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# Deep Learning-Based Assessment of Crown Density and Foliage Transparency of Broadleaved Trees as Tree Health Indicators

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**ABSTRACT**

Crown density and foliage transparency are key visual indicators in forest health monitoring (FHM), but field assessment with reference cards remains labor-intensive and dependent on observer expertise. This study evaluates the use of transfer learning for classifying crown density–foliage transparency levels from ground-based images of broadleaved tree crowns. A total of 2,965 images were collected from four broadleaved species, namely Theobroma cacao, Durio zibethinus, Hevea brasiliensis, and Aleurites moluccana. Each image was assigned to one of ten crown density–foliage transparency classes using reference scale cards and majority voting from trained respondents. The images were resized to 224 × 224 pixels and divided into training, validation, and testing subsets at a 70:10:20 ratio. Two convolutional neural network architectures, MobileNet and VGG-16, were trained and evaluated using accuracy, precision, recall, and F1-score. MobileNet generally showed better generalization than VGG-16, with the highest test accuracy of 85.54% obtained for Durio zibethinus. VGG-16 achieved competitive performance only for Aleurites moluccana but showed stronger overfitting in several datasets. The results indicate that lightweight transfer learning models can support image-based forest health assessment, although performance remains species-dependent and limited by dataset size, crown overlap, and background complexity. Future work should expand the image dataset, include additional tree species, and incorporate crown segmentation to improve classification reliability.

## 1. INTRODUCTION

A forest is deemed healthy when it sustains ecosystem equilibrium to fulfill human needs. Various techniques exist for evaluating forest condition, with one such method being the forest health monitoring (FHM) approach [1]. The FHM method is employed to monitor, evaluate, and report on the present state, alterations, and long-term trends of forest ecosystem health through quantifiable ecological indicators. The evaluation of these indicators provides a thorough description of forest conditions [2]. The tree crown is a fundamental component for monitoring forest health. It is the primary site of photosynthesis and provides insights into the tree's physiological condition, thereby closely correlating with its overall health. The crown of a tree refers to the foliated region sustained by a single stem, commonly known as the trunk or bole. This crown comprises the crown stem, branches, twigs, buds, seeds, cones, and foliage [3].

FHM can be carried out using vitality assessment indicators, which encompass several parameters, including crown density (CD) and foliage transparency (FT). A forest is classified as healthy if the CD score exceeds 55% and the FT ranges from 0% to 45% [3]. This measurement relies on a scale card to measure CD and FT, which determines the amount of sunlight reaching the forest floor. This evaluation is conducted for all tree types, particularly broadleaved trees, characterized by their expansive, circular crowns, sturdy trunks, and broad leaf structures [4]. The conventional approach to assessing CD and FT with the crown density-foliage transparency card is considered inefficient because it depends on direct observation and requires professional expertise. This issue can be addressed by utilizing digital image technology, such as deep learning, which is expected to make measurements more accessible and enhance work efficiency, thereby allowing a wider range of individuals to perform these tasks.

Deep learning, a branch of machine learning, is widely applied to image classification, object detection, and etc [5]. The Convolutional Neural Network (CNN) is a deep learning algorithm highly suitable for image identification [6]. CNN has various architectures, such as MobileNet and VGG-16, which have been trained for image classification using the ImageNet dataset. MobileNet features 28 layers with a depthwise separable convolution concept to reduce the number of parameters and computation, making it suitable for devices with limited computing power, such as mobile and IoT devices [7]. VGG-16 is a CNN architecture constructed with 16 layers, containing 13 convolutional layers with a 3x3 kernel size and 3 fully connected layers [8].

Previous research using FHM shows that forest health conditions in Tahura WAR vary, with 25% of the area in the very good category, 38% in the good category, 12% in the medium category, and 25% in the very poor category [9]. Previous research on deep learning applied to the FHM method was carried out to identify types of tree damage. This research uses two CNN architectures, which are LeNet and MobileNet. LeNet achieved 88.99% accuracy, while MobileNet achieved 99.06% [10]. Research using VGG-16 has been conducted to classify diseases in soybean leaves by Sahu et al. [11] and compared with several other architectures such as AlexNet, ResNet-18, ResNet-50, VGG-19, and GoogleNet. VGG-16 achieved an accuracy of 91.96%, while the highest accuracy was obtained by ResNet-50 at 93.02%, and the lowest accuracy was obtained by AlexNet at 90.63%.

