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COMPARISON OF MOBILENET AND CNN METHODS FOR IDENTIFYING TOMATO LEAF DISEASES

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Abstract

Tomato plants are usually easily attacked by diseases, either viruses or fungi, resulting in a significant reduction in the quality and quantity of crop production. Tomato production is at risk from various diseases affecting the leaves. Early diagnosis of these diseases allows farmers to take preventive action and protect their crops. The use of artificial intelligence, especially deep learning, has greatly improved plant disease detection systems. Advances in computer vision, particularly Convolutional Neural Networks (CNN), have shown reliable results in image classification and identification. Below is previous research on identifying tomato leaf diseases.
This research is focused on identifying leaf diseases in tomato plants using the MobileNet and CNN methods. The dataset used in this research is tomato leaf disease image data which is grouped into 10 classes. The dataset is separated into training data, validation data and testing data. Total dataset are 5.416 dataset. In preprocessing, the image is rescaled to 1/255 with an input image size of 256x256. The input data is tomato leaf disease image data which consists of 10 classes consisting of bacterial spot, early bright, healthy ,late blight, leaf mold, septoria leaf spot, spider mites, target spot, mosaic virus, yellow leaf curl virus.
The MobileNet and CNN methods were compared to determine the best accuracy and data handling time. The MobileNet model achieved 96% accuracy, while the CNN model reached 98.67% in the testing process. The average handling time was 0.35 seconds for MobileNet and 0.28 seconds for CNN.

Keywords: cnn, deep learning, leaf, identification, tomato

1. INTRODUCTION

Tomatoes are fast growing plants and mature in 90 to 150 days [1]. This product, which is available throughout the world, has rich nutritional value [2] and can be cultivated in almost any dry land [3]. Tomato is a vegetable that is ranked the sixth most abundant vegetable in the world according to the annual production statistics of the Food and Agriculture Organization (FAO) in 2022 [4]. Based on statistics, 80% of tomatoes are consumed fresh and 20% are consumed in the form of puree, soup, tomato sauce, pickles, juice, sauce, etc. [5]. Moreover, an increase in demand of 3.3% is estimated from 2024 to 2032 [6].

However, tomato plants are usually easily attacked by diseases, either viruses or fungi, resulting in a significant reduction in the quality and quantity of crop production [3]. Tomato production is threatened by various types of diseases that appear on tomato leaves. However, early diagnosis of this type of disease can help farmers to take preventive measures and save their crops.
The implementation of artificial intelligence, especially deep learning, has made a significant contribution to efforts to detect plant diseases with a more accurate system. Advances in computer vision, especially Convolutional Neural Networks (CNN) have demonstrated reliable findings in the field of image classification and identification. The following is previous research related to identifying leaf diseases in tomatoes. In research conducted by Sanida etc, using a collection of datasets from PlantVillage with the hybrid CNN method and obtaining an accuracy of 99.17% [7]. Nguyen etc., used the MobileNet method with a data set of 2,064 tomato leaf images to classify tomato leaf diseases. The result was an accuracy of 0.980 [8]. Disease prediction using synthetic images. Apart from diagnosing leaf diseases on tomato plants, research has also been conducted reporting on tomato plant root diseases [9], tomato plant seeds [10], identification of tomato pests [11], and tomato yields using Neural Networks [12]. Chongke Bi conducted research on apple leaf disease data using the MobileNet method and obtained accuracy results of 73.5% with an average data handling time of 0.22 seconds [13]. Gokulnath et. al. [14] suggested a loss-fused CNN model for disease identification on the PlantVillage dataset, with an accuracy of 98.93%. Vimal Singh [15] Conducted research on bean leaf disease data using several CNN methods with

