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Classification of Diseases in Snake Plants Using Convolutional Neural Network

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ABSTRACT

Snake plant has an important role in human life, as well as in increasing the aesthetic value of the environment. Limited knowledge about diseases in snake plants has a crucial result in improper handling and control when the plant is attacked by disease. Advances in deep learning technology and Convolutional Neural Network (CNN) have presented high opportunities with their advantages in recognizing patterns and features from image data. This research will use a CNN model with VGG-19 architecture to classify diseases in the leaves of the snake plant. It is expected that by using the pre-trained VGG-19 model, the model can recognize complex visual patterns in snake plants. Diseases to be classified include several types of diseases that often attack snake plants such as anthracnose, rust, water soaked lesion, and healthy plants for comparison. The highest value of training accuracy reached a value of 98.08%, validation accuracy of 94.02%, and testing accuracy reached 94%.

Keywords: Convolutional Neural Network, Image Classification, VGG19, Lidah Mertua

INTRODUCTION

Sansevieria, also known as the snake plant, is a unique and diverse decorative plant highly sought after by domestic and foreign customers, namely Singapore, South Korea, and United States of America (Kompas.com, 2018). According to CNN Indonesia, there has been a 14% increase in the export of snake plants compared to 2019. The Indonesian Ministry of Agriculture's Quarantine Agency reported that 17,839 snake plant specimens were ready for export in February 2021, with expectations of further increases in the following periods (CNN Indonesia, 2021). The Ministry of Agriculture continues to strive to improve the export process of snake plants, which is considered as one of the commodities that have a high opportunity to boost economic growth in order to achieve Golden Indonesia 2045.

In addition to enhancing aesthetic value, snake plants also offer other benefits, such as serving as natural and environmentally friendly air purifiers. Based on a study conducted by the Government of Grujugan Village, Kebumen Regency, snake plants can help alleviate Sick Building Syndrome (SBS) by improving poor room temperature and air quality caused by inadequate air conditioning, heating, or ventilation systems (Mubarok, 2021). As reported by Kompas, snake plants are capable of absorbing toxins and various harmful air pollutants, such as benzene, formaldehyde, xylene, and toluene. These plants can produce high levels of

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oxygen and reduce the risk of airborne allergies. The effectiveness of pollutant absorption increases with the age and density of the snake plant (Mahdang, 2014). Therefore, to maximize pollutant absorption, proper prevention and treatment tailored to the specific diseases affecting the plant are necessary. However, the similarity in symptoms or visual manifestations of these diseases can lead to incorrect diagnoses and, consequently, improper treatment by cultivators. Some of these diseases include *anthracnose, water soaked lesion,* and *rust.*

Based on the information provided above, this research aims to identify diseases in snake plants using the Convolutional Neural Network method with the VGG-19 model. The Convolutional Neural Network is a proven method for classifying high-complexity images. This method can adaptively learn various features in images through the backpropagation algorithm, using various layers such as convolutional layers, pooling layers, and fully connected layers (Yamashita et al, 2018).

LITERATURE REVIEW

Based on the results of research conducted by Mohammad Farid Naufal together with colleagues regarding the comparison of the performance of machine learning and deep learning algorithms in image classification with trials on the image dataset of the Indonesian sign system. The study shows that the accuracy results of deep learning algorithms are much higher than machine learning. CNN algorithm outperformed SVM and KNN algorithms with an accuracy result of 99.57% (Naufal & Kusuma, 2023).

In a study conducted by Wahyudi Setiawan entitled "Comparison of Convolutional Neural Network Architecture for Fundus Classification", the results of the study stated that VGG 19 and VGG 16 architectures are the best architectures compared to AlexNet, Residual Network (ResNet) 50, ResNet101, GoogleNet, Inception-V3, InceptionResNetV2 and Squeezenet.VGG-19 architectures succeeded in overcoming AlexNet, Residual Network (ResNet) 50, ResNet101, GoogleNet, Inception-V3, architectures InceptionResNetV2 and Squeezenet with an accuracy rate of 89.3% (Setiawan, 2019).

