Potato Leaf Disease Classification Using Deep Learning Approach

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***Abstract*— Potato is one of the staple foods that widely consumed, becoming the 4th staple food consumed throughout the world. Also, the world demand for potato is increasing significantly, primarily due to the world pandemic coronavirus. However, potato diseases are the leading cause of the decline in the quality and quantity of the harvest. Inappropriate classification and late detection of the disease's type will drastically worsen the plant conditions. Fortunately, several diseases in potato plants can be identified based on leaf conditions. Therefore, in this paper, we present a system to classify the four types of diseases in potato plants based on leaf conditions by utilising deep learning using the VGG16 and VGG19 convolutional neural network architecture model to obtain an accurate classification system. This experiment has achieved an average accuracy of 91%, which indicates the feasibility of the deep neural network approach.**

Keywords*— *Leaf Disease Classification, Deep Learning, VGG16, VGG19, Potato Plant

I. INTRODUCTION

Food security and nutrition improvement are some of the significant challenges faced by the agricultural sector and Potatoes become one of the staple foods that are expected to be able to suffice these needs in terms of quantity and quality. They are rich in nutrients, most notably vitamins C and B6 and the minerals, potassium, magnesium, and iron [1]. Besides being a popular staple food in Indonesia, potatoes are the fourth most consumed vegetable crop in the world. Potato agricultural products in Indonesia have developed rapidly in this decade. Every year, the amount of production can reach around 850,000 tons. The amount is produced from an area of about 60,000 hectares. The area of planting and production has increased by approximately 10% per year, making Indonesia the largest potato producing country in Southeast Asia. However, potatoes can be affected by many diseases which affect both pre and post-harvest stage of the plant [2]. The presence of disease during this growth period can reduce the quality and quantity of agricultural products. Also, it can lead to harvest premature and harvest failure. These problems are mostly caused by the late identification of diseases in potato plants and mistakes in disease diagnosis.

Fig. 1. Input Image of Potato Leaf Disease Classification. The input image used in this study is not more than 224x224 pixels.

Fig. 2. Output Image of Potato Leaf Disease Classification. The output image will give the percentage result of the image classification.

The identification of diseases in potato plants quickly and accurately is highly essential to reduce the impact of diseases on plants. Manual monitoring activities carried out by farmers become difficult and impractical because it takes a long time and in-depth knowledge. Identification of plants diseases types that are slow will trigger the spread of diseases in plants uncontrollably. Besides, farmers generally identify diseases in plants in a way that is approximately and assumptions that allow inaccurate identification results because the symptoms on the leaves appear to have similarities that are difficult to describe at a glance. Farmers use the results of personal identification without expert advice in the field of plant diseases as a reference in the prevention of plants infected with the disease. As a result, preventive measures taken by farmers may be ineffective and can damage crops due to inadequate knowledge and misinterpretation of disease intensity, excessive dosage, or lack of dosage [3]. This problem is the foundation of the proposed research to facilitate farmers in identifying and classifying diseases in potato plants that are fast and accurate.

The proposed research methodology focuses on the classification and identification of healthy and disease-infected leaf conditions using the Deep Learning approach as in Fig. 2. The architecture used in this study is VGG16 and VGG19, which is a Convolutional Neural Network architecture model of the VGG Network Group. VGG Network is a simple architecture with a smaller kernel compared to the previous architecture [4]. Both architectures have five layers of convolution and have a difference in the number of layers. In accordance with the names of the two, VGG16 has 16 layers, and VGG19 has 19 layers. The architectural layer allows us to study effective features for classifying diseases through leaves.

II. RELATED WORK

Research in the field of disease classification in plants has been carried out even with various methods. However, it is considered still lacking [5] and become one area of research that continues to be developed because the subject in this field

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varies significantly. Thirty-seven papers in agriculture were published in the 2015-2017 period. More precisely, 15 papers were published in 2017, 15 in 2016, and 7 in 2016. This fact shows how new and modern this technique is in the agricultural domain [6].

In order to learn an effective features representation, a deep learning-based method can be devised. Deep learning [7] has shown very good performance in many visual perception tasks, such as text detection [8], [9], victims detection, [10], [11], target tracking [12], [13], object detection [14], [15], [16]. A deeper network can boost accuracy. Interestingly, the work [10] has been proven theoretically and empirically that the last layers of the deep network can capture more semantics information or abstraction; thus, it is more robust to variation of pose, colour, scale, and deformable object, that is it could be suitable to classify the leaf diseases robustly.