accuracy results, namely EfficientNetB6 with Adam optimizer achieved the highest validation accuracy of 91.74%. Furthermore, MobileNetV2 with Nadam optimizer attained 91.73% validation accuracy and MobileNetV2 with RMSprop optimizer gave 91.72% validation accuracy. Li Mingxuan in his research identified tomato leaf diseases using the LMBRNet method. Using a smaller kernel size, namely 1*1, can increase model efficiency. The results on 8000 images show that the overall identification accuracy is about 99.7%, higher than ResNet50(97.48%), GoogleNet(98.96%) etc [16]. Amitava etc. in his writing, created a mobile application-based system for intelligent disease detection on tomato leaves developed using a convolutional neural network (CNN). This study uses a transfer learning approach to fine-tune well-known CNN architectures such as AlexNet, ResNet-50, SqueezeNet-1.1, VGG19, and DenseNet-121 on a dataset consisting of tomato leaf images from the PlantVillage dataset. Over 95% accuracy was achieved by all trained CNN models, with DenseNet-121 leading the way with an accuracy rate of 99.85%[17]. Li Zhang optimizes the MobileNetV3 network by adjusting the number of input channels, the size of the convolution kernel, and the number of channels in the remaining blocks. The experimental results show that the identification accuracy of MobileNet-SCA for tea diseases is 5.39% higher than the original model. This method can balance the identification accuracy and identification time of tea leaf diseases accurately and quickly which is applied on a mobile device. The MobileNet model is one of the CNN models implemented in the mobile application [18].

Although CNN models for tomato leaf disease identification based on deep learning have been carried out by many previous studies, there are still few studies on targeted tomato leaf disease identification algorithms. The same tomato leaf disease may have great differences in different growth stages, different disease stages, and different environmental conditions, while different tomato leaf diseases may show very similar characteristics. Therefore, it is necessary to design a CNN model that focuses on the characteristics of tomato leaf diseases as seen from the texture of the leaves affected by the disease.

This research focuses on comparing mobile net methods and modifications to CNN architecture designs that can be applied to mobile devices. The CNN model design proposed in this research is designed so that it can be implemented for mobile devices such as android. In mobile devices handling time is a parameter to determine system access speed. The proposed CNN model design needs to be tested to obtain good accuracy and relatively small handling time compared to the MobileNet model. The MobileNet method has advantages in data handling speed because it has a 28 layer architecture and more efficient computing resource speed. The improve of this research in the CNN architecture which was designed by optimizing layers by improving the Batch Normalization Layer and ReLU activation function layers so that they have better accuracy than the MobileNet model and this part is used to increase the speed of computing. Batch normalization data will be processed at each hidden layer. This will reduce dsata distribution for both training and testing images so that the processes at each layer in the network are relatively independent.

2. RESEARCH METHOD

The research methodology used in this research starts from using a public data set of Indonesian rice leaf diseases obtained via the Kaggle site. Next, carry out pre-processing and augmentation on the available dataset. The data set used consists of 10 classes. Then proceed with data training using the MobileNet-V2 architecture and proposed CNN architecture with the addition of a Bach Normalization layer and ReLu activation using the Adam optimizer. The final stage evaluates and compares the MobileNet-V2 and CNN models using an accuracy for both models. The MobileNet-V2 architecture implemented in this research can be seen in table 1.

Table 1. Architecture of MobileNet [19]

Type/Stride	Filter Shape	Input Size
Conv / S2	3 × 3 × 3 × 32	224 × 224 × 3
Conv dw / s1	3 × 3 × 32 dw	112 × 112 × 32
Conv / s1	1 × 1 × 32 × 64	112 × 112 × 32
Conv dw / s2	3 × 3 × 64 dw	112 × 112 × 64
Conv / s1	1 × 1 × 64 × 128	56 × 56 × 64
Conv dw / s1	3 × 3 × 128 dw	56 × 56 × 128
Conv / s1	1 × 1 × 128 × 128	56 × 56 × 128
Conv dw / s2	3 × 3 × 128 dw	56 × 56 × 128
Conv / s1	1 × 1 × 128 × 256	28 × 28 × 128
Conv dw / s1	3 × 3 × 256 dw	28 × 28 × 256
Conv / s1	1 × 1 × 256 256	28 × 28 × 256
Conv dw / s2	3 × 3 × 256 dw	28 × 28 × 256
Conv / s1	1 × 1 × 256 × 512	14 × 14 × 256
5 × Conv dw /s1	3 × 3 × 512 dw	14 × 14 × 512
5 × Conv / s1	1 × 1 × 512 1024	14 × 14 × 512
Conv dw / s2	3 × 3 × 512 dw	14 × 14 × 512
Conv / s1	1 × 1 × 512 × 1024	7 × 7 × 512
Conv dw /s2	3 × 3 × 1024 dw	7 × 7 × 1024
Conv / s1	1 × 1 × 1024 × 1024	7 × 7 × 1024
Avg Pool / s1	Pool 7 × 7	7 × 7 × 1024
FC / s1	1024 × 1000	1 × 1 × 1024
Softmax / s1	Classifier	1 × 1 × 1000