In the study "Vehicle License Plates with Convolution Neural Network" conducted by Djarot Hindarto and Handri Santoso to compare several deep learning algorithms, the results of the study stated that the accuracy results using VGG-19 were much higher than VGG-16, NasNetLarge and DenseNet12(Hindarto & Santoso, 2021). Based on the results of the study, it shows that VGG-19 has a higher level of accuracy and successfully outperforms several other deep learning algorithms.

In a study conducted by Elly Firasari and F Lia Dwi Cahyanti entitled "Classification of Potato Leaf Diseases Using Convolutional Neural Network", the highest accuracy results of 97.53% were obtained in classifying three classes, namely early blight, late blight, and healthy leaves(Firasari & Chayati, 2023).

Therefore, this study will apply the VGG-19 algorithm to build a disease classification model in snake plants.

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METHOD

The following are some stages of research system design that can be seen in Figure 1.

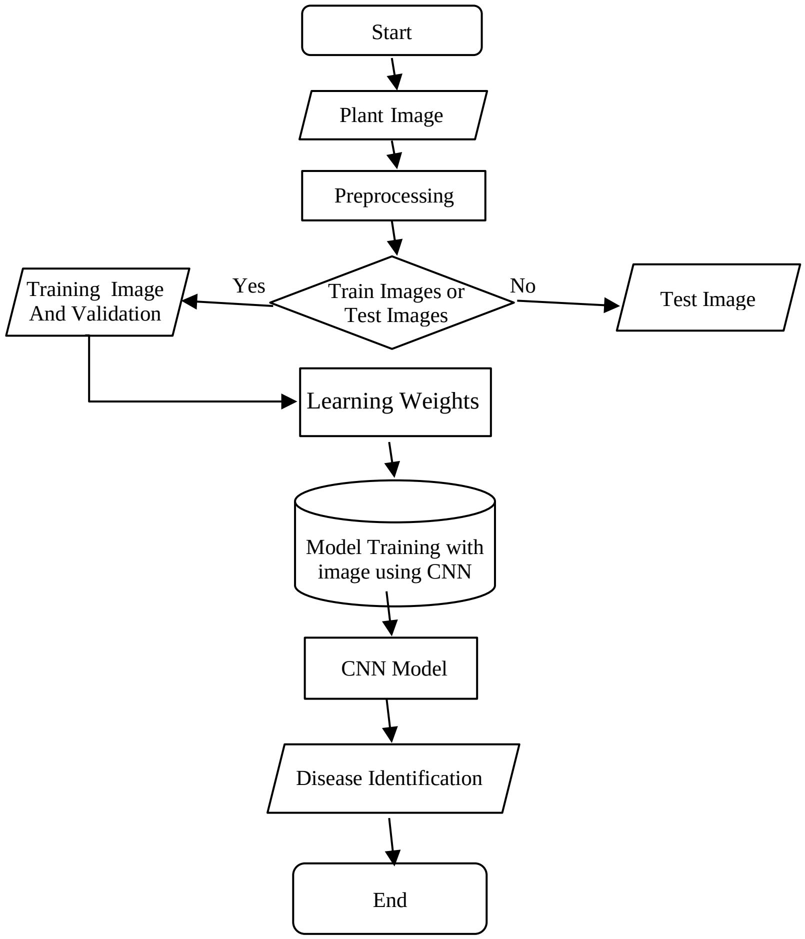

Figure 1. Data Flow Diagram

Data

The data that will be used in this study is the image data of snake plant leaves. The data collected were images of leaf diseases consisting of four classes, namely *anthracnose*, *water soaked lesion*, *rust*, *and healthy*. The dataset was obtained privately using a phone camera. The total amount of data used was 2,081 images, with 1,663 images used for training and 418 images used for validation. This image will later serve as input for pre-processing that will separate the data into training and testing datasets. The pixels in the image will be *resized because* VGG-19 only accepts images with a resolution of 224x224 pixels and data is added to change the image by augmenting the data.

