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CNN Method to Identify the Banana Plant Diseases based on Banana Leaf Images by Giving Models of ResNet50 and VGG-19

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Abstract

Identify banana plant diseases using machine learning with the CNN method to make it easier to identify diseases in banana plants through leaf images. It employs the CNN method, incorporating ResNet50 because ResNet50 is one of the best models and a suitable model for the dataset used, and the VGG-19 model is used because VGG-19 was one of the winning models of the 2014 ImageNet Challenge and is a model that also fits the dataset used. The research objectives encompass dataset processing, model architecture development, evaluation, and result reporting, all aimed at enhancing disease identification in banana plants. The ResNet50 model achieved an impressive 94% accuracy, with 88% precision, 91% recall, and an 89% F1-score, while the VGG-19 model demonstrated strong performance with 91% accuracy, surpassing prior research and highlighting the effectiveness of these models in identifying banana plant diseases through leaf images. In conclusion, the ResNet50 model's exceptional accuracy positions it as the preferred model for CNN-based disease identification in banana plants, offering significant advancements and insights for agricultural practices. Future research opportunities include exploring alternative CNN models, architectural variations, and more extensive training datasets to enhance disease identification accuracy.

Keywords: banana disease identification; data processing, machine learning; convolutional neural networks

1. Introduction

This research identifies banana plant diseases using machine learning with the CNN (Convolutional Neural Network) method to make it easier to identify diseases in banana plants through leaf images [1]–[3]. The choice to use the ResNet50 model is because ResNet50 is one of the best and most suitable models for the dataset used, and ResNet50 also has a total of 50 layers [4], [5] The VGG-19 model is used because VGG-19 was one of the winning models of the 2014 ImageNet Challenge and is a model that also fits the dataset used. VGG-19 has a total of 47 layers, consisting of 16 convolutional layers and three fully connected layers, making it a robust network. In the VGG-19 model, VGG-19 is a CNN model that has the most and deepest layers and can reduce the number of parameters because each convolution layer uses a tiny filter of size 3x3, so it is well applied and produces an error rate of 7.3%. CNN consists of three layers: convolutional, pooling, and fully connected [6], [7]. Therefore, the CNN method with the VGG-19 and ResNet50 models was used in this research because the VGG-19 and ResNet50 models match the dataset used in this research.

One of the things that are making Computer Vision develop very rapidly at the moment is the techniques contained in the Deep Learning method or what is usually called Deep Neural Network, especially Convolutional Neural Network (CNN). Convolutional Neural Networks (CNN) is a type of neural network in deep learning that is used to process data in the form of images [8], [9]. These methods are one of the methods included in the machine intelligence category. CNN has made significant developments in the problems of image classification, object detection, object localization, and image segmentation. Two things that make the CNN method prevalent for use in Computer Vision problems can be seen in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) competition [10]. So, this research was conducted to assist in identifying banana plant diseases using the CNN method. The choice of using the CNN method is to make it easier to recognize diseases in banana plants through leaf images. CNN is a development of MLP (Multilayer Perceptron), which aims to manage 2D data. CNN also has many models that can be used, such as ResNet50, VGG-19, and many others [11], [12]. The use of CNN method has also been widely used in

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various kinds of research, such as several studies have been conducted by [13]–[15], and previous research used as a reference in this research is the research of Andreanov Ridhovan, Aries Suharso and Chaerur Rozikin (2022) [13].

In the process of identifying banana plant disease images, a classification process is needed to sort each image into a certain category based on its features. This is an important technique used for image recognition that allows you to identify items in the dataset and categorize them according to their class or level [16]. An image of banana leaf disease that has been classified based on its class, namely, health, Sigatoka, Cordana, and Pestaloptiosis, will be identified by a machine that has been programmed using the CNN method. The machine will identify banana plant diseases through the banana leaf image dataset used so that it can provide results in identifying banana plant diseases.

ResNet is a type of deep network-based residual learning. This learning can facilitate network training by considering the input layer as a reference. ResNet-50 is a variant of ResNet that has 50 layers. If, in the previous ResNet variant, there was a skip connection of 2 layers, then ResNet-50 skips three layers, and there is a 1 X 1 convolution layer [17], [18]. So that makes ResNet-50 one of the best models. The research was conducted by Jawad Yousef Ibrahim Alzamily, Syaiba Balqish Arifin, and Samy S. Abu Nasr [19]. The research obtained a high accuracy value of 99.75% using the ResNet-50 model. In the VGG-19 model, VGG-19 is a CNN model that has the most and deepest layers and can reduce the number of parameters because each convolution layer uses a tiny filter of size 3x3, so it is well applied and produces an error rate of 7.3%. The VGG-19 model has 138 million parameters and ranks 2nd in classification and 1st in localization at ILSVRC 2014. The VGG-19 model can train more than 1 million images and can classify images into 1000 types of objects [20], [21]. Research conducted by Showmick Guha Paul and colleagues using the VGG-19 model obtained an accuracy value of 95% [22].