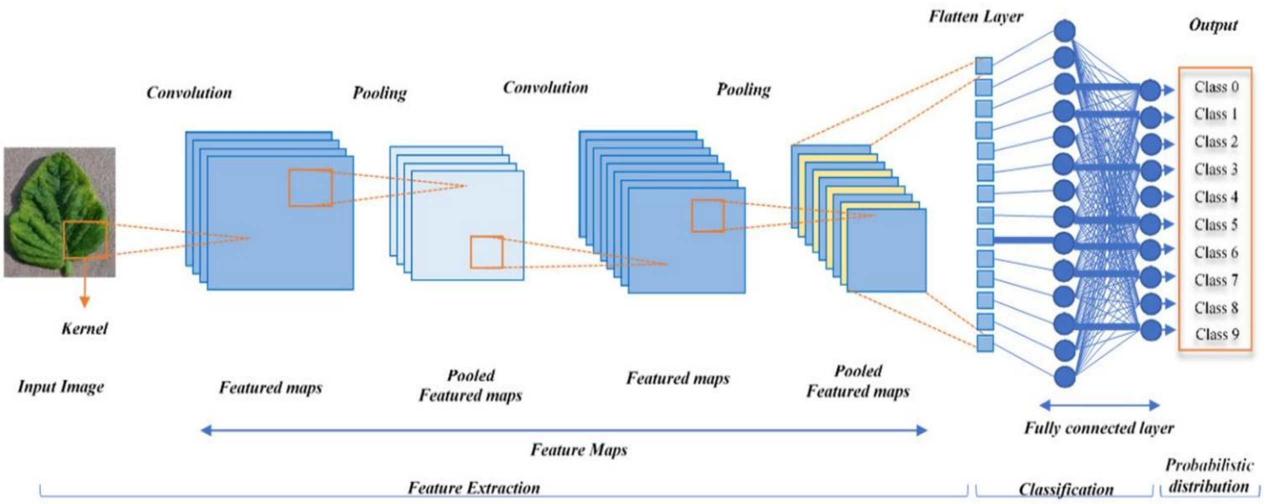

Figure 1. CNN Model For Identification Disease Leaf Tomato [20]

The flow of the CNN method applied in this research can be seen in Figure 1. The first layer, or what is called the convolutional layer, is the outermost part whose job is to identify simple things about the image. Meanwhile, the second layer of convolutional neural networks is called the pooling layer. Different from the task in the previous layer which is simpler, the pooling layer or what is known as down sampling is tasked with following up on object identification for a visual and audio object. Finally, there is a layer called the fully-connected (FC) layer which is the most core part of a convolutional neural network. That means, this layer is the most complex compared to the previous layers. If the first layer's job is to identify colors, this layer's job is to recognize objects and shapes so that it can find the actual object in question.

In table 2 below is the implementation of the proposed CNN architecture. The CNN architecture uses 256x256 data input with RGB image data type. Each concolution layer adds Bach Normalization, Max Pooling.

