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The Impact of Tree Density on Automated Oil Palm Tree Counting Accuracy

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ABSTRACT

The rapid development of oil palm plantations in Kualuh Leidong Subdistrict, Labuhanbatu Utara District, North Sumatra Province has led to an increased need for effective and efficient monitoring and supervision of oil palm trees. One method that supports such monitoring and supervision is the use of an automatic counting method using orthophoto data. This orthophoto data was used for automatic tree counting using a deep learning method with the Faster R-CNN algorithm. The study considered two planting patterns: regular planting patterns 4 to 9 meters and random planting patterns with varying spacing. Data processing involved an epoch value of 80 and a batch size value of 4. The accuracy of the automatic oil palm tree counting was evaluated based on the density of the spacing between trees with reference to the ground truth. The findings indicated that the deep learning Faster R-CNN algorithm achieved higher accuracy in automatic calculations for regular planting patterns.

Key words: Orthophoto; Automatic oil palm counting; Deep learning; Faster R-CNN

1. Introduction

According to data from the Central Statistics Agency of North Sumatra Province, the area of oil palm plantations in Labuhanbatu Utara Regency from 2019 to 2021 experienced an increase each year (BPS, 2022). Therefore, with the increasing development of oil palm plantation areas in Labuhanbatu Utara Regency, monitoring and supervision of oil palm plantations using the latest technology is needed. One such technology is the use of Unmanned Aerial Vehicles (UAVs). UAVs have high mobility to collect data flexibly without geographical limitations. Photogrammetry using UAVs will produce orthophoto data. Then the orthophoto data is used to automatically count the number of trees using deep learning on the Faster R-CNN algorithm against variations in the spacing between trees. This study uses two planting patterns, namely regular planting patterns and random planting patterns. It uses a deep learning method to evaluate the accuracy of calculating the number of oil palm trees against the density of the spacing between trees using orthophoto data.

The Faster R-CNN algorithm, one of the deep learning algorithms, has been proven to have a better accuracy rate. This study uses the Faster R-CNN algorithm, which is one of the deep learning methods, because based on research conducted by Ammar et al. (2021), the Faster R-CNN algorithm has been proven to have a better accuracy rate than several other methods. The data used in this study is orthophoto data of oil palm trees with regular planting patterns and random planting patterns. In regular planting patterns, the spacing between oil palm trees in one row is around 4 to 9 meters, while for random planting patterns spacing between trees varies. The elevation result based on the density of the spacing between trees will be tested for accuracy with reference to the Ground Truth. The main objective of this applied research activity is to evaluate the accuracy of oil palm trees counting against the density of spacing between oil palm trees, focusing on regular and irregular planting patterns.

Based on the previous explanation, with the increasing development of oil palm plantations in Kualuh Leidong Subdistrict, North Labuhanbatu Regency, North Sumatra Province, monitoring and supervision of oil palm plantations using state-of-the-art technology is required. One such technology is using Unmanned Aerial Vehicles (UAV) and automatic counting of oil palm trees using deep learning methods with the Faster R-CNN algorithm. Deep learning methods were chosen because they can process large amounts of data with high accuracy and have the ability to automatically extract important features from the data used.

1.1. Orthophoto

An orthophoto is a photograph that presents a representation of objects in their correct orthographic position. Geometrically, orthophotos are equivalent to planimetric maps because they display objects in their actual geographic locations. The main difference between orthophotos and maps is that orthophotos consist of feature images, while maps use lines and symbols plotted to scale to represent features (Wolf et al., 2014).

1.2. Deep Learning

Deep learning can implement computational models consisting of multiple processing layers to learn data representations with varying levels of abstraction. This approach can significantly improve capabilities in aspects of speech recognition, visual object recognition, object detection, and various other fields such as drug discovery and genomics. Deep learning can find complex structures in large datasets. Deep learning uses backpropagation algorithms to instruct machines. This algorithm trains the machine to adjust its internal parameters. This adjustment of internal parameters is used to generate the representation of each layer (Lecun et al., 2015).

