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Classification of crown density and foliage transparency scale for broadleaf tree using VGG-16

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ABSTRACT

Crown density and foliage transparency are important parameters for tree crown conditions. Previously, observers had performed crown density and foliage transparency assessments manually, which could be a less efficient process. This research aims to use the VGG-16 deep learning architecture to classify the density and transparency of broadleaf tree crowns. In this study, crown data sets for broadleaves trees were collected for four types of broadleaves tree: cacao (theobroma cacao), durian (durio zibethinus), rubber (havea brasiliensis), candlenut (aleurites moluccana); then the data is labeled based on the crown density and foliage transparency scale card. Research applies resize and augmentation preprocessing. The model training process uses a scenario of 80% train data, 10% test data, and 10% validation data. After training using the VGG-16 model, the test results showed impressive accuracy, with the highest accuracy reaching 98.40% for candlenut trees, rubber (96.00%), cacao (92.00%), and durian (86.60%). This research shows quite good results in classifying the scale of crown density and foliage transparency with four types of broadleaves tree (cacao, durian, rubber, and candlenut) using VGG-16.

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1. INTRODUCTION

Conservation forests encompass areas with distinct characteristics and a primary goal of preserving diverse plant and animal species and their ecosystems [1]. The characteristic of healthy forests is their ability to maintain ecosystem balance and fulfil human needs [1]. The evaluation of forest health involves the application of Forest Health Monitoring (FHM), which incorporates various indicators, including the vitality indicator with parameters to assess the condition of the crown [2]. Assessment of crown condition consists of five parameters, two of which are crown density and foliage transparency [3]. A forest is healthy if the crown density is 55% or higher and the transparency level is between 0 and 45% [4]. This assessment is based on a crown density and foliage transparency scale card, which assesses the percentage of sunlight reaching the forest floor [5]. The manual measurement of crown density and foliage transparency is carried out by an observer positioned below the tree being assessed. This assessment is carried out for all types of tree, including broadleaves tree. The broadleaves have large and round crowns, hard woody trunks, and wide leaf shapes [6]. Manual crown density and foliage transparency measurements tend to be less effective because the assessment uses the observer's visual vision. This can be overcome by using technology that can manage digital images, one of which is deep learning.

Deep learning is a discipline in machine learning that can be implemented to classify objects [7]–[10]. A deep learning algorithm that can be used for image recognition is a convolutional neural network (CNN) [11]–[13]. The basic concept of CNN is inspired by how the human brain processes image information. Visual Geometric Group (VGG-16) is a CNN architecture that shows significant results for image classification problems [14], [15]. VGG-16 is a CNN architecture that consists of sixteen layers, including 13 convolutional layers with a kernel size of 3x3 and three fully connected layers [16].

Research on VGG-16 was carried out to identify diseases in sugarcane leaves. This research used a dataset downloaded from the Kaggle platform, with 864 images of sugarcane leaves classified as healthy or diseased. During the research, the data were devided into three segments: 80% of the data was used to train the model, 10% for validation, and the remaining 10% for model testing. The research results showed that the accuracy level reached 98%, with a precision level of 100%, a recall of 97% and an F1 value of 98% [17].

Another study utilizing the VGG-16 architecture aimed to classify diseases in grape leaf images into four classes: black measles, leaf spot, healthy leaves, and leaf blight. The study achieved an accuracy of 97.25% using test data obtained from the grape leaf dataset and 95% test data obtained from outside the grape leaf dataset [18].

In addition to images of grape leaves and sugar cane leaves, research on coffee leaf diseases has also been carried out using the VGG-16 architecture. This research encompassed four data splitting scenarios, where the best results were obtained in the last scenario, namely 60:40, with an accuracy of 89% in the training data and 95% in the validation data [19].

The VGG-16 architecture has been used to detect individual tree species. This study performed a comparative analysis of accuracy results between VGG-16, random forest, and gradient boosting. The results of this research show that the VGG-16 architecture has superior accuracy compared to the random forest and gradient boosting, where the accuracy of VGG-16 is 92.13%, while random forest have an accuracy of 83.57% and gradient boosting is 80.12% [20].