Table 2. Architecture of Proposed CNN

Layer	CNN
Input	256 × 256 × 3
Batch Normalization	Filter size: 5 × 5
	Number of filters: 32
Conv. + Batch Normalization + ReLU	Filter size: 2 × 2
Max-pooling	Filter size: 3 × 3
Conv. + Batch Normalization + ReLU	Number of filters: 64
Max-pooling	Filter size: 2 × 2
Conv. + Batch Normalization + ReLU	Filter size: 5 × 5 Number of filters: 64
	Filter size: 2 × 2
Max-pooling	
latten	128
Fully connected	64
Dense	16
Dense	C0–C9
Output	

3. EXPERIMENTS AND RESULTS

The dataset used is an image of diseased tomato leaves dataset with 3651 training data, 1218 validation data and 547 testing data, each divided into 10 classes consisting of bacterial spot, early bright, healthy ,late blight, leaf mold, septoria leaf spot, spider mites, target spot, mosaic virus and yellow leaf curl virus.

The input image size used in this research using the MobileNet and CNN methods is 256 x 256 pixels with RGB image data type (3 channels) and a bach size of 32. Preprocessing begins by changing the data scale with the image generator function. The data scale is changed to 1/255 so that the dataset has a pixel range of 0 to 1. The MobileNet method used here is the architecture used by V.Singh [15] but with an input image size of 256 x 256 pixels.

The result of training and validation accuracy of MobileNet model with 25 epoch process can be seen in the Figure 2.

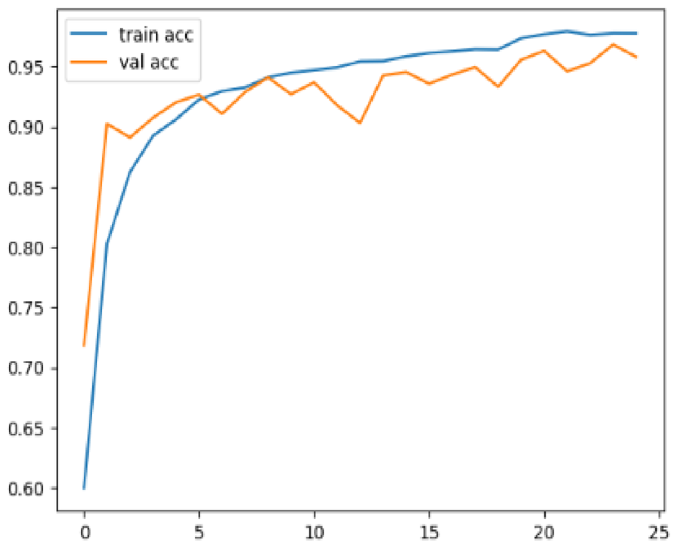

Figure 2. Graphic Result of Training and Validation Accuracy MobileNet

The result of training and validation loss of MobileNet model with 25 epoch process can be seen in the Figure 3.

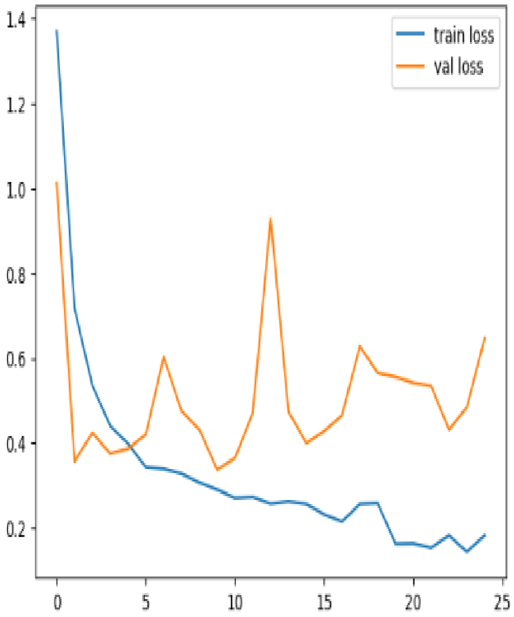

Figure 3. Graphic Result of Training and Validation Loss MobileNet

The result of training and validation accuracy proposed CNN model with 17 epoch process can be seen in the Figure 4.

