Classification of Paddy Leaf Disease Using MobileNet Model

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***Abstract*— Paddy is a rice-producing plant as a staple food raw material for most of the population in Indonesia. The rice planting process cannot be separated from pests and diseases that can cause crop failure and impact on rice production stocks. Currently, the process of monitoring the development of rice plants is done conventionally by direct observation by farmers. Meanwhile, in this paper, a classification model and determination of object detection in rice plants infected with pests and diseases is proposed based on leaf color. Leaf classification applies convolution conditional network algorithm with mobilenet as the architecture. The leaf image dataset was taken from public data from kaggle.com by involving 4 classes, namely healthy leaf images, brownspot, hispa and leafblast images. In each class the leaf images are grouped into 2 groups, namely 70% training and 30% validation. On the mobilenet backbone, it produces 97% accuracy and 22% loss with the time required for 195s 19s/step in 1 epoch round.**

Keywords—mobilenet, classification model, paddy leaf, leaf classification

I. Introduction

Indonesia is an agricultural country with a standard area of 7.46 million hectares of rice fields in 2019 according to data from the Central Statistics Agency and produces a variety of agricultural products. One of the agricultural products, namely rice, which produced a rice harvest in 2019 of 54.60 million tons of Milled Dry Grain or decreased by 4.60 million tons or 7.76 percent compared to 2018. If the rice harvest is converted to rice as a staple for the community, rice production in 2019 was 31.31 million tons or decreased by 2.63 million tons or 7.75 percent compared to 2018. Rice is a staple food for the people of Indonesia and in various countries, almost 75% the world's population consumes rice [1] and the Asian region controls rice production by 40% of world rice production [2].

The success of rice production is influenced by the presence or absence of pests that cause disease in rice plants. There are several types of diseases in rice plants, namely bacterial blight, brown spot, sheath rot and blast disease [3]. The presence of diseases in rice plants requires the detection of rice plant diseases quickly, accurately and precisely. Prior to the existence of artificial intelligence (AI), plant disease detection was carried out by direct monitoring by experienced farmers and it took time [4] and observations were very possible based on each farmer's subjective perception [5]. The existence of artificial intelligence technology changes the paradigm and revolutionizes the world of agriculture in protecting crops from several factors such as climate change, population growth to food security. Artificial Intelligence is also able to manage irrigation problems with the help of sensors and drones so that plant needs can be measured as needed [6]. In addition, AI can also be applied to the detection of dangerous objects, which endanger flights [7].

Classification and detection of rice plant diseases requires fast, accurate and precise time because to prevent damage to rice which results in decreased rice yields. Two jobs are carried out simultaneously by combining object classification and detection methods which aim to simplify the computational process and reduce the required resources. Classification as backbone using mobilenet architecture.

The use of the MobileNet architecture is due to the shorter computing time required so that fewer resources are needed [8]. The difference between MobileNet and other architectures lies in the convolution layer process which is divided into 2 parts, namely depthwise convolution and pointwise convolution. With the process in the convolution layer which is divided into 2 parts, it can reduce the computational process by one-eighth than before.

In a study on apple object detection conducted by Yunong Tian., et al in 2019 stated that real time detection of apple objects in plantations is one method to monitor the growth of apples and also to predict several parameters of apples namely size, color, density and other growth characteristics. Traditionally, monitoring of apple plant growth is carried out directly by farmers, but this method has a drawback, namely that growth monitoring can only be carried out at certain phases.

MobileNet divides the convolution layer into 2 parts, namely the depthwise and pointwise sections. The MobileNet architecture uses convolution layers with filter thickness adjusted to the thickness of the input image. There are 2 parameters that distinguish it from other architectures, namely the width multiplier and the resolution multiplier. The function of the width multiplier is to streamline the network at each layer simultaneously to reduce the number of filters. While the resolution multiplier serves to reduce the image resolution. By playing some combinations of width and resolution multiplier values will produce a smaller model but will affect the overall accuracy [9].

