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AUTOMATIC OIL PALM TREE COUNTING AND HEIGHT ESTIMATION USING DIRECT GEOREFERENCING PHOTOGRAMMETRY, CANOPY HEIGHT MODELLING, AND TEMPLATE MATCHING

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ABSTRACT

The rising global demand for palm oil necessitates more efficient plantation management, yet the accuracy and effectiveness of monitoring remain limited. Photogrammetric technology provides a precise solution for tree counting and height estimation, traditionally relying on aerial imagery and ground control points (GCPs). However, advancements in direct georeferencing photogrammetry enable accurate tree detection without GCPs. This study validates automatic segmentation using direct georeferencing aerial photographs, comparing results with manual methods. A template matching algorithm was applied for segmentation, while tree height estimation was derived from a canopy height model (CHM) using digital elevation model (DEM) data. The DEM was processed into a digital terrain model (DTM) and digital surface model (DSM) to generate CHM values. The eCognition oil palm application (OPA) software detected trees across homogeneous, semi-homogeneous, and heterogeneous areas. Accuracy results showed high precision (96.2%–98.8%), recall (99.4%– 100.0%), and F1-scores (98.0%–99.0%) across all areas. CHM-derived height estimates averaged 5.1 ± 1.8, 5.2 ± 2.0, and 6.9 ± 3.5 m, respectively. The results for each sample were consistent with the characteristics of the area, as seen from the differences in standard deviation, which is an indicator of the degree of variation in tree height. These findings highlight direct georeferencing photogrammetry as an effective, scalable approach for accurate tree counting and height estimation, supporting sustainable oil palm management.

Keywords: plantation tree assessment, tree inventory, UAV imagery.

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INTRODUCTION

Oil palm is the primary commodity in the production of vegetable oil and contributes the highest foreign currency income for Indonesia (Wulandarie et al., 2024). This makes oil palm a main agricultural commodity in many developing countries, with a significant contribution to the agricultural sector as well as its role in providing a living for around one million people involved in the industry (Kipli et al., 2023). Teo et al. (2025), highlight that monitoring oil palm plantations is essential for accurate and consistent controled productivity. The oil palm plantation management is crucial in exploring the various factors that influence variations in plant growth. In addition, effective management also contributes to improved operational efficiency and sustainability in the oil

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palm industry (Beese et al., 2022). Such conditions prompt oil palm companies to enhance their performance in oil palm cultivation, which includes identifying the number of trees and estimating their height measurements.

Traditional monitoring methods, however, can be time-consuming and labour-intensive, necessitating more efficient technological approaches. In this regard, photogrammetric technology offers a practical solution for assessing oil palm plantation conditions (Uktoro, 2017). By using the concept of photogrammetry, surveyors only need to use aerial photographs as input data for monitoring oil palm plantation land, where the total number of trees can be calculated accurately (Handayani & Caeli, 2016). One method is utilising ground control points (GCPs), points with precision coordinates on the ground surface. GCPs serve as geospatial references for aligning images with their actual positions in the field, improving the accuracy of mapping results and geospatial corrections (Teppati Losè et al., 2023).

Nevertheless, a study by Rizaldy and Firdaus (2012) stated that aerial photographs without using GCPs in the acquisition process can still be used for image processing by utilising integrated position and camera information from the platform used through a direct georeferencing process. Moreover, direct georeferencing on images with high visualisation can improve the efficiency of photogrammetric surveys and result in high precision (Teppati Losè et al., 2023). Direct georeferencing is an effective solution for hard-to-reach locations or emergencies, as it eliminates the presence of GCPs (Han & Han, 2024). Then, segmentation processing will be performed using existing aerial photography data, with acquisition criteria without GCPs. Although the geometrical accuracy is lower compared to those using GCPs, the processing of classification methods is not only influenced by accuracy but also by the visualisation of detected objects in the image (Srestasathiern & Rakwatin, 2014). The ability to discriminate features can be analysed by evaluating two histograms obtained from the index values, one representing the palm trees and one representing the background.

Despite these advantages, challenges persist in classification and analysis, particularly in aerial photographic image processing and feature extraction, where both processing time and accuracy remain key concerns (Oliveira et al., 2021). To address these issues, automatic segmentation methods have been widely adopted in oil palm plantation management (Wulandarie et al., 2024). These methods enable accurate palm tree counting while significantly reducing processing time (Irsanti et al., 2019). Template-matching algorithms and object-based classification techniques have proven more effective than manual delineation in identifying and counting palm trees (Irsanti et al., 2019).

Moreover, according to Visano et al. (2020), palm tree height is also one of the parameters to consider in determining the harvesting process; different heights of palm trees will determine different difficulty levels in the harvesting process. Palm trees with height of 2–5 m tend to be easier to process, using lighter equipment for harvesting that takes a height of more than 5 m (Visano et al., 2020). In addition, tree height data is essential for land monitoring and inventory as it helps to count the number of trees more efficiently and supports accuracy analysis in the automatic counting process (Mukti et al., 2023). Therefore, calculating the height of oil palm trees from aerial photography data is essential for decision-making and managing oil palm plantations, especially during the harvest process (Handayani & Caeli, 2016).