Research related to crown density and foliage transparency was carried out in the Wan Abdul Rachman Forest Park (Tahura WAR) by Pertiwi in 2020 to assess the forest health condition. The research stated that up to 25% (2 cluster plots) were in a good category, 38% (3 cluster plots) were in a good category, 12% (1 cluster plot) were in the medium category and 25% (2 cluster plots) were classified as very poor [21].

Research on crown density and foliage transparency using deep learning has yet to be previously explored. In the field of flora, particularly employing the VGG-16 architecture, deep learning has focused primarily on plant objects such as leaves for disease identification and trees for detecting individual tree species. This study is motivated by the absence of such investigations and aims to classify the crown density and foliage transparency scales for four different types of broadleaf trees. The classification is based on a crown density-foliage transparency scale card, encompassing 10 classes from 5% to 95%, with a 10% interval. This research is expected to contribute to facilitating the measurement process and improve accuracy in evaluating crown density and foliage transparency.

2. METHOD

The procedures of this research involve a sequence of organized and deliberate processes designed to achieve the research objectives. The steps described, illustrated in Figure 1, were implemented for this research.

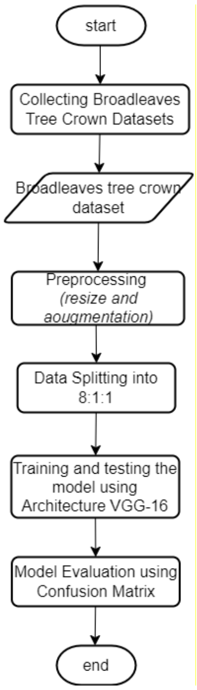

Figure 1. Research method

Based on Figure 1, the first stage of this research was collecting the broadleafe tree crown dataset. In this case, four types of broadleaf tree are used: cacao tree, durian tree, rubber tree, and candlenut tree. After the images have been collected, label the images into 10 classes of crown density and foliage transparency. The next stage is preprocessing with resizing and augmentation before training the model. After the preparation of the data set, the next step is to train the model. This research proposes the VGG-16 architecture for training and building models. The final stage is to evaluate the model using a confusion matrix.

Collecting Broadleaf Tree Crown Dataset

Collecting broadleaves tree crown datasets is the first step in the research. Because the broadleaves tree crown dataset was unavailable online, we took an image of the crown, which became our data set. The image of the crown of the broadleaf tree was obtained from the traditional block and candlenut plantation of Tahura WAR, Kemiling, Bandar Lampung. Images of broadleaves trees are taken when light can penetrate the forest floor. The image of the crown of the broadleaf tree was obtained by taking an image of the crown from below and a distance of 10-20 cm from the trunk for all four sides of the tree. After collecting the data set, the label was carried out according to the type of tree and a crown density and foliage transparency scale card, which has 10 scale levels, as shown in Figure 2.

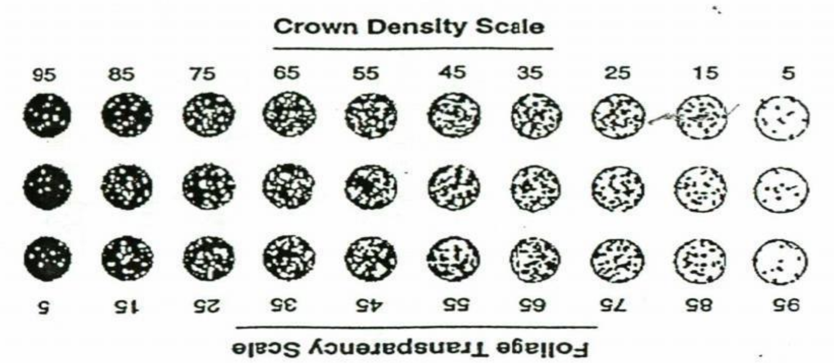

Figure 2. Crown density and foliage transparency scale card

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The broadleaf tree crown images were then grouped according to each type of tree(cacao tree durian tree, rubber tree, and candlenut tree), and labeling was carried out on each image. After being labeled, the results will be verified manually by 15 respondents. The respondents in this study consisted of five students from the Computer Science Department who participated in forest health research and 10 students from the Forestry Department. These respondents are needed to ensure that the images have been grouped into the correct classes. This is done to determine the correct label for each image based on the majority vote of the respondents. The results of this stage are four broadleaves tree crown datasets with a total of 2557 crown images, as shown in Table 1.

