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Implementation of Dual Channel Convolution Neural Network Method for Detecting Rice Plant Diseases

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Abstract: Rice is one of the strategic and important food crops for the economy in Indonesia. Rice can be infected with diseases caused by fungi, bacteria and viruses. The diseases that attack rice plants are not realized by farmers and often farmers do not understand the diseases that attack rice plants so that they are late in handling to diagnose symptoms causing rice plant production to decrease. To solve this problem, it is necessary to carry out the process of detecting diseases in rice plants. In this study, the Dual-Channel Convolutional Neural Network (DCCNN) method will be used. This DCCNN method consists of two channels, namely deep channel and shallow channel. The process of detecting rice plant diseases using the DCCNN method will start from the process of extracting the leaf part from the input image using the Gabor Filter method. After that, the Segmentation Based Fractal Co-Occurrence Texture Analysis method will be used to carry out the process of extracting features, colors, and textures from the extracted leaf parts. Finally, the DCCNN method will be applied to carry out the classification and detection process of rice plant diseases. The results of this study are that the DCCNN method can be used to detect types of leaf diseases in rice plants. The accuracy of disease detection results with the DCCNN method depends on the number of datasets in the system with an accuracy level of 85%. However, the more datasets will cause the execution process to take a long time.

Keywords: digital image; Dual-Channel Convolutional Neural Network method; Gabor Filter method; rice plant disease

INTRODUCTION

Rice is one of the strategic and important food crops for the economy in Indonesia (Lismawati & Isyanto, 2021). Rice plants are plants that have important spiritual, cultural, economic, and political values for the Indonesian nation because they affect the lives of many people (Nuramyadany, Nur, & Rahmah, 2023). Rice can be infected with diseases caused by fungi, bacteria and viruses. Types of diseases that infect rice include bacterial Leaf Blight caused by the bacteria Xanthomonas oryzae and Brown Spot caused by fungi. This disease initially appears as spots on infected rice leaves (Pustika, Widyayanti, & Supriadi, 2023). These diseases have different characteristics in the shape, size, and color of the symptoms of the disease. Some diseases may be brown or yellow. Some diseases may have the same color, but different shapes; while some have different colors but the same shape (Jauhari & Agrawal , 2023). The diseases that attack rice plants are not realized by farmers and often farmers do not understand the diseases that attack rice plants so that they are late in handling to diagnose symptoms, causing rice production to decrease (Purnamawati, Nugroho, Putri, & Hidayat, 2020).

Expert supervision is usually required to monitor and reduce diseases to prevent crop losses. With limited availability of crop protection experts, manual disease diagnosis becomes more difficult and expensive (Farmadi & Muliadi, 2023). The delay in the manual diagnosis process causes the disease in rice plants to reach a severe stage due to the lack of knowledge of farmers and assuming that the symptoms are common during the planting season, resulting in crop failure. Proper control is not only when the attack has occurred, but the most important thing is preventive measures (Alidrus, Aziz, & Putra, 2021). Efforts to overcome this problem have been carried out with various approaches, one of which is through the use of computer-based disease detection technology (Farmadi & Muliadi, 2023). Early and accurate detection of plant diseases can help farmers take timely preventive measures, thereby reducing crop losses. Image-based detection methods have developed rapidly with the presence

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of new algorithms that are able to identify and classify plant diseases automatically and efficiently (Krisdianto, Sonalitha, & Gumilang, 2024).

Rice leaves and stems are the main part in rice plant investigation monitoring that provides information on plant health status that affects the quality and quantity of rice crop yields. Monitoring through leaf and stem digitization results can classify rice plant diseases as types of disease classes based on data obtained from agricultural image database repositories (Farmadi & Muliadi, 2023). There are many types of diseases in rice plants that cause a decrease in the quality and quantity of rice crop yields which indirectly affects rice production for food needs in Indonesia. Of all types of rice plants, this will focus on three classifications of diseases in rice plants, namely bacterial leaf blight, brown spot, and leaf smut, then this disease attacks the leaves of rice plants (Santosa, Nur Fu'adah, & Rizal, 2023).