There are three main methods in deep learning, namely unsupervised, semi-supervised, and supervised (Alzubaidi et al., 2021).

a. Deep Un supervised Learning
This method allows for the learning process to be carried out without labeled data (data that is given information).

b. Deep Semi-supervised Learning
This method uses a partially labeled and partially unlabeled dataset to train a deep learning model.

c. Deep Supervised Learning
This method uses labeled data, which is data that has already been given information or a label that is predicted by the model.

1.3. Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNNs) are a type of deep learning method widely used for image and photo classification (Hemanth & Estrela, 2017). CNNs have an architecture that consists of one input layer and hundreds of feature detection layers. The hidden layer generally contains convolution layers, pooling layers, normalization layers, Rectified Linear Unit (ReLU) layers, fully connected layers, and loss layers (Suyanto et al., 2019).

a. Convolution Layer
Convolution in CNNs is implemented using convolution filters or kernels (Hemanth & Estrela, 2017). Kernels have specific sizes designed to activate specific features in the image. The input data for this operation is called the input feature maps. In the convolution operation, each element in the kernel is multiplied by the corresponding pixel value in the input feature map. The result of this multiplication is then summed to produce a new value.

b. Pooling Layer
The purpose of the pooling operation is to reduce the size of the feature map by using specific functions to perform down sampling. Common functions used are average pooling and max pooling (Hemanth & Estrela, 2017).

c. Fully Connected Layer
The fully connected layer is a layer where all active neurons in the previous layer are connected to neurons in the next layer, resembling an artificial neural network. Each activity in the previous level must be converted into one-way data before being connected to all neurons in the fully connected level. Fully connected layers are generally used for the MLP approach and aim to process data so that it can be categorized. The difference between a fully connected layer and a convolution layer lies in the connectivity of its neurons. In the convolution layer, neurons are only connected to a specific input area, while in the fully connected layer neurons are fully connected (Putra, 2016).

1.4. Faster R-CNN

Object detection is a process that automatically locates and classifies an object (Wu et al., 2020). Based on their operation, there are two types of object detectors: two-stage detectors and one-stage detectors. Faster R-CNN is a two-stage detection system. This system consists of two modules. The first module is a deep fully convolutional network that serves as a proposal generator. This module identifies areas in the image that have the potential to be objects. The second module is the fast R-

CNN detector, which uses the proposals from the first module to perform classification and bounding box regression. These two modules are integrated into a single object detection network.

1.5. Evaluation of Deep Learning Models

In the evaluation of deep learning models, there are several variables involved, namely accuracy and loss. Accuracy represents the percentage of correct predictions for the test data. It is calculated by dividing the number of correct predictions by the total number of predictions. On the other hand, loss is a value that reflects the cumulative error in the model. This loss value is used to determine the accuracy of the results. The model's loss consists of training loss and validation loss (Sornapudi et al., 2018).

Training loss is a measure used to assess the deep learning model based on the training data. This measurement evaluates the model's errors on the training set. The training set is a portion of the dataset used to train a model. Training loss is measured after each training session and visualized with a training loss curve. Validation loss, on the other hand, is a measure used to evaluate the performance of a deep learning model on a validation set. The validation set is a portion of the dataset used to evaluate the model's capabilities. Validation loss is similar to training loss and is calculated based on the errors in each validation set. Validation loss is also measured after each epoch and visualized with a validation loss curve.

There are three possible conditions that can occur: Under-fitting, Over-fitting, and Optimum-fitting (Bashir et al., 2020).

1.6. On Screen Digitization

Digitization is the process of converting data from analog maps (raster data) into digital maps (vector data) performed on-screen on a computer monitor, thereby producing digital maps according to specific requirements. The principle of on-screen digitization involves transforming spatial features from the map into a collection of x,y coordinates. The outcome of on-screen digitization depends on the quality of the data source and the precision of the operator handling it. Accurate results require high-quality analog data sources and operators with high precision (Lens et al., 2014).