Table 1. Results of determining broadleaves tree crown image labels

Crown Density and Foliage Transparency Class	Broadleaf tree types			
	Cacao	Durian	Rubber	Candlenut
CD5_FT95	32	41	78	100
CD15_FT85	14	33	69	88
CD25_FT75	14	60	75	62
CD35_FT65	17	40	62	98
CD45_FT55	7	100	48	80
CD55_FT45	15	92	35	99
CD65_FT35	45	100	60	100
CD75_FT25	100	100	15	100
CD85_FT15	90	100	23	100
CD95_FT5	58	100	7	100
Total for each types of tree	392	766	472	927
Total	2557			

notes:
CD = crown density
FT = foliage transparency

The metric CD, which denotes the density of the crown, serves as an indicator of the biomass of the crown, representing the volume of all components within the crown, including the foliage, branches, and reproductive structures [22]. Canopy transparency, which indicates the amount of sunlight reaching the forest floor, is expressed as FT (Foliage Transparency) [23].

Preprocessing and Data Splitting

Pre-processing is a stage designed to prepare data before model training to improve model performance [24]. The applied pre-processing techniques include resizing and augmentation. We carry out the augmentation process to increase the number of datasets and reduce overfitting [25]. The addition of data sets is implemented to improve the network's classification capability of the network [26]. Initial preprocessing involves resizing, reducing the image size from its original 1600x1600 pixels to 224x224 pixels [17]. Later, augmentation is applied to the images, involving rescaling by a factor of 1/225, horizontal and vertical flips, random rotation within a range of 25 ° (both maximum and minimum) [26], zooming in at 0.8 [27], adjusting brightness upward within the range of 1.0 to 1.5, and decreasing brightness to 0.8 [28]. The augmentation process will increase the number of images to 5000 for each tree type.

We perform data splitting by dividing the dataset into three subsets: training data, testing data, and validation data. Training data are employed for the model training process, testing data is utilized to assess the model's performance, and the validation data is instrumental in mitigating overfitting during the model validation phase. The data splitting ratio used in this research is 80% training data, 10% test data, and 10% training data [17], [28].

Deep Learning Architecture VGG-16

Visual Geometry Group (VGG-16) is an AlexNet that has undergone modifications to the convolution filter, where the filter used is 3x3 smaller than the 5x5 or 11x11 filters [9]. AlexNet is a groundbreaking deep neural network developed in 2012 for image classification and won the ImageNet LSFRC-2010 competition with 62 million trainable parameters [29]. The VGG-16 architecture has more parameters and network depth than AlexNet, with 138 million parameters. VGG-16 is faster in training than AlexNet because it has implicit regularization. Implicit regularization is caused by greater depth and smaller convolution filters, so the network can generalize better from training data to test data [30].

