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Rice Plants Disease Identification Using Deep Learning with Convolutional Neural Network Method

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Abstract: Indonesia is an agricultural country where most of the population grows rice and most farmers cannot detect early if there is a pest attack on rice plants . This research discuss about deep learning implementation to classify or identify diseases in rice leaves using mobile application. This system will make users easily to diagnose diseasesby displaying diagnostic results in the form of the name of the disease along with its taxonomy, disease description and drug recommendations for disease solutions. There are four classes of leaves used in this research, including Healthy Leaves (HL), Bacterial Leaf Blight (BLB), Brown Spot (BS) and Potassium Deficiency (PD). The design of the model uses two approaches, one of them are modeling convolutional neural network from the scratch and modeling with transfer learning using inception v3 architecture. Both models will go through training process to produce a model thatis ready to be used for classification. In application testing, a comparison is made between two models. From the tests that have been carried out, it is concluded that the system with model made using transfer learning approach, produce good accuracy with an accuracy of 90%. Meanwhile the System with the other model gain an accuracy of 62%. So when the data used in research are extremely low, it is best to use transfer learning as an approach to design a mode.

Keywords: *Deep Learning, From the Scratch, Inception V3, Rice Leaves Identification, Transfer Learning,*

INTRODUCTION

Today, rice plants disease detection is still mostly done by conventionally and involving agricultural experts thus those disease can be identified accurately. Those things forces a lot of time and costs. Rice plants identification must be done immediately thus can escalate the agricultural productions. (Minarni & Warman, 2017)

Through the description before, this study intended to scheme a mobile – based application with implementing Deep Learning. Deep Learning has beneficial capabilities in computer vision. One of the capability is object classification from an image. Deep Learning nowaday method that has the most major result is Convolutional Neural Network. This is because CNN tries to emulate the image recognition system in the human visual cortex, thus has the ability to process image information (Santosa & Ariyanto, 2018)

In this study, Deep Learning is used for the rice plants disease diagnosis and the Convolutional Neural Network method is used. Convolutional Neural Network (CNN) read, acknowledge, and detect an object on an image by restructureing image into pixel. Technically, CNN is an architecture that can be trained and composed from several stages. Input and output from every stages composed from several arrays that called as feature map. Every stages consists of three layers which are convolution, activation function layer and pooling layer. (Alwanda, Ramadhan, & Alamsyah, 2020)

This study, the most considered thing is the number of the images needed and also the right activation function thus it will result the more accurate of the output layer.

The problem formulation in this study is to design and build a mobile – based application to identify rice plants disease and find the outcome and the accuracy of the disease diagnostic application on rice plants.

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LITERATURE REVIEW

1. Image

Image is defined as a function of two variables, for example a(x,y) where the "a" is the amplitude of the image at coordinates (x,y). According to Ian T.Young et. Al, a digital image a[m,n] is an image in 2D discrete space dervived from analog image a(x,y) in 2D continous space through sampling, which is usually called as digitization. According Maria, digital image is an image of f(x,y) which has been discrete in spatial coordinates and brightness. (Hidayatulah, 2017)

A digital image is representated by a set of two – dimensional arrays when each array represents one color channel. The digitized brightness value is called the gray level value. Each element of the array is called as pixel which stands for picture element. Image dimension are usually described in the length and height format (e.g 640 x 480 pixels). (Kadir & Adhi, 2013)

2. Artificial Intelligence

According to Stuart Russel and peter Norvig, Artificial Intelligence definition are divided into 4 categories, which are :

a. *Thinking humanly: The cognitive modeling approach*
b. *Acting humanly: The turing test approach*
c. *Thinking rationally: The laws of thought approach*
d. *Acting rationally: The rational agent approach* (Russell, 2010)

Since "Thinking humanly" and "Acting humanly" have comprehensive messages and the machine are not yet able of imitating human consideration and behaviors that those are out of ratio, which are reflex and intuitive (related to emotional feelings), this definition is still considered inaccurate at this time. This places human behavior and ways rationally that can still be imitated by machines. (Hidayat, Eka, & Abdullah, 2021)

The imitation of the way of thinking is divided into two, which is artificial thinking process and artificial computational process. The artificial thinking process goes towards to an expert system, while the artificial computational process develops towards a fuzzy system, artificial neural networks and genetic algorithms.