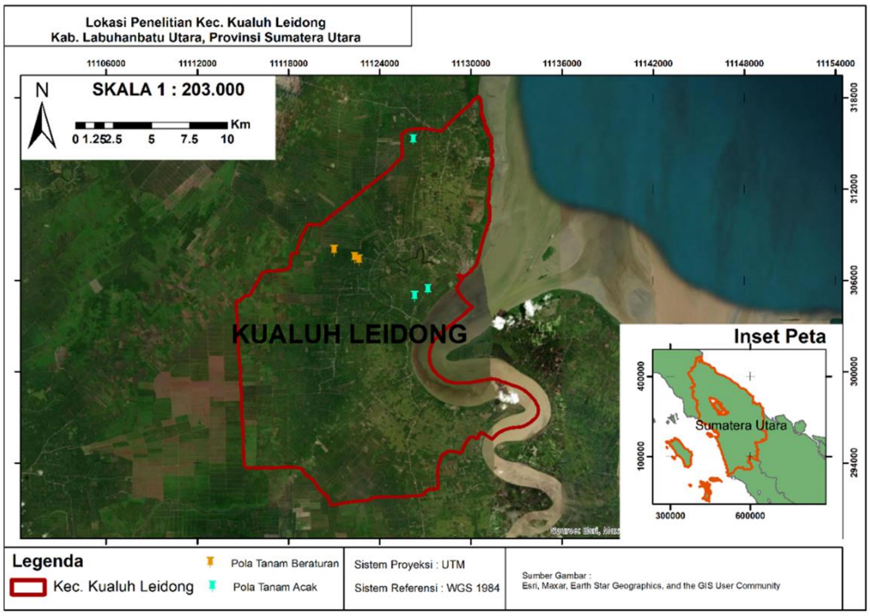


Figure 1. Study Area.

2. Data

2.1. Materials

The materials used in this study are as follows:

a. Aerial photo data of oil palm plantation areas in Kualuh Leidong Subdistrict, Labuhanbatu Utara District, North Sumatra Province, with a flight altitude of 349 m and Ground Sampling Distance (GSD) of 4.27 cm/pixel. The source of data for this research is secondary data obtained from PT. Geo Survey Persada Indonesia in 2022.

b. Geotagging data for aerial photos of oil palm plantations in Kualuh Leidong Subdistrict, Labuhanbatu Utara District, North Sumatra Province, from the results of Post Processing Kinematic (PPK) processing obtained from PT. Geo Survey Persada Indonesia in 2022.

2.2. Equipment

a. Asus A456U laptop used for storing aerial photo acquisition data.
b. Surveying And Mapping Technology Department of Earth Technology Intel Core i9 PC used for aerial photo processing and deep learning method processing for automatic tree counting.
c. Agisoft Metashape Professional software is used to convert aerial photo data into orthophotos.
d. ArcGIS Pro software is used for processing tree counting data using the deep learning method with the Faster R-CNN algorithm and for manual digitization.