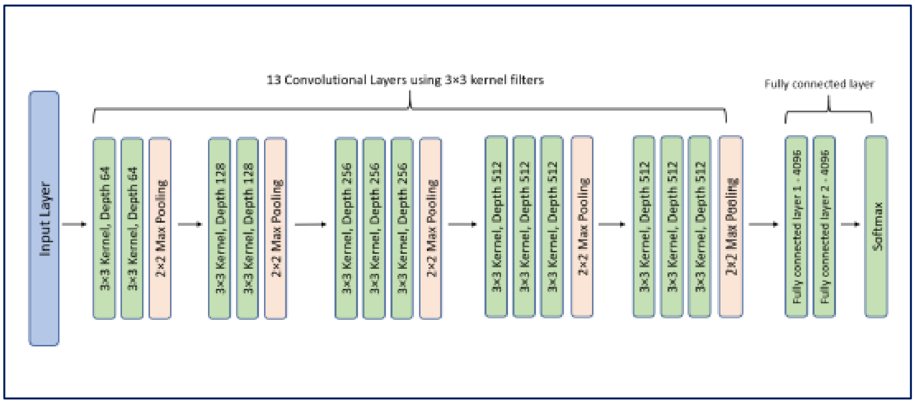


Figure 3. Visual geometry group (VGG-16) architecture

The VGG-16 architecture consists of 13 convolution layers, five pooling layers, two fully connected layers, and one output layer, as shown in Figure 3 [16]. The VGG-16 model training process involves the utilization of training data and hyperparameters to enhance model performance. These hyperparameters encompass the epoch, batch size, optimizer, and learning rate.

The broadleaves tree crown dataset comprises 5000 images for each tree type, with 500 images per class. Consequently, the cumulative images for the four broadleaf tree crown datasets amount to 20,000. The selected tree species include cacao, durian, rubber, and candlenut, each exhibiting distinct characteristics. Therefore, different hyperparameter configurations are required to achieve the best accuracy. The epoch hyperparameter uses the early stopping callback function. To streamline the training process, we implement early stopping, which discontinues model training upon a decline in performance in the validation dataset.

Table 2. The structure of the VGG-16 model for broadleaves tree

VGG-16 Model Structure of Broadleaf Tree			
Cacao	Durian	Rubber	Candlenut
Input Layer	Input Layer	Input Layer	Input Layer
Conv2D	Conv2D	Conv2D	Conv2D
MaxPooling2D	MaxPooling2D	MaxPooling2D	MaxPooling2D
Flatten	Flatten	Flatten	Flatten
Dense (10)	Dropout (0,4)	Dropout (0,2)	Dense (10)
	Dense (10)	Dense (10)	

Table 2 presents the architecture of the VGG-16 model applied for the broadleaves tree, specifically the VGG-16 base model (input layer, Conv2D and MaxPooling2D) with the addition of flatten layer and dense layers with units of 10 that adjust the number of classes on the crown density-foliage transparency scale cards. Nevertheless, there are subtle divergences in the structure of the VGG-16 model for the four distinct types of broadleaves tree. Durian and rubber trees use dropout layers of 0.4 and 0.2 to help increase model accuracy and reduce overfitting by randomly ignoring some units in each training epoch [31]. In addition to the structure of the VGG-16 model, the combination of hyperparameters in the four types of trees also has slight differences. Hyperparameters applied to four types of broadleaves tree can be seen in Table 3.

Table 3. Hyperparameters of the VGG-16 model for broadleaves tree [32]

Hyperparameter	Broadleaves tree types			
	Cacao	Durian	Rubber	Candlenut
Epoch	31	13	11	35
Batch Size	32	32	32	64
Learning Rate	0,0001	0,0001	0.0001	0,001
Optimizer	Adam	Adam	Adam	Adam

The training of the VGG-16 model initially set epochs at 100, but the early stop function with patience 4 stopped the training process when the model did not show a significant increase for 4 consecutive epochs.

Model Evaluate

Evaluation of the VGG-16 deep learning model involves the use of two key metrics: the Confusion Matrix and the classification report. The confusion matrix assesses true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), providing insight into the model's classification accuracy. Meanwhile, the classification report further explores, offering information on precision, recall, F1 score, and accuracy, contributing to a comprehensive understanding of the effectiveness [33]. This section explains accuracy, precision, recall, and F1-score [34], [35].

The accuracy value is obtained by dividing the true positive classifications by the total number of samples in the test data. The accuracy value is calculated using Equation 1.

$$\text{Accuracy} = \frac{\text{TP}}{n_{\text{samples}}} \tag{1}$$

Precision can be interpreted as the relevance between the requested information and the response to that request. The precision is formulated as in Equation 2.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{2}$$

Recall measures the model's ability to detect true classes predicted as other classes or the true class predicted correctly. The recall value is formulated as in Equation 3.