Previous research has shown the success of using MobileNet in identifying types of tree damage in the FHM method and VGG-16 leaf disease. However, the MobileNet and VGG-16 architectures have never been used to measure broadleaved trees' CD and FT. To address this gap, the present study aims to classify CD and FT in broadleaved trees utilizing MobileNet and VGG-16 architectures. This research seeks to advance the digitalization of FHM by providing a practical and efficient tool that can enhance work productivity and be easily used by non-specialists, making forest assessments more accessible and scalable.

## 2. RESEARCH METHODOLOGY

The research procedures conducted are illustrated in Figure 1.

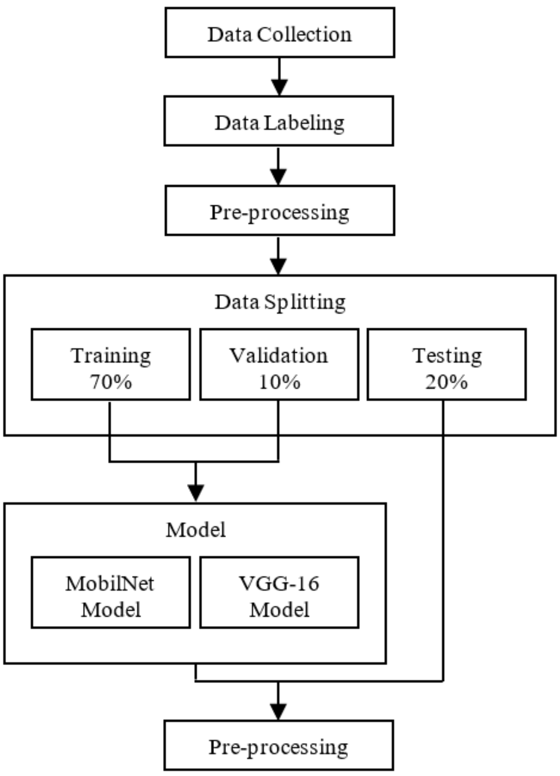


**Figure 1.** Flowchart of our research methology in deep learning for classification of crown density (CD) and foliage transparency (FT)

### 2.1 Data collection

The initial step of this research began with collecting a dataset of broadleaved tree crown images. This was necessary because a dataset containing images of tree CD and FT, particularly those of broadleaf species, was not yet available. These images were obtained from the traditional block and candlenut garden of Tahura WAR, Kemiling, Bandar Lampung. The images were taken using a Canon EoS 250D camera with ISO 100, shutter speed of 1/30, an aspect ratio of 1:1, and saved in JPG format. This setting adjusts to where the image is taken. The site is in an open area and relies on natural light coming through the forest crown. Images were taken standing under the tree 10–20 cm away from the tree trunk. The original size of the image was 1600 × 1600 pixels. The broadleaved trees used in this study include *Theobroma cacao, Durio zibethinus, Hevea brasiliensis, and Aleurites moluccana*. The number of images obtained for each broadleaved tree species can be seen in Table 1.

**Table 1.** Broadleaved tree species and the number of images

| No. | Tree Species | Number of Images |
|---|---|---|
| 1 | Theobroma cacao | 620 |
| 2 | Durio zibethinus | 818 |
| 3 | Hevea brasiliensis | 600 |
| 4 | Aleurites moluccana | 927 |
| **Total number of broadleaved tree crown image** | | **2965** |

### 2.2 Data labeling

The data labeling phase involved 15 respondents evaluating each image and categorizing it into 10 classes based on the crown density-foliage transparency scale cards, ranging from 5% to 95%, as illustrated in Figure 2. Images were allocated to a category (classes) based on the majority of votes. This study involved five students from the Computer Science Department, who took part in forest health research, and ten students from the Forestry Department. Their participation was essential to confirm that the images were accurately classified into the appropriate categories. The results of the data labeling phase are shown in Table 2.

