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MOBILENET-BASED TRANSFER LEARNING FOR DETECTION OF EUCALYPTUS PELLITA DISEASES

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Abstract

Currently, the pulp industry in Indonesia is ranked eighth in the world and the paper industry is ranked sixth in the world. One of the advantages in supporting the industry is that Indonesia has a large Industrial Plantation Forest (HTI) where the plants for pulp and paper raw materials originate. Eucalyptus pellita species belonging to the Myrtaceae family is one of the priority species for Industrial Plantation Forests (HTI) because of its adaptability and its wood can be used as raw material for pulp. Industrial Plantation Forests of this type can be found mainly in Kalimantan and Sumatra. This species shows good growth in stem shape, growth speed and good wood quality and has high germination and has a shorter cutting cycle of about 7-8 years so that it is quickly harvested. Prevention and treatment of leaf disease is one of the main processes of planting. Early diagnosis and accurate recognition of Eucalyptus Pellita disease can control the spread of the disease and reduce production costs and treatment costs. Disease detection on Eucalyptus pellita leaves can be done automatically faster by utilizing digital image processing and artificial intelligence. In this study, we propose a detection method with Deep Learning architecture. Our proposed method is based on pre-trained transfer learning using MobileNet. Image datasets from PT. Surya Hutani Jaya's land in East Kalimantan were used to train the model. The dataset is divided into three classes where 1 class is healthy leaves and 2 classes are sick leaves, namely Xanthomonas Bacteria and Cylindrocladium Fungi. With a dataset ratio of 70: 20: 10 the number of training datasets is 2370, validation is 591, and Testing is 177. Hyperparameter scenarios were carried out on the MobileNet model to optimize performance on the Eucalyptus Pellita leaf dataset. The experimental results show a fairly good accuracy, reaching 98%.

Keywords: Pulp Industry, Eucalyptus Pellita, Deep Learning, Transfer Learning, MobileNet

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INTRODUCTION

The mainstay of the plantation sector in Indonesia for more than 20 years has been two species of acacia, Acacia mangium on mineral soils and A.crassicarpa on peatlands. However, since the mid-2000s, A. mangium resources in mineral soils have been subject to substantial threats from two major diseases, Ganoderma philippii and Ceratocystis spp. To maintain plantation productivity, the forestry industry was forced to quickly introduce a replacement species, Eucalyptus pellita [1] .

Classification of plant diseases is an important research topic as it can prove useful in monitoring large areas of crops, and thereby automatically detecting diseases from symptoms that appear on plant leaves.[2]. There are two types of leaf diseases used in this study, namely Xanthomonas bacterial disease and Cylindrocladium fungus.

Xanthomonas bacteria are Gram-negative bacteria that can cause leaf blight in several plants, one of which is the Eucalyptus Pellita. Plant parts infected with Xanthomonas, especially leaves, will slowly experience tissue death around the point of attack. To avoid the spread of these attacks to other networks. This is manifested in the symptoms of small spots and discoloration on the leaves. If environmental conditions are conducive to disease, the spots will develop into blight [3]. Then the second type of leaf disease is the fungus Cylindrocladium sp which is a pathogen that causes symptoms of foliar spot disease and leaf blight on Eucalyptus pellita. Causes diseases of the roots, root neck, shoot blight, leaf blight, and leaf spot. Spread in large numbers that usually occur on the leaf surface [4].

The impact of disease on eucalyptus pellita can affect the company's production. So, in this study will build a system to detect eucalyptus pellita plant diseases with leaf images using deep learning methods. Plant disease detection on Eucalyptus pellita leaves at PT. Surya Hutani

Jaya is still done manually by the plant disease specialist staff who work there. Early diagnosis and accurate recognition of Eucalyptus Pellita disease can control the spread of the disease and reduce production and treatment costs. Disease detection on Eucalyptus pellita leaves is done automatically faster by utilizing digital image processing and artificial intelligence.