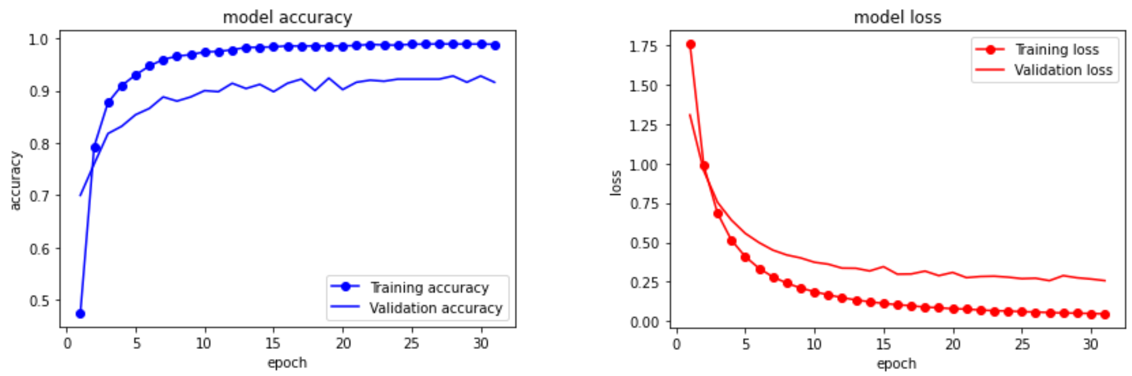
$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{3}$$

The F1-score is the average value of recall and precision. The f1-score value is formulated as in Equation 4.

$$\text{F1-Score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall+Precision}} \tag{4}$$

3. RESULTS AND DISCUSSIONS

VGG-16 Model Evaluate For Cacao Tree



(a) (b)

Figure 2. (a) accuracy and (b) loss VGG-16 model for cacao tree

The VGG-16 model for cacao trees, trained on the Tesla K80 machine, exhibits an accuracy of 93.40% and a loss of 26.93%. The accuracy and loss trends for the cacao tree model during training and validation are illustrated in Figures 4a and 4b, respectively. Figure 4a indicates a relatively stable accuracy trend, with no significant variations observed from the first to the 32nd epoch. In Figure 4b, the loss value shows a decreasing trend over the same epoch range, signifying a reasonably stable reduction in loss, particularly in the training phase.

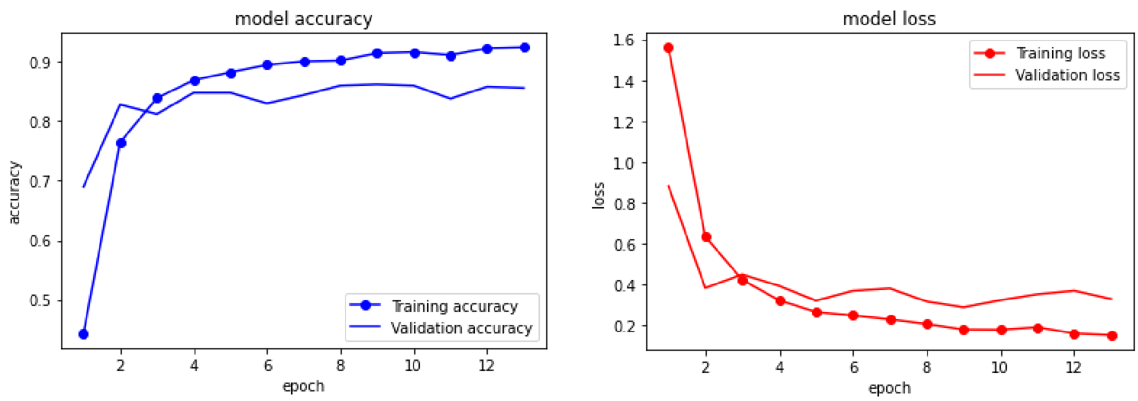
The test results for the VGG-16 cacao tree model have an accuracy of 92.00%. Performance metrics, including accuracy, precision, recall, and F1 score, were computed based on the confusion matrix to assess the predictive accuracy. Table 4 provides a detailed breakdown of the accuracy, precision, recall, and F1-score values for the VGG-16 cacao tree model.