II. METHODOLOGY

The rice image used as a dataset uses public data from kaggle as many as 4 classes, namely healthy, brownspot, hispa and leafblast. An overview of the number of datasets per class is shown in Figure 1.

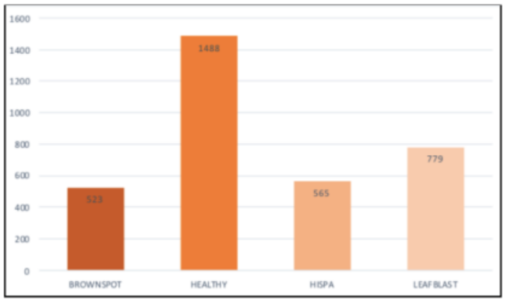


Figure 1. Number of datasets for each class

The dataset before being used has gone through the augmentation stage to ensure the images can be used and have the same size 416 x 416. Each class will be divided into 2 groups with a ratio of 70-30. Training data is 70% and testing data is 30%.

Figure 2 is a simple display of the image of each class.

Figure 2. Simple view of the dataset

At the classification stage using the mobilenet architecture because the resources needed are simpler when computing. The architecture of the mobilenet and the stages of Batch Normalization (BN) and ReLU are shown in Figure 3. Batch normalization is added to the convolution layer which functions to improve performance and stability system in artificial neural networks. While the ReLU used on the mobilnet is ReLU6 because the computational process is less precise but prevents too large an activation.

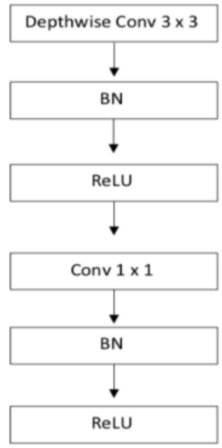


Figure 3. BN and ReLU block [10]

The concept of MobileNet architecture is based on an inverted residual structure which means that the basic network is still the same but there are improvements in feature extraction. MobileNet undergoes a training and testing process using the Python programming language and the Tensorflow library as well as using Google Colab to graphically present the performance of accuracy and loss in the training or validation sector. Training using a computer with a processor specification of 1.8 GHz Intel core i5 memory 8 GB 1600 MHz DDR3 and graphics Intel HD Graphics 6000 1536 MB and macOS Mojave.

Figure 4 is an illustration of the stages of the classification process which in outline goes through 6 main stages, namely collecting datasets of 4 classes of paddy leaf diseases, data augmentation, MobileNet, training and testing, performance calculations and rice leaf disease classification. The training process of all datasets on the neural network will be returned to the initial process for 1 training round which is usually called an epoch. MobileNet's performance in this classification will use epochs 50 and 100 times to determine the effect of epochs on classification performance.

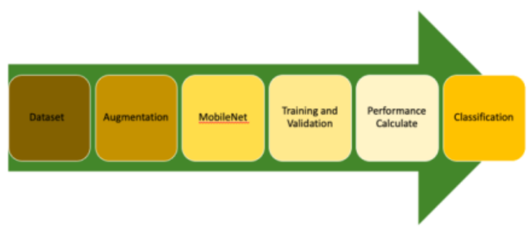
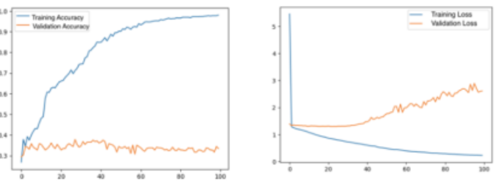


Figure 4. The main stages of rice leaf disease classification

III. RESULT AND DISCUSSIONS

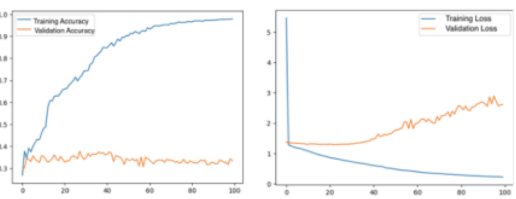
In this discussion, 2 epochs are used to determine the accuracy and loss of the model used, namely epoch 50 and epoch 100. As in Figure 4, it shows a training graph and validation of accuracy for each dataset. Figure 4.a shows a significant increase in accuracy training starting from data 0 and increasing until it reaches a value of 1. However, on the accuracy side, the validation data shows a stagnant trend at values between 0.3 to 0.4 which indicates the dataset needs improvement at this augmentation stage. While, in Figure 4.b is a graph regarding training loss which shows the loss that occurs is getting drastically smaller in the first epoch, while in validation the loss is fluctuating and tends to increase but is still within the tolerance level of the loss.



