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Classification of Clove Leaf Blister Blight Disease Severity Using Pre-trained Model VGG16, InceptionV3, and ResNet

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Abstract

Clove is one of the precious plants produced in Indonesia. Clove has many benefits for humans, but clove cultivation often experiences problems due to disease attacks, including Leaf Blister Blight Disease(CDC). The handling of CDC disease is carried out based on the severity of the symptoms that can be seen on the affected leaves. This research was conducted to obtain a CDC disease classification model, so appropriate treatment can be carried out. This study used the pre-trained VGG16, InceptionV3, and ResNet models for classification. VGG16 got the highest average accuracy of 96.7%. Aside from that, k-fold cross validation improved the model's accuracy.
Keywords: *Pre-trained Model, CNN, Clove Leaf Disease Classification, VGG16, ResNet, InceptionV3, Deep Learning.*

1. Introduction

Indonesia is the largest clove-producer country in the world[1]. Apart from being the largest producer, Indonesia is also the largest consumer of clove cigarettes, and clove is one of the ingredients in kretek cigarettes. This is supported by data that states that Indonesia has the largest number of adult smokers in ASEAN[2] and ranks second in the world[3]. Cloves are known as the raw material for clove cigarettes, although the use of cloves has been developed for other things such as medicines[4], food seasoning[5], pesticides[6], and others.

Clove cultivation in Indonesia is spread in various regions such as Wonogiri, Pemalang, Karang Tengah, and Moga[7]. Proper handling is needed to produce quality clove products. In addition, pest and disease attacks will also affect clove production. A serious threat in clove cultivation in Indonesia is the presence of leaf blister blight disease (CDC), which leads the leaf to fall prematurely, reducing productivity significantly. The disease is caused by a plant pathogenic fungus infection, namely *Phyllosticta*. The initial symptom of leaf blister blight (CDC) is a typical black spot with red edges on the leaf [8]. However, at the early stage of infection, the disease is hard to be detected since the further development of infection is not followed by a necrotic appearance.

Handling CDC diseases is done based on the severity of the disease. The treatment for clove trees that CDC attacks with mild severity is to sanitize the leaves, twigs, and seeds. While for plants with severe CDC, felling and burning must be carried out to reduce the source of inoculum. One of the signs of the severity of the disease can be seen in the leaves. Good observation is needed to determine the severity of the disease plants suffer so that appropriate treatment can be carried out for plants affected by the disease. One way of observing is to look at the symptoms that arise on the surface of the leaves.

Computer vision is one of Artificial Intelligence that allows computers to recognize, identify and classify an image-based object. Computer vision is very commonly used to help humans to speed up the process of identifying an object. Computer vision is considered a low-cost method, with small errors and has high efficiency [9]. The algorithm often used as a framework for analyzing computer vision-based images is deep learning architecture [10]. The application of Deep Learning, which is part of intelligence is inspired by the neural network of the human brain [11]. CNN is the most popular Deep-Learning method used, especially in image recognition [12]. There have been many studies on image recognition using the CNN method. CNN is often considered as an architecture with good performance and a low error rate. However, even though it is considered to have good performance, CNN is considered to be less efficient at working with limited datasets[13]. One of the methods to overcome the large demand for datasets is to use a pre-trained model. [14]. The pre-trained model makes it possible to use the weight taken from training in the previous dataset for other similar tasks so that the training process does not need to be done from scratch. [15]. Several pre-trained models that have been widely used include VGG16, ResNet, and InceptionV3.

2. Previous Research

In previous studies, VGG16, ResNet, and InceptionV3 have successfully classified plant diseases using leaf datasets and produced relatively high accuracy[16,17,18,19].In this study, clove plants affected by CDC disease were classified using leaf image datasets. The deep learning architectures used are VGG16, InceptionV3, and ResNet. This research aims to build a model that can classify leaves affected by CDC and then compare the performance of the three models produced. It is expected that this system can become the basis of an early detection system for CDC diseases that attack clove plants.