Table 4. Results of the VGG-16 model for the cacao tree

Class	Precision	Recall	F1-score
CD5_FT95	83,02%	88,00%	85,44%
CD15_FT85	90,91%	80,00%	85,11%
CD25_FT75	92,31%	96,00%	94,12%
CD35_FT65	100,00%	98,00%	98,99%
CD45_FT55	96,00%	96,00%	96,00%
CD55_FT45	88,46%	92,00%	90,20%
CD65_FT35	95,83%	92,00%	93,88%
CD75_FT25	87,27%	96,00%	91,43%
CD85_FT15	91,30%	84,00%	87,50%
CD95_FT5	96,08%	98,00%	97,03%
Macro Average	92,12%	92,00%	91,97%
Accuracy		92,00%	
Error		8,00%	

According to Table 4, implementing the VGG-16 model on cacao trees, using a specific set of hyperparameters, gives quite good results in classifying the images of the crown of cacao trees into crown density and foliage transparency classes. This result is indicated by an accuracy value of 92%, average precision of 92.12%, average recall of 92%, f1-score value of 91.97%, and error of 8%.

VGG-16 Model Evaluate for Durian Tree



(a) (b)

Figure 3. (a) accuracy and (b) VGG-16 loss model for durian tree

The training process of the VGG-16 model for durian trees resulted in an accuracy of 86.20% and a loss of 28.78. The progression of the accuracy of the model during the training and validation stages is depicted in Figure 5a. Training accuracy exhibited an incremental trend with occasional minor fluctuations, notably in the 11th epoch, where a slight decrease occurred. On the contrary, the movement of the validation accuracy graph fluctuated quite a bit at each epoch. Figure 5b illustrates the loss of the VGG-16 durian tree model during the training and validation stages. Both training and validation loss values experienced a reduction, demonstrating a tendency to stabilize at each epoch. The test results for the VGG-16 model for durian trees resulted in an accuracy of 86.60%. The accuracy, precision, recall and f1-score values obtained from the confusion matrix for the VGG-16 model for classifying durian tree crown density and foliage transparency can be seen in Table 5.

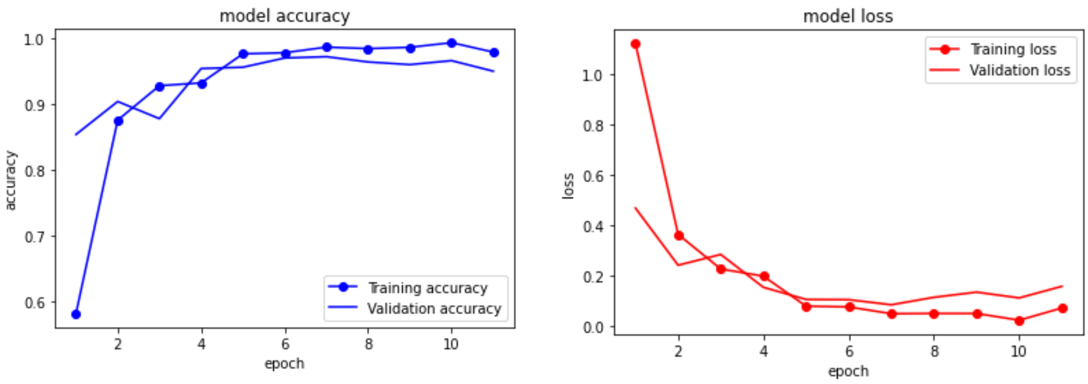
Table 5. Results of the VGG-16 model for durian tree