Prajwala *et al.* [3] use the LeNet architectural model in this paper, Convolutional Neural Network model architecture to detect and identify tomato leaf diseases that are commonly found in tomato additions; Septoria Leaf Spot and Yellow Leaf Curl. The dataset was obtained by researchers from one of the Open Access image databases, PlantVillage. The level of accuracy resulting from the methodology proposed for this paper is 94% -95%.

Experimental results on a developed model by Srdjan Sladojevic *et al.* [17] with a new approach to recognise diseases in five types of plants and 13 different kinds of diseases using the convolutional neural network (CNN) method. From this study, an average accuracy of 96.3% was obtained. Using the same method but with a different architecture, Erika Fujita *et al.* [18] made a disease diagnosis system in cucumber plants using the Convolutional Neural Network method by adopting the AlexNet architecture and obtaining an average accuracy of 82.3%.

A total of 2000 images of corn leaf were obtained by Raja P *et al.* [19] from the open-access image database, PlantVillage. The dataset is used as an object classification of 3 types of diseases in maise leaves using a bag of features with the Multiclass SVM (Support Vector Machine) method. On this occasion, the researchers also evaluated the accuracy of the method compared to the histogram method and feature-based grey level co-occurrence. The results obtained show that the SVM (Support Vector Machine) Multiclass method is entirely accurate. Pranjali B. Padol and Prof. Anjali A. Yadav [20] uses segmentation with K-mean clustering to found the disease region, and then the colour and texture of the image are extracted. While for classification, they use the SVM (Support Vector Machine) Classifier method and get an accuracy of 88.89%.

Jobin Francis *et al.* [21] was adopting the Backpropagation Neural Network method to classify disease types in pepper plants and GLCM (Gray Level Co-occurrence) for feature extraction step. Types of pepper plant diseases that can be detected are Berry Spot Disease, a kind of fungal infection found in pepper and Rapid Disease, a kind of disease caused by mineral deficiencies such as nitrogen, magnesium, and potassium. Eftekhar Hossain *et al.* [22] used the same method for the classification of diseases such as Alternaria Alternata, Anthracnose, Bacterial Rot, Leaf Spot, and Plant Leaf Cancer. The performance of the KNN disease detection system in this paper is 96.76% accuracy.

Aakanksha Rastogi et al. [23] conducted a study using artificial neural networks and fuzzy logic methods to detect diseases in plants based on leaf conditions. This study focuses on identifying and classifying diseases in maple and hydrangea leaves. The condition of leaves of plants affected by the disease is divided into two categories, namely leaf spot, and scorch leaf. Leaf spots are where the disease on the leaves is at specific points of the leaf, while scorched leaves are where the disease on the leaves spreads evenly on the leaves.

III. Proposed Methodology

As shown in Fig. 3. The proposed methodology in this paper includes the following four main steps: data acquisition, data pre-processing, data augmentation, and image classification.

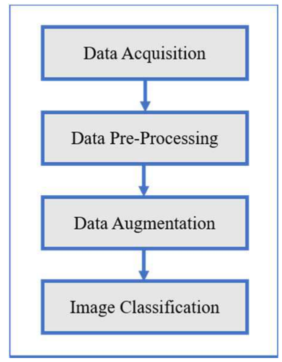

Fig. 3. Diagram Block Proposed Methodology. The methodology proposed in this study consists of data acquisition, data pre-processing, data augmentation, and image classification.

A. Data Acquisition

Different image resolutions and sizes were obtained from several sources, including those collected by authors from a potato plantation in Malang, Indonesia, PlantVillage [24] an open-access image database, and Google images. Obtained a dataset of about 5,100 images and divided into class five: diseases caused by Alternaria Solani as in Fig. 4. healthy as in Fig. 5. Phytophthora Infestans as in Fig. 6. Viruses as in Fig. 7. and Insects as in Fig. 8.

Fig. 4. Alternaria Solani. Symptoms in this disease are leaves with brown, non-glossy dead spots, concentric rings in a target-board pattern.

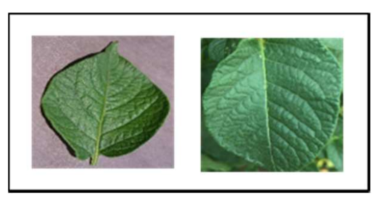

Fig. 5. Healthy.

Fig. 6. Insect. The symptom of an attack from insects is visible holes in the leaves.