Bananas are a very popular plant in Indonesia and have a large production level; bananas also contain lots of vitamins, carbohydrates, and minerals that are beneficial to humans [23], so machine learning is urgently needed to help identify banana plant diseases. This research is an effort to identify banana plant diseases using machine learning. It seeks to improve accuracy in identifying banana plant diseases using the CNN method and can be a complement and explanation of the deficiencies in previous studies [24]. Based on the formulation of the problem above, the research that will be carried out can exceed the results of previous studies [13] by using a new architecture, a new layer, and two different models with the proposed model, namely, ResNet-50 and VGG-19.

Based on this description, this research was conducted to get the best results in identifying diseases in banana plants using the CNN method. That research is needed to identify banana plant diseases using machine learning with the CNN (Convolutional Neural Network) method to make it easier to identify diseases in banana plants through leaf images because the quality and quantity of banana plants themselves can be affected by various factors such as pests, dry leaves, broken leaf sheaths, leaves rubbing against fruit, and Sigatoka disease, which causes a significant failure rate in banana production for banana plantations [25], [26]. Therefore, this research sets targets, namely (i) Processing datasets and architectural models and (ii) Obtaining model evaluation results from both schemes and reporting. So, it is hoped that this research can surpass the results of previous studies in identifying diseases in banana plants and can help other researchers in conducting similar research.

2. Research Methods

This research was conducted at the University of Muhammadiyah Malang from December 2022 to February 2023. Research materials and tools are needed to achieve each research objective through several stages of implementation. The research materials used are datasets obtained through the Kaggle website. The dataset from Kaggle that has been classified is shown in Figure 1.

The research tools used are the Acer Nitro An515 Laptop, Google Colaboratory, and the Python programming language. The selection of the algorithm used is in the form of a flowchart. The research methods in the form of a flowchart are shown in in Figure 2.

Based on Figure 2, the initial stage after starting the research is to determine the title or topic of the research being carried out, after getting the title or topic. After that, determine the research targets shown in Figure 2, there are two objects with four important stages in this research, namely (i) processing of datasets and architectural models and (ii) obtain model evaluation results from the two schemes and reporting. In the first object, namely (i) processing of datasets and architectural models. At this stage, dataset processing will be carried out which begins with first classifying the banana leaf image data obtained through the Kaggle website. Then after processing the dataset has been carried out correctly, it enters the model architecture creation stage.

At the model architecture stage, data will be processed in accordance with the use of a predetermined architectural model, and in this study using the proposed models, namely ResNet50 and VGG-19 to manage data. After the creation of the model architecture is done correctly, go to the second object, namely, (ii) obtain model evaluation results from the

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two schemes and reporting. This stage aims to get an evaluation results model. This model will show the results of evaluating the two models, ResNet50 and VGG-19, that were used to find diseases in banana plants by looking at images of their leaves.

At this stage, it will be divided into two schemas, namely Schema 1 to evaluate the ResNet50 model and Schema 2 to evaluate the VGG-19 model. After successfully getting the best results from the two schemes, the final stage is preparing a report. Where this stage is carried out by making a report in a comparison of the results of the two models and the results of previous research [13] in order to get the best results.