In previous studies, deep learning methods have been used to classify and detect plant diseases using leaf images such as rice, tomatoes, grapes, potatoes and others. The previous research title was "Identification of rice diseases using deep convolutional neural networks"[5] using the image of rice leaves with an accuracy of 95.48%, then there is the image of tomato leaves with the research title "smart mobile application to recognize tomato leaf diseases using convolutional neural network" [6] has an accuracy value of 90.3%. Then the image of a potato leaf entitled "Potato Leaf Disease Classification Using Deep Learning Approach" [7] has an accuracy value of 91%. So in this study using a new object that is the image of Eucalyptus pellita leaves to detect types of plant diseases with the MobileNet-based transfer learning method.

STUDY LITERATURE

A. Eucalyptus Pellita

Eucalyptus Pellita F. Muell is a plant species native to North Queensland, Irian Jaya and Papua New Guinea. This plant is classified as a fast-growing species with straight stems and dense crowns. 1 year old Eucalyptus pellita plant in figure 1.

Figure 1. Eucalyptus Pellita

Specifically in Indonesia, Eucalyptus pellita plantations have an important role in supporting the survival of the pulp and paper industry in the future. It also has a strategic position regarding global climate change mitigation because large areas of commercial Eucalyptus plantations can become carbon. However, the ability of the Eucalyptus pellita plant to absorb carbon and maintain the sustainability of the forestry industry is highly dependent on its productivity. In general it has been established to supply raw materials to the pulp and paper industry [2].

B. Deep Learning

In recent years, artificial intelligence has developed very rapidly. Complex problems were previously solved by humans. Therefore, with the existence of artificial intelligence, this problem can be solved easily. Artificial intelligence has problems in applying some intuition in its knowledge so that to solve this problem it uses the concept of deep learning. Deep Learning uses a simple representation but with this concept the computer can build complex concepts as shown in Figure 2. The Deep Learning model grows along with the development of computers, both hardware and software [8].

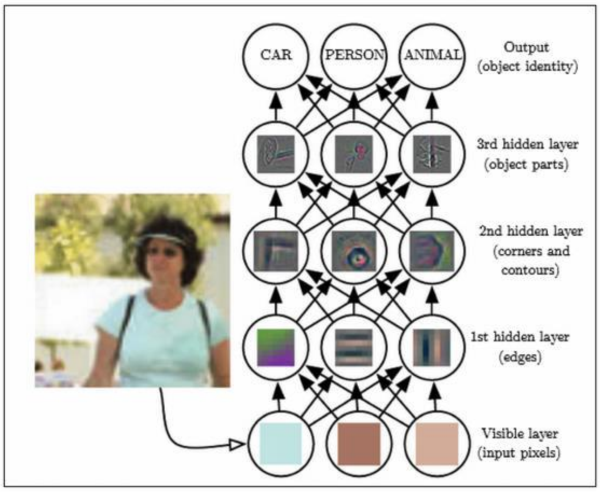

Figure 2. Deep Learning Illustration

By learning only one or two layers, it can be called learning that is not really deep. The deep learning method is a multi-layered learning method, obtained by constructing simple but non-linear modules each of which converts representations at one level (starting with raw input) into representations at a higher level [9].

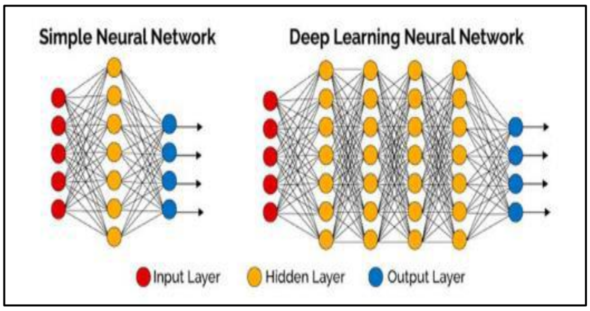

Figure 3. Comparison of Machine Learning and Deep Learning Layers

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Figure 3 shows that every deep learning can be called machine learning but every machine learning cannot be called deep learning. By using deep learning, data learning will have more layers and layers compared to machine learning which only uses one or two layers [10].

