Identification of Chili Plant Diseases Based on Leaves Using Hyperparameter Optimization Architecture Convolutional Neural Network

Murinto, Sri Winiarti, Ardi Pujiyanta
Department of Informatics, Universitas Ahmad Dahlan Yogyakarta, Indonesia

***Abstract*—This paper proposes a method to detect chili plant diseases based on leaves. Studies in recent years have shown that chili production in Indonesia has decreased. This is because there are several influencing factors. One common factor is the presence of diseases in chili plants that cause less than optimal harvest production. Fungi or pests on chili leaves usually cause diseases that often appear in chili plants. Chili leaf diseases have a negative impact on chili harvest yields. Chili leaf diseases can result in significant decreases in both the quantity and quality of chili harvests. Accurate disease diagnosis will help increase farmer profits. This study identified four major leaf diseases, namely leaf curl, leaf spot, yellowish, and white spot. In this research images were taken using a digital camera. These diseases were classified into five classes (healthy, leaf curl, leaf spot, yellowish, and white spot) using two different pre-trained deep learning networks, namely MobileNetV2 and VGG16, using chili leaf data through deep learning transfer. The experimental results showed the model with the best performance was the VGG16 model. This model achieved a validation accuracy of 94% on public and own data sets. Meanwhile, the next best-performing model is MobileNetV2, which achieved an accuracy of 90%, followed by the Traditional CNN Model, which achieved a validation accuracy of 88%. In future developments, we intend to deploy it on mobile devices to automatically monitor and identify various types of chili plant disease information based on leaves.**

Keywords*—*Chili leaf; deep learning; MobileNetV2; transfer learning; VGG16

I. Introduction

In several agricultural countries, the country's main income is agricultural products. The condition of the soil environment and land requirements are important influences on the harvest produced. However, farmers need help with several problems, such as water shortages, natural disasters, plant diseases, etc. However, some of these problems can be reduced by providing technical facilities for farmers. An automatic plant disease identification and prevention system is one solution that can help farmers. This type of system can overcome the problem of lack of knowledge about plant diseases because there are very few experts in this field [1],[2],[3]. The automatic system will also save time and help increase farmers' profits [4]. In agriculture, detecting and classifying leaf diseases is important because farmers often have to decide whether the cultivated plants are thriving.

Generally, examination through observation of leaves, roots, stems, flowers and fruits can identify the type of food crop that is suffering. This manual approach does not guarantee accuracy in identifying the plant disease. In addition, not all plant diseases in plants can be identified manually. Likewise, manual identification of plant diseases takes a long time. The research that is currently being done is to identify and classify plant diseases automatically using the help of artificial intelligence. Automation in monitoring types of food crops will greatly assist farmers in monitoring their plants. If the plant disease can be detected early, the possibility of producing a good harvest will be achieved [5].

Automatic detection of plant diseases based on images is one of the jobs in Computer Vision. One of the techniques used in Computer Vision is Machine Learning Techniques. In the field of agriculture, machine learning techniques can produce very significant improvements when applied. Detection and classification of plant diseases using deep learning is one example used to help farmers detect types of plant diseases. Research on the identification, detection and classification of plant diseases using deep learning techniques has become a subject of much research in recent years. Conventional computer vision algorithms, support vector machine (SVM) [6], K-nearest neighbors (KNN) [7], and K-means clustering methods [8] of machine learning algorithms have been used for early detection in various fields.

The process of grouping an object based on certain parts is called classification. Classification is one part of the work in machine learning. While machine learning itself is part of Artificial Intelligence (AI). In general, AI is a branch of computer science that focuses on development that has human intelligence capabilities. One part of Machine Learning is Deep Learning [9]. In Deep Learning, several algorithms are already known and often used, including the algorithm is Recurrent Neural Networks (RNN) [10], Convolutional Neural Networks (CNN) [11], [12], [13], and Deep Generative Model (DG) [14]. Convolution Neural Network is a model in deep learning that is usually widely used in classification work. One of the known classifications is how chili plant diseases are classified into several types based on their leaves.