Given the importance of tree height data for efficient harvesting and plantation management, an accurate and reliable method for height estimation is required. The canopy height model (CHM) provides a representation of the height of vegetation objects by calculating the difference between the canopy and ground surface, enabling accurate tree height estimation (Wu et al., 2019). The estimated height data can be obtained by subtracting surface height from the ground elevation around the object (Wu et al., 2019). According to Zhang et al. (2024), vegetation height can be obtained by processing digital elevation model (DEM) data based on classification results. The DEM obtained from orthophoto processing, which is then filtered, will obtain the height of the object canopy in the form of digital surface model (DSM) data minus the ground elevation using digital terrain model (DTM) data. CHM identifies the height difference between the object's canopy and the ground surface by utilising unmanned aerial vehicle (UAV) acquisition without GCPs for aerial image capture, which is then processed through georeferencing to define the coordinates, size, and shape of objects in the image according to the actual conditions in orthophoto processing (Kulpanich et al., 2022). Several studies have successfully demonstrated the CHM workflow derived from UAV to quantify tree height in oil palm plantations (Avtar et al., 2020; Fawcett et al., 2019; Kulpanich et al., 2022).

This study explores the potential of automated methods in calculating the number of oil palm trees from aerial photo data via direct georeferencing. By showing different perspectives on the data, this study expected to provide new insights and alternatives that can be considered in future endeavours. This approach through the concept of direct georeferencing can also open opportunities for the development of more comprehensive analytical methods, allow comparison with other techniques, and add to the literature in the field of oil palm plantation monitoring. Along with creating oil palm tree height data using CHM calculations, this data can be used to design more structured harvesting strategies, optimise resource allocations, and improve efficiencies in monitoring land conditions. With this information, harvesting can be planned with better precision, reducing wastage of time and resources and supporting sustainable plantation management more effectively.

MATERIALS AND METHODS

Location and Materials

This study is located on the selected land of the Tani Makmur Village, Pematang Jaya Subdistrict, Langkat Regency, North Sumatra Province, Indonesia with coordinates 4°14′58.64″ N and 98° 9′ 7.26″ E. The primary data used in this study is aerial images acquired using a quadcopter, DJI Phantom 4 Pro (DJI, China), with a built-in global navigation satellite system (GNSS) system and 1 inch CMOS of 20 MP resolution. The drone flight altitude is set to 100 m, resulting in a ground sampling distance (GSD) of about 2.74 cm/pixel. High spatial resolution aerial imagery obtained from unmanned vehicles has proven effective in providing detailed physical information, especially on oil palm canopy objects (Izzuddin et al., 2020). The study area consists of oil palm trees with medium, tall, short, and mixed sizes, which is the main reason for selecting an area that consisted of multiple variables.

Figure 1 illustrates the classification of data samples based on the level of homogeneity: homogeneous (red polygon), semi-homogeneous (yellow polygon), and heterogeneous (blue polygon). The homogeneous area has uniform characteristics in structure and density. The semi-homogeneous site indicates an area with less uniformity and some variations. Meanwhile, the heterogeneous area shows significant variations in the observed objects' structure, height, or density.

Research Design

All stages of the study implementation are illustrated in *Figure 2*. The primary dataset used is aerial photos acquired by a multi-copter UAV, and the final output is annotated oil palm trees with height information. The detailed workflow is described in the following sections.

The study started with selecting oil palm areas and using aerial photos with varying land conditions, which were then segmented based on patterns, shapes, colours, and textures. The DSM data processed by Agisoft Metashape (Agisoft, Russia) was filtered into DTM as the basis for CHM calculations. The segmentation process was carried out using two methods, manual and automatic, to produce oil palm tree samples. Next, analysis and validation were carried out to ensure the quality of the output before it was used in the next stage. After validation, tree height calculations were performed by integrating the segmentation results with DSM and DTM using the CHM concept (DSM – DTM = CHM) through the field calculator in ArcGIS (Esri, USA).