C. Convolutional Neural Network (CNN)

CNN is preferred as a deep learning method in this study. CNN which can easily identify and classify objects with minimal pre-processing, is successful in analyzing visual images and can easily separate required features with its layered structure. It consists of four main layers: convolution layer, pooling layer, activation function layer and fully connected layer. Figure 4 shows a typical CNN architecture [11].

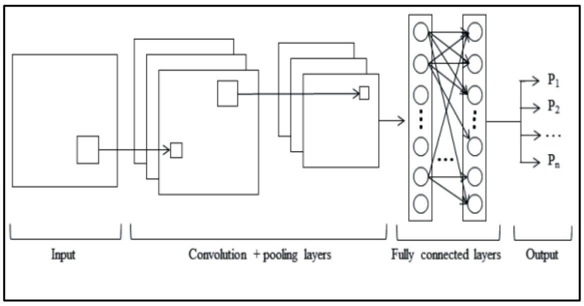


Figure 4. CNN Architecture

D. MobileNet

Mobilenet is a class of convolutional neural network (CNN) that is lightweight and easy to run on mobile devices such as smartphones. Mobilenet is designed to effectively maximize accuracy while considering the limited resources of a device or application. Mobilenet offers a network architecture that allows the development of models for small networks that have limited resources such as latency and size [12].

MobileNet architecture which consists of a convolution layer, depthwise convolution layer followed by BN layer and ReLU layer, pointwise convolution layer also followed by BN and ReLU layer, Global Average Pooling layer, Reshape layer, Dropout layer, Convolutional layer, SoftMax layer, and Reshape layer. This model contains about four million parameters which is very small compared to other models [13]. In Figure 5 MobileNet with a depthwise separable convolutions process, which consists of depthwise convolutional and pointwise convolutional. Batch normalization layers and fixed linear units are added at the end of each convolutional layer [14].

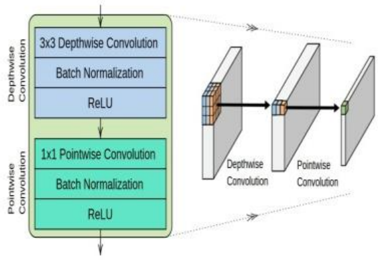


Figure 5. MobileNet Architecture

E. Confusion Matrix

The confusion matrix is a visual evaluation tool used in classification systems. This confusion matrix is useful for measuring how well the classification model has been made. The confusion matrix is of size n n, where n is the number of different classes. The confusion matrix determines the accuracy obtained from the values of several parameters, such as True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) [15]. The confusion matrix table is shown in Table 2 below.

Table 2. Confusion Matrix

True Class	Classification Result Class	
	Predicted	**Predicted**
Actual	True Positive (TP)	True Negative (TN)
Actual	False Positive (FP)	False Negative (FN)

Based on the values of True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN), the classification evaluation is analyzed from several indicators, including indicators of accuracy, specificity, and sensitivity. Accuracy is the ratio between the number of correctly predicted from all data. Specificity is a value that indicates a lot of negative value data that can be correctly classified into the negative class. Sensitivity is a value that shows a lot of positive value data that can be correctly classified into the positive class. The indicator is calculated by the following equation:

$$Accuracy = \left(\frac{TP+TN}{TP+TN+FP+FN}\right) \times 100\,\% \quad (1)$$

$$Specificity = \left(\frac{TP}{TP+FP}\right) \times 100\,\% \quad (2)$$

$$Sensitivity = \left(\frac{TP}{TP+FN}\right) \times 100\,\% \quad (3)$$

METODE

A. Dataset

The dataset in this study is the image of Eucalyptus Pellita leaves taken from PT. Surya Hutani Jaya's land in Kutai Kertanegara Regency, East Kalimantan Province. Taking pictures of leaves using a cellphone camera with the results of one photo for one leaf on a field background with direct sunlight. To create a model that can study plant disease characteristics, each leaf image is taken under varying conditions according to the type of leaf disease to be detected. Data training, data validation and data testing with a ratio of 70: 20: 10 for all data. The dataset that has been divided by ratio will produce the amount of each data shown in Table 3.