A large number of parameters need to be trained in CNN and its variants, while training these CNN architectures also requires several labelled samples and substantial resources from scratch to assess their performance of the technique. Collecting a large labelled dataset is a challenging task. Despite its limitations, previous investigations have successfully demonstrated the potential of deep learning algorithms. In particular, deep transfer learning alleviates the problems classical deep learning methods face. The solution consists of using a pre-trained network where only the parameters of the final classification level need to be inferred from scratch. Some existing deep learning transfers include the following: Alexnet [15], VGG16 [16], MobileNetV2 [16], GoogleNet [17], Resnet [18]. However, not all deep learning transfers suit all problems. Transfer learning has been widely used in several recent studies, including MobileNetV2 and VGG16, which have been applied in various fields.

This study aims to apply the latest transfer learning deep learning technique for chili plant disease recognition based on visible leaf images. Traditional Convolutional Neural Network (CNN) is used to perform the classification, which is then compared with existing transfer learning models, namely MobileNetV2 and VGG16. This study recognizes diseased plants based on symptoms to achieve recognition without the influence of several disease symptoms that appear on one leaf.

II. Materials and Method

A. Materials

A dataset of images containing symptom images of four chili plant diseases, namely yellowish, leaf spot, leaf curl, and white spot, was created. Based on this dataset, CNN, MobileNetV2, and VGG16 models were trained to recognize chili plant diseases.

1) Dataset chili plant diseases: The trained dataset contains several diseases that attack chili plants. Using a mobile phone camera, images are collected under several conditions depending on the time (e.g., lighting), season (e.g., temperature, humidity), and location of the image capture. For this reason, we have visited several chili plantations in the Semarang and Klaten Regencies. Other data was obtained from Kaggle.com, which is public data. The data we use consists of 250 images of chili plant leaves. The images are divided into 5 categories: a healthy image class and four classes of diseased images representing four diseases: whitefly, curl leaf, gray mold, and yellowing. The four types of chili plant diseases are:

a) Yellowish. Symptoms of this disease are leaves that appear wilted, starting from the bottom, then turning yellow up towards the young branches. The body parts of the chili plant infected with this disease will be covered in white hyphae like cotton. If the chili plant is attacked while it is still growing, fruit can still be produced. However, if the disease has spread to the stem area, the young chilies will fall off. Fig. 1 shows several examples of chili plant diseases based on leaves called yellowish.

b) White fly. Yellow virus is also commonly called bule or bulai disease, the yellow virus causes chili plants to appear yellow. This disease caused by the gemini virus can be carried from seeds or seeds and transmitted by lice. Because it is caused by a virus, chemical poisons will not work to overcome it. Therefore, control must be carried out from the beginning, namely by selecting superior seeds that are resistant to virus attacks. In addition, of course, eradicating vector pests, such as lice. Fig. 2 shows several examples of chili plant diseases based on leaves called white fly.

Fig. 1. The example of yellowish disease.

Fig. 2. The example of white fly disease.

c) Leaf spot. Symptoms of chili plants affected by leaf spots are the appearance of round brown spots on the leaves. These spots are usually about 1 inch in size with a pale to white center with darker colored edges. Caused by the fungus Cercospora capsici, this disease can be carried by wind, rainwater, vector pests, and agricultural tools. Among the supporting factors for leaf spots are environmental conditions that are always rainy. To prevent it, you can choose healthy seeds that are free of pathogens. In addition, improving drainage and choosing the right planting time also need to be done to minimize the possibility of attacks. Fig. 3 shows several examples of chili plant diseases based on leaves called leaf spot.

Fig. 3. The example of leaf spot.

d) Curl leaf. Finally, leaf curl or mosaic is a disease caused by Cucumber Mosaic Virus (CMV). Insects can transmit diseases from one tree to another. If the chili plant is attacked by leaf curl, its growth becomes stunted and the size of the leaves is smaller. The possibility of spreading disease can be reduced,the destruction of chili plants that have been attacked needs to be done. Fig. 4 shows several examples of chili plant diseases based on leaves called curl leaf.