Augmentation Data

The augmentation process was carried out to increase the amount of data due to limited imagery of snake plant diseases. There are several things that can be done in the augmentation process, such as modifying images by rotating images, enlarging images, cropping images randomly, changing color

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intensity, merging images, increasing space in images, and so on. The augmentation process is one method that has proven effective in supporting the improvement of the accuracy of models for classifying images(Shorten & Khoshgoftaar, 2019).

Convolutional Neural Network

CNN is one of the development algorithms of Multilayer Perceptron in deep learning that is able to classify images, videos, and detect objects in the image or even the region in the image. CNNs are made up of many neurons that have trainable weights and biases. Each neuron on the CNN can receive input, perform computational operations, produce output, and connect with other neurons(Adie 2018). In CNNs there are receptors that can respond to various features. Such as activation functions, loss, optimizer, which can teach CNN to learn what we want. On CNN there are 4 main layers, namely *Convolutional Layer, Pooling Layer, Activation Layer, and Fully Connected Layer*(Li et al., 2022).

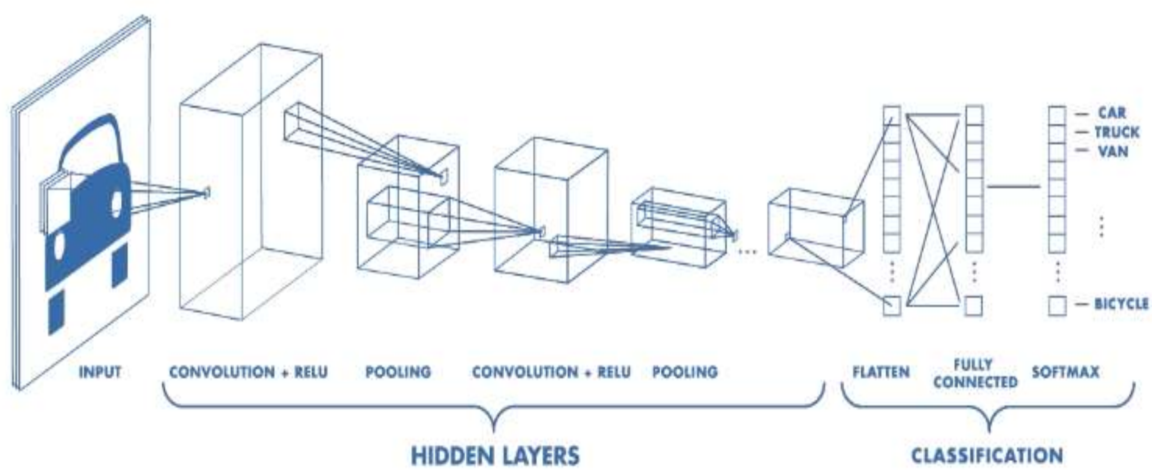

Figure 2. *Convolutional Neural Network* (Saha, 2018)
Source : https://saturncloud.io/blog/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way/

VGG-19

VGG19 is one of the highly profound convolution neural network (CNN) architectures first introduced by a team of researchers from the University of Oxford. The name "VGG19" refers to the number of layers in this model, which is 19 layers included in the architecture. The VGG 19 architecture consists of a series of convolution layers, a ReLU *(Rectified Linear Unit) activation* layer, and a *pooling* layer. The main feature of this model is the use of small 3x3 convolution kernels in almost all convolution layers, which allows this model to extract features with different levels of hierarchy.

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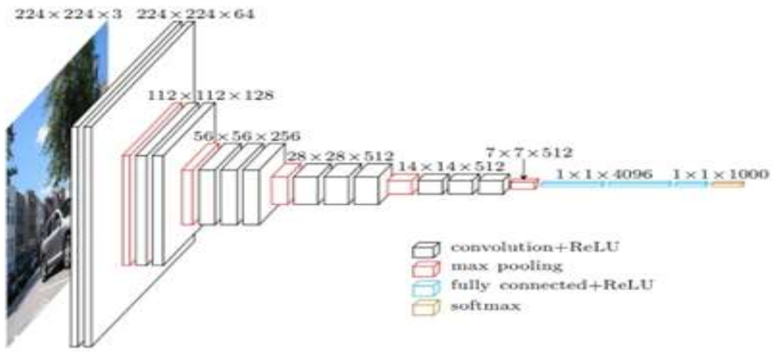