Fig. 7. Virus. There are several types of viruses that attack potato leaves, but the symptoms are limited by leaves that have necrotic spots.

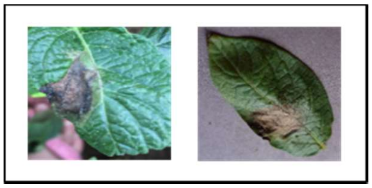

Fig. 8. Phytophthora Infestans. Symptoms of this disease are leaves with irregular, dark brown to black spots on leaves.

B. Data Pre-Processing

The first step is to minimise the noise in the image by cutting the part of the image that is not the region of interest. If there is excessive noise in the image, it will not be used. Images collected from multiple sources of different sizes must be resized to 224x224 pixels to standardise input images in the dataset.

C. Data Augmentation

Deep Learning (Deep Network) requires much data when compared to the shallow network of machine learning. The lack of training data and the balance of the amount of data in each class are common problems in Machine Learning and Deep Learning [25]. The method used to overcome this problem is data augmentation. Data augmentation is a technique of manipulating data without losing the essence of the data. Data augmentation needs to be applied in this study because 5100 datasets are still inadequate to get optimal performance. The augmentation parameters used in this study are carried out automatically by applying simple geometric transformations, such as translations, rotation, change in scale, shearing, vertical and horizontal flips.

D. Image Classification

Deep learning (DL), similarly known as deep neural learning or deep neural network, is part of machine learning (ML) in artificial intelligence (AI). The term "deep" means that Deep Learning has more layers than Machine Learning. Deep learning methods have improved the state-of-the-art in image classification, speech recognition, visual object recognition, object detection, and many other domains [7]. In Deep Learning, Convolutional Neural Network is one of the popular classes. Some studies use the convolutional neural network method to detect diseases in plants based on leaf conditions [3] [17] [18]. Convolutional Neural Networks generally consist of one or more convolutional layers that are grouped by function. Often the subsampling layer is followed by one or more layers that are fully connected as a standard neural network. Each feature layer receives input from a feature set located in a small area on the previous layer. LeNet was the beginning of the CNN architecture model and has now evolved into modern CNN architectural models such as AlexNet, VGG network, GoogLeNet, residual networks (ResNet), densely connected networks (DenseNet) [26].

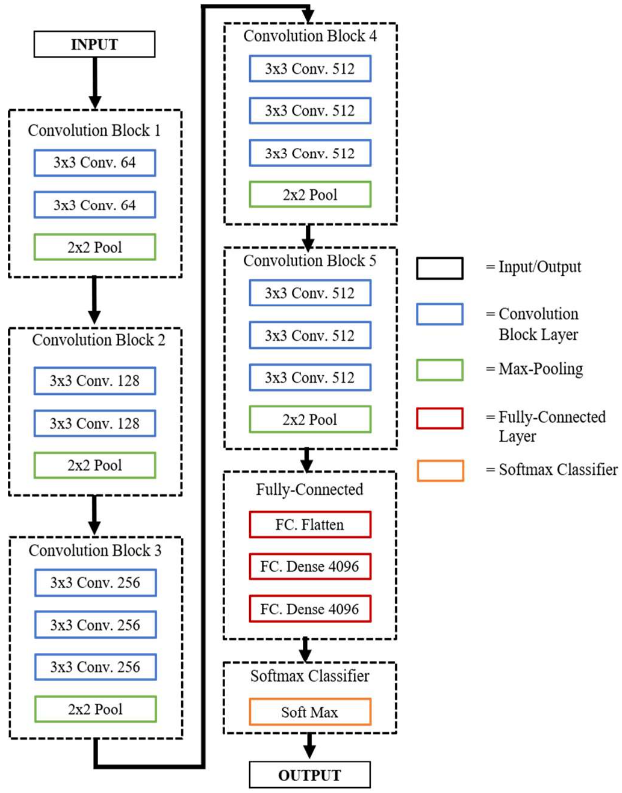

Fig. 9. VGG16 Architectural Model.