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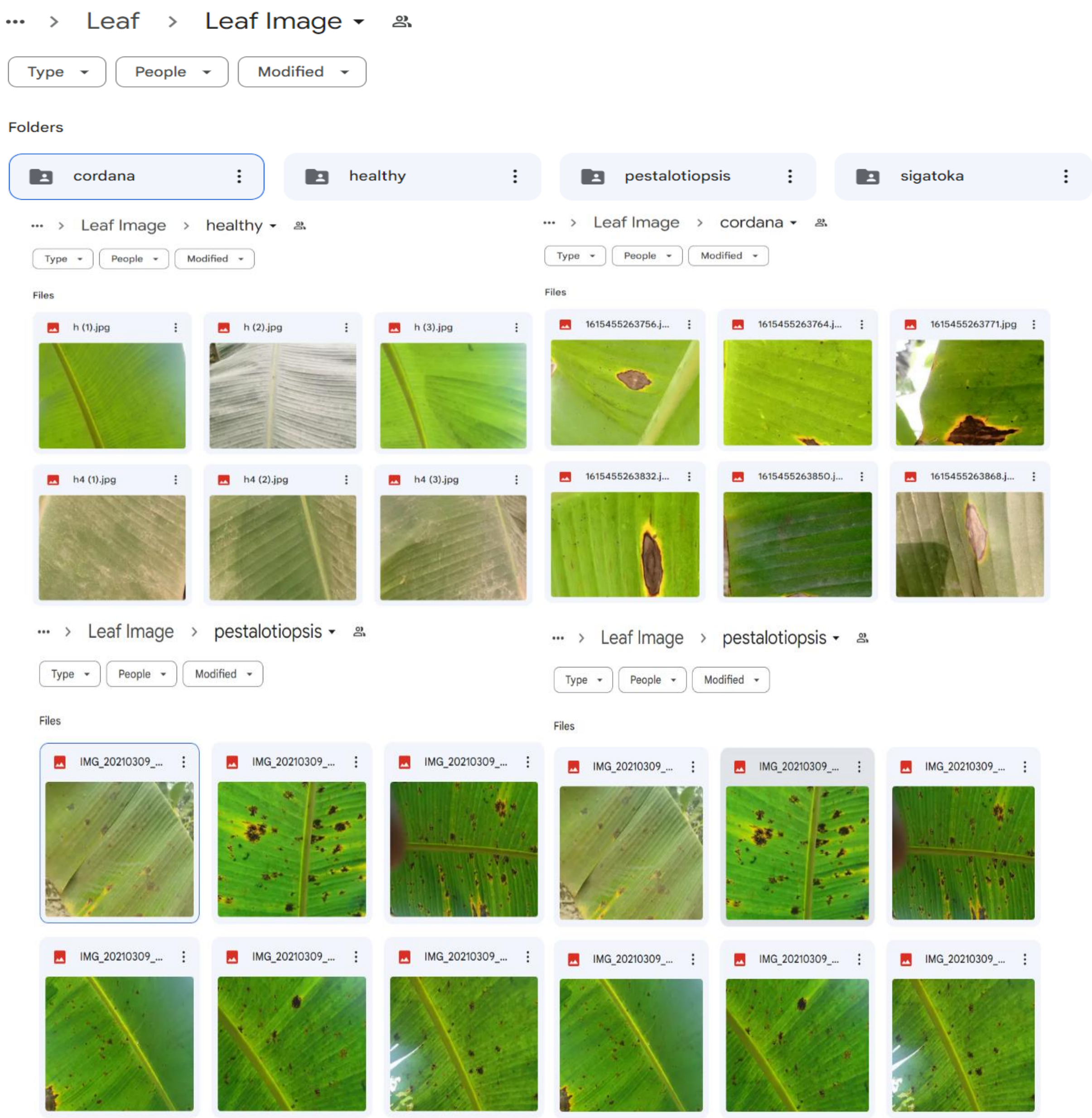

Figure 1. The research method in the form of a flowchart.

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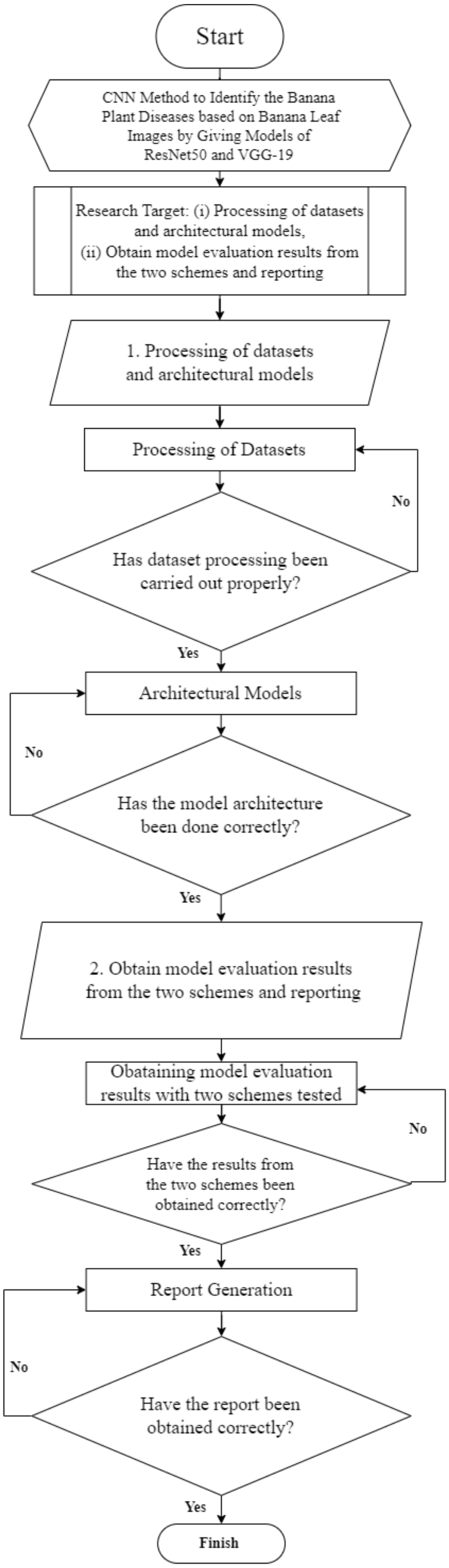

Figure 2. The research mthod in the form of a flowchart.