A system that can artificiate the way human thinking are consists of 2 categories, those are a system that can emulating one's expertise (knowledge based expert system) and system capable of performing intelligence computations based on computational intelligence.

To assist extend human thinking and learning processes, a programmed intelligence or smart system is made. In order for a system to emulate the human brain's ability to think, associate, differentiate and interpret what is experienced, the system must understand how the human brain model draw the conclusions. (Devianto & Dwiasnati, 2020)

3. Deep Learning

The history of deep learning begins with the creation of a neural network model of the human brain by Warren McCuloch and Walter Pitts in 1943, where they combined algorithms and mathematics which they called "threshold logic". Since then deep learning has developed steadily until now.

According to Geoffrey Hinton, deep learning is defined as a branch of machine learning based on data representation. Machine learning can use supervised learning, semi – supervised learning or unsupervised learning.

The difference between machine learning and deep learning lies in the presence or absence of a human role in the learning process. In machine learning, computers rely on humans to perform what is called "feature extraction" which is then entered into the machine so that the computer can perform a classification. In deep learning, all learning is carried out by computers independently of the data that has been provided by humans. (Primartha, 2018)

4. Convolutional Neural Network

Convolutional Neural Network is a method or alhorithm used in deep learning to classify data in the form of images. Applicatively, many CNN alogrithm are implemented in devices that have cameras, such as mobile phones, computers, robot, etc. (Saputra, Wasyianti, Adi, & Saefudin, 2021)

Convolutional Neural Network imitates the way humans work in recognizing objects they see. CNN is a Multilayer Perceptron (MLP) designed to identify two – dimensional images. Just like artificial neural networks in general, the CNN algorithm also consists of neuron that have weights, biases, and activation function. (Nisa, Puspaningrum, & Yulia, 2020)

The CNN algorithm, the process is diviided into two, the first is feature learning where the convolution and downsampling processes are located. Furthermore, there is a classification process where the fully – connected layer is tasked with classifying the input images that have passed the convolution process. (Hidayat, Darusalam, & Darusalam, 2019)

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METHOD

Image Acquisition

The data collecting process for rice plants was taken using mobile phone camera. Objects are captured by placing the camera over the object and using a plain white paper background. The rice plants taken were three types of diseased leaves and 1 healty leaf. The type of leaves include, brown spots, bacterial leaf blight, potassium deficiency and healty leaves. From left to right. (a)Brwon spots, (b)Healty leaves, (c)Bacterial leaf blight, (d)Pottasium defficiency

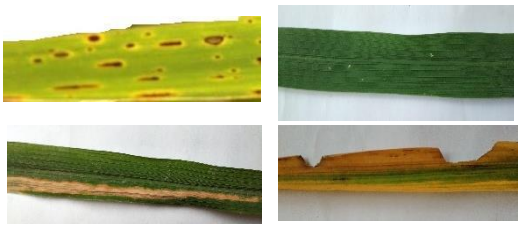

Fig. 1 Rice Plants Images

Data separation

The dataset has gone through a selection process to obtain good and clear data with a total of 800 images. The dataset is then separated into training data, validation data, and test data. The training data consists of 528 images, the validation consists of 128 images, while the test data consists of 144 images. (Shah, 2018)

Pre-processing

Due to the limited objects and data retrieval capabilities at the research site, when conducting the dataset training process, the augmentation process must first be passed. Data augmentation is a technique used to increase the amount of data by manipulating the image without reducing the content and information contained in the image. Data augmentation needs to be done to get high performance and avoid overfitting in the training process. Before data augmentation is performed, the images must go through the normalization process. (Abadi, Chu, & Goodfellow, 2016)

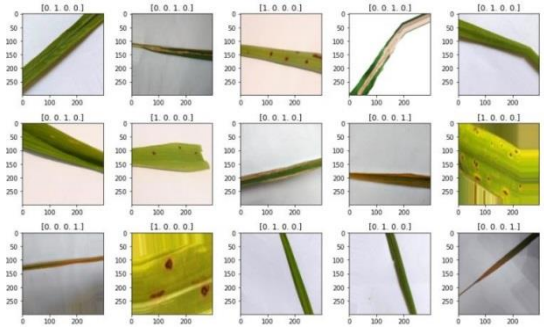

Fig. 2 Rice Plants Images

CNN Model

In this study, modeling was carried out using two approaches. The first approach uses the transfer learning method and the second approach by creating a model from scratch.