In previous studies, pre-trained VGG16 has been widely used to detect and classify plant diseases using leaf datasets, with relatively high accuracy[20,21,22]. An example of previous research used 1500 tobacco leaf images, the majority of which were brown, VGG16 used to classify pest on tobacco. The accuracy obtained from the research was between 87.33% and 99.11%. The other research used a grave leaf dataset to identify grape plant, the accuracy obtained was 98.35%. In addition, the research used imbalanced dataset to detect disease in apples based on leaf images, with 100 epochs, the resulting model obtained an accuracy of 92.94%.

Other model InceptionV3 is known as a model that has good performance on a small dataset[23]. In previous study[24], the classification of gingko leaf disease was carried out using VGG16 and InceptionV3. The results obtained indicated that InceptionV3 resulted in more stable performance for both datasets taken in the laboratory and datasets taken in the field. Several previous studies have shown that the use of the Resnet model produces better accuracy compared to traditional machine learning[25,26].

This research used CNN architecture, namely VGG16, ResNet, and InceptionV3. By using these three architectures we compares the performance of each resulting model. Performance comparison was seen from model size, training time, number of parameters and accuracy. the goal is to produce a small, well-performing model that can run quickly on mobile devices

3. Method

3.1 Dataset

This study used image datasets taken on several clove plantations. A total of 666 images consisted of three classes: healthy leaves, leaves with mild CDC, and leaves with severe CDC. Each class has 222 images. The image was a single leaf picked from a tree and then photographed with a white background. Examples of healthy leaf, leaf with mild CDC and leaf with severe CDC can be seen in the Figure 1. In the picture, it can be seen that healthy leave look fresh without any spots or blisters on the leaf surface. The leaf samples were categorized mild symptom if spots like oil droplets present on the leaf lamina that covering less than 40% of the leaf surface. Leave with severe CDC has more spots on the surface of the leave, with obviously blisters covering up to 40% on the surface of the leave. On leave with severe CDC, a reddish color usually appears, and changes in the shape of the leaves become curly and wavy. All images were saved in RGB form with different sizes. The dataset was divided into training data and testing data.

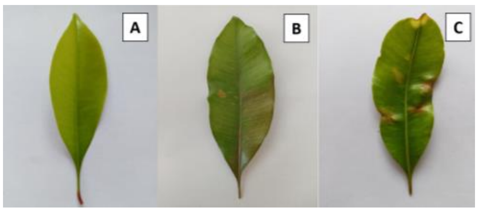

Figure 1. The examples of three categories of the CDC affected leaf. (A) healthy, (B) Mild, (C) Severe.

Table 1. Distribution of datasets in the training process.

No	Dataset	
	Training	Testing
1	12	20
2	52	20
3	102	20
4	152	20
5	202	20

In this experiment, we conducted training 4 times for each CNN architecture. Training is carried out using the smallest dataset first, namely 12 training data, then increasing to 202 training data. The testing data for each experiment remains the same, namely 20 testing data. Details of the dataset number of images distribution can be seen in the Table 1.

3.2 Augmentation

In addition to deep learning, augmentation is a method that is frequently applied. This is because deep learning training requires extensive datasets[27]. Augmentation is believed to be effective and efficient method strategy to increasing the number of datasets[28]. augmentation is done by making variations of the original image with several transformation processes such as flipping, rescaling, cropping skewing, and others. augmentation is one way to overcome overfitting. one image that goes through the augmentation process will produce several images with different variations. In this augmentation process, 1 leaf image can produce 6 new image variations. so that the images that will go through the training process are 6 times the dataset. The example of augmentation result can be seen in Figure 2.

Figure 2. The example of augmentation images result.