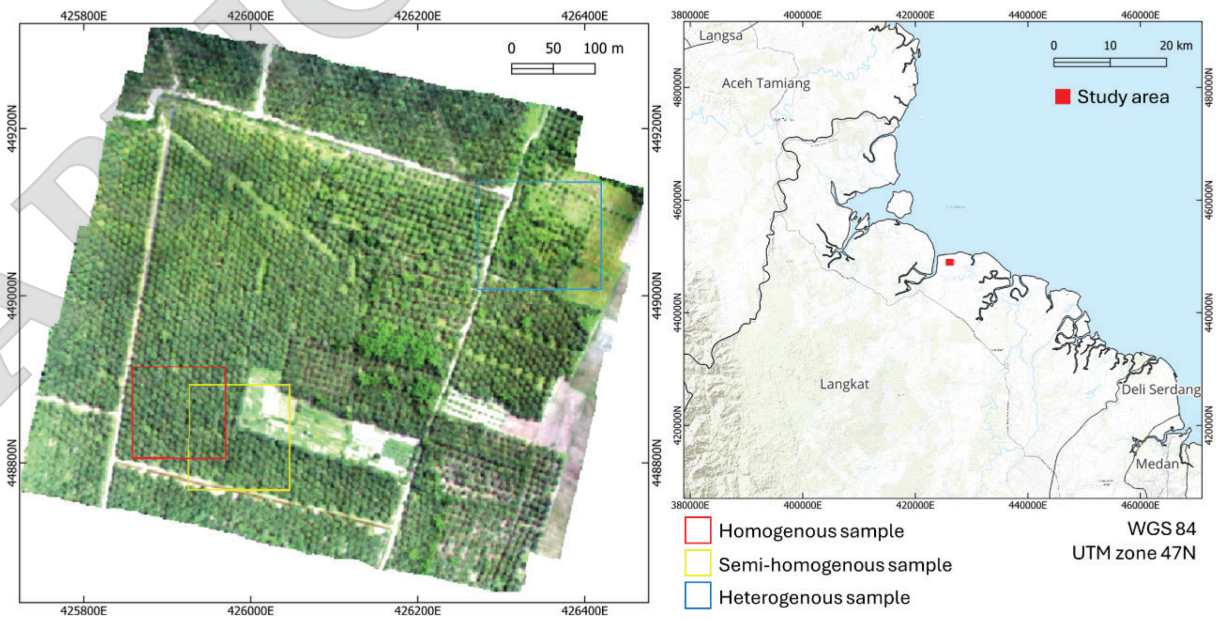

Figure 1. The study location is in Langkat Regency, Indonesia.

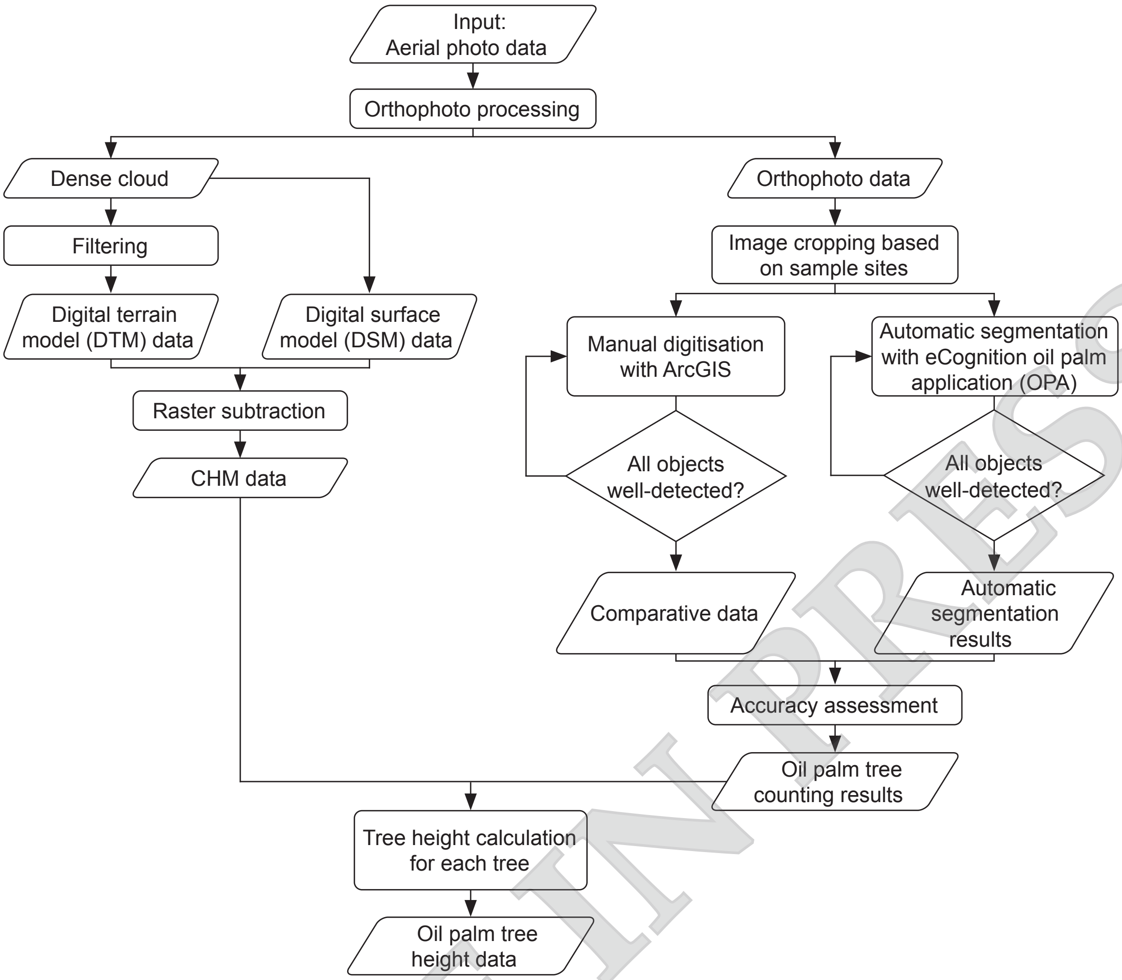

Figure 2. Flowchart of oil palm tree processing and height estimation procedures.