The basic concept of transfer learning is to take a previously trained model with a large dataset and transfer knowledge in the form of paraneters and weights to train a smaller dataset. The transfer learning method used in this study is Inception V3. (Wojna, 2015)

The stages that take place in the convolutional neural network are generally divided into two, namely the feature extraction stage and the classification stage. The input image used is 299 x 299 pixels and has 3 color channels, namely Red, Green, and Blue. After the image is inputed into the input layer of CNN, the image will go through a convolution and pooling process to study the features in the image. The convolution layer has a different number of kernels and filters. After the feature extraction stage is complete, the 3D tensor image will be flattened to convert the feature map into a vector form (Fausset, 1993)

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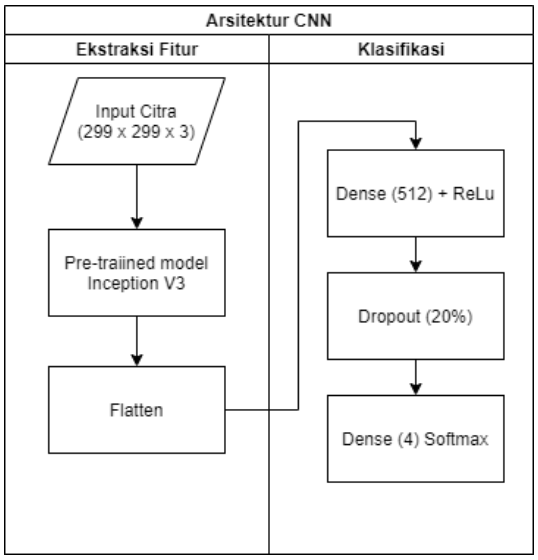

Fig. 3 Transfer Learning Architecture

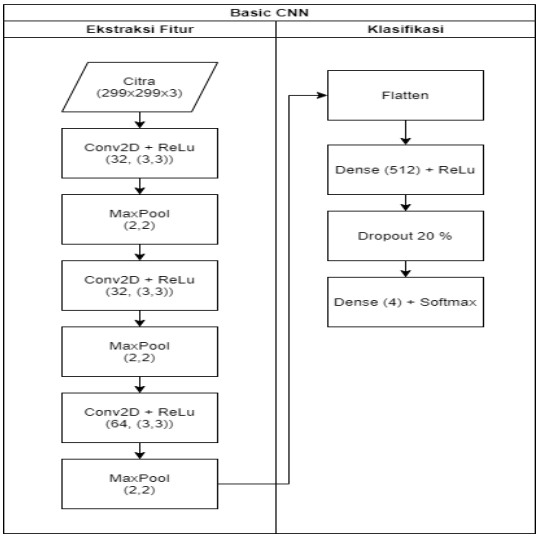

Fig.4 Arsitektur Model *Scratch*

Training Parameter Configuration

The parameters used in the training are as follows, the number of epochs used in the training is 15 epochs. The epoch indicates how many times a training data has passd to complete one lesson. Then the number of batch sizes used is 64 and the learning rate used is 0.001.

Training

Based on CNN architecture that has been made above, the training process is carried out according to the model architecture. This training process is also known as model fitting.

By calling the model.fit() funtion, the model will automatically work and execute the data. In this training the model will run as many as 15 epochs. Where every one sample epoch in the dataset has the same opportunity to update its parameters.

a. Input Image

The input image is a rice leaf plant that has been labeled with an image dimension of 299 x 299 pixels and has 3 channels, namely Red, Green, and Blue. In the training process, the image will be converted into a three – dimensional matrix with dimension of length x width x channel. The value of the matrix has a range from 0 to 255. Therefore, before training, the image is normalized so that the value range becomes 0 to 1 to facilitate the training process.