The detection process is carried out through several stages, namely feature extraction using Gabor Filter to highlight relevant leaf parts, then texture and color analysis using the Segmentation-Based Fractal CO-Occurrence Texture Analysis method. After that, the DCCNN method consisting of deep channels and shallow channels works in parallel to process features and classify diseases faster than conventional CNN methods. Model accuracy is influenced by dataset quality, data augmentation techniques, model parameters, and feature extraction methods used. Compared to CNN, the DCCNN method has advantages in execution time efficiency because it uses two feature processing paths in parallel. Performance testing is carried out by comparing evaluation metrics such as accuracy, precision, PSNR values, and structural similarity.

In this study, the disease recognition process was carried out by comparing the detected rice disease images with a rice disease database, so that the results can be used as conclusions in determining the disease that attacks the rice.

LITERATURE REVIEW

Similar research that has been done previously such as the Expert System for Detecting Diseases in Rice Plants Using the Forward Chaining Method (Tobing, Pawan, Neno, & Kusrini, 2019). However, the research conducted was in the form of an expert system application that used the concept of questions and answers and did not use visual images so that the results obtained were less accurate. Another study, namely Disease Detection in Rice Plant Leaves Using the Convolutional Neural Network Method (Alidrus, Aziz, & Putra, 2021). However, the CNN method has a weakness where the training process takes a long time. To increase the execution time of the CNN algorithm, it is necessary to modify the CNN method. The new method resulting from the modification of CNN is called Dual-Channel Convolutional Neural Network (DCCNN). The DCCNN method consists of two channels, namely deep channel and shallow channel (Yuantao, et al., 2019). The process of detecting rice plant diseases using the DCCNN method will start from the process of extracting the leaf part from the input image using the Gabor Filter method. After that, the Segmentation Based Fractal Co-Occurrence Texture Analysis method will be used to carry out the process of extracting features, colors, and textures from the extracted leaf parts. Finally, the DCCNN method will be applied to carry out the classification process and detection of types of rice plant diseases. The DCCNN method was chosen to carry out the process of detecting rice plant diseases considering that this method is still new (introduced in 2019) and this method is a development of the CNN method, where based on the tests carried out, this method has better PSNR and structural similarity values than other methods (Yuantao, et al., 2019).

METHOD

Convolutional Neural Network (CNN) is a method to transform the original image layer by layer from the image pixel value into the class scoring value for classification. And each layer has hyperparameters and some do not have parameters (weights and biases on neurons) (Nurani, Yanuar, & Putra, 2022). Convolutional Neural Network is a combination of deep learning algorithms and artificial neural networks that are commonly used to process pixel and image data. CNN architecture has several components, namely: Convolution layer, Rectified Linear Unit (ReLu), Pooling layer, Fully connected layer, and softmax activation (Handoko, Rosid, & Indahyanti, 2024). Deep learning with convolutional neural networks (CNN) is widely used to classify, detect, and predict images. The deep learning method is a representation-learning method that consists of various levels of representation at a certain level into a representation at a higher level, to an abstract level (Linda S.R, Kusrini, & Hartanto, 2024).

Dual Channel Convolution Neural Network (DCCNN) uses two layers, namely "deep and shallow", using 13 levels and 3 levels respectively, in a two-channel network; the shallow channel is used to restore the overall outline of the image, while the deep channel is used to recover rich texture information. Therefore, the combination of these two channels can effectively improve the training efficiency, enhance the feature fitting ability, and reduce the computational complexity of the entire model. Based on the above factors, the parameters of the shallow channel with the convolutional kernel are selected while adjusting the depth of the deep channel network, so that the shallow channel is mainly responsible for the convergence performance of the network to reduce the time

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complexity of the model. In addition, the deep channel is mainly responsible for more detailed texture recovery and for improving the precision of network restoration. It is more efficient to learn high-level texture information, and the image fitting features are more accurate, considering that the use of residual blocks and skip results leads to faster convergence than a simple increase in the number of network layers and also reduces gradient dispersion and feature loss. The working process of DCCNN can be seen in Figure 1.