Fig. 4. The example of curl leaf disease.

B. Research Method

Fig. 5 shows a detailed overview of the detection and classification of chili plant diseases based on leaves proposed using deep transfer learning techniques with the first stage of collecting chili plant disease images based on leaves, the second is image pre-processing and image augmentation, the third part is the process of forming a mode where this stage includes the training, validation and testing processes, while the fourth process is the results and evaluation process. In the third process, the transfer learning models used are VGG16 and MobileNetV2.

C. Convolutional Neural Network

The convolutional neural network architecture model has four main components, namely: convolution layer, pooling layer, activation function and fully-connected layer. One of the known activation functions is the non-linear activation function Rectified Linear Unit (ReLU). The CNN Architecture model is shown in Fig. 6. The convolutional neural network architecture model consists of an input image measuring 28x28x1. When using a color image, the input image size is 28x28x3. RGB color images have three channels, namely Red (R), Green (G) and Blue (B). Furthermore, the input image is fed into the convolution layer using a valid padding kernel measuring 5x5. This process produces n1 channels with an image size of 24x24x1. The next process is max pooling 2x2 which produces an image measuring 12x12x1. Stride 2 is used to reduce the convolution layer in the next layer. This process is then repeated by running the convolution process and then max pooling again. After the max pooling process is complete. Furthermore, the process is carried out through a Fully-Connected Neural Network using the ReLU activation function. The result of this process is the classification of objects into several previously determined classes. In this study, the Softmax activation function was used in the last layer because the object of chili plant disease based on leaves has more than two classes.

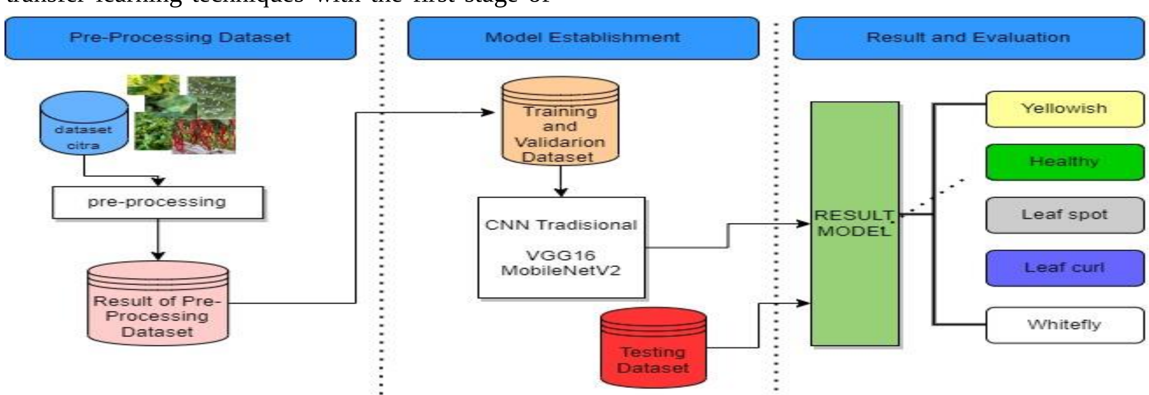

Fig. 5. Methodology of the detection and classification of chili plant diseases based on leaves.

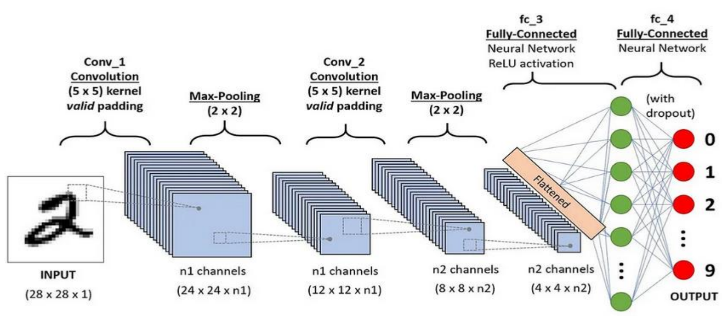

Fig. 6. The architecture of the CNN model.