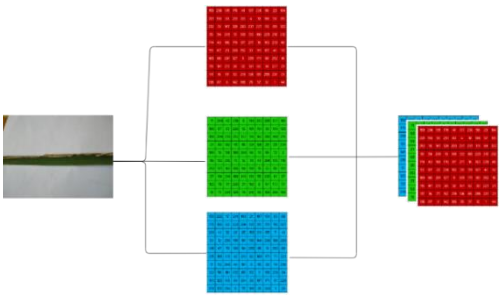

Fig. 5 Input Image

b. Convolutional Layer

In the convolution layer the samples in the dataset will go through a feature extraction process. Convolution is a process in which data is multiplied by a set of weights. The data sent through the input is three – dimensional data, so multiplication is also done with a three – dimensional filter or kernel.

The output of multiplying the filter by the input array is a single value. The filter will be applied or multiplied repeatedly by the input array and produces a two – dimensional output in each color channel. This

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operation is called feature map. After a feature map is created, the values contained in the feature map can be applied to non – linearity calculations such as ReLu.

After generating a map feature from the multiplication between the set of weights and the input array, the next layer performs the activation process. Here the activation aims to activate the neurons and determine the output. The activation function used in this study is the Relu activation function

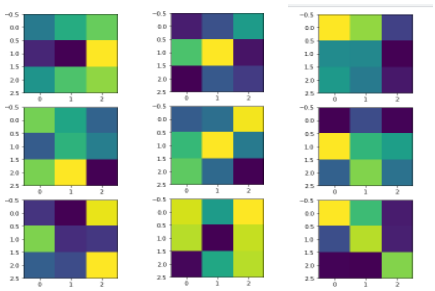

Fig. 6 Filter Visualization

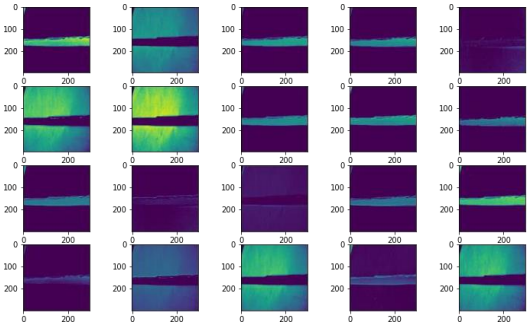

Fig. 7 Convolutional Feature Map on First Layer

c. Pooling Layer

The function of the pooling layer is to reduce the size of the image and also reduce the parameters to facilitate the training process. This layer recives input from the convolution layer that has gone through activation. The pooling or down – sampling size is 2x2 and with 2x2 strides, this means that the image will be reduced in dimension to 50% of its original size.

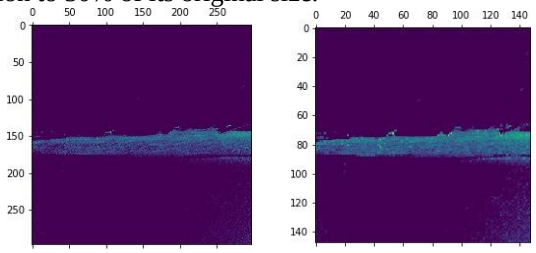

Fig. 8 *Downsampling*

d. Classification

Towards the classification layer, the last output after convolution which is still in the form of a three – dimensional array will be converted into a one – dimensional array with the Dense function. The first fully – connected layer is 512 and the second layer is 4 outputs accodring to the label or category of the dataset.