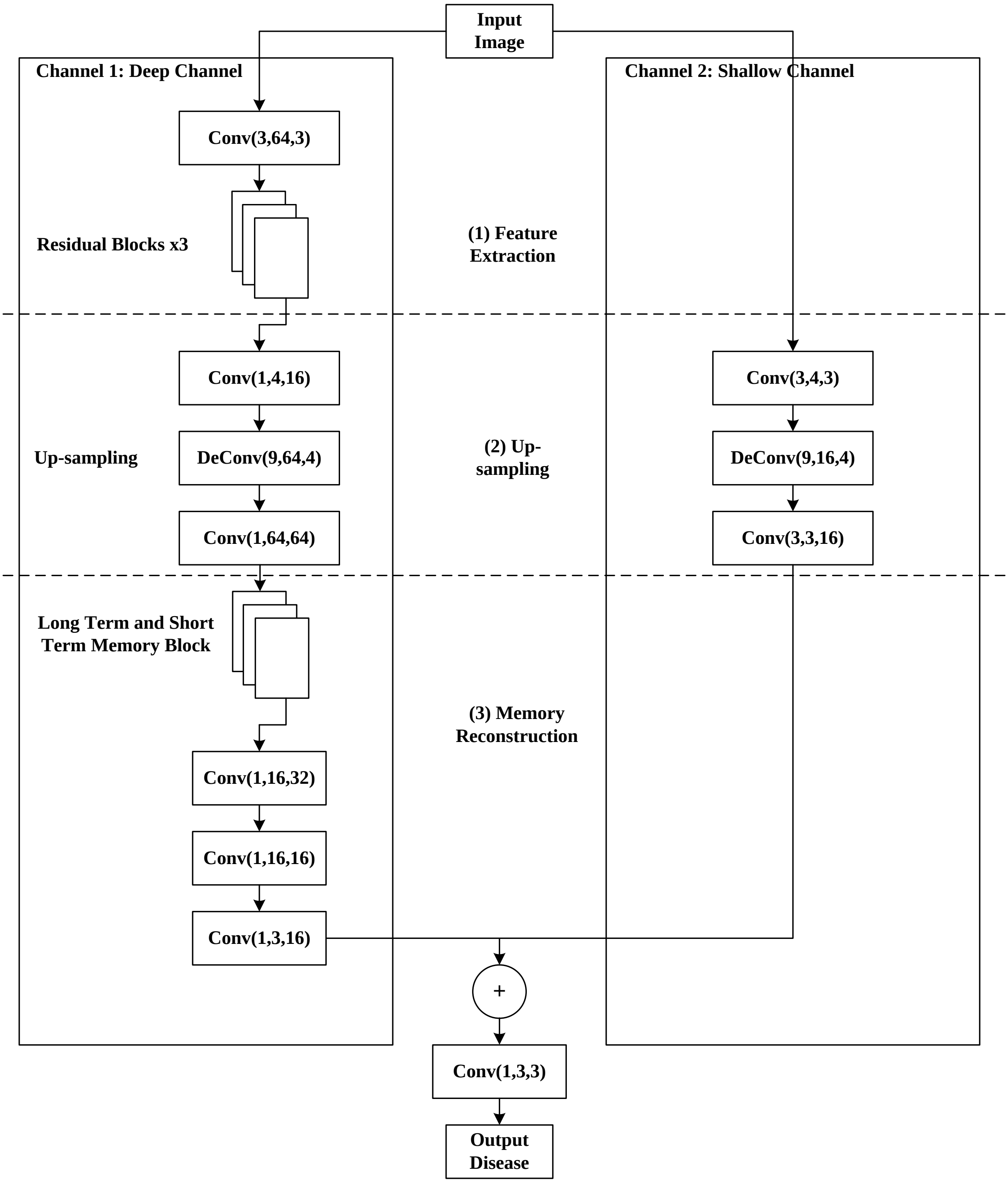

Figure 1. Procedure of DCCNN Method

The flowchart design of the work process of the Dual Channel Convolution Neural Network method in detecting diseases in rice plants is described in Figure 2 and Figure 3.