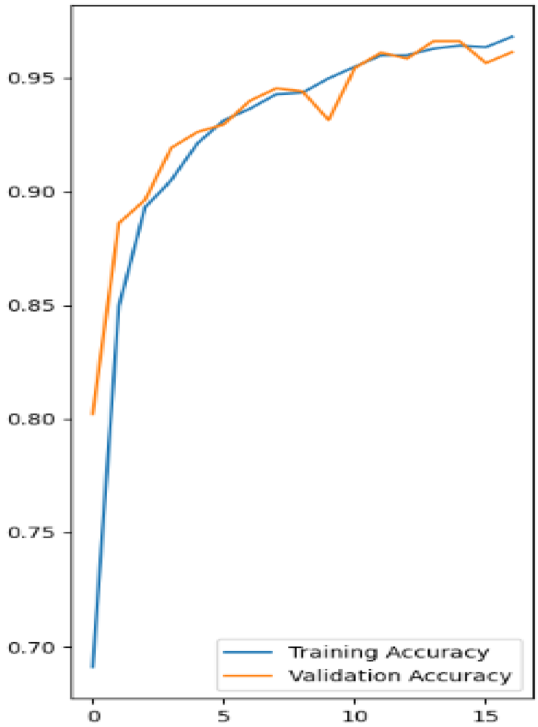

Figure 4. Graphic Result of Training and Validation Accuracy CNN

The result of training and validation loss proposed CNN model with 17 epoch process can be seen in the Figure 5.

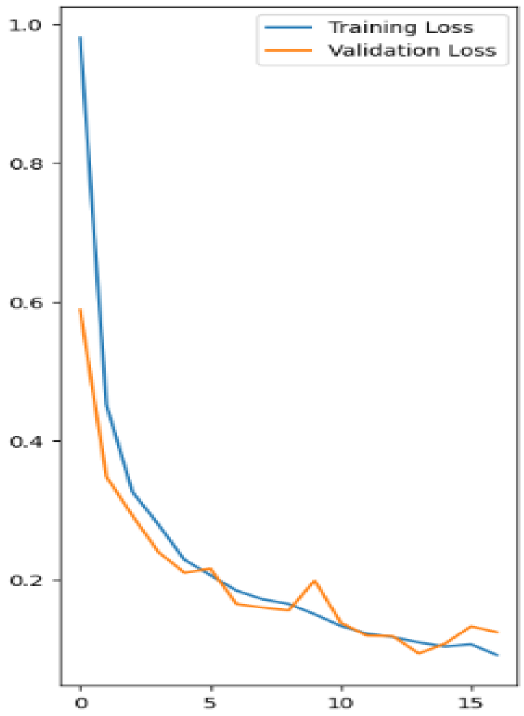

Figure 5. Graphic Result of Training and Validation Loss CNN

The comparison results for access handling time of the MobileNet and CNN methods can be seen in table 3.

Table 3. Result of Comparison Deep Learning Models For Tomato Leaf Diseases Identification

Deep Learning Models	**Accuracy**			**Average handling time (s) for each image**
	Training Data	**Validation Data**	**Testing Data**	
MobileNet	97.12%	95.34%	96.84%	0.35
Proposed CNN	97.78%	96.48%	98.67%	0.28

The comparison results for loss access of the MobileNet and CNN methods can be seen in table 4.

Table 4. Result of Loss Access In Comparison Deep Learning Models For Tomato Leaf Diseases Identification

Deep Learning Models	**Loss Access**		
	Training Data	**Validation Data**	**Testing Data**
MobileNet	0.189	0.452	0.618
Proposed CNN	0.108	0.122	0.100

It can be seen in Table 4 that the access loss on the CNN model is lower than the Mobile Net model. This means that the CNN model is better because the error rate of the CNN model is less than the Mobile Net model. Access loss also shows how effective the model used is.