3.3 VGG16

After pre-processing, the dataset is ready for training using the CNN architecture. The first CNN architecture used for making a model was VGG16. VGG is one of the CNN architectures that produce a low % error rate of 7.3%[29]. VGGNet is made to replace AlexNet's enormous 1x1 and 5x5 kernel sizes with multiple 3x3 kernels with pooling sizes of 2x2. Using a 3x3 kernel size will cut down on the trainable amount of variables. Having fewer trainable variables results in quicker learning and more resistance to overfitting. The training was carried out on a dataset that is 224x224x3 in size. In VGG16, the image is process through 13 convolution layers and 3 fully connected layers. The training hyperparameters used in this experiment can be seen in Table 2.

Table 2. VGG model training hyperparameter.

Hyperparameter	Value
Optimizer	Adamax
Number of epoch	50
Activation	Softmax
Learning rate	0.001
Drop out	0.15-0.60

3.4 InceptionV3

The second training was carried out using the InceptionV3 architecture. InceptionV3 is a CNN architecture developed by Google in 2014[30]. This architecture became the runner-up of ILSVRC (ImageNet Large Scale Visual Recognition Competition) in 2015. In this architecture, ways to increase network depth are identified in a way that aims to use computation as efficiently as possible with factorized convolution and aggressive regularization[30]. This is done by adding a 1×1 convolution process to reduce dimensions, thereby reducing the amount of computation. The reduced computation allows this architecture to increase network depth and width. The training hyperparameters used can be seen in the Table 3.

Table 3. InceptionV3 model training hyperparameter.

Hyperparameter	Value
Optimizer	Adamax
Number of epoch	50
Activation	Softmax
Learning rate	0.0001
Drop out	0.2-0.6

3.5 ResNet

The third training was carried out using the ResNet architecture. The residual function shows that the residual network is easier to optimize. This is done by using a skip/shortcut connection to fit input from the previous layer to the next layer without changes, this is done to ensure all features are detected so that the network can be built deeper[31]. The training hyperparameters used can be seen in the Table 4.

Table 4. ResNet model training hyperparameter.

Hyperparameter	Value
Optimizer	Adamax
Number of epoch	50
Activation	Softmax
Learning rate	0.001
Drop out	0.4-0.6

3.6 Evaluation

The evaluation was done by calculating the testing accuracy of each model produced. Analysis was also carried out by looking at the confusion matrix generated by each model's classification process. The confusion matrix is a table that displays the original labels as well as the predicted dataset results from each class. By looking at the confusion matrix, it can be seen whether there is a tendency to misclassify one class against another. The confusion matrix consists of a combination of 4 predictive values, namely:

- True Positive (TP): Represents positive data that is predicted correctly.
- True Negative (TN): Represents negative data that is correctly predicted.
- False Positive (FP): It is negative data but is predicted as positive.
- False Negative (FN): Is positive data that is predicted to be negative.

Accuracy calculation is as equation (1):

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (1)$$

Although accuracy is a well-known evaluation criteria, it is not necessarily dependable. As a result, additional indicators must be evaluated in order to determine the model's accuracy. Recall is defined as the ratio of true positive predictions to all data that truly belongs to the class, whereas precision is defined as the ratio of true positive predictions to all positive predicted results. Precision measures how many relevant items are chosen, whereas recall reflects how many relevant items are chosen. and the formula for calculating Recall (R) and Precision (P) can be seen in Equation (2) and Equation (3). In addition to recall and precision, F1 Score is also calculated, which is a comparison of the weighted average precision and recall. How to calculate the F1 score can be seen in Equation (4).

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

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

$$F1\ Score = \frac{2*(Recall*Precission)}{Recall+Precission} \quad (4)$$

4. Result and Discussion

One models is generated from each experiment in the training phase. The training was carried out using the smallest dataset, namely 12, then further training with an additional training images until finally reaching 202 training data per class. This was done to see the effect of increasing the number of datasets on the quality of the resulting model. It is hoped that the resulting model can be implemented on mobile devices. The smaller the model size and the higher the accuracy, the better it would be, so that not many resources are used for this software and the application can run faster.