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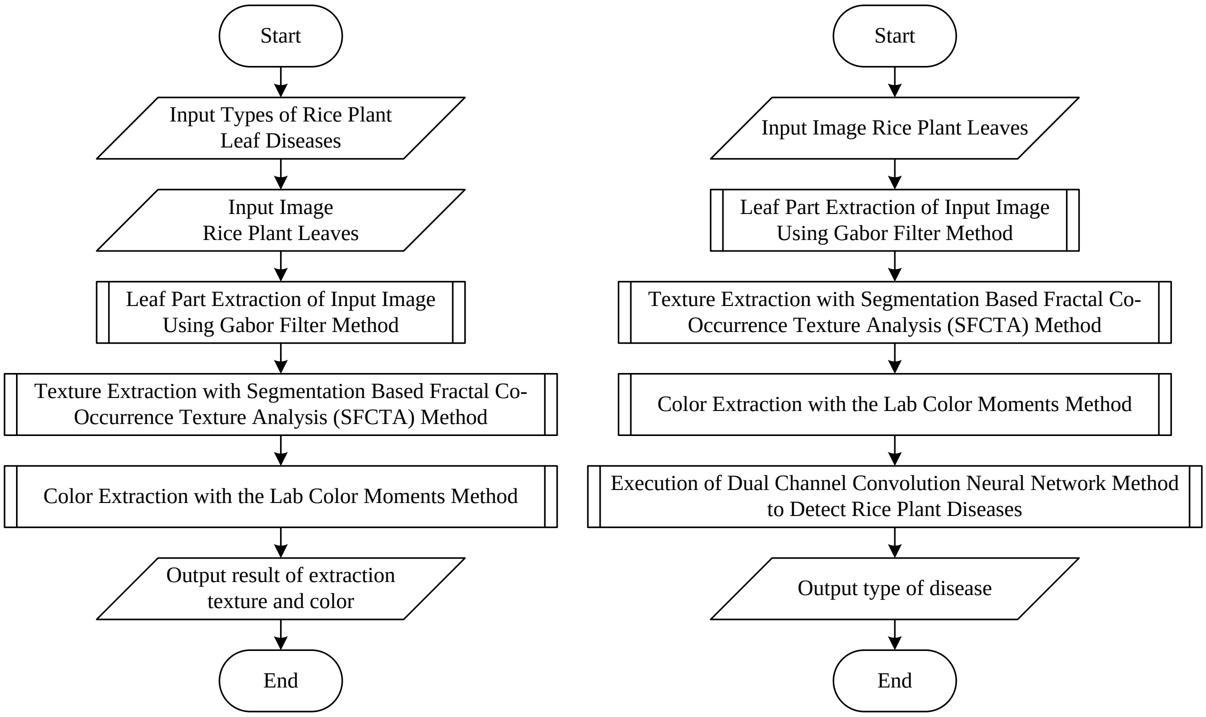

(a) (b)

Figure 2. (a) Training Process (b) Testing Process

This study will apply Gabor Filter as a feature extraction method. This feature extraction aims to bring out features in an image based on a combination of orientation and scale, in addition this method is also often used in extracting biometric features (Putri, Arnia, & Muharar, 2024). Gabor filters are used for smoothing, blurring, removing details and removing noise (Telaumbanua, Ibnutama, & Elfitriani, 2025). The working procedure of the Gabor filter method can be seen in the flowchart image as shown in figure 3.