Data Collection Methods

The data used in this study are derived from orthophotos captured via UAVs employing a direct georeferencing method, which relies on exterior orientation (EO) parameters and pre-analysed flight altitudes to ensure positional accuracy (Rizaldy & Firdaus, 2012). This approach produces high-resolution orthophotos suitable for validating direct georeferencing algorithms, particularly under varying land surface conditions (Santos et al., 2023). Direct georeferencing has proven to be a suitable solution for mapping dense areas by demonstrating a high degree of position detection capability in a mapping context (Salas López et al., 2022). The concept of direct georeferencing will be analysed further by considering the diversity of land variations to obtain more accurate and applicable results.

This study aligns with Kulpanich et al. (2022) as both discuss the innovative use of UAVs to estimate the height of oil palm stands by utilising CHM. However, our primary focus is on the data type used, especially those integrated with direct georeferencing.

The orthophoto data is cropped to generate the best sample areas for analysis, representing homogeneous, semi-homogeneous, and heterogeneous land types to ensure adequate variability. This step is crucial, as the density of objects within the study area significantly influences the detection performance with lower object density, which often leads to increased detection errors (Smith et al., 2025).

Processing

For the automatic segmentation method, eCognition Oil Palm Application (OPA) software (Trimble, USA) is used with the algorithm concept of template matching. This software integrates a deep learning system to detect palm tree objects automatically. Deep learning methods utilised for object counting, especially in oil palm, show results with high accuracy, reaching an accuracy above 90% (Kipli et al., 2023; Minarto et al., 2024). The OPA tool was developed using Trimble eCognition software and relies on the object-based image analysis (OBIA) method that combines image segmentation and feature extraction (Wulandarie et al., 2024). This method enables the identification of oil palm tree objects based on shape, texture, and spectral characteristics, resulting in the estimation of the number of trees with a high level of accuracy (Wulandarie et al., 2024). The information obtained through this method can be used to support planning, maintenance, and fertiliser scheduling in plantation management more efficiently. The manual method of processing with ArcGIS software is digitisation based on interpreting objects considered as palm tree objects.

The following process is filtering for ground and off-ground segments to create a DTM that will be integrated using DSM data, processed by Agisoft Metashape software. This concept is used to obtain the net height of the palm tree object, called CHM, which is calculated using the field calculator function in ArcGIS software.

Data Analysis

The analysis stage is based on individual sample data, with different results and analyses obtained with each sample used. Validation was performed by comparing the manual processing results with the automatic segmentation results to determine the accuracy for each sample used.

Accuracy Test

The accuracy test of the processing result was done by examining the evaluation matrix in the form of precision, recall, and F1-score values. The value of this matrix parameter is generally used for detection and counting processing. Precision measures the extent to which the classification object correctly identifies the object (positive) [Equation (1)]. Recall measures the extent to which the classification object correctly classifies all (positive) examples [Equation (2)]. F1-score is a measure that combines precision and recall into a single number [Equation (3)].

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

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

$$\text{F1-score} = \frac{(1 + a) \times \text{Precision} + \text{Recall}}{a \times \text{Precision} + \text{Recall}} \tag{3}$$

where, true positive (TP) is the number of palm points successfully identified using the automatic method. Meanwhile, false negative (FN) is the number of palm tree objects that have not been detected. False positive (FP) is defined as a wrong detection of an object as a palm tree.

RESULTS AND DISCUSSION

Figure 3 below displays the parameters of the data processing results in the Agisoft software, which includes the number of photos used, the number of tie points generated in the alignment stage, and the number of points in the resulting dense cloud. A dense cloud is generated by processing aerial photos using high-quality processing, which results in a dense cloud of 49,283,375 points as shown in the following Agisoft processing parameters.

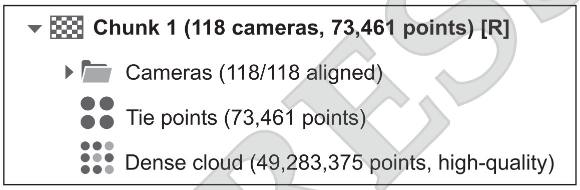

Figure 3. Agisoft processing parameter results.

From the results of the processing that has been completed, utilising aerial photography data without GCPs is faster and more efficient as it does not require the placement and measurement of control points on the ground, making it more practical for surveying and mapping in hard-to-reach areas. However, the geometrical accuracy might be reduced because, in the absence of GCPs, aerial photography relies solely on data from the navigation and internal positioning systems integrated into the vehicle, which are prone to errors. The resulting visualisation already defines various topographic conditions and can be displayed according to the conditions on the ground. With some previous parameters, there are no holes or blank areas, ensuring a consistent and thorough representation of the topography mapped and sampled. *Figure 4* and *5* show the processing results of DTM and DSM.