Class	Precision	Recall	F1-score
CD5_FT95	100,00%	98,00%	98,99%
CD15_FT85	47,62%	40,00%	43,48%
CD25_FT75	45,61%	52,00%	48,60%
CD35_FT65	98,00%	98,00%	98,00%
CD45_FT55	97,96%	96,00%	96,97%
CD55_FT45	98,00%	98,00%	98,00%
CD65_FT35	100,00%	94,00%	96,91%
CD75_FT25	89,09%	98,00%	93,33%
CD85_FT15	95,83%	92,00%	93,88%

Class	Precision	Recall	F1-score
CD95_FT5	94,34%	100,00%	97,09%
Macro Average	86,65%	86,60%	86,52%
Accuracy		86,60%	
Error		13,40%	

Based on Table 5, the VGG-16 model applied to durian trees, using a combination of hyperparameters, exhibits favorable results in classifying durian tree crown images into crown density and foliage transparency classes, except for the CD15_FT85 and CD25_FT75 classes. These two classes show lower precision, recall, and f1-score values due to the higher number of errors in class classification. This can be caused by similar characteristics in the CD15_FT85 and CD25_FT75 classes or by errors during the data labeling process. The VGG-16 model for durian trees achieved an accuracy value of 86.60%, an average precision of 86.65%, an average recall of 86.60%, an f1-score of 86.52%, and an error rate of 13.40%.

VGG-16 Model Evaluate for Rubber Tree



(a) (b)

Figure 4. (a) accuracy and (b) VGG-16 loss model for rubber tree

The training phase for rubber trees yielded an accuracy of 97.30% and a loss value of 8.33%, as illustrated in Figure 6. Figure 6a is a graph of model accuracy with training and test data. The graph shows movement that was less stable at the beginning of the epoch but after the fourth epoch, it was stable at a value of 0.9. Figure 6b illustrates the loss graph during the training phase of the rubber tree VGG-16 model, with a significant decrease in loss values observed in the second epoch and relative stability after that.

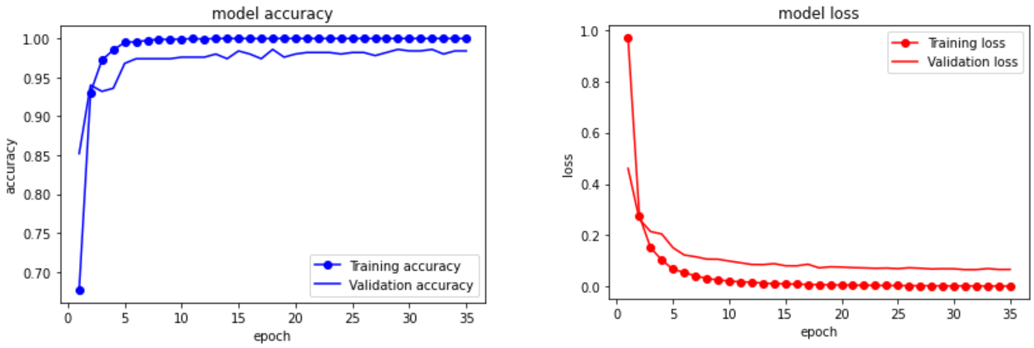
Evaluation of the VGG-16 model for rubber trees through testing resulted in a test accuracy of 96.20%. The corresponding accuracy, precision, recall, and f1-score values obtained from the confusion matrix for the VGG-16 model in the classification of rubber tree crown density and foliage transparency are detailed in Table 6.

Table 6. Results of the VGG-16 model for rubber tree

Class	Precision	Recall	F1-score
CD5_FT95	97,83%	90,00%	93,75%
CD15_FT85	92,45%	98,00%	95,15%
CD25_FT75	95,74%	90,00%	92,78%
CD35_FT65	96,00%	96,00%	96,00%
CD45_FT55	90,91%	100,00%	95,24%
CD55_FT45	96,15%	100,00%	98,04%
CD65_FT35	100,00%	92,00%	95,83%
CD75_FT25	96,15%	100,00%	98,04%
CD85_FT15	98,00%	98,00%	98,00%
CD95_FT5	100,00%	98,00%	98,99%
Macro Average	96,32%	96,20%	96,18%
Accuracy		96,20%	
Error		3,80%	

According to Table 6, the VGG-16 model applied to rubber trees with a combination of hyperparameters gives good results in classifying rubber tree crown images into crown density and foliage transparency classes. This is indicated by an accuracy value of 96.20%, This is indicated by an accuracy value of 96.20%, average precision of 96.32%, average recall of 96.20%, f1-score value of 96.18%, and error of 3.80%.