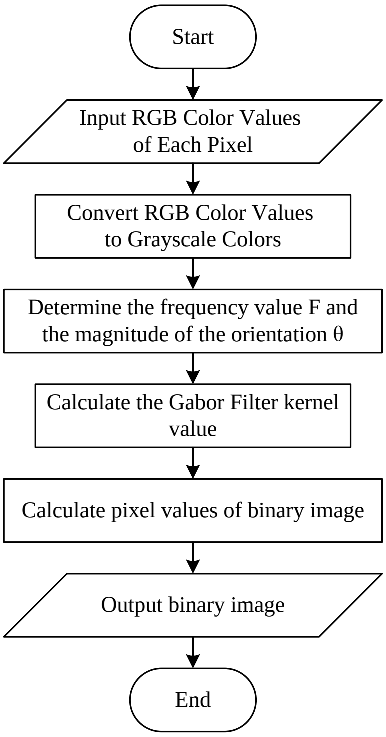

Figure 3. Gabor Filter Figure

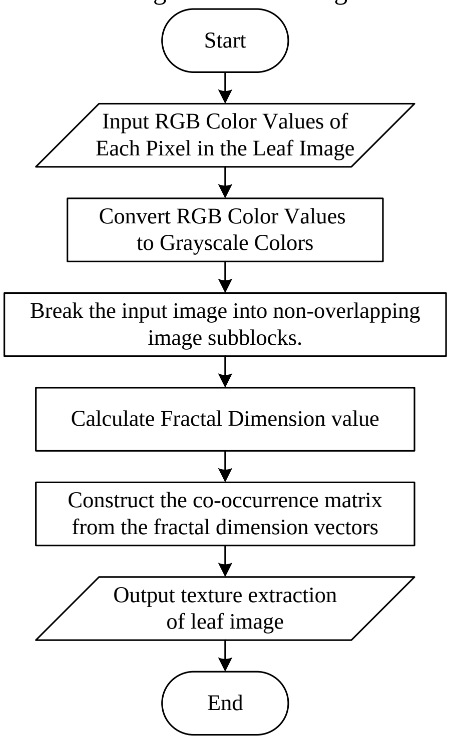

Figure 4. SFCTA Method

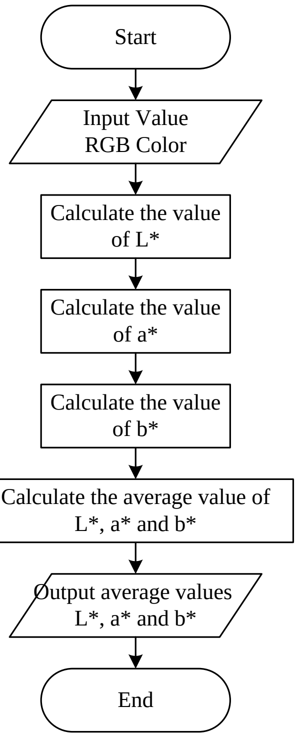

Figure 5. Lab Color Moments Method

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Meanwhile, to carry out the texture extraction process, the segmentation based fractal co-occurrence texture analysis (SFCTA) method will be used (Marantika, Gultom, Agustine, Sinuhaji, & Aisyah, 2024). The working procedure of the SFCTA method can be seen in the flowchart image as shown in figure 4. Finally, to carry out the color extraction process, the Lab Moments method will be used. Color moments is a method to distinguish an image based on the characteristics of the image color. The basis of this Color Moment method is to use three main moments of the color distribution of an image, namely the average (mean), standard deviation, and skewness. So this Color Moment method produces three values for each color component (Astutik, Widiyanto, & Nugrahaeni P.D, 2022). The way the Lab Moments method works can be seen as shown in figure 5.

RESULT

Testing will be carried out using various types of images with different types of rice leaf diseases in the images. The following are detailed results of the tests carried out. The dataset entered into the database is 180 pieces with details of each type of disease containing 60 images. The testing process will be carried out on 20 rice leaf disease images for each type of disease so that the total is 60 test images. The results of the tests carried out can be detailed as follows:

Table 1.
Bacterial Leaf Blight Disease Test Results

Test Image	Detection Result	Description
	Brown Spot	**FAILED**
	Bacterial Leaf Blight	SUCCEED
	Leaf Smut	**FAILED**
	Bacterial Leaf Blight	SUCCEED
	Bacterial Leaf Blight	SUCCEED
	Bacterial Leaf Blight	SUCCEED
	Leaf Smut	**FAILED**
	Bacterial Leaf Blight	SUCCEED
	Leaf Smut	**FAILED**
	Bacterial Leaf Blight	SUCCEED
	Leaf Smut	**FAILED**
	Bacterial Leaf Blight	SUCCEED
	Bacterial Leaf Blight	SUCCEED
	Bacterial Leaf Blight	SUCCEED
	Bacterial Leaf Blight	SUCCEED
	Bacterial Leaf Blight	SUCCEED
	Leaf Smut	**FAILED**
	Bacterial Leaf Blight	SUCCEED
	Bacterial Leaf Blight	SUCCEED
	Bacterial Leaf Blight	SUCCEED

Total image = 20

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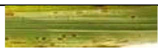
True Positive = 16
True Negative = 0
False Positive = 4
False Negative = 0
Accuracy = $^{(16+0)}/(16+4+0+0)$ * 100% = $^{16}/20$ * 100% = 80%.
Error Rate = $^{(4+0)}/(16+4+0+0)$ * 100% = $^{4}/20$ * 100% = 20%.
Precision = $^{16}/(16+4)$ * 100% = $^{16}/20$ * 100% = 80%.
Recall = $^{16}/(16+0)$ * 100% = $^{16}/16$ * 100% = 100%.