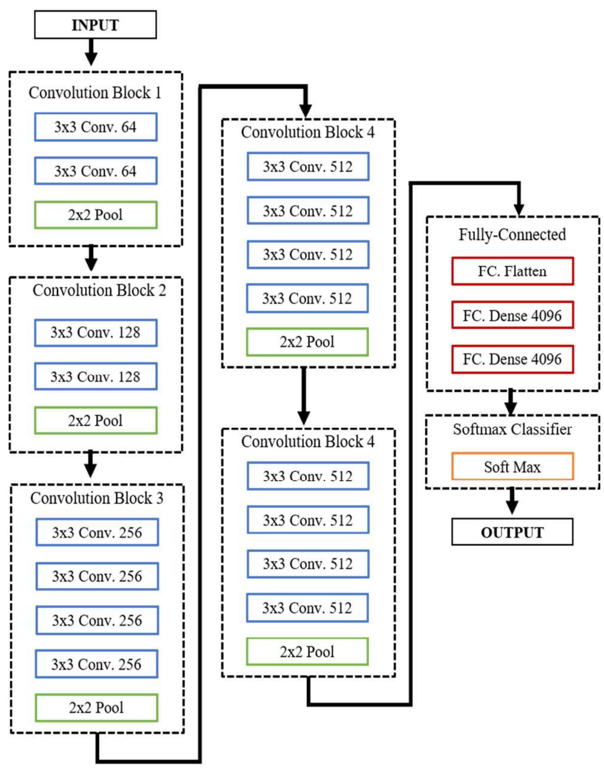

Fig. 10. VGG19 Architectural Model.

The architectural model used in this study to detect potato leaf disease is VGGNet. This architecture is the development of the AlexNet architecture model by changing the kernel size to smaller, several filters measuring 3X3 one by one. Stacked small kernels are considered more efficient and cheaper compared to large kernels. In VGGNet, the input as in Fig. 1. Passed through 5 convolutional layer blocks where each block consists of an increase in the number of 3x3 filters. The ReLU activation layer is applied in each block to recognise non-linearity so that the model can more easily adapt to various data. Dropout management techniques are used with a fixed probability of 0.25 to reduce overfitting conditions. Max-pooling layer separates blocks. Three fully connected (FC) layers follow five convolutional layer blocks. The softmax layer is the last layer to produce class probabilities. VGGNet evaluates very deep convolution networks in up to 19 layers. In this study, the authors used the two most popular types of VGGNet. VGG16 architecture shown in Fig. 9. contained 16 layers while VGG19 architecture shown in Fig. 10. contained 19 layers. The difference between the VGG16 architectures and VGG19 architecture is in the number of layers, as shown in Fig. 7. and Fig. 8.

IV. Experiment Result

A. Training Process

The dataset learning experiment was carried out using the Neural Network Convolutional method using the VGGNet family architecture model, specifically VGG19, which has 19 layers and VGG16, which has 16 layers. The epoch specified in this study was 250 epochs with 64 batch size, and a learning rate is 0.01 to improve the performance of the model. The learning process means that the algorithm with the proposed method seeks to come across values in the image dataset to be able to recognise new images. Each step of the epoch must be the same as the value of the image being trained. The results of the epochs will be recorded to determine the value of loss and accuracy. Loss is an indication of a bad value on the model, the value of the loss obtained must be close to zero or equal to zero and accuracy value is a parameter of the success level of the system in classifying objects.

The results of the Loss values are presented in both plots using VGG19 in Fig. 11. and VGG16 in Fig. 12. getting values close to zero. VGG16 had more oscillation values in the early epoch. The accuracy value presented in both architectures related to training with all datasets containing original images after the 250th epoch reaches 91%.

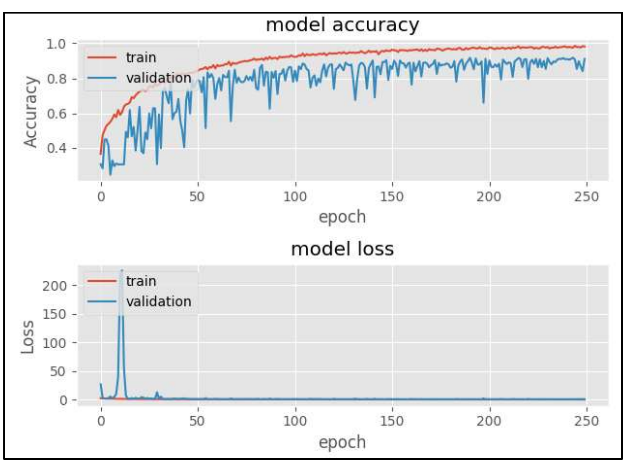

Fig. 11. The Plot of Accuracy and Loss using VGG19.