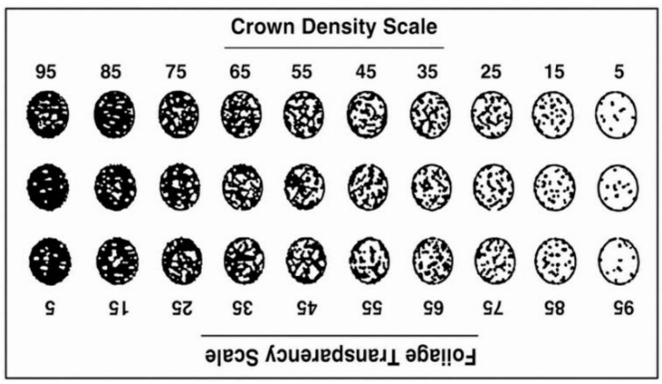


**Figure 2.** Crown density (CD) and foliage transparency (FT) scale card [12]

Based on the labeling results, the number of datasets used in this study are 4 datasets, including crown density-foliage transparency datasets of *Theobroma cacao trees, Durio zibethinus trees, Hevea brasiliensis trees,* and *Aleurites* *moluccana trees*, with a total of 2965 images of broadleaved tree crowns across all datasets. CD and FT are two interrelated parameters used to measure the amount of sunlight reaching the forest floor. CD measures the amount of light obstructed by the tree crown, while FT measures the amount of light that can penetrate the tree crown. CD and FT have inverse values, meaning that the higher the CD, the lower the FT.

**Table 2.** Number of image for each broadleaved tree species in the crown density (CD) and foliage transparency (FT) classes

| Crown Dencity and Foliage Transparency Class | The Number of Image for Each Type of Broadleaved Trees | | | |
|---|---|---|---|---|
| | Theobroma Cacao | Durio Zibethinus | Hevea Brasiliensis | Aleurites Moluccana |
| CD5-FT95 | 58 | 100 | 51 | 100 |
| CD15-FT85 | 90 | 100 | 50 | 100 |
| CD25-FT75 | 100 | 100 | 52 | 100 |
| CD35-FT65 | 55 | 100 | 60 | 100 |
| CD45-FT55 | 52 | 92 | 53 | 99 |
| CD55-FT45 | 57 | 100 | 50 | 80 |
| CD65-FT35 | 53 | 60 | 62 | 98 |
| CD75-FT25 | 54 | 60 | 75 | 62 |
| CD85-FT15 | 51 | 55 | 69 | 88 |
| CD95-FT5 | 50 | 51 | 78 | 100 |
| Total number of images of CD-FT classes for each tree type | 620 | 818 | 600 | 927 |
| Total | 2965 | | | |

Note: CD = Crown Density; FT = Foliage Transparency

### 2.3 Pre-processing

Pre-processing is preparing data for processing to improve a model's performance. The pre-processing technique used in this study is resize. Resize was used to reduce the size of the images from 1600 × 1600 pixels to 224 × 224 pixels. Resizing input images provided numerical stability to the CNN model so it can enhance the model's performance.

### 2.4 Data splitting

The dataset is partitioned into three subsets: training, validation, and test data. Training data is used to look for patterns and relationships in the data [13]. Validation data is used to evaluate model performance on data different from the training data [14]. Test data is used to test the performance of the model [15]. The purpose of splitting the data is to guarantee optimal performance of the generated model on previously unseen data. The data allocation for MobileNet and VGG-16 models involves allocating 70% for training, 10% for validation, and 20% for testing [10].

There are several reasons for selecting a 70% training, 10% validation, and 20% testing data split. The 70% allocated for training is intended to ensure sufficient data for the training process. The 10% for validation is meant to provide a representative dataset for validating the model and tuning the hyperparameters. The 20% allocated for testing aims to avoid evaluation bias and enhance the model's generalization ability.

### 2.5 Convolutional Neural Network architectures

This study utilized MobileNet and VGG-16 to train each dataset. The datasets included in this research comprised the crown density-foliage transparency of *Theobroma cacao* trees, the crown density-foliage transparency of *Durio zibethinus* trees, the crown density-foliage transparency of *Hevea brasiliensis* trees, and the crown density-foliage transparency of *Aleurites moluccana* trees, totaling 2965 images across all datasets. MobileNet and VGG-16 architectures are used to train each tree type with multiple configurations. Configuration is carried out by setting several hyperparameter values and adding several additional network layers to the built model.

2.5.1 MobileNet architecture

MobileNet is a CNN architecture designed to maximize accuracy while minimizing computation. This architecture has 28 layers consisting of input layer, convolution layer, depthwise separable convolutional layer, fully connected layer, and output layer. Depthwise separable convolution divides convolution into two stages, which are depthwise and pointwise. The results of the last layer of depthwise separable convolution are used as input for the fully connected layer before entering the output layer in the image classification task [7]. This depthwise separable convolution concept can be seen at Figure 3.