Table 2.
Brown Spot Desease Test Results

Test Image	**Detection Result**	**Description**
	Brown Spot	SUCCEED
	Brown Spot	SUCCEED
	Brown Spot	SUCCEED
	Brown Spot	SUCCEED
	Brown Spot	SUCCEED
	Brown Spot	SUCCEED
	Brown Spot	SUCCEED
	Brown Spot	SUCCEED
	Brown Spot	SUCCEED
	Brown Spot	SUCCEED
	Bacterial Leaf Blight	**FAILED**
	Leaf Smut	**FAILED**
	Brown Spot	SUCCEED
	Brown Spot	SUCCEED
	Bacterial Leaf Blight	**FAILED**
	Brown Spot	SUCCEED
	Brown Spot	SUCCEED
	Brown Spot	SUCCEED
	Brown Spot	SUCCEED
	Brown Spot	SUCCEED

Total image = 20
True Positive = 17
True Negative = 0
False Positive = 3
False Negative = 0

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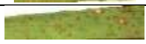
Accuracy = $^{(17+0)}/(17+3+0+0)$ * 100% = $^{17}/20$ * 100% = 85%.
Error Rate = $^{(3+0)}/(17+3+0+0)$ * 100% = $^{3}/20$ * 100% = 15%.
Precision = $^{17}/(17+3)$ * 100% = $^{17}/20$ * 100% = 85%.
Recall = $^{17}/(17+0)$ * 100% = $^{17}/17$ * 100% = 100%.

Tabel 3.
Leaf Smut Desease Test Results

Test Image	Detection Result	Description
	Leaf Smut	SUCCEED
	Leaf Smut	SUCCEED
	Leaf Smut	SUCCEED
	Leaf Smut	SUCCEED
	Leaf Smut	SUCCEED
	Bacterial Leaf Blight	**FAILED**
	Leaf Smut	SUCCEED
	Leaf Smut	SUCCEED
	Leaf Smut	SUCCEED
	Leaf Smut	SUCCEED
	Leaf Smut	SUCCEED
	Bacterial Leaf Blight	**FAILED**
	Leaf Smut	SUCCEED
	Leaf Smut	SUCCEED
	Leaf Smut	SUCCEED
	Leaf Smut	SUCCEED
	Leaf Smut	SUCCEED
	Leaf Smut	SUCCEED
	Leaf Smut	SUCCEED
	Leaf Smut	SUCCEED

Total image = 20
True Positive = 18
True Negative = 0
False Positive = 2
False Negative = 0
Accuracy = $^{(18+0)}/(18+2+0+0)$ * 100% = $^{18}/20$ * 100% = 90%.
Error Rate = $^{(2+0)}/(18+2+0+0)$ * 100% = $^{2}/20$ * 100% = 10%.
Precision = $^{18}/(18+2)$ * 100% = $^{18}/20$ * 100% = 90%.
Recall = $^{18}/(18+0)$ * 100% = $^{18}/18$ * 100% = 100%.

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Overall:
Total image = 60
True Positive = 51
True Negative = 0
False Positive = 9
False Negative = 0
Accuracy = $^{(51+0)}/_{(51+9+0+0)}$ * 100% = $^{51}/_{60}$ * 100% = 85%.
Error Rate = $^{(9+0)}/_{(51+9+0+0)}$ * 100% = $^{9}/_{60}$ * 100% = 15%.
Precision = $^{51}/_{(51+9)}$ * 100% = $^{51}/_{60}$ * 100% = 85%.
Recall = $^{51}/_{(51+0)}$ * 100% = $^{51}/_{51}$ * 100% = 100%.

DISCUSSIONS

From the test results conducted on 60 images, it was obtained that the precision value was 85%, the recall value was 100%, and the accuracy value was 85% and the error rate was 15%. This means that the level of accuracy of the prediction results is 85%. Meanwhile, the level of accuracy between the information requested by the user and the answer given by the system is 85%. Finally, the success rate of the system in rediscovering information is 100%. The number of datasets will affect the accuracy of the disease identification results using the DCCNN method. However, the more datasets will cause the execution process to take longer.

The prediction system using the DCCNN method is able to provide prediction results for the type of disease by entering images of leaves from rice plants. This can certainly save more time than using an expert system based on questions and answers. However, the Gabor Filter method used to carry out the process of extracting the leaf part of the rice plant requires determining the appropriate angle and frequency parameters in order to obtain accurate extraction results. This can be a problem, especially for system users who are still unfamiliar with computer science. Further development of the disease detection system can be done by using the edge detection method to carry out the process of extracting leaves from rice plants so that users do not need to determine certain parameters in order to obtain optimal results.

CONCLUSION

From the previous discussion, it could be concluded that the DCCNN method can be used to detect and recognize various types of diseases in rice plants with varying image inputs. The accuracy of the disease detection results with the DCCNN method depends on the number of datasets in the system with an accuracy level reaching 85%. The process of detecting diseases in rice plants can be done easily, without having to manually check each leaf on the rice plant one by one.

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