Figure 3. VGG-19 architecture (Boesch, 2021)
Source : https://viso.ai/deep-learning/vgg-very-deep-convolutional-networks/

Hyper-parameter Optimization

Hyper-parameter optimization is an important component in the model training process. *Hyper-parameters serve to build the structure of the model, such as the activation function and accuracy of model training. Examples of Hyper-parameters* are batch size and optimizer (Yu & Zhu 2020). The purpose of using *Hyper-parameters* is to improve the quality of the model. Each *Hyper-parameter* has a different way of working so that its use will be different in each case. So the use of *Hyper-parameters* must be adjusted to what is to be achieved(Yang & Shami, 2020).

Evaluation

At the evaluation stage, the *Confusion Matrix* method is used to measure the performance of the model against 4 predetermined classes. In this method, *Accuracy, Precision, Recall, and F1-Score are used* to analyze the classification results. Accuracy measures the accuracy of the model, Precision assesses the accuracy of positive predictions, Recall measures the ability of the model to identify positive data, and F1-Score is the average of Precision and Recall. This method calculates these values based on *True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (*FN) in cases with more than two output classes (D et al., 2023) .

$$Accuracy = \frac{TP + TN}{TP+FP+TN+FN}$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 - Score = 2\ x \frac{Precision\ \ x\ Recall}{Precision\ \ + Recall}$$

Precision : Shows a comparison of the data predicted to be correct with the overall data predicted by the system.
Recall : Shows a comparison of the predicted correct data with the overall actual data.
F1-Score : Average of the comparison of Precision and Recall.
Accuracy : Shows how accurate the model is in classifying correctly.

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RESULT

This experiment will use a dataset of 2,081 images with a data ratio ratio of 80:20 using a batch size of 32, a learning rate of 0.001 and an epoch count of 30 with a scenario comparing 3 different optimizers. Here are the results of the scenario testing that can be seen in Table 1:

No	Scenario	Training Accuracy	Loss Accuracy	Test Accuracy	Loss Accuracy
1	Adam	0.9808	0.0599	0.9402	0.1351
2	SGD	0.8166	0.4949	0.8158	0.4968
3	RMSprop	0.9657	0.1034	0.9522	0.1527