In one iteration or epoch, the last stage is backpropagation. Where backpropagation is an algorithm to improve weitghts and biases to reduce loss in training. The smaller the loss generated in the iteration, the better the model in predicting the data. Loss reduction in this study uses stochastic gradient descent with the algorithm used is Adam.

```
Epoch 1/15
8/8 [==============================] - 130s 15s/step - loss: 0.9918 - accuracy: 0.5481 - val_loss: 0.4033 - val_accuracy: 0.8359
Epoch 2/15
8/8 [==============================] - 90s 12s/step - loss: 0.2743 - accuracy: 0.8858 - val_loss: 0.2380 - val_accuracy: 0.9219
Epoch 3/15
8/8 [==============================] - 90s 11s/step - loss: 0.2051 - accuracy: 0.9197 - val_loss: 0.2589 - val_accuracy: 0.9375
Epoch 4/15
8/8 [==============================] - 89s 11s/step - loss: 0.1337 - accuracy: 0.9357 - val_loss: 0.1721 - val_accuracy: 0.9609
Epoch 5/15
8/8 [==============================] - 88s 11s/step - loss: 0.1657 - accuracy: 0.9403 - val_loss: 0.1775 - val_accuracy: 0.9375
Epoch 6/15
8/8 [==============================] - 90s 11s/step - loss: 0.1080 - accuracy: 0.9645 - val_loss: 0.2054 - val_accuracy: 0.9297
Epoch 7/15
8/8 [==============================] - 88s 11s/step - loss: 0.1399 - accuracy: 0.9511 - val_loss: 0.1609 - val_accuracy: 0.9141
Epoch 8/15
8/8 [==============================] - 89s 12s/step - loss: 0.1478 - accuracy: 0.9344 - val_loss: 0.1965 - val_accuracy: 0.9609
Epoch 9/15
8/8 [==============================] - 89s 11s/step - loss: 0.0834 - accuracy: 0.9692 - val_loss: 0.1101 - val_accuracy: 0.9688
Epoch 10/15
8/8 [==============================] - 89s 12s/step - loss: 0.0851 - accuracy: 0.9676 - val_loss: 0.2164 - val_accuracy: 0.9062
Epoch 11/15
8/8 [==============================] - 89s 11s/step - loss: 0.1016 - accuracy: 0.9679 - val_loss: 0.1190 - val_accuracy: 0.9609
Epoch 12/15
8/8 [==============================] - 89s 12s/step - loss: 0.1158 - accuracy: 0.9480 - val_loss: 0.0912 - val_accuracy: 0.9766
Epoch 13/15
8/8 [==============================] - 92s 12s/step - loss: 0.1189 - accuracy: 0.9578 - val_loss: 0.2889 - val_accuracy: 0.8828
Epoch 14/15
8/8 [==============================] - 88s 11s/step - loss: 0.1783 - accuracy: 0.9276 - val_loss: 0.0801 - val_accuracy: 0.9844
Epoch 15/15
8/8 [==============================] - 88s 11s/step - loss: 0.0927 - accuracy: 0.9662 - val_loss: 0.0970 - val_accuracy: 0.9766
```

Fig. 9 *Loss* and *Accuracy*

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RESULT

Testing

After the CNN training is complete, the model will go through a testing process to test how accurately the model perfroms in classifying images. The daya to be tested is new data that has never been trained by the model. The test data used are 144 images.

After the training process is complete, the model will be evaluated how well it recognizes the image. The results obatined from the training of rice leaf imagery are in the form of fluctuating graph. The highest validation loss from training is 1.35 and the smallest loss is 0.79. While the highest training loss is 9.5 and the lowest loss is 0.85

Based on transfer learning model that uses the Inception V3 algorithm, the highest validation loss obtained is 0.5 and 0.09 at the lowest validation loss value, 1.13 for the highest training loss and 0.07 for the lowest training loss. Training loss indicates how well the model fits the training data. The validation loss indicates how well the model will perform with the new data. The smaller the loss, the better the model will do its job.

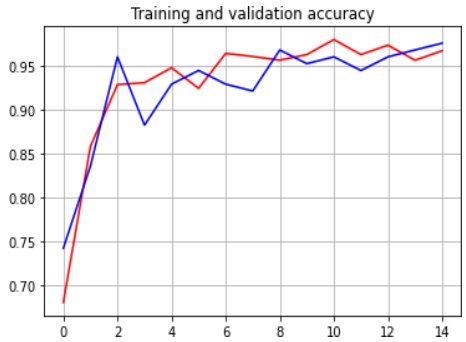

Fig. 10 *Loss* CNN *Scratch*

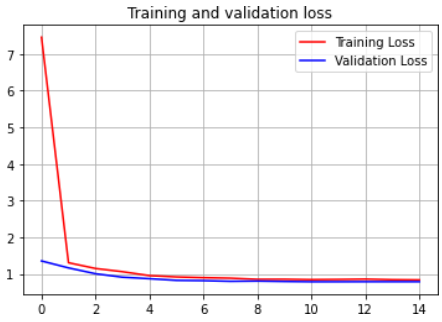

Fig. 11 *Loss* CNN *Transfer Learning*

The accuracy obtained after training the CNN model is as follows. The highest validation accuracy value is 0.75and the value is 0.33 for the smallest validation accuracy. Meanwhile the highest training accuracy values are 0.68 and 0.23 for the smallest training accuracy values.