Table 6. The Result of Actual and Predictions CNN Method For Tomato Leaf Diseases Identification

	Actual	Prediction
0	Tomato__Early_blight	Tomato__Early_blight
1	Tomato__healthy	Tomato__healthy
2	Tomato__Tomato_Yellow_ Leaf_Curl_Virus	Tomato__TomatoYellow _Leaf_Curl_Virus
3	Tomato__mosaic_virus	Tomato__mosaic_virus
4	Tomato__Early_blight	Tomato__Early_blight
5	Tomato__Leaf_Mold	Tomato__Leaf_Mold
6	Tomato__Leaf_Mold	Tomato__Leaf_Mold
7	Tomato__Early_blight	Tomato__Early_blight
8	Tomato__mosaic_virus	Tomato__mosaic_virus
9	Tomato__Target_Spot	Tomato__Target_Spot
10	Tomato__Bacterial_Spot	Tomato__Bacterial_Spot
11	Tomato__Leaf_Mold	Tomato__Leaf_Mold
12	Tomato__healthy	Tomato__healthy
13	Tomato__Leaf_Mold	Tomato__Leaf_Mold
14	Tomato__healthy	Tomato__healthy
15	Tomato__Late_blight	Tomato__Late_blight
16	Tomato__Bacterial_Spot	Tomato__Bacterial_Spot
17	Tomato__Bacterial_Spot	Tomato__Bacterial_Spot
18	Tomato__Septoria_leafspot	Tomato__Septoria_leaf_ spot
19	Tomato__Spider_mites Two-spotted_spider_mite	Tomato__Spider_mites Two-spotted_spider_mite
20	Tomato__mosaic_virus	Tomato__mosaic_virus
21	Tomato__Septoria_leaf_ spot	Tomato__Septoria_leaf_ spot
22	Tomato__Leaf_Mold	Tomato__Leaf_Mold
23	Tomato__Septoria_leaf_ spot	Tomato__Septoria_leaf_ spot
24	Tomato__Target_Spot	Tomato__Target_Spot
25	Tomato__Late_blight	Tomato__Late_blight
26	Tomato__healthy	Tomato__healthy
27	Tomato__mosaic_virus	Tomato__mosaic_virus
28	Tomato__Target_Spot	Tomato__Target_Spot
29	Tomato__mosaic_virus	Tomato__mosaic_virus
30	Tomato__Late_blight	Tomato__Late_blight
31	Tomato__Target_Spot	Tomato__Target_Spot

Table 6 shows the results of identifying tomato leaf diseases based on labels in the actual dataset from proposed CNN models.

4. DISCUSSION

The architecture of MobileNet model can be seen in table 1 but in this study the input image used has a resolution of 256x256. Because the greater the image resolution, the greater the detail of feature extraction. but also adjusted to the speed of computing accessed.

In figure 2, the MobileNet model accesses the epoch process for 25 epochs and there is no early stopping. This is because the MobileNet model process was repeated for 25 epochs, the training dataset did not experience over fitting. In table 3, it can be seen that the accuracy resulting from the data testing process in MobileNet model was 96.84%. With a handling time for each image access of 0.35 seconds.

The architecture of proposed CNN can be seen in table 2. In figure 4, in the proposed CNN model, the epoch process accessed was 17 epochs for data training dan data validation. Because in the CNN model, the accuracy of the access process is stable from the 17th epoch to the 25th epoch. In table 3, it can be seen that the accuracy resulting from the data testing process was 98.67%. With a handling time for each image access of 0.28 seconds. From table 4 it can be seen that the data access loss in the proposed CNN model is smaller than the MobileNet model. This means that the proposed CNN model has better feature extraction on the dataset so that not much information on the dataset is lost. The higher accuracy of the proposed CNN model suggests that the additional Batch Normalization and ReLU activation layers significantly enhance its performance 2,67%. The longer handling time of the MobileNet model is due to its more complex architectural layers of 28 layers so it requires more computing resources. The example of result of actual and predictions of proposed CNN model can be seen in figure 6 as many as 30 examples. The actual dataset is taken from the image testing dataset which has 10 class names. In table 6 it can be seen that the actual and predicted datasets have the same class names.

5. CONCLUSIONS AND FUTURE WORKS

From table 3 it can be concluded that the average accuracy for the MobileNet model is 96.153% and the average accuracy for the proposed CNN is 97.643%. And the average access loss in the MobileNet model is 0.42. Meanwhile, the average access loss on the proposed CNN is 0.11.

The proposed CNN model has higher accuracy compared to MobileNet and has a smaller average handling time so that for further research it can be implemented into mobile device example android and IoT-based tool for detecting leaf diseases in tomatoes.

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