Table 1. Test results using 3 optimizers

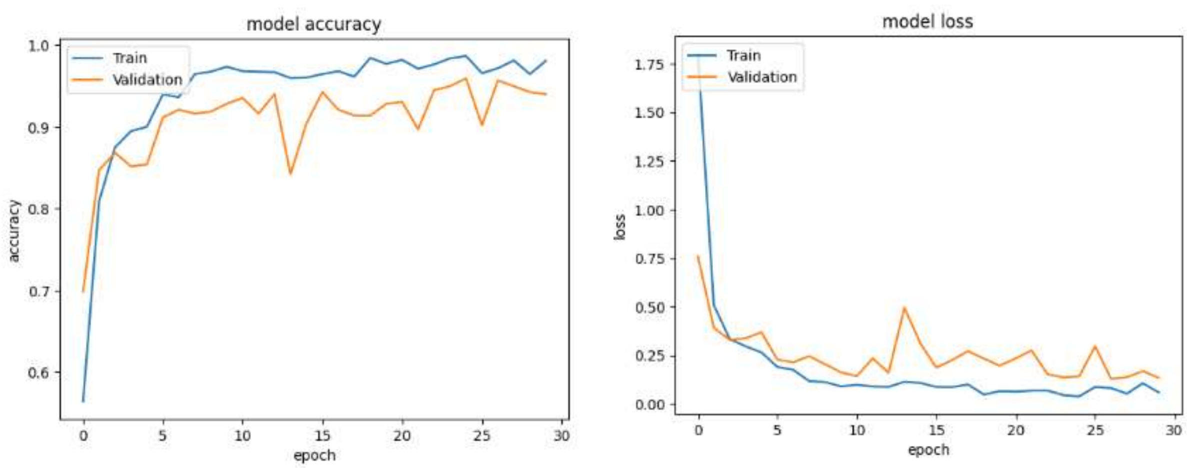

Figure 4. Accuracy and loss model graphs on training data with Adam optimizer

Figure 4 shows the *accuracy* *and* loss *results of* the data train *and* validation data on the original image test. Results were obtained through training with *a batch size* scenario of 32, *learning rate* of 0.001, *epoch* 30 and *Adam optimizer*. The last accuracy value obtained was 0.9808 and this value is good because it is close to number one. As for the last loss obtained by 0.05599 and this value is also good because it is close to zero. Further details about the confusion matrix and classification report could be seen in Figure 5 and Table 2.

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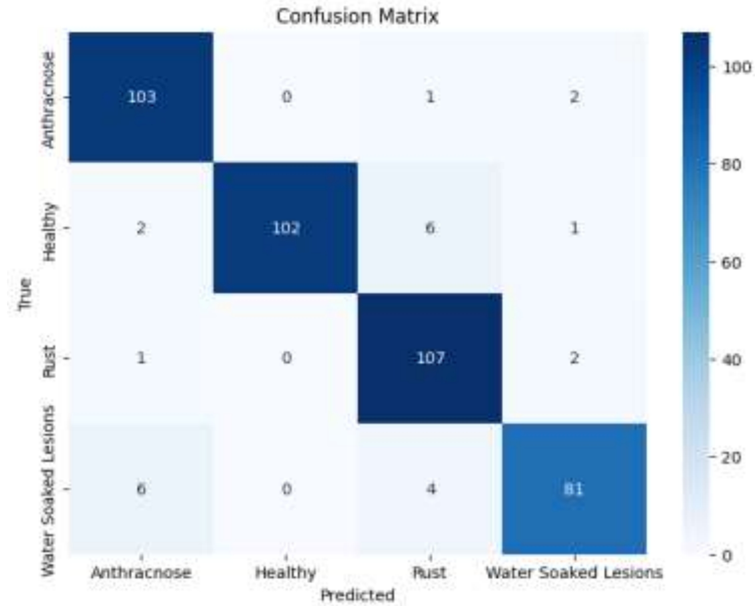

Figure 5. Confusion matrix result for Adam

Disease	Precision	Recall	F1-Score	Support
Anthracnose	0.92	0.97	0.94	106
Healthy	1.00	0.92	0.96	111
Rust	0.91	0.97	0.94	110
Water Soaked Lesions	0.94	0.89	0.92	91
Accuracy			0.94	418