(a) (b)

Figure 4 (a). Training and validation of accuracy epoch 100 (b). Training and validation of loss epoch 100

Round at one time dataset analysis process using MobileNet is a step to produce a classification model. Figure 5.a shows the accuracy of training and validation at epoch 50 which shows almost the same results at epoch 100. While in Figure 5.b the results from training and validation loss show similar results to epoch 100.



(a) (b)

Figure 5 (a). Training and validation of accuracy epoch 50 (b). Training and validation of loss epoch 50

As described earlier, epoch is a series of training processes for a neural network for the classification of certain cases. As the reason, the epochs used are worth 50 and 100 because the training process is not enough if it only goes through 1 training process, but several times the training process is needed. Therefore, epochs were performed at values of 50 and 100 to determine the effectiveness of epochs. In outline, epoch 50 and 100 produce similar values, but epoch 100 is slightly better than epoch 50, so epoch 100 is recommended over epoch 50.

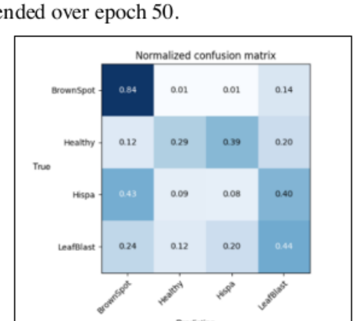


Figure 6. Normalized confusion matrix at 100 epoch

Normalization of the results of the training process is used for evaluation during the training process and the normalization that is often used is the confusion matrix. The evaluation process also serves to measure the performance of the best model. The confusion matrix at epoch 100 can be shown in Figure 6. The matrix has gone through a normalization process to simplify the value but remains in the corridor of the actual value.

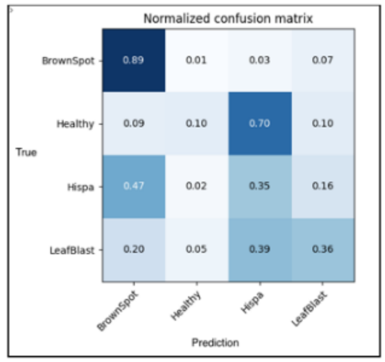


Figure 7. Normalized confusion matrix at 50 epoch

The normalization of the confusion matrix at epoch 50 produces a value that is almost the same as epoch 100. Four classes consisting of brownspot, healthy, hispa and leafblast are manifested in the form of a table that is connected to each other to produce accuracy and loss values in training and validation data. Table 1 shows the results of the accuracy and loss values in the training data and validation data.

Table 1. Recapitulation of Accuracy and Loss

Epoch	Time	Training Accuracy	Training Loss	Validasi Accuracy	Validasi Loss
50	162s-18s/step	0.9983	0.0324	0.3547	4.2954
100	195s 19s/step	0.9797	0.2280	0.3345	2.6100

The training process in epochs 50 and 100 takes almost the same time every 1 round of the training process. However, the overall time required for the training process at epoch 100 is longer because there are more rounds.

IV. Conclusions

The training process for disease classification in rice leaves using the MobileNet architecture using 2 epochs 50 and 100 resulted in the following conclusions::

1. Accuracy at epoch 50 produces a better value of 99%, loss is 3% and at epoch 100 produces a value of 97%, loss is 22%.
2. The time required at 1 round of epochs are 162s-18s/step on epoch 50 and 195s 19s/step on epoch 100.

3. From the two epochs, the disease classification on rice leaves resulted in values that were not too much different or could be called almost the same.

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