D. VGG16 Model

The VGG model developed by A. Zisserman and K. Simonyan from the University of Oxford (2014) [19] is a CNN architecture with about 138 million parameters. The feature of this architecture is that it always has the same convolutional layers using 3x3 filters with a stride of 1 and the same padding and max pooling layers using 2x2 filters with a stride of 2. The VGG16 architecture follows this arrangement of convolutional and pooling layers consistently across the architecture. Finally, there are 3 FC layers, the first with ReLU and the last with SoftMax activation function. This architecture contains 16 layers, and the input layer takes an image of 224x224 pixels in size. VGG-16 A convolutional neural network model called the VGG model, or VGGNet, which supports 16 layers, is also known as VGG16. This model significantly outperforms Alexnet by replacing some 3x3 kernel-sized filters with large kernel-sized filters. VGGNet-16 has 16 layers and can classify photos into 1000 different object categories. This model also accepts images with a 224 x 224 x 7 resolution. The VGG16 Architecture model is shown in Fig. 7.

E. MobileNetV2 Model

The MobileNetV2 CNN model was introduced by Sandler et al. (2019). This model is based on the MobileNetV1 architecture by Howard et al. (2017). MobileNetV2 is a lightweight CNN model with 53 deeper layers, fewer parameters, and an input size of 224 × 224. The MobileNetV1 architecture uses the concept of depth wise separable convolutions that apply one filter to each input channel, and pointwise convolutions (1 × 11 × 1) aim to combine the outputs of depth wise convolutions. The MobileNetV2 model is a CNN architecture that attempts to perform well on mobile devices. This architecture is based on an inverse residual structure where residual connections are between the bottleneck layers. The intermediate expansion layer applies lightweight depthwise convolutions to filter features, introducing non-linearity. Overall, the MobileNetV2 architecture contains an initial complete convolution layer with 32 filters, followed by 19 residual bottleneck layers. The MobileNetV2 Architecture model is shown in Fig. 8.

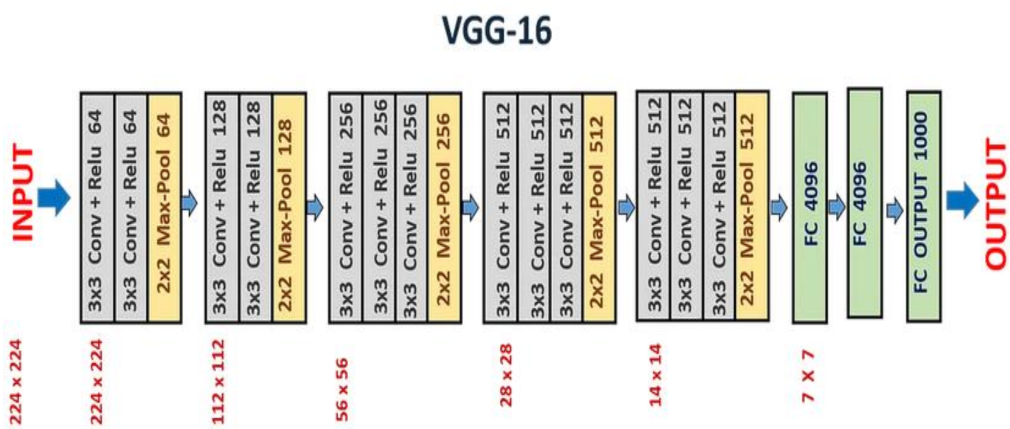

Fig. 7. The architecture of the VGG16 model.