Table 3. Total Dataset of Eucalyptus Pellita Leaves

Label	Normal	bakteri Xanthomonas	jamur Cylindrocladium	Total
Training	790	790	790	2370
Validation	197	197	197	591
Testing	59	59	59	177

B. MobileNet

The structure of MobileNet is built on deep separable convolution as mentioned in the previous section except for the first layer which is full convolution. By defining a network in such simple terms, we can easily explore the network topology to find a good network. The MobileNet architecture is defined in Table 4. All layers are followed by batchnorm and ReLU nonlinearity with the exception of the final fully connected layer which has no nonlinearity and is put into the SoftMax layer for classification [16].

Table 4. MobileNet Architecture

Type / Stride	Filter Shape	Input Size
Conv / s2	3 x 3 x 3 x 32	224 x 224 x 3
Conv dw / s1	3 x 3 x 32 dw	112 x 112 x 32
Conv / s1	1 x 1 x 32 x 64	112 x 112 x 32
Conv dw / s2	3 x 3 x 64 dw	112 x 112 x 64
Conv / s1	1 x 1 x 64 x 128	56 x 56 x 64
Conv dw / s1	3 x 3 x 128 dw	56 x 56 x 128
Conv / s1	1 x 1 x 128 x 128	56 x 56 x 128
Conv dw / s2	3 x 3 x 128 dw	56 x 56 x 128
Conv / s1	1 x 1 x 128 x 256	28 x 28 x 128
Conv dw / s1	3 x 3 x 256 dw	28 x 28 x 256
Conv / s1	1 x 1 x 256 x 256	28 x 28 x 256
Conv dw / s2	3 x 3 x 256 dw	28 x 28 x 256
Conv / s1	1 x 1 x 256 x 512	14 x 14 x 256
5 x Conv dw / s1	3 x 3 x 512 dw	14 x 14 x 512
5 x Conv / s1	1 x 1 x 512 x512	14 x 14 x 512
Conv dw/ s2	3 x 3 x 512 dw	14 x 14 x 512
Conv / s1	1 x 1 x 512 x 1024	7 x 7 x 512
Conv dw / s2	3 x 3 x 1024 dw	7 x 7 x 1024
Conv / s1	1 x 1 x 1024 x 1024	7 x 7 x 512
Avg Pool / s1	Pool 7 x 7	7 x 7 x 1024
FC / s1	1024 x 1000	1 x 1 x 1024
Softmax / s1	Classifier	1 x 1 x 1000

RESULTS AND DISCUSSION

A. General Architecture

The general architecture as shown in Figure 6 where the dataset has additional data with a comparison of training data, validation data, and testing data is 70:20:10. With 70% training data augmentation, then training data and validation data are normalized then data is normalized by setting hyperparameters where fine tuning is with layer -6, using the Adam optimizer, learning rate 0.0001, epochs 20, batch size 32, and using loss categorical_crosentropy, that is for multi-class classification, then SoftMax for the classification layer with more than two classes, is suitable for classification of Eucalyptus pellita leaf disease which has three classes that is the normal or healthy class and two disease classes, there are Xanthomonas bacteria and Cylindrocladium fungi. Furthermore, the data training process to produce a MobileNet classification model then the testing process using 10% testing data to produce an output value of accuracy, confusion matrix, and kappa score.