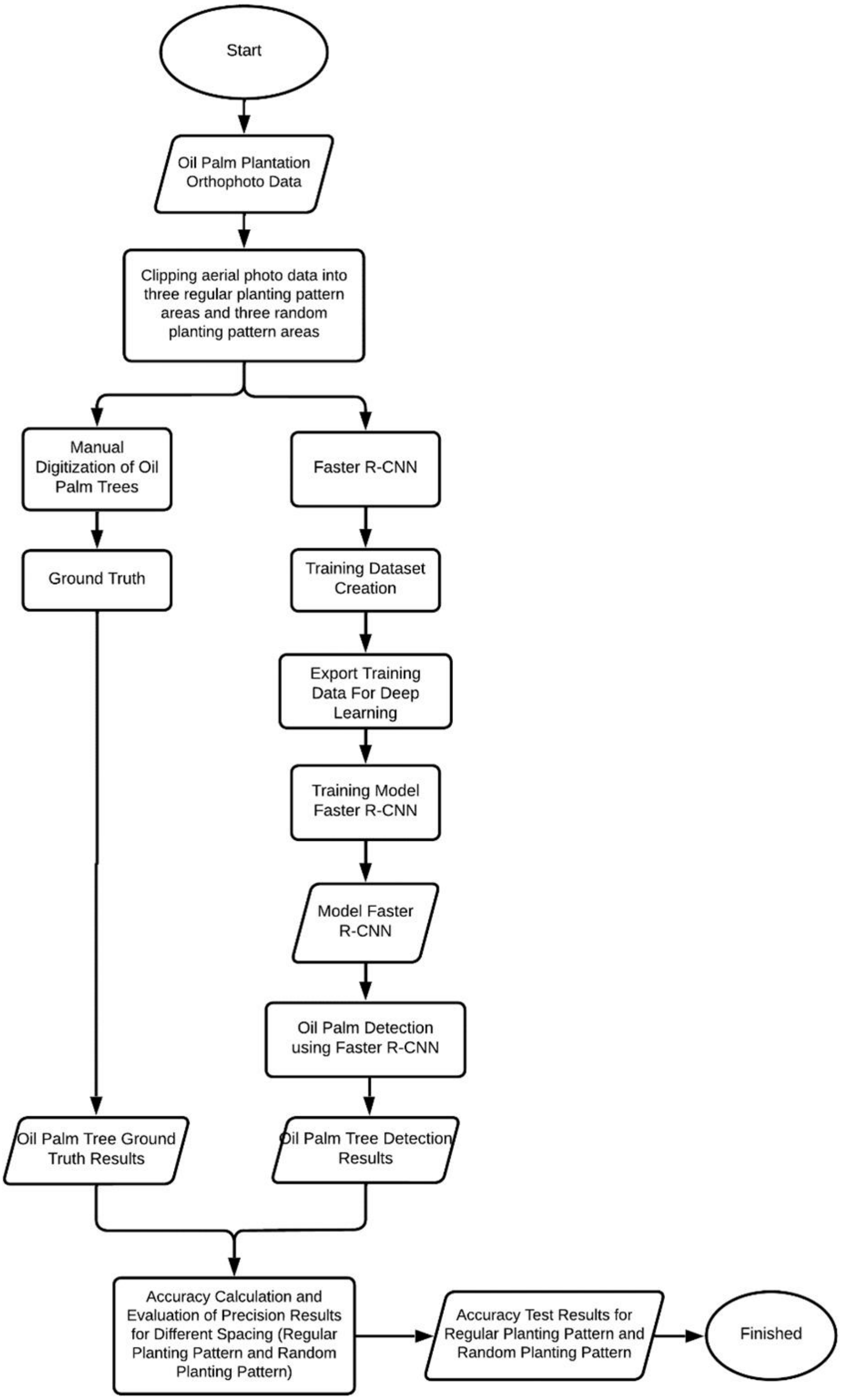


Figure 2. Flowchat of Implemention.

2.3. Study Area

The study area is in Kualuh Leidong Subdistrict, Labuhanbatu Utara District, North Sumatra Province, as shown in Figure 1. The area of the research area for regular planting patterns is around 25 hectares, and for irregular planting patterns, it is around 25 hectares, with each planting pattern having three research areas.

3. Method

The flowchart of implementation involves collecting aerial photo data, processing orthophoto data, processing data using the deep learning method with the Faster R-CNN algorithm, performing accuracy tests of automatic counting results against ground truth, and evaluating accuracy test results against the density of spacing between oil palm trees based on data processing results. The research flowchart is shown in Figure 2.

The orthophoto data of oil palm trees are cut based on its pattern, namely regular planting pattern and random planting pattern. The regular planting pattern and random planting pattern have an area of 25 hectares each with each pattern having three areas. Then manual digitization is carried out on three areas of regular planting patterns and three areas of random planting patterns. This manual digitization will produce data as Ground Truth. The next step is to perform automatic calculations using deep learning. The stages of this automatic calculation consist of creating samples that are used as training sample data, then processing the training model using the Faster R-CNN algorithm using the training sample data used to detect oil palm trees using deep learning. After obtaining the oil palm tree detection results, the next step is to evaluate and test the accuracy using the equations namely Detection Percentage (DP) and Branch Factor (BF) proposed by Lin & Nevatia, (1998). Detection Percentage (DP) describes how many oil palm trees are correctly detected by automatic counting. Branch Factor (BF) describes how many oil palm trees are incorrectly detected by automatic counting.