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This stage aims to get an evaluation results model. This model will show the results of evaluating the two models, ResNet50 and VGG-19, that were used to find diseases in banana plants by looking at images of their leaves. At this stage, it will be divided into two schemas, namely Schema 1 to evaluate the ResNet50 model and Schema 2 to evaluate the VGG-19 model. After successfully getting the best results from the two schemes, the final stage is preparing a report. Where this stage is carried out by making a report in a comparison of the results of the two models and the results of previous research [13] in order to get the best results.

3. Results and Discussions

3.1 Processing of Datasets and Architectural Models

The dataset used in this research comes from the Kaggle website with the title Banana Leaf Disease Dataset. This dataset has four classes: healthy, Cordana, Sigatoka, and Pestalotiopsis. The details of the amount of data obtained are: 936 images of banana leaves with 128 images of healthy leaves; 162 images of Cordana disease; 473 images of Sigatoka disease; and finally, 173 images of Pestalotiopsis disease [13]. An example of a dataset of image data from the four classes is shown in Figure 3.

This dataset is classified manually for each existing class, namely healthy leaves, Cordana, Sigatoka, and Pestaloptiosis. The classification of these classes is done on Google Drive so that it can be easily accessed by machines using Google Colaboratory. After the dataset is ready for use, the next step is to resize the image data to 224x224. After changing, the next data size is the data division or data split in the form of train data and validation data, which has a comparison ratio of 80% train data and 20% validation data.

After the dataset has been processed, the next step is to create the architectural model that will be used in this study. The method used in this study uses the CNN method , with the proposed models being ResNet50 and VGG-19, to get the best results in identifying banana plant diseases through banana leaf images. The choice to use the ResNet50 model is because ResNet50 is one of the best models and a suitable model for the dataset used, and ResNet50 also has a total of 50 layers [18],[27]. The VGG-19 model is used because VGG-19 was one of the winning models of the 2014 ImageNet

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Challenge and is a model that also fits the dataset used. VGG-19 has a total of 47 layers and consists of 16 convolutional layers and three fully connected layers, making it a robust network [22], [28]. CNN consists of three layers: convolutional, pooling, and fully connected [29], [30].