Dai et al. (2024) displayed that DEM data generated from aerial photo processing using UAV-based photogrammetry technology can be used to analyse topographic elevation variations of an area accurately and efficiently. In this study, we utilised DEM from aerial photo processing because objects detected at the points in orthophotos also elevated directly from aerial photos used in processing so that gaps and distance tolerance errors can be reduced. Our processing results derived from eCognition OPA software successfully detected and calculated the number of oil palm trees based on aerial photo data. Processing includes aerial photography data covering three different sample areas, which is expected to provide more analysis of the capabilities of the methods and software that have been used in the process. The processing results from each sample is shown in *Figure 6*.

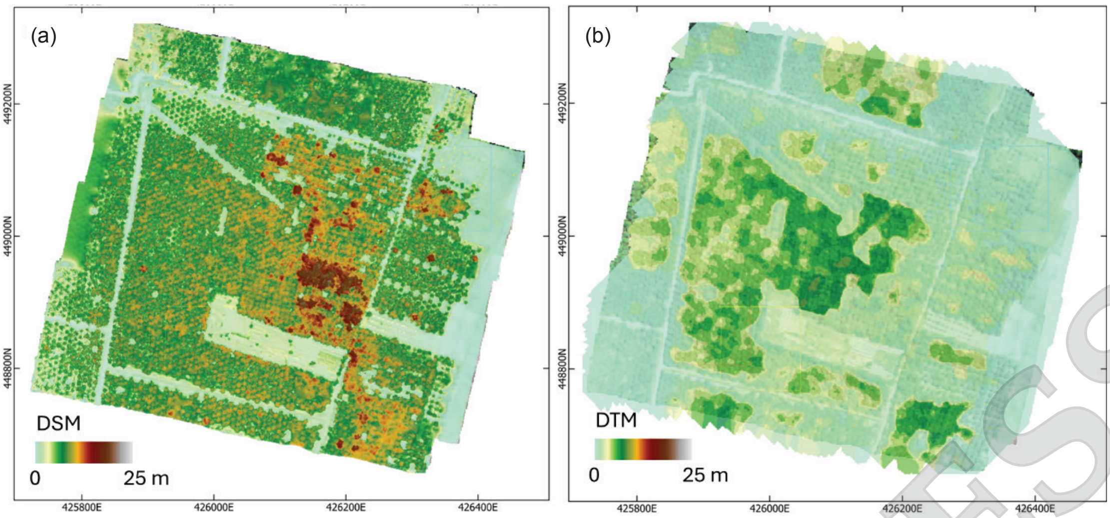

Figure 4. (a) Digital surface model (DSM) and (b) digital terrain model (DTM) of the study area.

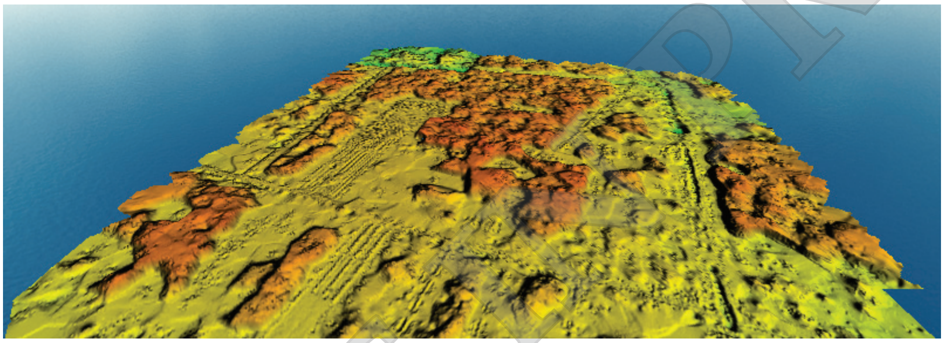

Figure 5. Side view of the digital terrain model (DTM) showing the topographical conditions.

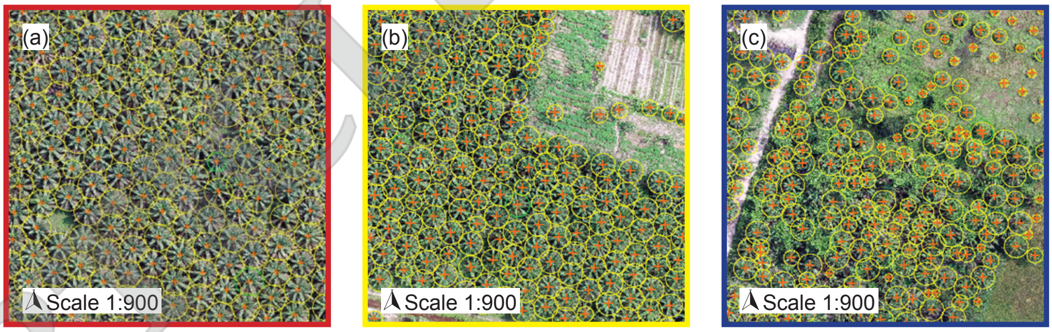

Figure 6. Oil palm detection results in three sample sites: (a) homogeneous, (b) semi-homogeneous and (c) heterogenous areas.