An example of an equation can be seen in equation (1) and (2) below.

$$DP = \frac{100xTP}{TP + TN} \tag{1}$$

$$BF = \frac{100xFP}{TP + FP} \tag{2}$$

Description:

TP: True Positive, is an oil palm tree that is correctly detected by visual interpretation and correctly detected by automatic counting.
TN: True Negative, is an oil palm tree that is correctly detected by visual interpretation but not correctly detected by automatic counting.
FP: False Positive, is an oil palm tree that is correctly detected by automatic counting but not correctly detected by visual interpretation.

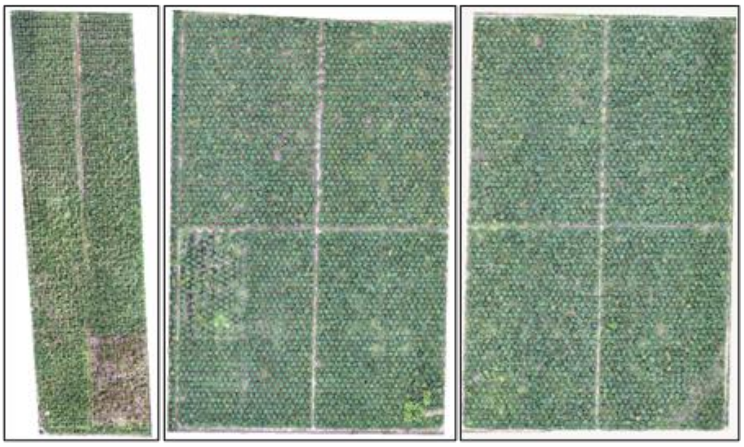
4. Result and Discussion

4.1. Processed Aerial Photo Results

The processing of aerial photos using Agisoft Metashape Professional software from 3804 total aerial photos resulted in orthophotos with a flight altitude of 349 m and a GSD of 4.27 cm/pixel, so the size of the smallest pixel that can be identified is 4.27 cm per pixel. The reference system used is WGS 1984, while the projection system is Universal Transverse Mercator (UTM) with zone 47N which is adjusted to the research area. After being processed, the orthophotos are then cut according to the regular planting pattern and random planting pattern with a size of 25 hectares each area. Here is one of the orthophotos from the regular planting pattern and random planting pattern shown in Figure 3.

4.2. Manual Oil Palm Tree Counting Results

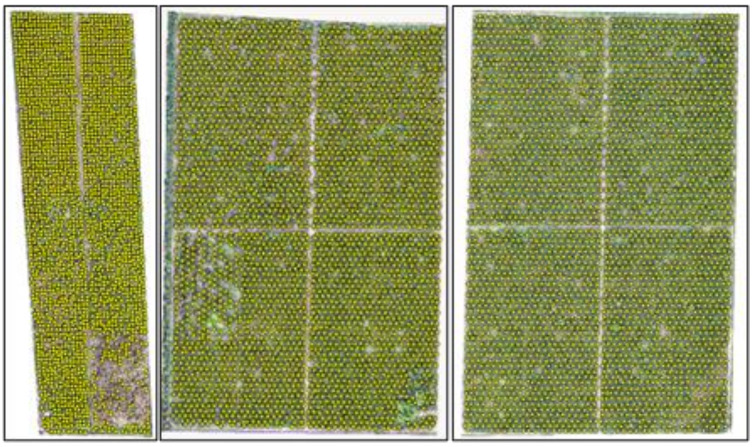
Oil palm trees were counted manually using the on-screen digitization method with visual interpretation using ArcGIS Pro software. The results of this manual calculation are used as ground truth data with the assumption that the number is close to the real conditions in the field. This manual digitization method requires researchers to be able to identify each oil palm tree correctly. Oil palm trees have several distinctive characteristics based on visual interpretation, namely spatial characteristics such as colour tone, shape, and size. The colour tone of oil palm trees is dark green, with a crown-shaped canopy and sizes that can be the same or different. When digitizing, researchers must be careful to distinguish oil palm trees from other plants. Here is one of the orthophotos when counting oil palm trees manually shown in Figure 4.



