Disease Detection of Rice and Chili Based on Image Classification Using Convolutional Neural Network Android-Based

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Abstract*— The development of machine learning makes it easier for humans to obtain information from images. Machine processing can increase the accuracy of the information provided in convincing the data recipient. Rice and chilli farmers in Indonesia often experience disease attacks from several plant diseases. Not many farmers understand or are good at predicting the diseases that attack their rice and chili plants, so many farmers experience crop failure. This research aims to build a disease detection system for rice and chili plants based on Android-based image classification using the Convolutional Neural Network (CNN) method with the Mobile Net version 1 model combined with the Sequential CNN and Tensor Flow Lite models. The results of training, validation, and testing evaluations on the Mobile Net version 1 and Sequential CNN models on rice and chilli plant diseases obtained a training accuracy value of 0.8827, a validation accuracy value of 0.8493, and a testing accuracy value of 0.8678. Because the accuracy results were close to 1, the training, validation, and testing were declared successful in classifying rice and chilli plant diseases. Meanwhile, from the effects of field tests on rice and chilli plants, good results were obtained by correctly detecting rice and chilli plant diseases with an accuracy percentage of 95%. CNN with the Mobile Net version 1 model and the Sequential model can classify images so that it has maximum information processing capabilities. This research can make it easier to help farmers identify diseases that attack their rice and chilli plants.*

Keywords: *rice and chili plant diseases, image classification, CNN, android, mobile net.*

Abstrak— Perkembangan *machine learning* memberikan kemudahan bagi manusia dalam mendapatkan informasi dari citra gambar. Adanya pengolahan dari mesin dapat meningkatkan keakuratan informasi yang diberikan dalam meyakinkan penerima informasi. Petani tanaman padi dan cabai di Indonesia banyak mendapatkan serangan penyakit dari beberapa jenis penyakit tanaman. Tidak banyak petani yang mengerti dan pandai menebak penyakit yang menyerang tanaman padi dan cabai mereka, sehingga banyak petani mengalami gagal panen. Tujuan penelitian ini adalah membangun sistem deteksi penyakit tanaman padi dan cabai berdasarkan klasifikasi citra berbasis Android menggunakan metode *Convolutional Neural Network* (CNN) dengan model Mobile Net versi 1 dikombinasikan dengan model *Sequential* CNN dan Tensor Flow Lite. Hasil evaluasi training, validasi dan testing pada model Mobile Net versi 1 dan Sequential CNN pada penyakit tanaman padi dan cabai mendapatkan nilai akurasi *training* sebesar 0.8827, nilai akurasi validasi sebesar 0.8493, dan nilai akurasi *testing* 0.8678. Karena hasil akurasi mendekati nilai 1, maka training, validasi dan testing dinyatakan berhasil melakukan klasifikasi penyakit tanaman padi dan cabai. Sedangkan dari hasil pengujian lapangan terhadap tanaman padi dan cabai diperoleh hasil yang baik dengan berhasil mendeteksi penyakit tanaman padi dan cabai secara benar dengan persentase akurasi sebanyak 95%. CNN dengan model Mobile Net versi 1 dan model *Sequential* dapat klasifikasi citra gambar sehingga memiliki kemampuan pengolahan informasi dengan maksimal. Adanya penelitian ini, dapat memudahkan dalam membantu petani mengetahui penyakit yang menyerang tanaman padi dan cabai mereka.

Kata Kunci*: penyakit tanaman padi dan cabai, klasifikasi citra, CNN, android,* mobile net*.*

INTRODUCTION

Indonesia is called an agricultural country because Indonesia has agriculture, which is the primary source of food (Hasanah, 2022). Agriculture is a particular priority for a country for food security in a social situation (Hidayah & Susanti, 2022)—agricultural development with the hope of increasing farmers' production results (Lase & Lestari, 2018). Achieving farmers' production results can improve people's welfare in the agricultural sector by increasing food crop production and increasing prices according to farmer productivity (Hidayah & Susanti, 2022). The products produced by farmers in Indonesia include rice, corn, chilies, soybeans, cassava, potatoes, and other crops. Food availability that remains stable is a necessity for the sustainability of the country to meet national food needs (Ridho, 2018).