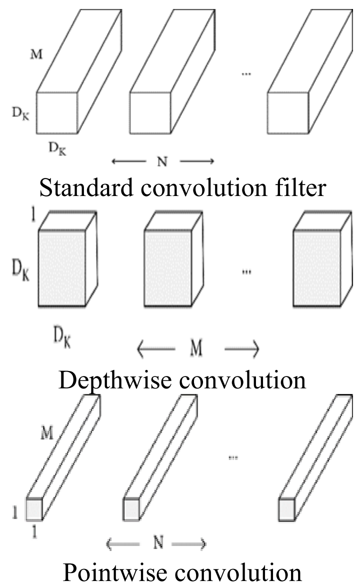


**Figure 3.** MobileNet architecture concept

The concept of depthwise separable convolution in MobileNet is implemented by dividing the convolution process into depthwise convolution and pointwise convolution. Depthwise convolution is used to process each input channel separately, while pointwise convolution combines and merges information from the various channels that have been processed in the previous stage. This separation significantly reduces the number of computational operations compared to traditional convolution, especially when the input has many channels. This division of convolution allows the model to process data more efficiently, requiring less computational power compared to standard convolution.

2.5.2 VGG-16 architecture

VGG-16, a modification of AlexNet in the convolution filter, utilizes 3 × 3-sized filters, smaller than 5 × 5 and 11 × 11 filters [13]. The architecture of VGG-16 encompasses more parameters and network depth compared to AlexNet, specifically 138 million parameters. Despite this, it requires less time for training or fine-tuning the network. VGG-16 architecture consists of 13 convolution layers, 5 pooling layers, 2 fully-connected layers, and 1 output layer, as illustrated in Figure 4 [8].

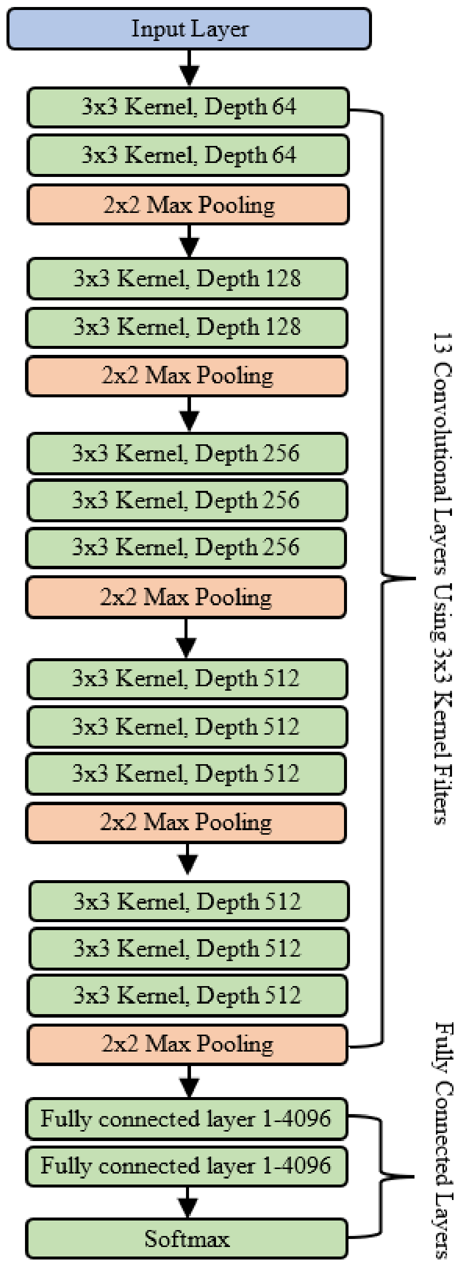


**Figure 4.** Layers in the VGG-16 architecture

**2.6 Model results**

Model results are a stage for evaluating the performance of the MobileNet and VGG-16 deep learning models. Evaluation is presented with a confusion matrix which contains information related to accuracy, precision, recall, and F1-score of the model [16].

Accuracy refers to the proportion of correctly classified data points out of the total data points evaluated. It's a measure of the model's overall performance in correctly predicting the classes of the input data [17]. The calculation of accuracy values according to Pedregosa et al. [18] is as follows:

$$(y, \hat{y}) = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} 1(\widehat{y_i} = y_i) \quad (1)$$

Precision is the ratio of true positives (correctly predicted positive cases) to the sum of true positives and false positives (incorrectly predicted positive cases). Precision quantifies the model's ability to avoid false positives [19]. the calculation of precision value shown in Eq. (2).