Aerial photography with direct georeferencing is applicable for image processing (Rizaldy & Firdaus, 2012). However, this concept is less relevant for areas with sloping topography because the pixel representation is not in the planimetric plane (Santos et al., 2023). Considering these factors, this study adopts direct georeferencing, as the study area (oil palm plantation) features a relatively flat topography. Moreover, the detection process is simplified in homogeneous regions where oil palm trees exhibit similar sizes and shapes, as the model can effectively recognise consistent patterns (Lee et al., 2024). In contrast, detection becomes more challenging in heterogeneous areas, where oil palm trees are interspersed with other crops and show significant variations in size and shape (Lee et al., 2024). Accordingly, the sample area for this study was chosen based on aerial photo data that visually represented the distribution of oil palm trees in the location. The template matching method detected a total of 179, 179, and 243 oil palm trees in homogeneous, semi-homogeneous, and heterogeneous sites respectively. We matched the results with the reference dataset and then assessed the accuracy, as reported in *Table 1*. Only two false positive objects were found in all areas, each in homogeneous and heterogeneous areas. Meanwhile, some oil palm trees were successfully detected by the algorithm, with the highest false negative in semi-homogeneous (seven trees), followed by heterogeneous (four trees) and homogenous areas (two trees). Although all sites achieved very high accuracy, overall, the homogenous area has the highest accuracy with an F1-score of 99%.

TABLE 1. ACCURACY TEST RESULTS

Area	Precision	Recall	F1-score
Homogeneous	98.8%	99.4%	99.0%
Semi-homogeneous	96.2%	100.0%	98.0%
Heterogeneous	98.3%	99.5%	98.8%

This study demonstrates that by leveraging aerial photographs combined with automatic processing, it is possible to accurately estimate the number of oil palm trees within plantations. However, automatic detection systems may incorrectly classify similar-looking objects as oil palm trees, leading to an increased false positive rate (Lee et al., 2024). Additionally, oil palm trees that are partially or fully obscured by other trees, shadows, or dense vegetation are at risk of being undetected or misclassified (Shaikh et al., 2024). Moreover, the use of UAV-based aerial imagery in this study proves to be more effective than satellite imagery, as UAVs capture higher-resolution images that enhance the precision of tree detection and counting (Chowdhury et al., 2022). Furthermore, the innovative approach of utilising aerial photographs without GCPs presents a viable alternative for managing oil palm plantations, particularly in remote or difficult-to-access areas where traditional mapping methods are challenging to implement.

In the era of technological development in various industries, using artificial intelligence (AI) with deep learning technology provides an alternative to the more efficient management of oil palm plantations (Mohamad Zaki et al., 2025). Based on Putra (2020), deep learning methods widely used in computer vision processing have also proven that the results can show high accuracy. With different concepts and software processing, computer vision based on the eCognition OPA software is carried out to calculate oil palm trees. In the same way as the results obtained, the accuracy calculation using the confusion matrix has been carried out to obtain a high accuracy value.

Building on the integration of deep learning and aerial photogrammetry in oil palm tree identification, these technologies also play a crucial role in extracting meaningful height data from CHM calculations. By applying template matching techniques, the height distribution can be analysed across different plantation areas, as depicted in *Figure 7*. The histogram of oil palm tree heights obtained from the canopy height model in homogeneous, semi-homogeneous, and heterogeneous areas is displayed with the X-axis representing tree height (m) and the Y-axis representing number of trees (frequency) (*Figure 7)*. It can be observed that the oil palm trees in the homogeneous area are the shortest among other areas with a mean value of 5.1 m. However, due to its homogeneity, this area has the lowest variability with a standard deviation of 1.8 m. A smaller standard deviation indicates lower variability, meaning that the data is more consistent and in accordance with the diversity of homogeneous samples in this study. The heterogeneous area managed to provide the highest overall height (mean = 6.9 m), nevertheless, the high variability is also shown with a standard deviation of 3.5 m. Meanwhile, the data distribution of the semi-homogeneous area is in between other areas (mean = 5.8 ± 2.0 m). This indicates higher variability than homogeneous sample data, meaning that there is more diversity of objects in semi-homogeneous samples in this study.

Additionally, the eCognition OPA software that we used also generated the crown diameter of each corresponding tree. We divided the crown diameter values into three classes, that is small (< 3 m), medium (3–6 m), and large (6–9 m) (*Figure 8*). A total of 178 objects of oil palm trees were detected in a homogeneous sample area, consisting of 29 and 149 trees with medium and large crown sizes, respectively, whereas no trees were detected with small crown diameters. Out of 179 trees in the semi-homogeneous area, 75% were large, 24% with medium crown diameter, and only 1% had a small crown. The variability in the heterogeneous area is much higher, with 51 oil palm trees having small crown sizes, while the trees with medium and large crown sizes were 100 and 92, respectively.