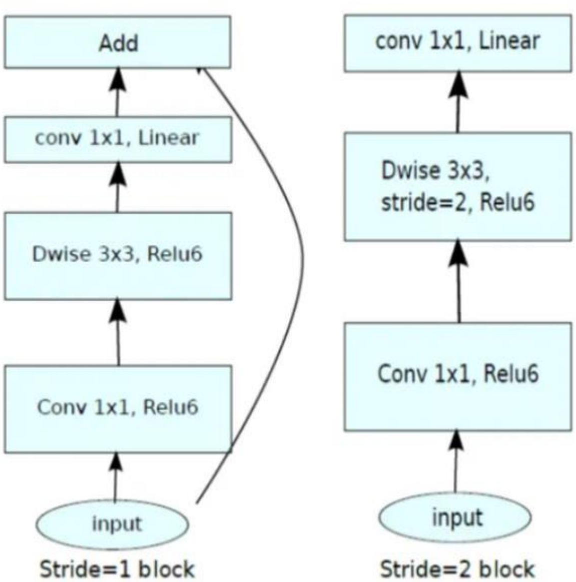

Fig. 8. The architecture of the MobileNetV2 model.

III. RESULT AND DISCUSSION

The model described in Section II was trained and tested using the parameters as shown in Table I. Training and testing were implemented using Python on Google Collab. The batch size of the training model was taken as eight, and a stochastic gradient optimizer was used. Image preprocessing algorithms, data augmentation, and deep learning algorithms were implemented using Python 3.7. The complete software and hardware specification for training on various images of chili plant leaves is Confusion Matrix. Considering the values in the confusion matrix obtained in the classification, the given metrics are calculated using indices such as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Here, TP is the number of disease images correctly classified in each category, while TN, on the other hand, represents the number of images correctly classified in all other categories except for the relevant category. FN gives the number of images incorrectly classified from the relevant category. FP gives the number of images incorrectly classified in all other categories except for the relevant category. In Eq. (1), (2), (3), and (4), each states precision, recall, accuracy, and F1-Score [20].

$$\text{precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{1}$$

$$recall = \frac{TP}{TP+FN} \tag{2}$$

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}} \tag{3}$$

$$F1\ Score = 2 * \left(\frac{Precision * Recall}{Precision + Recall}\right) \tag{4}$$

The performance of the pre-trained networks VGG16 and MobileNetV2, tested, is tested by transfer learning in this section. The features learned by VGG16 and MobileNetV2 are then transferred to the new task of chili plant disease recognition based on leaves. The training parameters used for VGG16 and MobileNetV2 are the same as mentioned before. The results of both transfer learning models are compared with the traditional CNN model. Fig. 9 to Fig. 11 show the accuracy and loss graphs of the models used in this study. Fig. 12 show result of confusion matrix in this research. Table I show the performance of Traditional CNN, MobileNetV2, and VGG16 with transfer learning. The results presented in Table I show that the VGG16 Model achieves better performance than MobileNetV2 and Traditional CNN. The accuracies of Traditional CNN, MobileNetV2, and VGG16 Model are 88.0%, 91.00%, and 94%, respectively. As expected, the VGG16 Model with transfer learning outperforms Traditional CNN and MobileNetV2 trained from scratch, which may be due to the reason that it has been trained on more than one million images. Therefore, the feature presentation is much richer than CNN trained from scratch.