VGG-16 Mode Evaluate for Candlenut Tree



(a) (b)

Figure 5. (a) accuracy and (b) VGG-16 loss model for candlenut tree

The training phase of the VGG-16 model for candlenut trees resulted in an accuracy of 98.40% and a minimal loss value of 0.29%. Figure 7a shows an accuracy graph during the training stage with training data and validation data up to the 35th epoch. The graph shows a relatively stable movement that tends to stabilize after the fourth epoch at 0.9. The training accuracy graph displays a slightly more stable trend than the validation accuracy graph, which shows fluctuations in model performance when evaluated with new data. These fluctuations can occur because the model adapts to new data. Figure 7b illustrates the graph of training and validation loss values, which exhibits a decreasing trend that stabilizes below 0.1 after the fourth epoch. Currently, the validation loss values exhibit stabilization after the 10th epoch, consistently remaining below 0.1.

The VGG-16 model testing stage for candlenut trees resulted in a test accuracy of 98.00%. The accuracy, precision, recall and f1-score values obtained from the confusion matrix for the VGG-16 The accuracy, precision, recall and f1-score values obtained from the confusion matrix for the VGG-16 model for classifying the crown density and foliage transparency of the candlenut tree crown can be seen in Table 7.

Table 7. Results of the VGG-16 model for the candlenut tree

Class	Precision	Recall	F1-score
CD5_FT95	100,00%	100,00%	100,00%
CD15_FT85	100,00%	100,00%	100,00%
CD25_FT75	96,15%	100,00%	98,04%
CD35_FT65	94,00%	94,00%	94,00%
CD45_FT55	100,00%	92,00%	95,83%
CD55_FT45	100,00%	100,00%	100,00%
CD65_FT35	96,08%	98,00%	97,03%
CD75_FT25	98,04%	100,00%	99,01%
CD85_FT15	96,00%	96,00%	96,00%
CD95_FT5	100,00%	100,00%	100,00%
Macro Average	98,03%	98,00%	97,99%
Accuracy		98,40%	
Error		1,60%	

Based on Table 7, the VGG-16 model applied to candlenut trees with a combination of hyperparameters gives quite good results in classifying candlenut tree crown images into crown density and foliage transparency classes. This is evident through various model evaluation metrics: an accuracy rate of 98.40%, an average precision of 98.03%, an average recall of 98%, an f1-score value of 97.99%, and an error rate of 1.60%.

4. CONCLUSION

This study demonstrates that the measurement of crown density and the foliage transparency scale can be implemented using VGG-16, similar to other research classifications of leaf diseases. The classification results for crown density and foliage transparency scales in four types of broadleaves trees (cacao, durian, rubber, and candlenut) using VGG-16 demonstrated good performance, as indicated by high testing accuracy, precision, recall and f1-score values. The test accuracy results were cacao trees (92.00%), durian trees

(86.60%), rubber trees (96.60%), and candlenut trees (98.40%). The average precision values, reflecting the accuracy in predicting data, were cacao trees (92.12%), durian trees (86.65%), rubber trees (96.32%), and candlenut trees (98.03%). Consequently, the average recall values for cacao trees (92.00%), durian trees (86.60%), rubber trees (96.20%), and candlenut trees (98.00%) were obtained. This research, conducted successfully with subjects from cacao, durian, rubber, and candlenut trees, anticipates future research to introduce variations in broadleaves tree crown data, encompassing diverse tree types, and to compare these variations with other deep learning architectures for potentially enhanced results.

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