Table 2. Classification report for Adam

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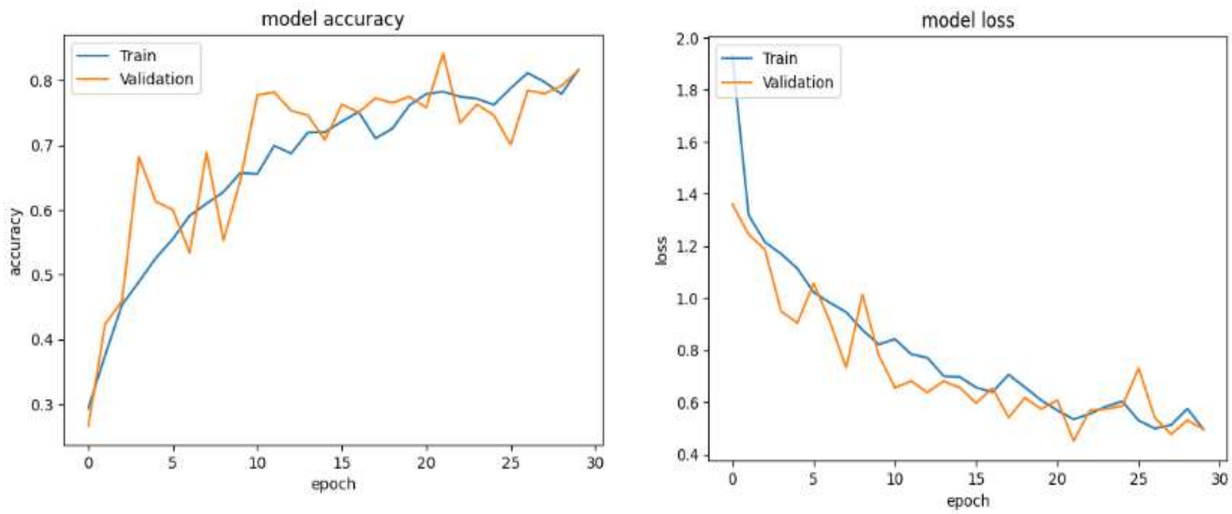
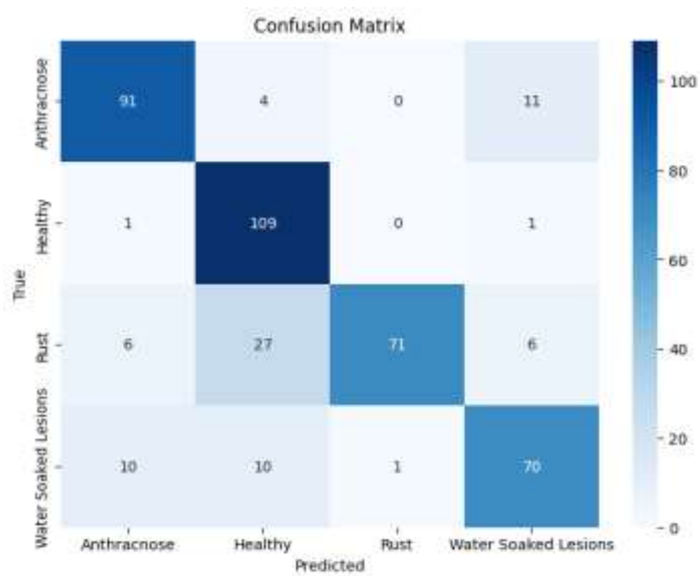


Figure 6. Graph accuracy and loss models in training data with SGD optimizer

Figure 6 shows the *accuracy and* loss *results of the* data train *and* validation data in the original image test. The results were obtained through training with *a batch size* scenario of 32, *learning rate* of 0.001, *epoch* 30 and *SGD optimizer*. The last accuracy value obtained was 0.8166 and this value is good because it is close to number one. As for the last loss obtained by 0.4949 and this value is also good because it is close to zero. Further details about the confusion matrix and classification report could be seen in Figure 7 and Table 3.



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Disease	Precision	Recall	F1-Score	Support
Anthracnose	0.84	0.86	0.85	106
Healthy	0.73	0.98	0.84	111
Rust	0.99	0.65	0.78	110
Water Soaked Lesions	0.80	0.77	0.78	91
Akurasi			0.82	418