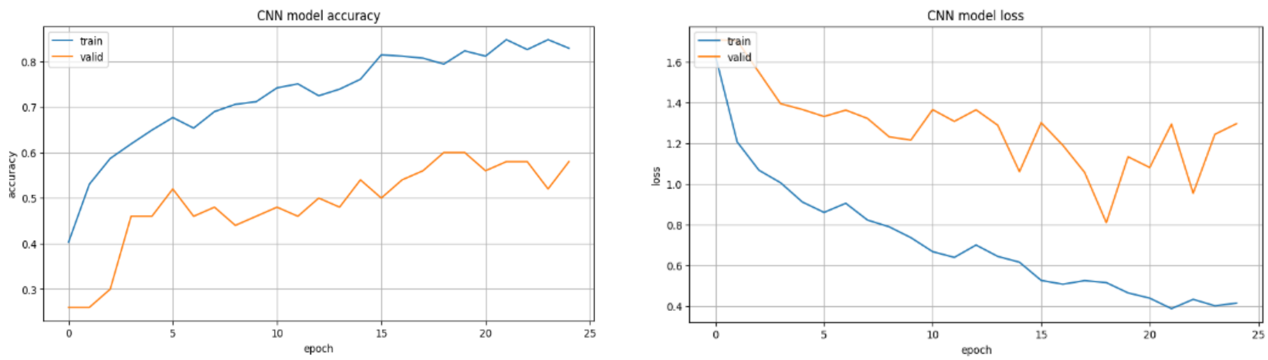

Fig. 9. The accuracy and loss CNN model.

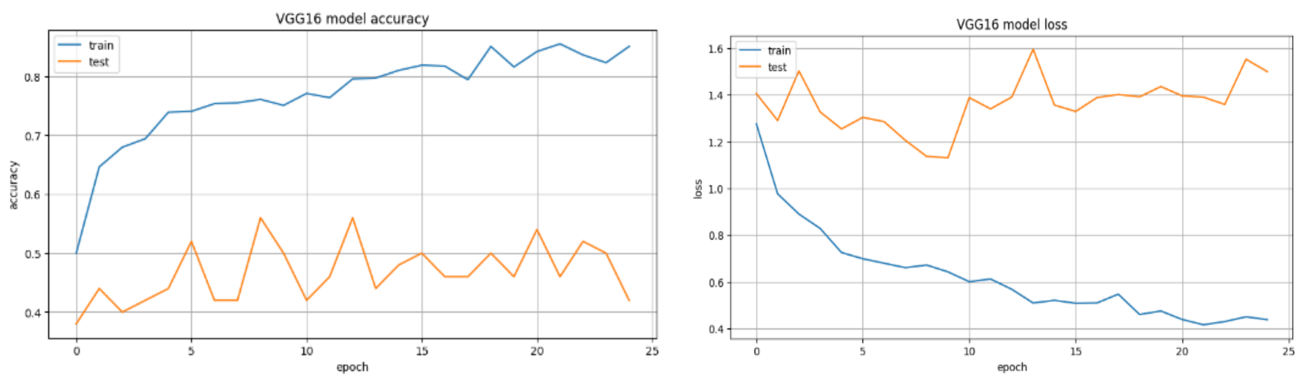

Fig. 10. The accuracy and loss VGG16 model.

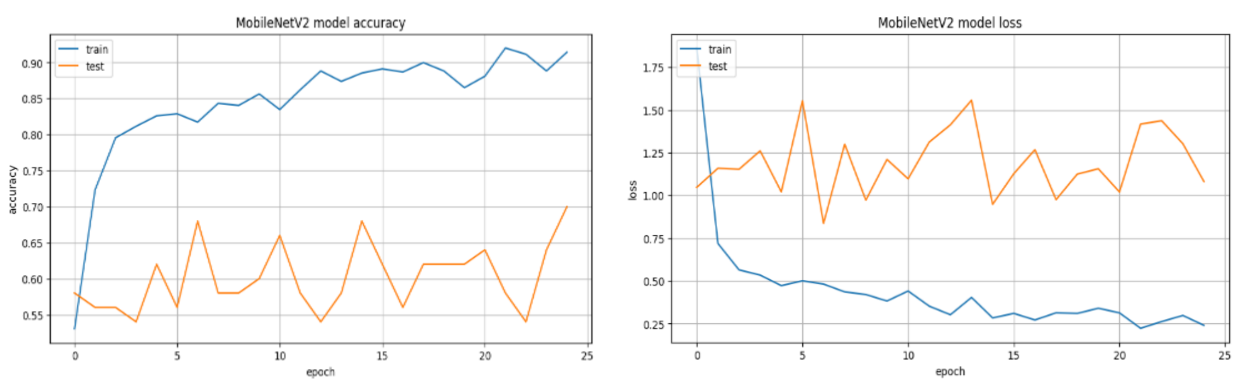

Fig. 11. The accuracy and loss MobileNetV2 model.