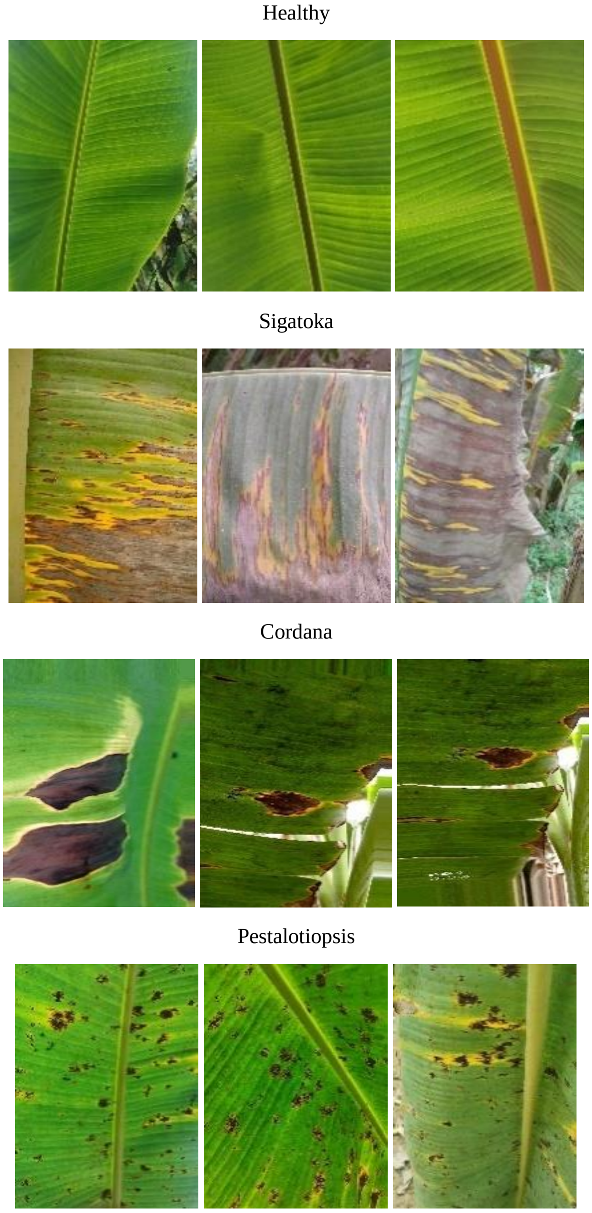

Figure 3. An example of a dataset of image data from the four classes

In this study, we used Global Average Pooling 2D, Dense (512), Dropout (0.3) [31], Optimizer Adam [32], and Relu activation. Global Average Pooling was made in order to avoid overfitting [33] and to use 2D Global Average Pooling to add average features to the selected image[34]–[37], [38]. The architectural design to be used is shown in Table 1.

Table 1. The architectural design to be used

Layer	Filter	Kernel Size	Activation
ResNet50 (Input 244,244)	-	-	-
GlobalAverage Pooling2D	-	-	-
Dropout	0,3	-	-
Dense	512	-	Relu
Dropout	0,3	-	-
Dense	224	-	Relu
Dense	3	-	Softmax

Based on Table 1, it is shown and can be explained, that the architectures to be used by the two proposed models are ResNet50 and VGG-19. The architectural details are Dropout = 0.3, Dense = 512 with relu activity, Dropout = 0.3, Dense = 224 with relu activity, and Dense = 3 with Softmax activity [39]. The optimizer used is Adam, and this research will conduct epoch or data training 50 times. After the architectures for the two models were made, this research was carried out with several schemes to obtain model evaluation results from the two proposed models, namely the ResNet50 and VGG-19 models. After getting the best results between the 2 test models, the research results done with previous research will be compared [13]. After processing the dataset and creating the model architecture are completed, there is a division of tests to obtain model evaluation results into two schemes: schema 1 for testing the ResNet50 model and Scheme 2 for testing the VGG-19 model. The test scheme table is listed in Table 2.

Table 2. The test scheme table

Scheme	Description	Filter
Model 1	ResNet50 (Input 224,224)	Dropout (0,3) Dense (512)
Model 2	VGG-19 (Input 224,224)	Dropout (0,1) Dense (512)

3.2 Obtain Model of Evaluation Results and Reporting

After processing the dataset and creating the model architecture, the next step is to get the results of the model evaluation by testing the two models, which are divided into two schemes: testing scheme 1 to get the evaluation results of the ResNet50 model and testing scheme 2 to get the evaluation results of the VGG-19 model.

After the architecture of the ResNet50 model has been made, it will go through the data training process, which takes place over 50 training times, or epochs, and is shown as a result plot graph with two result graphs: the accuracy graph and the loss graph. The function of the result graph is to see whether or not there is an increase in the model for each train and whether there is overfitting or underfitting in the ResNet50 model test. The accuracy graph of the test is listed in Figure 4.

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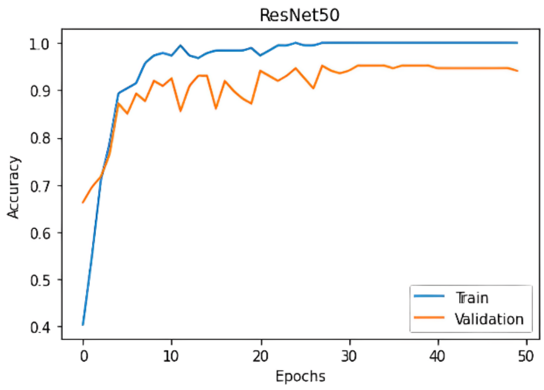

Figure 4. Results of the graphic accuracy plot ResNet50 model

Based on Figure 4, it can be explained that the results of the accuracy graph plot from training, at epoch 0 to epoch 30, the graph moves up and down or is unstable, and at epoch 30 to epoch 50, the graph starts to show stable movement. The cause of the instability of the graph movement is that the model is still learning or is in the learning stage. After the model has studied the data, the graph's movement begins to stabilize. The graphic loss plot of ResNet50 model is shown in Figure 5.

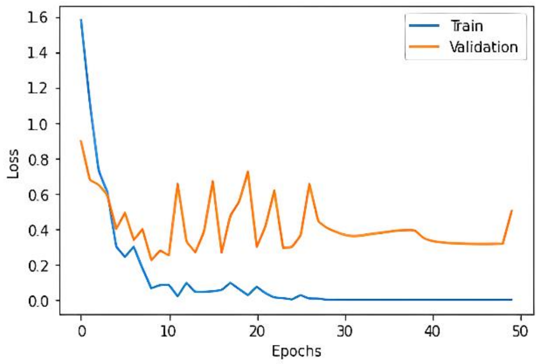

Figure 5. The graphic loss plot of ResNet50 model

Based on Figure 5, it can be explained that the graph of the results of the loss plot, it can be seen that the chart movement is overfitting and unstable, starting from epoch 0 to epoch 30. Then, from epoch 30 to epoch 50, the chart movement is quite stable, although several times it has seen a bit of unstable movement. The cause of the unstable movement of the graph is poor learning models.