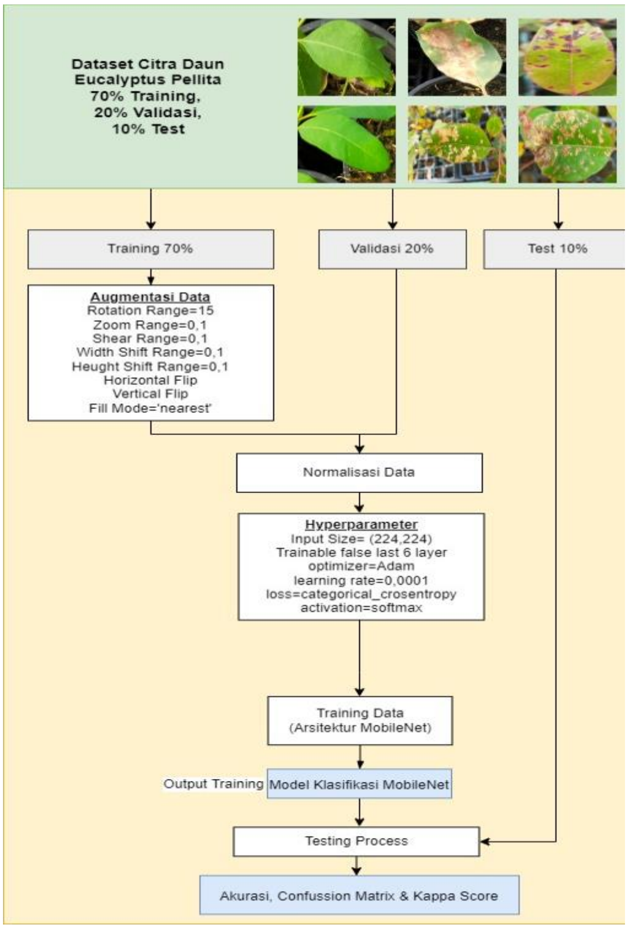


Figure 6. General Architecture

A. Experimental Result

Experiments with MobileNet by fine tuning -1 to -12 using the Adam optimizer, learning rate 0.0001, epochs 20, batch size 32 are shown in Table 5 that is the order of testing accuracy values from highest to lowest.

Table 5. Experimental Result

Model	Layer	Testing Accuracy	Validation Accuracy
Mobile Net	-6	98,8	99
	-8	98,8	99
	-9	98,8	99
	-10	98,8	99
	-11	98,8	99
	-13	98,8	99
	-1	98,3	98
	-2	98,3	98
	-7	98,3	98
	-1	97,7	98
	-3	97,7	98
	-4	97,7	98
	-5	97,7	98
	-12	97,7	98

From table 5 the highest testing accuracy values are fine tuning layers -6, -8, -9, -10, -11, -13 with a value of 98.8%. The graphic display of training and validation in the MobileNet experiment with fine tuning layer -6 can be seen in Figure 7. The train loss value is 0.0197 and the train accuracy is 0.9966 then the validation loss value is 0.0022 and the validation accuracy is 1.000.