Rice is a rice-producing plant, and the majority of the population in Indonesia makes rice their staple food (Saputra et al., 2021). It is essential to pay attention to aspects of the quality and health of rice plants to maintain the productivity of rice farmers (Saputra et al., 2021). In cultivating rice plants, we cannot be separated from disease attacks. Farmers do not understand diseases that attack rice plants, so it is too late to treat them (Purnamawati et al., 2020). Recently, the Indonesian people have experienced an increase in the price of rice. One of the reasons for the increase in rice prices is the failure of harvests in several rice-producing areas (Kominfo, 2023; Kompas.com, 2023; Nasional, 2022). In Ngawi district, around 150 hectares of rice plants are threatened with crop failure due to being attacked by the dwarf virus (Nasional, 2022). They are also influenced by harmful weather factors, making the harvest small (Kompas.com, 2023).

Apart from the price increase in rice, the price increase was also experienced in chilies. Almost everyone consumes chili, an important horticultural crop (Mustakim & Yanti, 2022). People often use chili as a food spice because it has a spicy taste (Desi Ernawati, Riki Andri Yusda, 2021). Chilli production yields have also decreased due to crop failures among farmers in several areas caused by attacks by plant pests and plant diseases (BBC News, 2022; Bisnis, 2022; Republika, 2023).

Deep Learning (DL) is a machine learning (ML) branch that models high-level data abstraction. Deep Learning has many layers of neurons consisting of complex structures (Hao et al., 2016). Deep Learning is a machine learning concept based on artificial neural networks (Christian et al., 2017). The most famous architecture in image recognition and recurrent neural networks is the Convolutional Neural Network (CNN) (Hao et al., 2016). The deep learning architecture is the most efficient in feature extraction compared to other methods (Rahman et al., 2020; Saputra et al., 2021). The CNN algorithm gets the most significant results in image recognition because CNN can imitate the image recognition system in the human visual cortex so that it can process image information (Peryanto et al., 2020). Image Classification is a machine that can extract data from an image for object recognition.

Several findings of problems experienced by the community have been described. The problem formulation in this research is how to detect rice and chili plant diseases based on image classification using an Android-based Convolutional Neural Network.

MATERIALS AND METHODS

In research (Rahman et al., 2020) using a Convolutional Neural Network by adopting the VGG16 and InceptionV3 architecture to recognize and detect rice diseases and pests by summarizing the experimental results, the proposed architecture obtained an accuracy of 93.3%, the model size was reduced significantly. The test is used to carry out 10-fold cross-validation for the six CCN architectures.

Research (Saputra et al., 2021) implemented a CNN algorithm using the MobileNet architecture method to detect rice leaf diseases using a dataset of 3 types of rice diseases. The training and validation results showed that the training accuracy was 1.0, the validation accuracy was 0.8333, and the confusion matrix accuracy value was 92%. The test used compares the test results with the prediction results obtained. The difference in accuracy results from the two studies can be triggered by the amount of data tested. And using different architectures can enable different accuracy results.

The results of research conducted by (Anggiratih et al., 2021) found accuracy results of 79.53% in the classification of rice leaf diseases using CNN on the Efficientnet B3 architecture with transfer learning using testing during classification with a dataset that had been segmented during data training. The same architecture is used in research (Lesmana et al., 2022) by implementing Transfer Learning, adding a multi-channel CNN to rice leaf disease by combining InceptionV3, Xception, ResNet50, and VGG16. CNN obtained training accuracy results of 100%, while testing accuracy on two and three CNN channels was 95.83%. The tests used are by looking at the effects of accuracy, validation, and testing during data analysis. Findings in research (Yuliany et al., 2022) apply three divisions of training data, testing data, and several parameters to reduce the overfitting problem. From the evaluation results, the data division of 90%:10% is the most suitable for use in the Rice pest classification dataset using CNN. The test used in this research compares the number of correct accuracies with the number of incorrect accuracies.