The value obtained after training the model using the transfer learning algorithm is 0.98 for the highest validation accuracy and 0.74 for the lowest validation accuracy. Meanwhile the highest training accuracy values are 0.98 and 0.55 for the smallest training accuracy values.

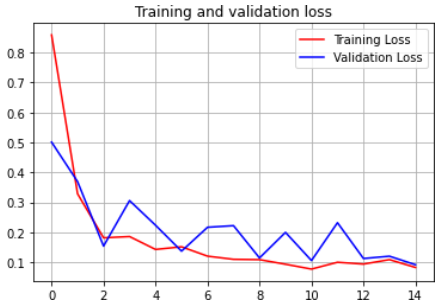

Fig. 12 . Accuracy CNN Scratch

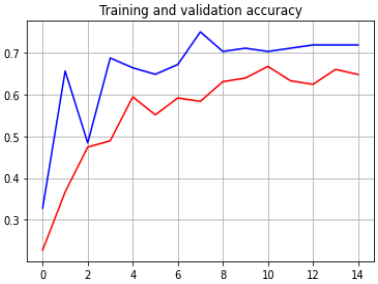

Fig. 13 *Accuracy* CNN *Transfer Learning*

The model testing in this study was carried out using a confusion matrix. By using test data consists of 144 pieces and divided into 4 folders, each of which is 34 pieces.

Table 1 CNN Model Testing Result

Matrix		Predicted Class			
		BS	HL	BLB	PD
Actua l Class	BS	24	10	0	0
	HL	0	26	3	9
	BLB	4	12	10	8
	PD	0	4	4	30

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Based on the test table from the CNN model above, there are some data that are wrong in its classification. Through 34 Brown Spots (BS) data, 10 data are wrong in class placement. 11 Healty Leaf (HL) data is wrong in class placement. In the Bacterial Leaf Blight (BLB), there are 24 rong data classes. 8 wrong class in Potassium Defficiency (PD) class. Based on the table above, the accuracy can be calculated as follows,

$$Accuracy = \frac{Correct\ Amount\ of\ Data}{Total\ Data} x\ 100\% \qquad (1)$$

$$Accuracy = \frac{90}{144}\ x\ 100\% = 62{,}5\%$$

From the calculation result above, the CNN model accuracy is 62.5%

Table 2. Model Transfer Learning Training Result

Matrix		Predicted Class			
		BS	HL	BLB	PD
Actual Class	BS	34	0	0	0
	HL	0	33	5	0
	BLB	0	0	34	0
	PD	0	0	9	29

Based on the test table from the CNN model above, all data on Brown spots and Leaf blight are correct in their class placement. In the Healy class, 5 data were incorrect in class placement, then 9 wron data in Potassium deficiency class.

$$Accuracy = \frac{120}{144}\ x\ 100\% = 90\%$$

From the result of the above calculation, the accuracy of the transfer learning model is 90%. This value is the same as the value generated in the test using the method.

After testing the CNN model and transfer learning model, it can be concluded that training using the transfer learning model obtained more accureate data than using the CNN model to classify and identify disease images on rice plants leaves.

1. *Implementation on Mobile Applications*

a. User Interface Simulation

Researchers run the application with their Smart Phone. The first page that will appear when the user opens the application is the main page. On the main page there is a date and weather feature so farmers can see the time quickly. On the main page there is also a gallery button and an image capturing button which will open then camera if the button is pressed.