Afterwards, a testing process was carried out on a total of 60 images to calculate the testing accuracy of each model. Based on the testing accuracy of each model that can be seen in Table 5, there is an increase in accuracy as the amount of training data increases. However, the accuracy obtained by the fewest images, namely 0.83 provided by VGG16, 0.7 produced by ResNet, and 0.78 produced by InceptionV3, is not too poor. There was a decrease in accuracy on 102 training data, even for VGG16 and InceptionV3, the accuracy produced with 52 training data is higher or the same as the accuracy produced using 102 training data. This means that by using only 52 training data the resulting accuracy is quite good, so that a fairly good model can be produced in a relatively faster time.

However, for the three CNN architectures used, the highest accuracy was obtained by using the most training data, namely 202 training images. With 202 training images, VGG16 got the highest accuracy of all at 93%, then InceptionV3 got 91% accuracy, while ResNet got 90% accuracy. Next, a comparison of the training performance of each model was carried out. Comparison of the training performance of the three models was done by comparing the visualization results in the form of loss and accuracy graphs.

Table 5. Comparison between different model and amount of images training vs accuracy.

Models	Number of training images				
	12	52	102	152	202
VGG16	0.83	0.90	0.66	0.83	0.93
ResNet	0.70	0.81	0.70	0.83	0.90
InceptionV3	0.78	0.83	0.80	0.83	0.91

Even though the VGG16 model gets the highest accuracy, if you look at the graph of accuracy and loss in Figure 3, Figure 4 and Figure 5, the InceptionV3 model produces the smallest gap among the three, but it can be seen that the graph produced by InceptionV3 has quite high fluctuations.

The testing process used 20 images in each class of healthy leaves (H), leaves with mild CDC (M), and leaves with severe CDC (S). The confusion matrix results obtained by each model used 202 training images can be seen in Table 6. All three models can classify healthy leaves well. Although the InceptionV3 model works very well on healthy and leaves with severe CDC, this model works less well on leaves with mild CDC.

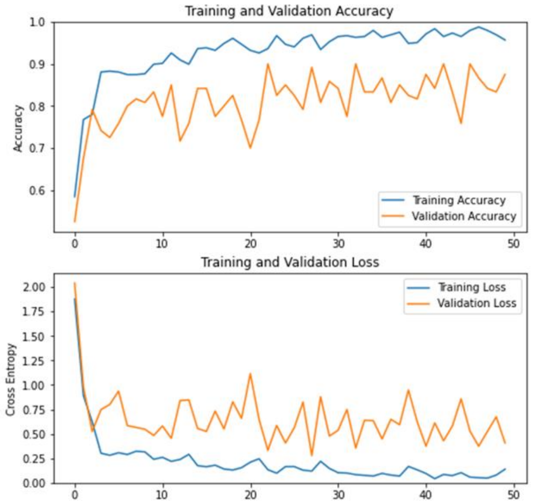

Figure 3. Plot of training and validation accuracy and loss for VGG16.

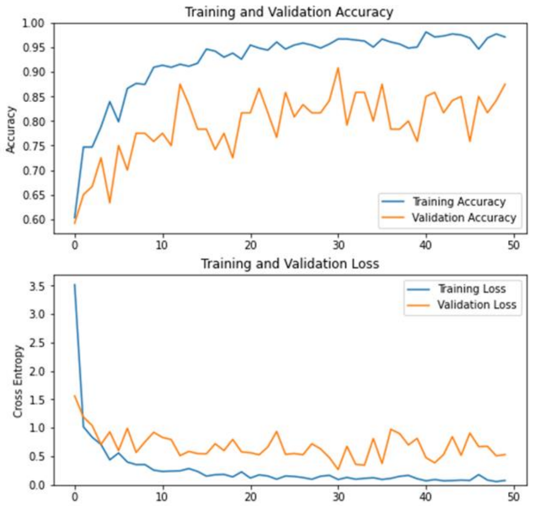

Figure 4. Plot of training and validation accuracy and loss for ResNet.

Figure 5. Plot of training and validation accuracy and loss for InceptionV3.

Table 6. Confusion matrix of three models.