After conducting the training and getting the results of the training graphics, the next step is to evaluate the performance of the model in Scheme 1. Model evaluation can be seen using the identification report and can also be seen in the confusion matrix image, the results of which have been obtained from the dataset training that was done previously. The identification results report for the ResNet50 model is listed in Table 3.

Table 3. The identification results report for the ResNet50 model

Identification Report	
Accuracy	94%
Precission	88%
Recall	91%
F1-Score	89%

Based on Table 3, it is shown and can be explained, that the results of the evaluation of the ResNet50 model obtained accuracy = 94%, precision = 88%, recall = 91%, and F1-score = 89%. Furthermore, after getting the report results from the evaluation of the ResNet 50 model and the results of the evaluation of testing scheme 1 with the ResNet 50 model, a confusion matrix will be made. The results of the confusion matrix in testing scheme 1 the ResNet50 model are shown in Figure 6.

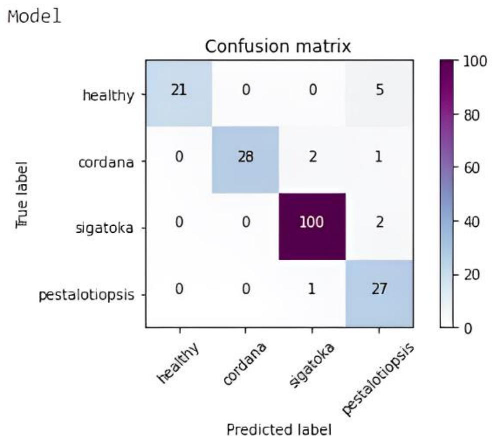

Figure 6. The results of the confusion matrix ResNet50 model

Based on Figure 6, it's easy to show that the results of the confusion matrix [40] ResNet50 model in testing scheme 1 will show the matrix results from each class, whether the model is able to predict disease in banana leaf image data or not. From the results obtained in the confusion matrix in Figure 6, there are four classification classes: healthy, Cordana, Sigatoka, and Pestalotiopsis.n testing scheme 1. It can be concluded that in the healthy class, there are 21 data that are predicted to be true and 0 data that are predicted to be wrong; in the Cordana class, there are 28 data that are predicted to be correct and 0 data that are predicted to be wrong; in the Sigatoka class, there are 100 data that are predicted to be correct and 3 data that are prefixed incorrectly; and in the Pestalotiopsis class, there are 27 data that are predicted correctly and 8 data that are predicted incorrectly.

After getting the model evaluation results from the confusion matrix, the evaluation results obtained will also be made through image prediction. Image

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prediction results in the ResNet50 model are shown in Figure 7.

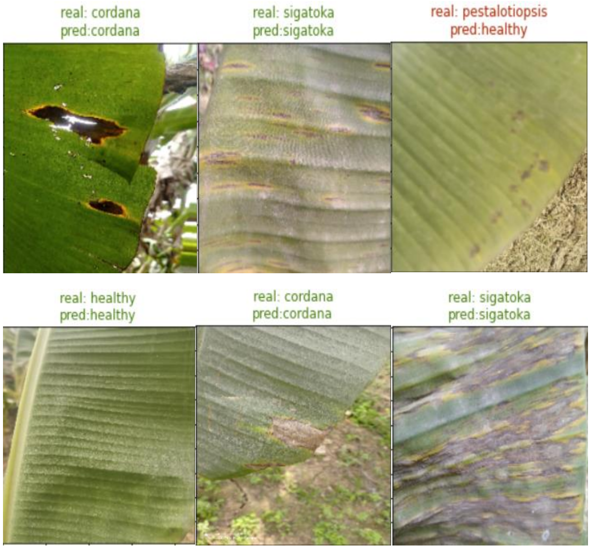

Figure 7. The image prediction results in the ResNet50 model

Based on Figure 7, it can be explained that the prediction results on the image from testing scheme 1 of the ResNet50 model so that there is still a prediction error or wrong identification where the model predicts healthy but the correct prediction is Pestalotiopsis. From the results of these predictions, it is quite accurate, with 5 out of 6 correct predictions, and the model tested also got very good results. The cause of the failure of the model to predict or identify is that the accuracy value is not up to 100%, and it is normal for the model to fail to identify images correctly or make predictions. The amount of data also affects it, and the photos or data held are ambiguous or challenging for the model to recognize. Then, overfitting, which occurs, can also result in unidentified images.