As shown in *Figure 8*, oil palm trees were distributed across several crown size classes, as determined from eCognition OPA results. *Figure 8* illustrates that trees with larger crown sizes generally have greater tree heights, as measured by the CHM, indicating a direct relationship between crown size and tree height. The boxplots shows the variation in tree height distribution in each land type and illustrates the relationship between crown size and tree height, which highlights the importance of accurate height estimation methods in oil palm plantations. While Visano et al. (2020) measured oil palm tree height from ground level to the fruit cluster, our study adopts a more comprehensive approach by utilising DEM processing. By referencing the

DTM as the ground surface and the DSM as the canopy height, we obtain the overall height of each palm tree object. On the other hand, Wu et al. (2019) demonstrated that height estimation using LiDAR data, particularly for buildings, achieved high accuracy, with a 97% success rate and an absolute mean error of 0.3 building floors. Adopting a similar concept to the CHM, this study employs aerial photography data to estimate tree heights, yielding statistical values that align with land sample criteria. However, direct field validation of height measurements has yet to be conducted.

Alternatively, this study can be expanded by incorporating aerial photography data covering larger areas with more complex terrain, allowing for a more in-depth analysis of automated methods in detecting and counting oil palm trees. Additionally, future studies could leverage this data to enhance oil palm production predictions by integrating height and crown size metrics into plantation management strategies. Before achieving this goal, further investigations should focus on monitoring oil palm tree health through these parameters, which could optimise fertilisation and irrigation schedules, ultimately improving yield efficiency and sustainability.

In addition, further studies can be developed by directly comparing aerial photographs with GCPs or without GCPs in the same area. The direct georeferencing concept employed in this study is prone to positional errors, especially if the device's built-in GNSS navigation sensor is not calibrated correctly. Such errors can affect geospatial accuracy and precision in measuring crown size and tree height (Padró et al., 2019). GCPs in photogrammetry perform as the primary reference points to improve mapping accuracy and ensure the precision of the resulting coordinates. However, in the direct georeferencing method, GCPs are no longer needed as ground coordinates are obtained directly from aircraft navigation and orientation data without external control points. Nevertheless, there is a risk that the accuracy of mapping with Direct Georeferencing is lower than the GCPs-based method (Rizaldy & Firdaus, 2012). Therefore, GCPs still play an important role as references for validation and quality control to improve the accuracy of the mapping results.

Consequently, detecting the growth of oil palms (especially young palms with small crowns) becomes challenging in aerial photographs, potentially leading to an incomplete representation of the land sample criteria. Moreover, the application of direct georeferencing is less effective in areas with undulating topography due to the lack of GCPs, which are crucial for correcting image distortion, allowing the performance of the two measurement methods to be directly compared. In addition, field validation of the CHM calculation needs to be carried out to ensure data conformity with conditions in the field.