True Label	Prediction								
	VGG16			ResNet			InceptionV3		
	H	M	S	H	M	S	H	M	S
H	19	1	0	20	0	0	20	0	0
M	1	18	1	3	16	1	3	15	2
S	0	1	19	0	2	18	0	0	20

Using ResNet's model, six images cannot be classified correctly. For the examples, one healthy leaf image in Figure 6(A) is classified as a leaf image with mild CDC. In this image, there are no visible spots or smallpox spots on the leaves, but the slightly reddish color of the leaves is likely to make the model incorrectly predict it as smallpox spots. The other three images Figure 6(B) which are leaves with mild CDC are classified as healthy leaves. Spots and smallpox on the leaf image that are visible enough cannot be recognized by the model as leaf pox.

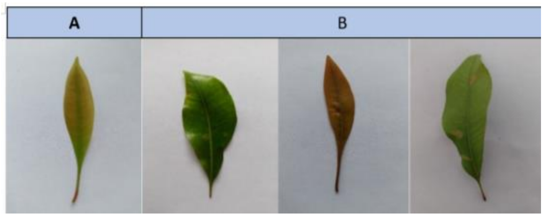

Figure 6. Misclassified images using ResNet Model. (A) Healthy leaf image classified as leaf with Mild CDC. (B) Leaf with Mild CDC images classified as healthy leaves.

The VGG16 model works better than ResNet in this testing process. Of the 60 testing data, only four images were not classified correctly. For the exmamples, one leaf in Figure 7(A) which is a leaf image with heavy CDC is classified as a leaf image with mild CDC, this could be because the model cannot see some spots that are obscured by the color of the leaf. The second image in Figure 6(B) is an image of a leaf with a mild CDC which is classified as a healthy leaf. This is because the model cannot detect spots on the edges of the leaves.

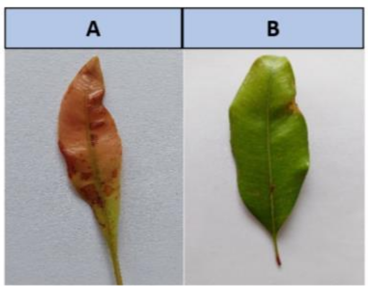

Figure 7. Misclassified images using VGG16 Model. (A) Leaf with severe CDC image classified as leaf with Mild CDC. (B) Leaf with Mild CDC images classified as healthy leaves.

Based on the InceptionV3 model classification results, five leaves with a light class have failed to be predicted. As can be seen in Figure 8, two leaves have a light CDC.The leaf in Figure 8(A) was incorrectly predicted to be a healthy leaf. This happened because the model could not detect the presence of smallpox spots on the leaves. Figure 8(B) also failed to be classified properly and was classified as a leaf with severe smallpox. This is probably due to the reddish color of the leaves, which causes the model to not distinguish the color of the shoots of leaves with reddish leaves due to CDC disease. It can be seen that both images are young leaves images which have a reddish color. This means that this model works less optimally on young, reddish leaves.

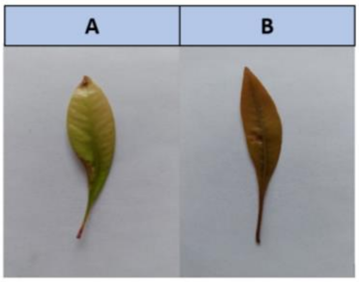

Figure 8. Examples of images that are not classified correctly.

Although the three models have different performance, judging from the resulting confusion matrix, it can be seen that the class of mild CDC obtains the lowest accuracy. In addition, it can be seen that there are no healthy leaves that are wrongly predicted to be leaves with severe CDC, and vice versa. This proves that the model can recognize the boundaries between healthy leaves and leaves with severe CDC.

Table 7. Performance of three models.