Furthermore, in testing scheme 2 for the VGG-19 model, after processing the dataset and creating the model architecture to be used, The process to be carried out is to test the dataset with training 50 times, which will be made in the form of plot graphs. Making plot graphs has two graph results, namely accuracy plot graphs and loss plot graphs. Just like the previous model, the aim of training and graphing the plot results is to see whether there will be overfitting or underfitting and whether there will be an increase or not in the train of the VGG-19 model. The graphic loss plot of the VGG-19 model is shown in Figure 8.

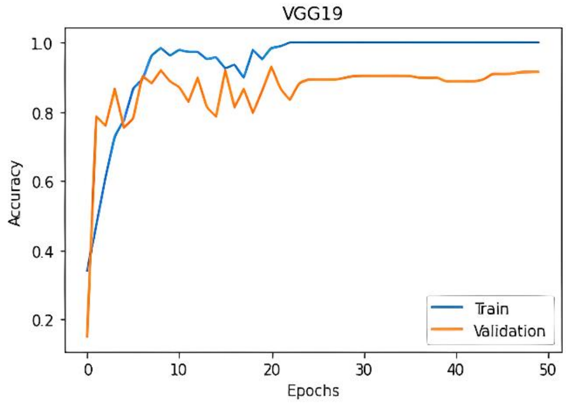

Figure 8. The graphic loss plot of the VGG-19 model

Based on Figure 8, it can be explained that the results of the training and the plotting of the accuracy graph during epoch 0 to epoch 23 the chart show that movement is unstable. After entering epochs 24 to 50, the chart movement, which previously showed instability, has moved stably. The cause of unstable graph movement is because the model is still learning or is in the learning process, but after entering epoch 24, the model has studied the data and has been moving stably.

Furthermore, after seeing the results of the accuracy graph plot. The graphic accuracy plot of the VGG-19 model is shown in Figure 9.

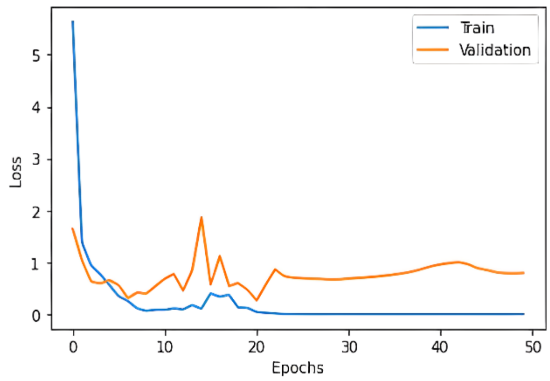

Figure 9. The graphic accuracy plot of the VGG-19 model

Based on Figure 9, it can be explained that the results of the model training on the loss graph plot show that from epoch 0 to epoch 22, the graph movement was unstable and there was overfitting, but the graph movement began to look stable after entering epoch 23 to epoch 50. The cause of the graphic movement is unstable because the model is still in the learning stage or in the data learning stage; after entering epoch 23, the model has successfully studied the data so that the graph movement has been moving stably.After getting the results of the accuracy graph plot and the loss graph plot, start evaluating the performance of the VGG-19 model. Evaluation of scheme 2 testing can be seen using the identification report and can also be seen in the

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confusion matrix image, the results of which have been obtained from testing the VGG-19 model scheme. The report on the results of model identification of the VGG-19 model is shown in Table 4.

Table 4. The report on the results of model identification of the VGG-19 model

Identification Report	
Accuracy	94%
Precission	88%
Recall	91%
F1-Score	89%

Based on Table 4, it is shown and explained that the details of the evaluation results from the VGG-19 model identification report, namely, accuracy = 91%, precision = 88%, recall = 91%, and F1-score = 89%. Furthermore, after getting the identification results from the evaluation of the VGG-19 model through the identification results report, the results of the evaluation of testing the VGG-19 model scheme can also be seen using the confusion matrix. The results of the confusion matrix of the VGG-19 is model are shown in Figure 10.

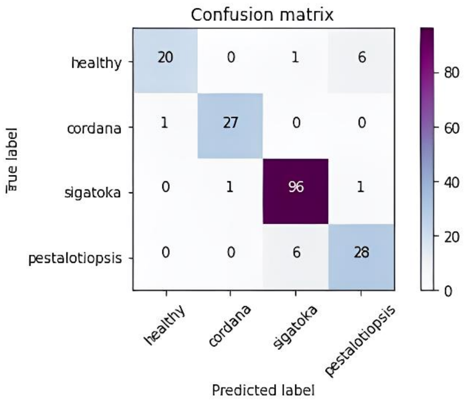

Figure 10. The confusion matrix of the VGG-19 model

Based on Figure 10, it can be explained, that the results of the evaluation of testing scheme 2 are shown through the confusion matrix. From the results of the evaluation, it was found that there were 4 classes in the confusion matrix: healthy, Cordana, Sigatoka, and Pestalotiopsis. The healthy class test, there are 20 data points that are predicted to be true and 1 data point that is predicted to be wrong; in the Cordana class, there are 27 data points that are predicted to be true and 1 data point that is predicted to be wrong; in the Sigatoka class, there are 96 data points that are predicted to be correct and 7 data points that are predicted to be wrong; and finally, in the Pestalotopsi class, there are 28 data points that are predicted to be correct and 7 data that are predicted to be wrong.