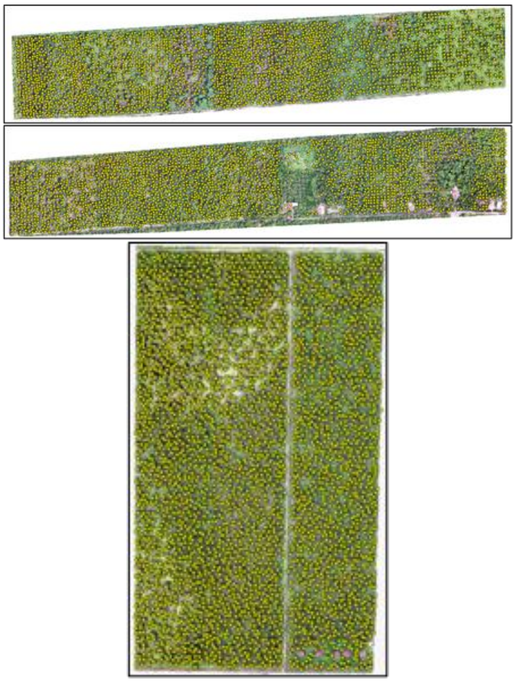
a

b

Figure 3. (a). Clipped orthophoto regular planting pattern (b). Clipped orthophoto random planting pattern



a



b

Figure 4. (a) Manual digitation regular planting pattern (b) Manual digitation random planting

4.3. Automatic Oil Palm Tree Counting Results Using the Faster R-CNN Algorithm

The automatic calculation of oil palm trees involves two sampling patterns: regular planting pattern and random planting pattern. These two planting patterns have significant differences in tree density, which results in different accuracy values. The automatic oil palm tree counting process goes through several stages, including creating a training dataset using the export training data for deep learning tools, creating a training model using the train deep learning model tools, and the final stage is to detect oil palm tree objects using the detect object using deep learning tools.

4.3.1. Regular Planting Pattern

The regular planting pattern has three research areas with an area of each area of about 25 hectares and sets the parameter for the number of epochs to 80 epochs and the number of batch sizes to 4 batch sizes. For more details, see Table 1.

Table 1. Number of epochs per research location

No	Location	Area (Ha)	Number of Epoch	Number of Batch Size	Early Stopping in Epoch
1.	Area 1	25,34	80	4	18
2.	Area 2	25,42	80	4	17
3.	Area 3	24,82	80	4	23

In the processing of automatic detection in the regular planting pattern, the amount of training data used as training samples has a different number for each research area, and the time required to process each area is also different. For more details, see Table 2.

Table 2. Results of automatic detection processing

No	Location	Area (Ha)	Number of Ground Truth	Number of Prediction	Number of Training Data	Model Training Time	Object Detection Time
1.	Area 1	25,34	2604	2388	776	59 min 23 sec	49 min 20 Sec
2.	Area 2	25,42	3293	3192	917	41 min 21 sec	32 min 42 Sec
3.	Area 3	24,82	3174	3144	856	51 min 41 sec	42 min 41 Sec

Based on Table 2, the number of training data samples and the results and prediction results for oil palm trees do not affect the time obtained for training the model or the detection object time. This can be proven in the first research area which has a longer time than the second and third research areas.

The next step is to perform the accuracy test. This stage consists of two stages, the first stage is to count or check the oil palm trees according to their classification and the second stage is to evaluate and test the accuracy.

1. Counting Oil Palm Trees According to Classification

There are three provisions when checking the oil palm trees. The first is True Positive (TP), which is the condition of oil palm trees that are correctly identified by visual interpretation and correctly identified by automatic calculation results. The second is True Negative (TN), which is the condition of oil palm trees that are correctly identified by visual interpretation but not correctly identified by automatic calculation. The third is False Positive (FP), which is the condition of oil palm trees that are correctly identified by automatic calculation but not correctly identified by visual interpretation. The results of calculating or checking oil palm trees can be presented in Table 3.