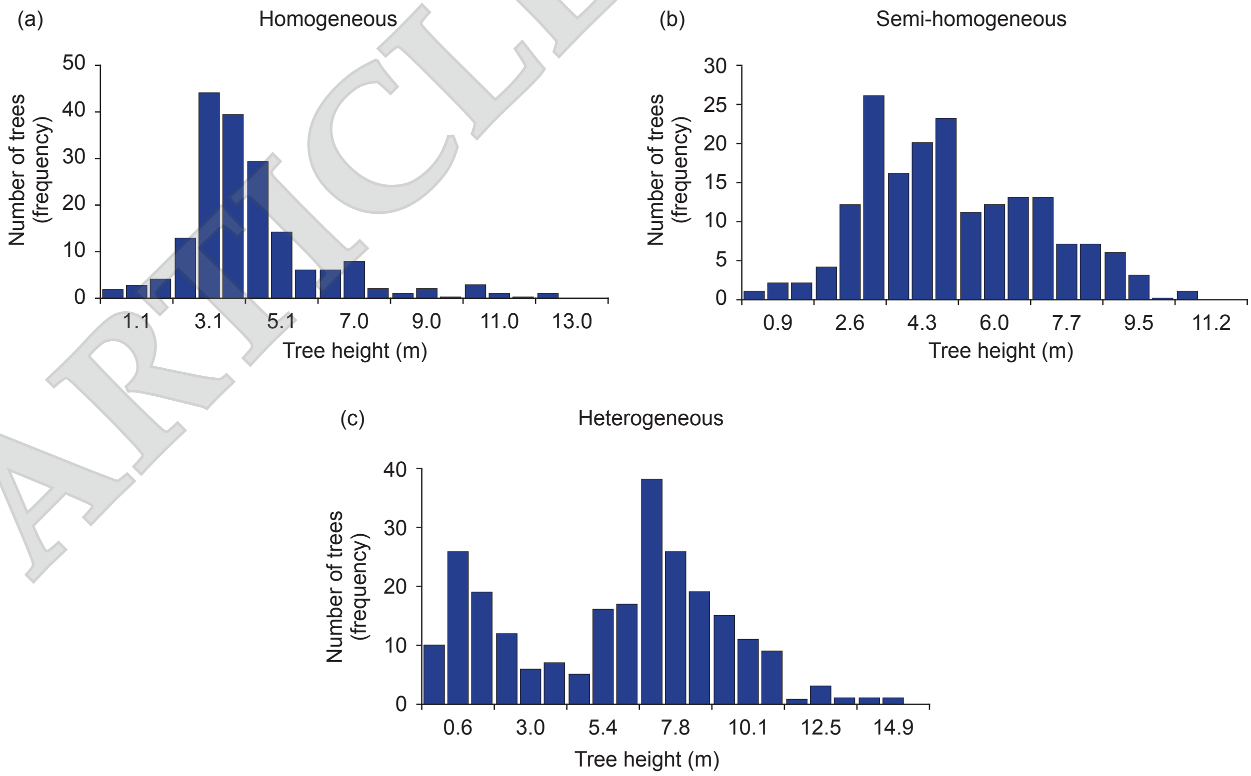

Figure 7. Histograms of oil palm tree height derived from the canopy height model in (a) homogeneous, (b) semi-homogeneous, and (c) heterogeneous areas.

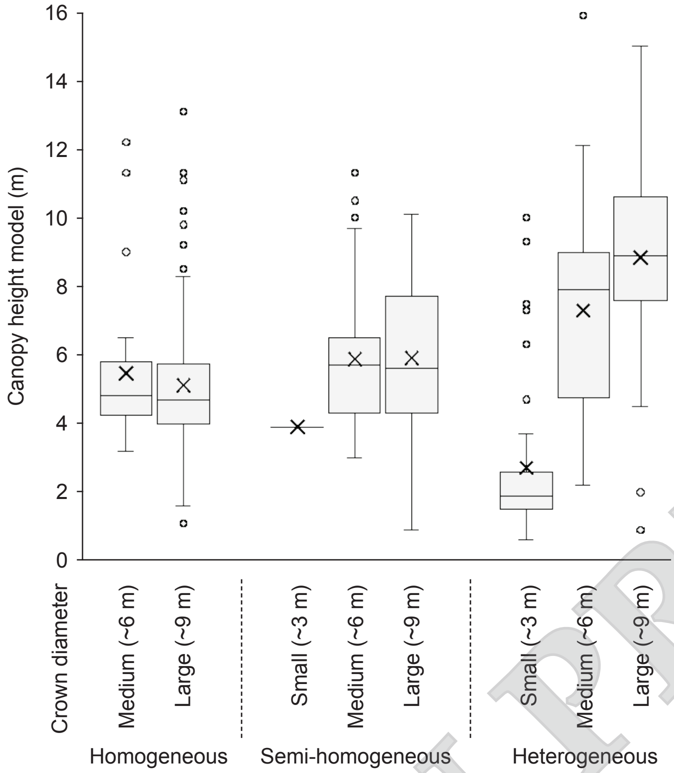

Figure 8. Boxplots showing the value distribution of the canopy height model (CHM) corresponding to crown diameter.

CONCLUSION

The automatic segmentation method using the eCognition OPA software on a homogeneous sample detected 179 objects. In contrast, manual detection found 178 objects, resulting in a difference of only one object. For the semi-homogeneous sample, manual detection identified 186 objects, while the automatic method detected 179 objects, resulting in a difference of seven objects. In the heterogeneous sample, manual detection identified 248 objects, while the automated method detected 243 objects, resulting in a difference of five objects. The detection and collection process were affected by the quality of the aerial photos as well as the variation of land and objects in the data.

Furthermore, the accuracy analysis of the detection and classification process of the data sample showed different results. With the accuracy indicators of precision, recall, and F1-score, the homogeneous sample obtained a precision of 98.8%, a recall of 99.4%, and an F1-score of 99.0%. The semi-homogeneous sample produced a precision of 96.2%, a recall of 100.0%, and an F1-score of 98.0%. In heterogeneous samples, precision reached 98.3%, the recall was 99.5%, and the F1-score was 98.8%.

Additionally, the CHM calculation on a homogeneous sample showed an average of 5.1 m with a standard deviation of 1.8 m. The semi-homogeneous sample had an average of 5.2 m and a standard deviation of 2.0 m. The heterogeneous sample showed an average of 6.9 m with a standard deviation of 3.5 m. The variability of the mean and standard deviation values illustrates the characteristics of each data sample. This study confirms that the application of automatic segmentation and CHM on aerial photographs of direct georeferencing results were successfully implemented.

Overall, this study highlights the effectiveness of direct photogrammetry in detecting and analysing oil palm trees across different plantation environments. However, challenges remain in detecting young palms and addressing positional errors associated with direct georeferencing. Future works should focus on integrating field validation to refine the accuracy of height estimation and comparing the performance of indirect and direct georeferencing to optimise geospatial precision. Expanding the study to more diverse landscapes and incorporating AI-driven analysis could further enhance automated oil palm tree detection, ultimately contributing to improved plantation management and yield predictions.

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