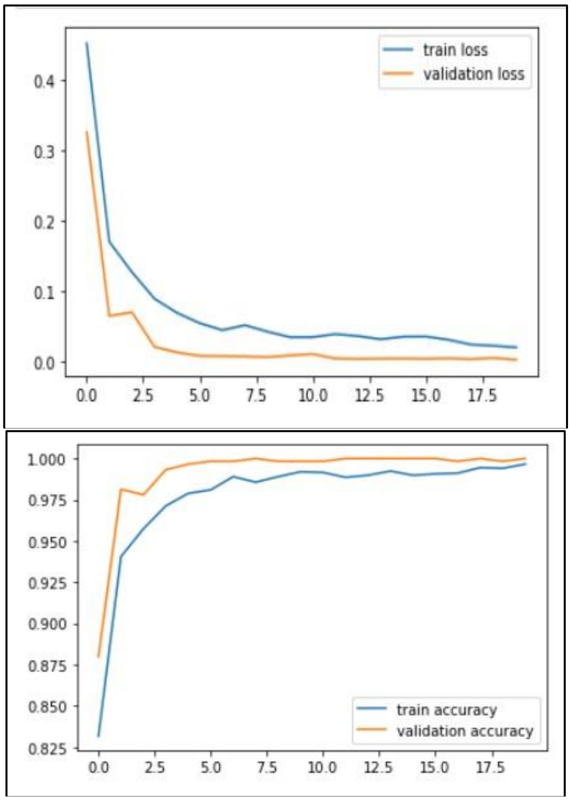
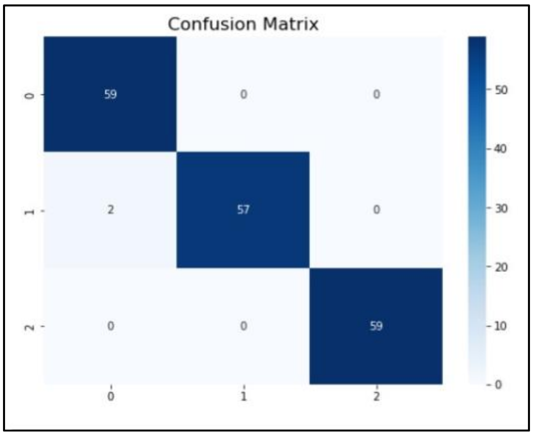


Figure 7. Training and Validation Graph

This experimental process produces a confusion matrix in Figure 8. Then a confusion matrix evaluation table is made in Table 6 so that the accuracy, precision, and recall values can be calculated.



Gambar 8. Confusion Matrix

From the results of manual calculations the accuracy, precision, and recall values in this study can be seen in table 6 where the accuracy value in the table is 99%.

Table 6. Results of the Confusion Matrix manual

Confusion Matrix MobileNet					
		Prediction Class			**Recall**
Actual Class		**0**	**1**	**2**	
	0	59	0	0	1.00
	1	2	57	0	0.97
	2	0	0	59	1.00
Precision		0.97	1.00	1.00	0.99

The results of calculating accuracy, precision, recall and f1-score can be seen in Table 7.

Table 7. F1-Score Value

	Precision	Recall	F1-Score	Support
0	0.97	1.00	0.98	59
1	1.00	0.97	0.98	59
2	1.00	1.00	1.00	59
Accuracy			0.99	177
Macro avg	0.99	0.99	0.99	177
Weighted avg	0.99	0.99	0.99	177

The f1-score accuracy value in table 7 is the value in the validation data where the values of precision, recall and accuracy reach 99%. Then the accuracy of the testing data is in Figure 9 which has a value of 98%. Where the accuracy results obtained are good and quite high accuracy values

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6/6 [==============================] - 1s 71ms/step - loss: 0.0834 - accuracy: 0.9887

Test accuracy:  0.9887005686759949
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Figure 9. Data Testing Accuracy Value

CONCLUSION

The conclusion obtained in this research is from experiments on several CNN architecture models that have been carried out, the determination in choosing a good architectural model in this study is that MobileNet besides having a fairly high accuracy MobileNet is also lightweight so it effectively reduces computational costs and the number of convolution parameters, has a size which is small and able to run on computers with not too high performance such as PCs or laptops.

This study used the MobileNet method and was able to classify Eucalyptus Pellita leaves with 3 classes, namely Normal, Xanthomonas Bacteria, and Cylindrocladium Fungus which resulted in an accuracy value of 98%.

The factors that make the level of accuracy not perfect in this study that has been done are errors that occur in the process of classifying Eucalyptus Pellita leaves. This is due to the similarity between the leaves of the Xanthomonas bacteria and the Cylindrocladium fungus which have the same spot color and almost similar spot pattern so that the system has difficulties when carrying out the classification process.

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