Table 3. Results of oil palm tree verification

No	Location	Area (Ha)	Ground Truth	TP	TN	FP
1.	Area 1	25,34	2604	2251	353	137
2.	Area 2	25,42	3293	3176	117	16
3.	Area 3	24,82	3174	3110	64	34

2. Accuracy Testing

The accuracy test calculation is based on equations (1) and (2). The results of calculating the accuracy for the regular planting pattern can be presented in Table 4.

Table 4. Results of accuracy test calculation

No	Location	Type of Plant	Ground Truth	Distance between Trees	DP (%)	BF (%)
1	Area 1	Oil Palm Tree	2604	4-9 meter	86,444%	5,737%
2	Area 2	Oil Palm Tree	3293	7-9 meter	96,447%	0,501%
3	Area 3	Oil Palm Tree	3174	7-9 meter	97,984%	1,081%
		Total	9071	**Average**	93,625%	2,440%

Based on Table 4, the DP value in the first area is lower than in the second and third areas. Based on observations with visual interpretation, in the first area there are many plants or trees other than oil palm trees. This causes plants or trees other than oil palms to overlap with oil palm trees and in some areas, there are also oil palm trees that overlap. The condition of the trees overlapping each other is because the spacing between trees is too close, namely around 4 meters. Although the first area is a regular planting pattern area, the conditions that have been mentioned can cause the resulting DP value to be lower.

The BF value in the first area is higher than in the second and third areas. Based on observations carried out with visual interpretation, because in the first area there are many plants or trees other than oil palm trees, this can affect the results of automatic object detection. There are several other plants or trees besides oil palm trees that are also detected by automatic detection, for example coconut trees that are visually slightly similar to oil palm trees from above. This is what causes the BF value in the first area to be larger than the second and third areas.

4.3.2. Random Planting Pattern

The random planting pattern has three research areas with an area of each area of about 25 hectares and sets the parameter for the number of epochs to 80 epochs and the number of batch sizes to 4 batch sizes. For more details, see Table 5.

Table 5. Number of epochs per research location

No	Location	Area (Ha)	Number of Epoch	Number of Batch Size	Early Stopping in Epoch
1.	Area 1	25,76	80	4	37
2.	Area 2	25,35	80	4	24
3.	Area 3	25,41	80	4	14

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In the processing of automatic detection in the random planting pattern, the amount of training data used as training samples has a different number for each research area, and the time required to process each area is also different. For more details, see Table 6.

Table 6. Results of automatic detection processing

No	Location	Area (Ha)	Number of Ground Truth	Number of Prediction	Number of Training Data	Model Training Time	Object Detection Time
1.	Area 1	25,76	4093	2606	707	1 hour 42 minute and 24 second	1 hour 03 minute and 57 second
2.	Area 2	25,35	2868	2284	757	1 hour 36 minute and 13 second	1 hour 09 minute and 15 second
3.	Area 3	25,41	3968	3074	885	54 minute 09 second	40 minute 51 second

Based on Table 6, the number of training data samples and the results and prediction results for oil palm trees do not affect the time obtained for training the model or the detection object time. This can be proven in the third research area which has a longer time than the first and second research areas.

The next step is to perform accuracy testing. This stage consists of two stages, the first stage is to calculate or check the oil palm trees according to their classification and the second stage is to evaluate and test the accuracy.

1. Counting Oil Palm Trees According to Classification

There are several classifications when counting oil palm trees as explained earlier, there are three classifications namely True Positive (TP), True Negative (TN), and False Positive (FP). The results can be presented in Table 7.

Table 7. Results of oil palm tree verification

No	Location	Area (Ha)	Ground Truth	TP	TN	FP
1.	Area 1	25,76	4093	2592	1501	14
2.	Area 2	25,35	2868	2188	680	96
3.	Area 3	25,41	3968	3073	895	1

2. Accuracy Test

The second stage is the accuracy test. The accuracy test is carried out using equations (1) and (2). The results of calculating the accuracy test for the random planting pattern can be presented in Table 8.

