability, the developed system contributes to sustainable agriculture by better enabling timely interventions, boosting yield, and reducing the environmental impact, thus demonstrating potential generalization to other precision agriculture uses

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