Findings in research (Khoiruddin et al., 2022) show that the CNN architecture produces high accuracy in classifying rice leaf diseases. Classification of rice leaf diseases into three types, namely Rice Blast, Bacterial Leaf Blight, and Rice Tungro Virus, using CNN. The dataset used was 6000, consisting of 80% training data, 10%

validation data, and 10% testing data and obtaining training accuracy results at epoch 100 with an accuracy of 98%. The tests used take into account the results of data analysis evaluation, getting good accuracy results. Research (Hawari et al., 2022) classified rice diseases from four types of rice leaves, namely Healthy Leaves, Blight, Brown Spot, and Brown Leaf, using the CNN algorithm. Can implement Deep Learning, namely CNN, to identify images of rice leaf diseases. The accuracy value of training data is 85%, validation data is 95%, and testing data is 86%. Meanwhile, research (Anggraeni et al., 2022) classified chili plant diseases using the CNN algorithm. There are three categories for the classification model, namely leaf curl, yellowish, and healthy, with validation results obtained on test data showing an accuracy of 60%. The test used is to test the application using random test data. The results obtained by the data application determine the disease name label correctly.

From the research above, differences can be drawn between the old analysis and the research carried out. Many previous studies have used the CNN architecture because this CNN architecture provides very high image classification accuracy results. However, in earlier research, no one has carried out image classification on two sample data on rice and chili plant diseases using CNN with Android-based MobileNet architecture. Also, the number of samples of types of rice and chili plant diseases used, consisting of four kinds of rice diseases, namely rice brown spot, rice hispa, rice leaf blast, rice neck blast, and one type of rice healthy plant dataset and four types of chili diseases, namely chili leaf curl, chili leaf spot, chili whitefly, chili yellowish and one kind of chili healthy plant. So, in this research, we will carry out image classification on two sample data on rice and chili plant diseases using Android-based CNN with MobileNet architecture. The research method used in this research is a Convolutional Neural Network (CNN) with the Mobile Net version 1 model and the Sequential CNN model. The following explains the research design for disease detection in rice and chili plants.

The first stage is collecting sample data regarding diseases of rice and chili plants. Sample data collection was taken from the kaggle.com website. Sample data on rice and chili plant diseases will be used for training and validation.

The second stage carries out training and validation data using the Python programming language with the Keras framework. The basic Mobile Net version 1 model was created and combined with the Sequential CNN model at this stage. After successfully carrying out the training data, the model is converted into Tensor Flow Lite for Android applications.

The third stage is system development. At this stage, system development is carried out using the Rapid Application Development (RAD) method, starting from needs analysis, system design, development, and implementation. The CNN model, which already knows rice and chili plant diseases, is also applied at this stage.

The fourth stage is testing and evaluation. At this stage, application testing was carried out using Black Box and Probability testing to detect rice and chili plant diseases. Figure 1 shows the research design for disease detection in rice and chilli plants.