Table 8. Results of accuracy test calculation

No	Location	Type of Plant	Ground Truth	Distance between Trees	DP (%)	BF (%)
1	Area 1	Oil Palm Tree	4093	Varies between Min 3 m Max 36 m	63,328%	0,537%
2	Area 2	Oil Palm Tree	2868	Varies between Min 3 m Max 36 m	76,290%	4,203%
3	Area 3	Oil Palm Tree	3968	Varies between Min 3 m Max 36 m	77,445%	0,033%
		Total	9071	**Average**	10929	2,440%

Based on Table 8, it can be observed that the first area has a lower DP value than the second and third areas. According to visual interpretation observations, the first area has a dense planting distance between trees, resulting in many overlapping oil palm trees. This condition is spread over several areas in the first area with a minimum distance between trees of around 3 meters. This can cause the automatic calculation results to be less accurate because there are many oil palm trees that are not detected due to overlapping oil palm trees. Therefore, the DP value of the first area is lower than the second and third areas.

The BF value in the second area has a higher value than the first and third areas. Based on visual interpretation observations, the second area has a diversity of plant types other than oil palm trees, and there are other variables such as buildings. Buildings in the second area are also detected by automatic calculation. This is what causes the BF value in the second area to be higher.

4.4. Object Detection Errors

Object detection errors in oil palm trees occur because the automatic calculation using deep learning with the Faster R-CNN algorithm does not detect oil palm trees accurately. This is influenced by several factors, such as the diversity of other types of plants or trees besides oil palm trees, the planting distance between oil palm trees that are too close so that the oil palm trees overlap, the different age ranges of oil palm trees, and other variables such as buildings that are also detected. The following are examples of object detection errors.

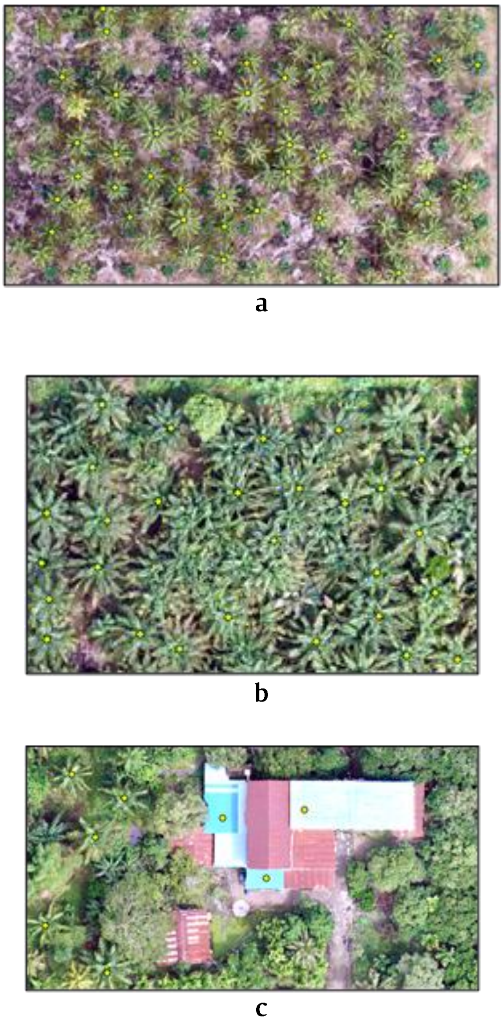

Figure 5. Various object detection errors in the research area

5. CONCLUSION

The results of the evaluation and accuracy test of automatic oil palm tree counting in regular planting patterns have an average Detection Percentage (DP) of 93.625% and a Branch Factor (BF) of 2.440%, while for random planting patterns, the average DP is 72.354% and BF is 1.591%. These results show that automatic calculation using the deep learning method with the Faster R-CNN algorithm has a higher accuracy value in regular planting patterns.

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