Users can identify rice plant leaves by pressing the image capturing button to open the camera from their smartphone and take a picuter or press the gallery button to select an image from the pre – capturing photo before in their smartphone photo album

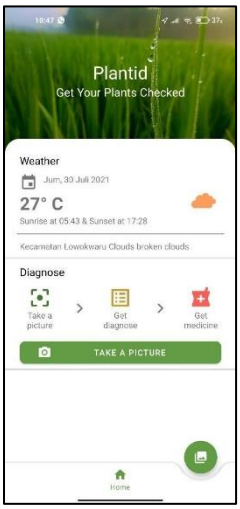

Fig. 14 Main Page

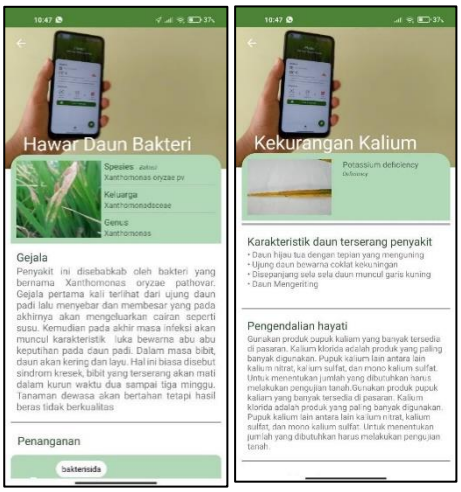

Fig. 15 Identification Pages

Fig. 16 Drug Description Page

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The picture above is the display when the user has identified either through the camera or from a photo album. This page will display a description of the disease name along with a brief taxonomy of the disease. This page will also display a list view containing drugs to treat diseased levaes. If the list view is pressed, the user will be directed to a form or drug detali page.

On this page will be displayed the content of the drug that must be purchased and the recommended drug

b. Testing

Researchers scanned the test data, which amounted to 144 images of the four clasess, namely . Brown Spots (BS), Healty Leaf (HL), Bacterial Leaf Blight (BLB) and Potassium Defficiency (PD). The results issued by the application will be recorded to calculate the accuracy for each model

Table 3. Mobile Based Application Testing Result on the CNN Model

Matrix		Predicted Class			
		BS	HL	BLB	PD
Actual Class	BS	24	10	0	0
	HL	0	26	3	9
	BLB	4	12	10	8
	PD	0	4	4	30

$$Accuracy = \frac{90}{144} x100\% = 62{,}5\%$$

From the calculation result above, the CNN model accuracy is 62.5%

Table 4. Mobile Based Application Testing Result on Transfer Learning Model

Matriks		Predicted Class			
		BS	HL	BLB	PD
Actual Class	BS	34	0	0	0
	HL	0	33	5	0
	BLB	0	0	34	0
	PD	0	0	9	29

$$Accuracy = \frac{120}{144} x100\% = 90\%$$

From the calculation result above, the accuracy of the transfer learning model is 90%. This value is the same as the value generated in the test using those methode.

c. Evaluation

Based on the test results obtained on the CNN model from the scratch and the CNN model using transfer learning with the Inception V3 architecture, with the same learning parameters, namely 15 epochs the learning rate used is 0.001. The batch size is 64, and the input images is 299 x 299 x 3. It can be concluded that the model using the transfer learning alhorithm has a high level of accuracy. The accuracy obtained is 90%. As for the CNN model that was made by researcher, the accuracy was 62%.

Although using the same parameters, the two models have significant differences. As can be seen in Figure 4.14, the CNN model trained with transfer learning can produce high accuracy in a short time.

Models that are trained without using the transfer learning method experience overfitting because the training data is very minimal. Thus the model has difficutly when faced with new data. Transfer learning focuses on transmitting knowledge that has been trained with beig data so that it can be overcome the above problems. (Zhuang, Fuzhen., ***et al***. 2020,h.22).

CONCLUSION

Based on the result obtained after conducting research in making the Convolutional Neural Network model, it can be concluded that this study generated two deep learning models with the Convolutional Neural Network method which can classify and identify 4 classes on rice plant leaves. The approach used in modeling is from the scratch and transfer learning using the Inception V3 algorithm.

This research also design an application that can perform classification by model. Testing on the application by scanning the test data, totaling 144 pieces of rice plant leaf images. Testing on the CNN from the scratch

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model produces an accuracy rate of 62%, while the model with the transfer learning method produces an accuracy rate of 90%

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