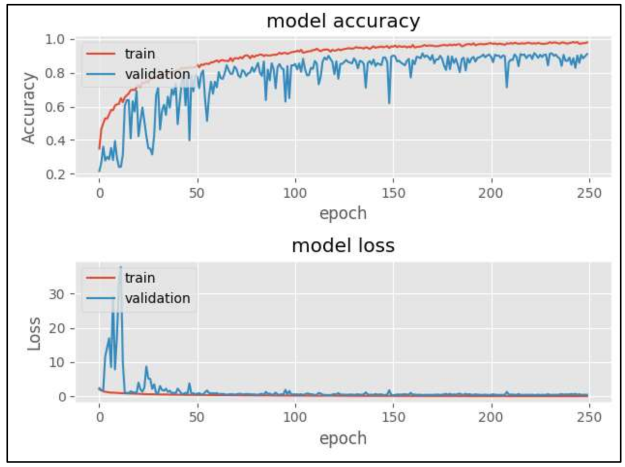

Fig. 12. The Plot of Accuracy and Loss using VGG16.

The results of the system will be validated to measure the performance of a classification system that provides performance information from the resulting model. The output data from the confusion matrix in Table I shows that most classes have a relatively high measure of model accuracy. In Alternaria Solani (Class 1) only slightly predicted wrong, so that the precision and recall produced reaches 99%. Healthy Class (Class 2) and Virus Class (Class 4) also provide good grades. However, some Healthy classes are classified as Viruses and classify Viruses as Healthy. This false identification is because the objects in some virus dataset are so small that they look like healthy leaves. The confusion matrix in the Phytophthora Infestant class (Class 3) produced little wrong predictive value. Then, the confusion matrix from the Insect class (Class 5) provides a value that is not precise enough because some data from another class is estimated to be the Insect class.

The output data from the confusion matrix in Table II. present that most classes have a relatively high measure of model accuracy. In Alternaria Solani (Class 1) only slightly predicted wrong that produces 99% recall, there are some data on the Phytophthora Infestans class which is predicted as Alternaria Solani so that the resulting precision reaches 95%. These wrong predicted will have an impact on the results of the classification of the class Phytophthora Infestant (Class 3). Similar to the VGG16 method that Healthy Class (Class 2) and Virus Class (Class 4) also generate pretty good grades. However, some Healthy classes are classified as Viruses and classify Viruses as Healthy. This false identification is because the objects in some virus datasets are so small that they look like healthy leaves. Then, the confusion matrix from the Insect class (Class 5) is quite precise, even though some data from other classes is predicted to be the Insect class.

TABLE I. Confusion Matrix using VGG16 Architecture.

Confusion Matrix using VGG16							
Actual Class		Prediction Class					Recall
		1	2	3	4	5	
	1	273	0	1	3	0	0,99
	2	1	183	3	31	5	0,82
	3	1	1	384	8	5	0,96
	4	1	26	1	216	7	0,86
	5	0	1	3	8	58	0,83
Precision		0,99	0,87	0,98	0,81	0,77	0,9131148

TABLE II. CONFUSION MATRIX USING VGG19 ARCHITECTURE.

Confusion Matrix using VGG19							
		Prediction Class					Recall
		1	2	3	4	5	
Actual Class	1	274	0	1	1	1	0,99
	2	0	187	1	31	4	0,84
	3	13	5	339	4	2	0,93
	4	0	25	4	219	3	0,87
	5	0	3	3	6	58	0,83
Precision		0,95	0,85	0,97	0,84	0,85	0,9096284

B. Testing Process

After conducting the training process on the collected datasets, we retrieve the new data outside the training datasets to be tested with each model; VGG16 and VGG19.

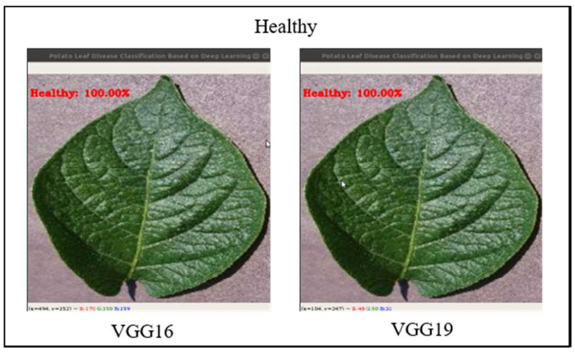

Fig. 14. Result of Healthy Leaf Testing.