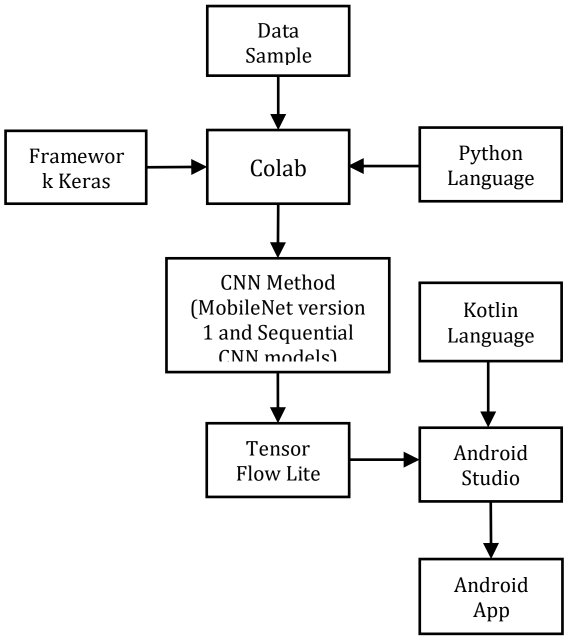

Figure 1. Research Design for Rice and Chili Plant Disease Detection

Data Sample

This research uses sample data on rice and chilli plant diseases from the www.kagle.com dataset. The number of samples used for types of rice and chili plant diseases consisted of four kinds of rice diseases, namely Rice Brown Spot, Rice Hispa, Rice Leaf Blast, Rice Neck Blast, and one type of Rice Healthy plant dataset and four types of chili diseases, namely Chili Leaf Curl, Chili Leaf Spot, Chili Whitefly, Chili Yellowish and one kind of Chili Healthy plant. The total number of datasets for diseases of rice and chili plants and healthy rice and chili plants is 4699. Below is a list of ten diseases of rice and chilli plants as well as healthy rice and chilli plants

1) Rice Brown Spot

Brown Spotted Rice is caused by Bipolaris Oryzae, Helminthosporium Oryzae, which are two tip cells that give rise to conidia, and Cochliobolus Miyabeanus, like many other fungi, which gives rise to inter and intra-cellular mycelium, which then turns brownish gray to dark brown mat like growth on infected plant tissue. (Barnwal et al., 2013; Sunder et al., 2014; Surendhar et al., 2021). The following Figure 2. shows Rice Brown Spot disease.

Figure 2. Rice Brown Spot Disease

2) Rice Hispa

The adult hispa is a beetle that is about 5 mm long. Adult Hispa feed by scratching the surface of the leaves so that white lines appear on the surface of the leaves. Female hispa lay eggs in these scrapings, and the population of this pest continues to increase rapidly (Burhan et al., 2020). The following in Figure 3. shows the Rice Hispa disease.

Figure 3. Rice Hispa Disease

3) Rice Leaf Blast

Rice Leaf Blast disease is caused by the Pyriculariaoryzae Cavara fungus, which attacks rice plants and reduces the quality of rice. Symptoms of disease: leaf spots usually start near the leaf's tip or edge. These symptoms appear as brown spots and grow into spindles pointed at both ends. The color of the lesion is usually pale green to greyish green, changing to yellow to grey in the centre of the dead spot (Abu Bakar et al., 2018). The following in Figure 4 shows the Rice Leaf Blast disease

Figure 4. Rice Leaf Blast disease

4) Rice Neck Blast

Neck blast (a close synonym for panicle blast) is the most destructive form of the disease, occurring during the reproductive stage and characterized by fungal infection at the base of the panicles and plant nodes. Fungal infection at the base of the panicle limits the flow of photosynthate to the developing grain, resulting in rough grains or empty panicles. The reduction in yield caused by Rice Neck Blast disease infection is twice as severe as Rice Leaf Blast disease (Kalia & Rathour, 2019). The following Figure 5. shows the Rice Neck Blast disease.

Figure 5. Rice Neck Blast Disease

5) Rice Healthy

Rice Healthy rice plants are not attacked by pests and diseases (Heviyanti & Mulyani, 2016) and have more chlorophyll than unhealthy rice plants. Chlorophyll in Greek choloros means green, and phyllos means leaf (Yuliantika et al., 2016). Below in Figure 6. shows a Rice Healthy plant.

Figure 6. Rice Healthy plant

6) Chili Leaf Curl

A begomovirus attack on chilies causes Chili Leaf Curl. Symptoms include thickening of the veins of the leaves, the edges of the leaves curling upwards, the leaf blades turning bright yellow, the new leaves becoming small, and the flowers falling off until they do not produce fruit. (Sulandari, 2006). The following in Figure 7. shows Chili Leaf Curl disease.

Gambar 7. Chili Leaf Curl Disease

7) Chili Leaf Spot

Chili Leaf Spot disease is caused by the fungus Cercospora Capsici (Lestari & Aini, 2021). The following Figure 8. shows the Chili Leaf Spot disease.

Figure 8. Chili Leaf Spot Disease

8) Chili Whitefly

Whitefly (Bamisia Tabaci) are pests that damage chili plants, and these pests nest on the underside of the leaves (Rahmi et al., 2022). The following Figure 9. shows the Chili Whitefly disease.