Table 3.Classification report for SGD

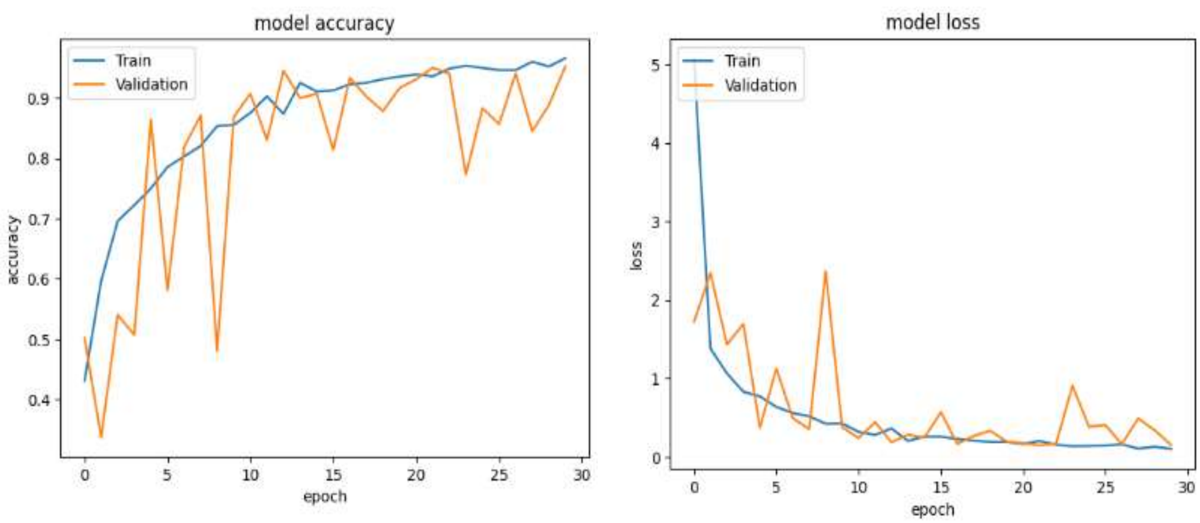

Figure 8. Graph accuracy and loss models in training data with RMSprop optimizer

Figure 8 shows the *accuracy and* loss *results of the* data train *and* validation data on the original image test. The results were obtained through training with *a batch size* scenario of 32, *learning rate* of 0.001, *epoch* 30 and *SGD optimizer*. The last accuracy value obtained was 0.9657 and this value is good because it is close to number one. As for the last loss obtained by 0.1034 and this value is also good because it is close to zero. Further details about the confusion matrix and classification report could be seen in Figure 9 and Table 4.

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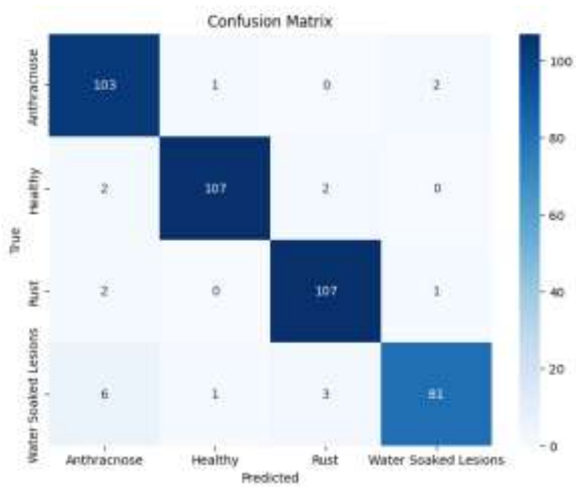

Figure 9. Confusion matrix result for RMSprop

Disease	**Precision**	**Recall**	**F1-Score**	**Support**
Anthracnose	0.91	0.97	0.94	106
Healthy	0.98	0.96	0.97	111
Rust	0.96	0.97	0.96	110
Water Soaked Lesions	0.96	0.89	0.93	91
Accuracy			0.95	418

Table 4. Classification report for RMSprop

DISCUSSION

This testing process was carried out using data from 40 original images of snake plants which were divided into 4 classes, namely *anthracnose, healthy, rust,* and *water soaked lesion.* Based on the results of tests that have been carried out on the 40 images, the accuracy results of testing using original data reached 94%. Based on the results of research that has been done, the VGG-19 method can be said to be a fairly good method in classifying the image of complicated snake plant diseases. This can be seen in the accuracy value between the validation results and test results that are not much different even though they use new data that has never been through the training process before. There are several factors that affect the test results of the image of the snake plant, namely class imbalance, image quality that is different from the training image such as lighting and color. In addition, the results of models trained using different *optimizers* can affect the test results, because each *optimizer* has a different impact on training the model.

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CONCLUSION

Based on the results of research that has been conducted using the Convolutional Neural Network method with the VGG-19 model, the system designed can classify the type of disease in the image of the snake plant well. The best accuracy results were obtained from models using the Adam optimizer with training accuracy of 98.08%, validation accuracy of 94.02%, and testing accuracy of 94%. The use of hyperparameters has an important role in model performance when conducting training and testing. The suggestions that can be given are to increase the number of images and improve the quality of the dataset to get more precise accuracy results, as well as develop adaptive algorithms to improve the ability of the model to classify disease images in snake plants. This app informs users of snake plant diseases and empowers them to take action to treat or prevent the spread of the disease to other parts of the plant.

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