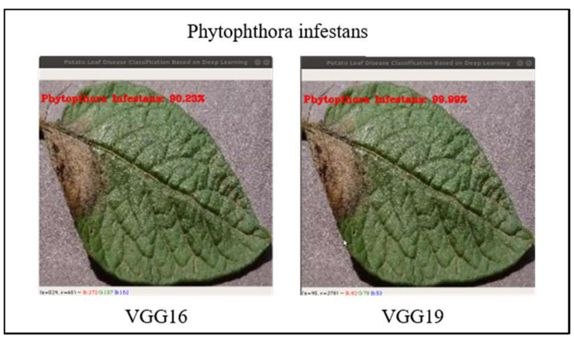

Fig. 15. Result of Phytophthora Infestans Testing.

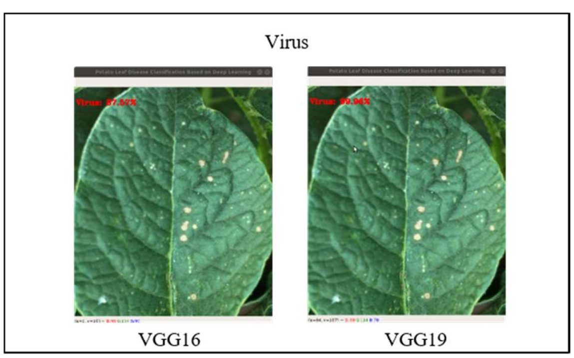

Fig. 16. Result of Virus Testing.

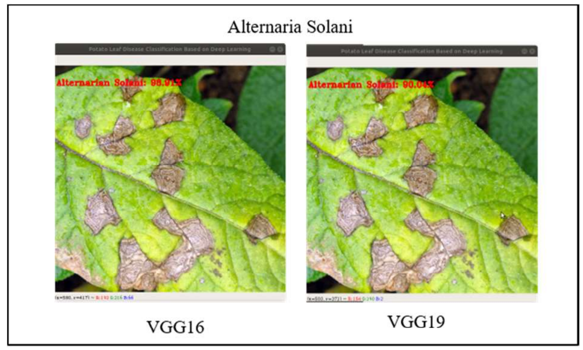

Fig. 17. Result of Alternaria Solani Testing.

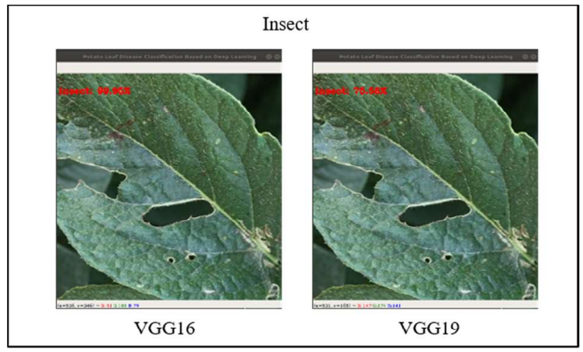

Fig. 18. Result of Insect Testing.

In this experiment, The accuracy value of the learning process between the two architectural models shows the same number, which is 91%. Then, we would like to look deeper into the accuracy values in the confusion matrix table of the two architectural models. In VGG16, the architectural model is detailed in Table I. gives an accuracy value of 0.9131148. Meanwhile, the VGG19 architecture model is detailed in Table II. gives an accuracy value of 0.9096284. VGG16 architecture model got 0.00349 better than VGG19. The accuracy value in the confession matrix is obtained from the total sample distribution operation, which is classified according to its class by all samples produced.

Training time using the parameter of epochs is 250, the learning rate is 0.01, and the batch size is 32. In VGG16, it takes an average time of 245 seconds per epochs so that for 250 epochs requires 61,250 seconds or equal to +/- 17 hours. In contrast to VGG19 which takes longer than VGG16, that is, an average of 305 seconds per epoch so that for 250 epochs it takes 76,250 seconds or equivalent to +/- 21 hours.

It is imperative to note that when testing the model is the precision of the leaf image object, noise in the image will result in poor classification results. Minimisation of noise in an image can be done by cutting off parts of the image other than the leaf object to be identified and making sure there is only one leaf in one frame.

V. ACKNOWLEDGEMENT

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VI. Conclusion and Future Work

In this research, VGG Network (VGG16 and VGG19) appears to be potential for studying effective features for image classification of leaf diseases. Added the data augmentation process in the dataset would produce a more robust system. Experiments show that our proposed method can achieve an average accuracy of 91%. We believe this work can bring many benefits in agriculture-related to world food security.

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