TABLE I. CONFUSION MATRIX OF CNN TRADITIONAL, MOBILENETV2 AND VGG16 MODEL

Chili Diseases	Precision	Recall	F1-Score	Precision	Recall	F1-Score	Precision	Recall	F1-Score
	CNN Model			VGG16 Model			MobileNetV2 Model		
Healthy	0.86	0.60	0.71	0.75	0.90	0.81	0.86	0.60	0.71
Leaf curl	0.50	0.40	0.44	0.67	0.60	0.63	0.50	0.40	0.44
Leaf spot	0.33	0.60	0.43	0.82	0.90	0.43	0.33	0.60	0.43
Whitefly	0.78	0.70	0.74	0.88	0.70	0.78	0.78	0.70	0.74
Yellowish	0.97	0.96	0.97	0.98	0.98	0.98	0.97	0.96	0.97
Accuration			**0.88**			**0.94**			0.91

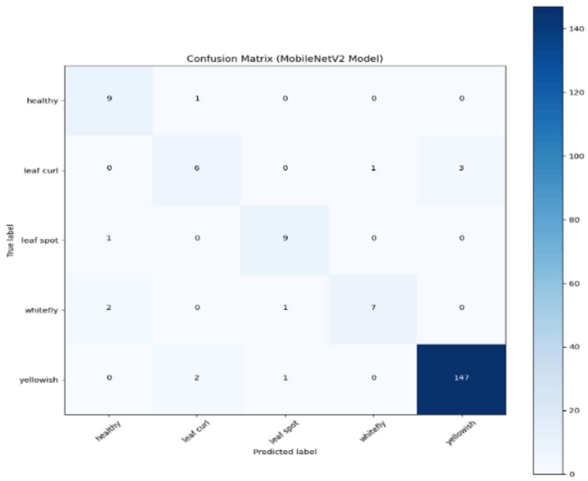

Fig. 12. The confusion matrix of MobileNetV2 Model.

Table I shows the data results on the chili leaf image dataset test. From the CNN architecture model confusion matrix, the accuracy value is 0.88 or 88% while the precision is 0.6860, ecall is 0.6520, F1-Score is 0.6580. In this study, three CNN architectures were used, namely: Traditional CNN Model, MobileNetV2 and VGG16. From the experimental results, it can be seen that the highest classification accuracy was obtained when using the VGG16 architecture model, which was 94%. These results indicate that when using the VGG16 architecture, there was a 6% increase in accuracy when compared to when using traditional CNN. An increase of 6% compared to when using traditional CNN is a positive trend. Classification accuracy is possible to be improved when using the transfer learning model. One way that can be used is through the appropriate hyperparameter setting. Through this hyperparameter setting, the CNN architecture used will be optimal. It is hoped that in the next study, hyperparameter optimization techniques can be used. One that can be used is to optimize using Particle Swarm Optimization and its Modifications, Genetic Algorithms and other optimization algorithms.

IV. CONCLUSION

This study identifies four significant diseases in chili plants based on leaves: leaf spot, yellowish, white fly, and curl leaf. The images used in this study were taken from the image dataset on Kaggle and also taken independently at the location of the chili plant, including healthy leaves labeled as healthy, so this study was divided into five classes. The chili leaf dataset is balanced, meaning that all classes have the same number of samples, namely 50 images per class and a total of 250 images with a size of 224 x 224 × 3. The experimental results show that the model with the best performance is the VGG16 model. This model achieves a validation accuracy of 94% on public and own data sets. The next best-performing model is MobileNetV2, which achieves an accuracy of 90%, followed by the Traditional CNN Model, which achieves a validation accuracy of 88%. In future developments, we intend to deploy it on mobile devices to automatically monitor and identify various types of chili plant disease information based on leaves. This study has limitations in terms of the dataset collected. Further research is expected to use a complete dataset so that training accuracy can be further improved.

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