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

Recall represents the proportion of actual positive cases that the model correctly identifies. It is mathematically expressed as the number of true positives (TP) divided by the total number of positive cases (P) that can be seen in Eq. (3) [19].

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

The F1-score, employed to assess the effectiveness of classification models, particularly in tasks involving binary and multi-class classification, is a metric derived from the harmonic mean of precision and recall, as shown in Eq. (4) [19].

$$F1 - Score = 2 \times \frac{Recall \times Precision}{Recall + Precision} \quad (4)$$

## 3. RESULT AND DISCUSSION

### 3.1 Model

In training each type of tree, a base model of the MobileNet and VGG-16 architectures was used with some customized configurations. Model configuration was performed by adding network layers. The configuration approach differed for each architecture to achieve optimal results.

**Table 3.** MobileNet and VGG-16 model structures

| | Model Structures | |
|---|---|---|
| **No** | **MobileNet** | **VGG-16** |
| 1 | Base model MobileNet | Base model VGG-16 |
| 2 | GlobalAveragePooling2D | Flatten |
| 3 | Dense (10) | Dense (10) |
| Total Params | 3,239,114 | 14,965,578 |
| Trainable Params | 3,217,226 | 14,965,578 |

Table 3 shows the model structure applied to train the four datasets of broadleaved trees CD and FT. Based on Table 3, the additional layers of the MobileNet model are a GlobalAveragePooling and dense layer. GlobalAveragePooling2D is added before the output to calculate the average of the output results of the previous layer [20]. Global Average Pooling can realize direct mapping between output channels and feature categories to reduce excessive model parameters. Global Average Pooling is more effective on datasets with complex backgrounds and diverse categories [21]. Meanwhile, the VGG-16 model structure was applied by adding flatten and dense layers. The flatten layer is implemented to transform the output from the previous layer, which is in the form of multi-dimensional arrays, into a one-dimensional array or vector in fully connected layer. The last dense layer with 10 units and softmax activation is used to output the class of the model [22].

**Table 4.** Model's hyperparameters

| Hyperparameters | Value |
|---|---|
| Epoch | 50 |
| Batch Size | Train: 16, Test: 8, Val: 8 |
| Optimizer | Adam |
| Learning Rate | 0,001 |

Based on Table 4, this study uses the same hyperparameters to train the MobileNet and VGG-16 models. The batch size applied to the model is 16 for training data, which is adjusted to the number of datasets owned; there are 429 images for the *Theobroma cacao* tree, 571 images for the *Durio zibethinus* tree, 417 images for the *Hevea brasiliensis* tree, and 648 images for the *Aleurites moluccana* tree. The batch size for the subset of validation and test data uses a batch size of 8 because it is adjusted to the number of datasets; there are validation data: 59 images on *Theobroma cacao* trees, 81 images on *Durio zibethinus* trees, 57 images on *Hevea brasiliensis* trees, and 91 images on *Aleurites moluccana* trees, as well as test data 132 images on *Theobroma cacao* trees, 166 images on *Durio zibethinus* trees, 126 images on *Hevea brasiliensis* trees, and 189 images on *Aleurites moluccana* trees. A batch size value of 16 in training allows the model to update parameters more frequently, which can improve convergence stability and prevent large spikes in the gradient direction that may occur with larger batch sizes.

### 3.2 Model results

The model results are shown by a confusion matrix. The confusion matrix consists of four main metrics, namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), which can be used to compute the accuracy, precision, recall, and F1-score of the model.

**Table 5.** Accuracy and loss results in training and testing phase

| Dataset | Architecture | Training Accuracy | Validation Accuracy | Testing Accuracy | Training Loss | Validation Loss | Testing Loss |
|---|---|---|---|---|---|---|---|
| *Theobroma cacao*'s crown | MobileNet | 98.83% | 59.32% | 59.85% | 0.1314 | 1.2920 | 1.2488 |
| density-foliage transparency | VGG-16 | 98.83% | 50.85% | 42.42% | 0.0317 | 4.2233 | 5.1617 |
| *Durio zibethinus*'s crown | MobileNet | 98.77% | 82.72% | 85.54% | 0.1324 | 0.6057 | 0.5471 |
| density-foliage transparency | VGG-16 | 100.00% | 81.48% | 83.73% | 9.9583e-06 | 3.5156 | 1.6732 |
| *Hevea brasiliensis*'s crown | MobileNet | 92.57% | 56.14% | 55.56% | 0.2955 | 1.1773 | 1.2820 |
| density-foliage transparency | VGG-16 | 100.00% | 49.12% | 55.56% | 1.6796e-05 | 10.0052 | 7.2238 |
| *Aleurites moluccana*'s | MobileNet | 85.01% | 69.23% | 62.43% | 0.5491 | 1.1079 | 1.0709 |
| crown density-foliage transparency | VGG-16 | 100.00% | 67.03% | 71.43% | 6.3925e-04 | 4.5296 | 4.3646 |