Models	P	R	F1
VGG	**0.95**	**0.93**	**0.94**
ResNet	0.90	0.90	0.90
InceptionV3	0.92	**0.93**	0.91

From the performance shown in the Table 7, it can be seen that the highest Precision(P), Recall(R) and F1 Score(F1) were produced by the VGG16 model. VGG16 baseline architecture uses three fully connected layers with the channel size as 4096, 4096, and 1000 respectively. Then a channel reduction experiment was carried out on VGG16. Each fully connected layer is set to 100 channels. Training was carried out with 202 training data for each class. The goal of this experiment is to speed up the training process and reduce the memory size of model and see if there is a decrease in model performance. The experimental results shown in the Table 8 show increased performance as well as reduced memory size of model and training time. This is in line with the aim of searching for small memory size of model and high-accuracy models that can be utilized on mobile devices without consuming a lot of resources.

Table 8. VGG16 baseline and proposed comparison.

Description	VGG baseline	VGG customised
Accuracy	0.93	**0.95**
Parameter	138,360,547	**14,714,688**
Training time (second)	10282	**6314**
Memory size of model	150MB	**87MB**

To increase accuracy, one method that can be used is K-Fold Cross Validation. From previous accuracy measurements, the best model was obtained by VGG16, therefore, the K-Fold Cross Validation method was then carried out on the VGG16 architectural model as an effort to increase accuracy. The accuracy of the results of the K-Fold Cross Validation method can be seen in the picture.

After carrying out the K-Fold Cross Validation method with K=10, it produced 10 models with varying accuracy. It can be seen in Figure 9 that the highest accuracy was obtained by the 5th Fold model, namely 0.97. Although not much, this method has succeeded in increasing the accuracy of the model.

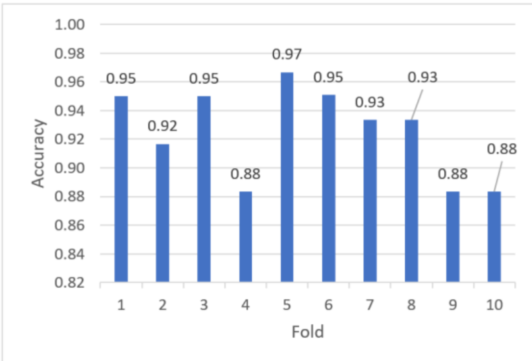

Figure 9. K-Fold Cross Validation accuracy.

Though approaching with other methods to improve the accuracy of the analysis may be needed still particularly for the samples with mild category. In addition, based on the analysis of misclassified images. There are images of reddish young leaves that are misclassified in all three models. This is likely due to the lack of young leaf image data at the training stage. To increase the accuracy of the resulting model, one effort that can be made is to add images of young leaves to the training process.

The current research findings should assist clove nursery growers in preventing the occurrence of leaf blister blight disease in the early stages of their plants. Growers can take preventative measures to keep their plants healthy and certified for distribution.

5. Conclusion and Future Work

Leaf Blister Blight Disease is one of the clove plant diseases that is often found in clove plantations. To be able to carry out proper handling, proper identification is also needed. CNN is a deep-learning architecture that is commonly used for image recognition. This study uses three CNN architectures, namely VGG16, ResNet, and InceptionV3. The three models produced can classify well and achieve fairly high accuracy. VGG16 got the highest average accuracy. The mild CDC class obtains the lowest accuracy of the three models. The pre-trained model succeeded in making a CDC classification model with high accuracy, even though the dataset used was relatively small.

All models apparently still has difficulty in identifying young leaves that have a reddish color. Therefore, for further research we will increase the dataset, especially images of young leaves, so that the training process can produce a better model for classification.

Other methods can also be applied such as ensemble methods. It can be seen from the confusion matrix, although the accuracy of InceptionV3 is lower than VGG16, InceptionV3 is very good in the class of healthy leaves and leaves with severe CDC disease, but works less well in the class of leaves with severe CDC. Meanwhile, VGG works better than InceptionV3 in the leaf class with light CDC. To cover each other's shortcomings, ensemble methods can be used to increase the accuracy of classification results.

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