After getting the evaluation results through the confusion matrix, the next step is to make predictions based on the images obtained. The prediction results of model scheme 2 shown in Figure 11.

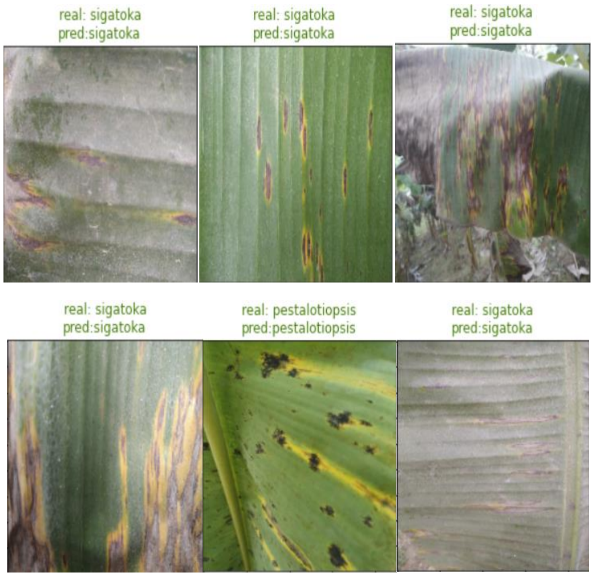

Figure 11. The prediction results of model scheme 2

Based on Figure 11, it can be explained that the prediction results from testing the VGG-19 model scheme. It can be concluded that the model successfully predicts or identifies well and accurately.

After getting the model evaluation results from the two schemes that were carried out, the report results for the best accuracy value have been obtained. In the tests carried out, the use of different model architectures and models affects the final results. The reports on the results of the two models tested are shown in Table 5.

Table 5. The reports on the results of the two models tested

Skema	Accuracy	Precission	Recall	F1-Score
Model 1 *(ResNet50)*	94%	88%	91%	89%
Model 2 *(VGG-19)*	91%	88%	91%	89%

Based on Table 5, it is shown and explained that the results of the evaluation reports of the two models that have been tested are: The ResNet50 model gets an accuracy value of 94%, and the VGG-19 model gets an accuracy value of 91%. Furthermore, after getting the best results from one of the proposed models, the report on the model evaluation results will be compared with previous studies [13]. Comparison reports with details between the research carried out and previous research are shown in Table 6.

Table 6. The comparison results report with details between the research carried out and previous research

Scheme	Dataset	Model	Accuracy
Adreanov et al [13]	*Banana Leaf Dataset*	*DenseNet*	84%
Model ResNet50	*Banana Leaf Dataset*	*ResNet50*	94%
Model VGG-19	*Banana Leaf Dataset*	*VGG-19*	91%

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Based on Table 6, it is shown and explained that the results report compares the accuracy results that have been carried out from the two models used with models from previous studies. Based on the results of the report that was successfully obtained, it can be concluded that the ResNet50 model has a very high fit with the dataset used in this study, thus obtaining the best accuracy value from the VGG-19 model and previous research [13] by obtaining an accuracy value of 94%.

4. Conclusion

The selection of two models, i.e., ResNet50 and VGG-19, managed to get the best accuracy results in identifying banana plant diseases through banana leaf images. Dataset processing and creating a new model architecture affect the final results obtained from evaluation tests of the proposed model. Based on the research objective, it can be concluded that the ResNet50 model managed to get an accuracy of 94%, which is higher than previous research by Adreanov and his colleagues with an accuracy of 84% and the VGG-19 model with an accuracy of 91%. By conducting this research, researchers managed to exceed the results of previous studies with results of 94% accuracy, 88% precision, 91% recall, and an 89% F1-Score, making this the best model for identifying banana plant diseases with the ResNet50 model. Hopefully, this research can help researchers or experts identify banana plant diseases using machine learning.

Suggestions for future research are to try using other CNN models such as EfficientNet and others, then to be able to use a different architecture from this research, and to be able to use more training data from this research to get better results and accuracy values in identifying banana plant diseases.

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