In Table 5, we present the accuracy and loss results during the training and testing phases of the models across all four types of datasets. Based on Table 5, the highest training accuracy results is 100.00% obtained on the *Durio zibethinus*'s crown density-foliage transparency, *Hevea brasiliensis*'s crown density-foliage transparency, and *Aleurites moluccana*'s crown density-foliage transparency datasets using the VGG-16 architecture, while the highest validation accuracy is 82.72% obtained on the *Durio zibethinus*'s crown density-foliage transparency dataset using the MobileNet architecture. The highest test accuracy was obtained on the *Durio zibethinus*'s crown density-foliage transparency dataset of 85.54% using the MobileNet architecture. In comparison, the lowest was obtained on the *Theobroma cacao*'s crown density-foliage transparency model of 42.42% using the VGG-16 architecture. The lowest training loss is 9.9583e-06 obtained by *Durio zibethinus*'s crown density-foliage transparency with the VGG-16 architecture, while the highest training loss is 0.5491 obtained by *Aleurites moluccana*'s crown density-foliage transparency with the MobileNet architecture. The lowest validation loss is 0.6057, obtained for *Durio zibethinus*'s crown density-foliage transparency with the MobileNet architecture, while the highest is 10.0052, obtained for *Hevea brasiliensis*'s crown density-foliage transparency with the MobileNet architecture. The lowest testing loss was obtained on the *Durio zibethinus*'s crown density-foliage transparency model of 0.5471 with the MobileNet architecture, while the highest was 5.1617 with the VGG-16 architecture.

This significant difference in accuracy and loss in training and testing indicates overfitting in the model. Overfitting occurs when the model is too biased on the training data and fails to generalize well on new data (validation subset and test subset). Factors influencing overfitting in the crown density-foliage transparency scale include the relatively small number of datasets. The dataset used for each broadleaved tree species is as follows: 620 images of *Theobroma cacao*, 818 images of *Durio zibethinus*, 600 images of *Hevea brasiliensis*, and 927 images of *Aleurites moluccana*. A limited dataset may not cover sufficient variation from different classes of data, especially the characteristics of each complex image, such as leaf color, leaf shape, twig or tree branch shape, and so on. Especially *Theobroma cacao* trees, which have relatively low trunks of around 4-8 meters, with branches starting from low trunks. The leaves also have quite a large width, its length is between 20-35 cm and the width is 6-10 cm, so it presents its own challenges in the image taking process.

In some cases, the images obtained cannot optimally represent the overall picture of the tree crown. Another cause is that the crown images obtained often overlap with the crowns of other trees, especially since the data collection location is in a traditional block consisting of various types of trees. MobileNet & VGG-16 use pre-trained weights from ImageNet, which has a relatively large capacity and can handle complex image classification tasks. VGG-16 has parameters totaling approximately 138 million parameters. Even though the model has been configured to fit the scale of CD and FT dataset of *Theobroma cacao*, *Durio zibethinus*, *Hevea brasiliensis*, and *Aleurites moluccana*, the number of parameters produced is still quite large, with approximately 14 million parameters. On the other hand, MobileNet parameters are about 3.2 million parameters. This number of parameters indicates that the model has quite a lot of parameters, and the model complexity is too high for a relatively small dataset.

Other factors may be caused by incorrect hyperparameter settings for the characteristics of the four types of datasets. These four types of datasets have different characteristics and quantities, so hyperparameter settings are required to achieve optimal results.

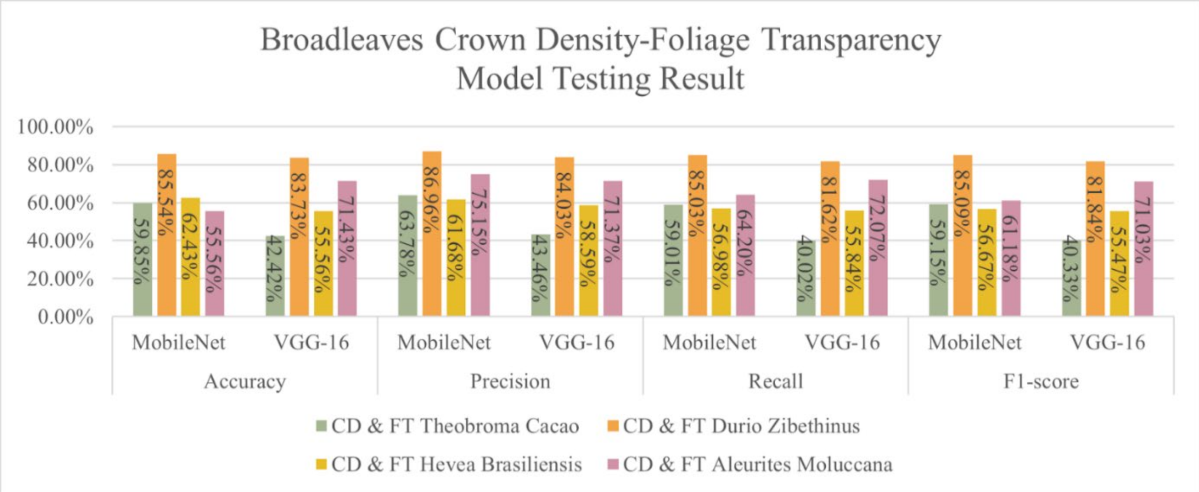


**Figure 5.** The comparison of accuracy results in testing phase of the broadleaved tress crown density-foliage transparency model using MobileNet and VGG-16 architectures

Model testing using test data from each dataset amounted to 20% of the entire broadleaved tree CD and FT dataset. The test results of the MobileNet and VGG-16 models are shown in Figure 5. Based on Figure 5, the *Theobroma cacao* tree CD and FT dataset achieves the best results with the MobileNet model. This is indicated by an accuracy value of 59.85%, precision of 63.78%, recall of 59.01%, and F1-score of 59.15%, which is higher than the VGG-16 model. The *Durio zibethinus* tree CD and FT dataset had the best results on the MobileNet model with an accuracy of 85.54%, precision of 86.96%, recall of 85.03%, and F1-score of 85.09%. The *Hevea brasiliensis* tree CD and FT dataset got the best results in the MobileNet model, with accuracy reaching 62.43%, precision at 61.68%, recall at 56.98%, and F1-score 56.67%. The *Aleurites moluccana* tree CD and FT dataset achieved the best results on the VGG-16 model with an accuracy of 71.43%, precision 71.37%, recall 72.07%, and F1-score 71.03%, which is higher than mobile MobileNet.

The *Durio zibethinus* tree CD and FT dataset with MobileNet architecture produces the best performance among the datasets and models tested. This can be seen from the model's relatively good performance during training and testing, with an accuracy percentage reaching more than 80%. MobileNet applies the concept of separable convolution, which significantly reduces computational operations and the number of parameters compared to VGG-16. This is particularly important as the dataset used is relatively small, and a large number of parameters could lead to overfitting in the model. Although the MobileNet model for this dataset can learn patterns on the training data well, its performance on new data is not optimal. On the other hand, the VGG-16 model for the *Theobroma cacao* and *Hevea brasiliensis* tree CD and FT datasets showed the worst performance. This can be seen in the low accuracy of the model and the relatively high difference in loss values. The high difference in loss values indicates that the VGG-16 model is overfitting. Overfitting is a condition where the model is too focused on the training data and cannot generalize well to new data. As a result, this model cannot correctly classify images into each class, especially on new data.

## 4. CONCLUSION

This research shows that the MobileNet architecture performs more satisfactorily than VGG-16. This is based on the evaluation of the two models in classifying tree CD and FT images. Although MobileNet shows quite good performance, further experiments are still needed to improve its performance. Further experiments are needed, especially for VGG-16, which shows susceptibility to overfitting. Further experiments are necessary to understand and correct the weaknesses associated with these two architectures. Several recommendations include increasing the dataset size for each broadleaved tree species, adding more species, or applying image segmentation techniques to ensure the model focuses solely on the broadleaved crowns, excluding the tree branches. Thus, the performance and reliability of the model can be improved for a wider range of applications.

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