Figure 9. Chili Whitefly Disease

9) Chili Yellowish

Chili Yellowish disease cannot be separated from the cause of the Gemini Virus. The spread of the Gemini Virus is related to the whitefly's population size, which is the insect vector of this virus. The increasing number of whitefly populations causes the spread of geminivirus with increased jaundice (Nurtjahyani & Murtini, 2015). The following Figure 10. shows Chili Yellowish disease.

Figure 10. Chili Yellowish Disease

10) Chili Healthy

Chili Healthy has bright green leaves, sharp and fresh-colored fruit, and no disease on the fruit. The following is in Figure 11. shows Chili Healthy disease.

Figure 11. Chili Healthy Disease

RESULTS AND DISCUSSION

Data Training and Validation

Training data is a collection of trial data that will later be used as learning for the data testing when determining the results, while validation is testing the correctness of the data against the data training. The dataset used in this training and validation data is four Rice Plant diseases consisting of *Rice Brown Spot* totaling 653, *Rice Hispa* totaling 565, *Rice Leaf Blast* totaling 981, *Rice Neck Blast* totaling 1000, and one Rice Healthy plant dataset totaling 1000. Also, four chili plant diseases consisting of Chili Leaf Curl totaling 100, Chili Leaf Spot totaling 100, Chili Whitefly totaling 100, Chili Yellowish totaling 100, and types of Chili Healthy plants totaling 100. All images of Rice and Chili

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plants are sized (200x200x3) using three color channels: Red, Green, and Blue (RGB).

This data training and validation was carried out via Google Colab (Collaboratory) using a Convolutional Neural Network with MobileNet version 1 architecture, the Python programming language, the Keras Framework as a library, and Tensorflow. In the data training and validation, a rice and chili plant disease dataset was taken and saved on Google Drive. Then, a list of disease names is carried out, classified according to the name of the disease folder for rice and chili plants, including rice healthy and chili plants. So we get a classification of disease names such as Rice_brown_spot, Rice_healthy, Rice_hispa, Rice_leaf_blast, Rice_neck_blast, Chili_yellowish, Chili_whitefly, Chili_leaf_curl, Chili_leaf_spot, and Chili_healthy. So, ten classifications are formed, including eight classes of rice and chili plant diseases and two classes of rice healthy and chili plants.

The dataset is divided into three types of data: data training, data validation, and data testing. The total number of datasets is 4699 measuring 200x200x3 pixels, divided into data training totaling 3759 (80%), data validation totaling 564 (12%), and data test totaling 376 (8%).

The next stage is building a Convolutional Neural Network. At this stage, modeling is carried out by applying the Mobile Net version 1 model and combining it with the Sequential model. The layers in the Sequential model used are Dropout, GlobalAveragePooling2D, and Dense. The Input Layer is used for images with a size of 128x128x3. Figure 12 explains the Mobile Net version 1 and Sequential models that detect rice and chili plant diseases.

Layer (type)	Output Shape	Param #
mobilenet_1.00_128 (Functional)	(None, 4, 4, 1024)	3228864
conv2d (Conv2D)	(None, 3, 3, 64)	262208
dropout (Dropout)	(None, 3, 3, 64)	0
global_average_pooling2d (GlobalAveragePooling2D)	(None, 64)	0
dense (Dense)	(None, 10)	650

Total params: 3491722 (13.32 MB)
Trainable params: 3469834 (13.24 MB)
Non-trainable params: 21888 (85.50 KB)

Figure 12. Mobile Net version 1 and Sequential models used to detect rice and chili plant diseases

Figure 12. explains combining the Mobile Net version 1 and Sequential models for better transfer learning. The CNN method uses a model from Mobile Net version 1, and Sequential CNN has been completed. Next, the model is given knowledge from images of rice and chili plant diseases through data training.

When carrying out data training and validation, determining the Epoch and Batch Size needs attention. Epoch is a hyperparameter that determines how often the CNN model passes through all datasets, while Batch Size is the number of data samples that pass through the CNN at a time. Use Epoch and Batch Size when the dataset is too large for training, and the computer memory is limited. In Figure 13. Results of data training and validation for rice and chili plant diseases

```
54/54 [==============================] - 19s 348ms/step - loss: 0.2933 - accuracy: 0.8913 - val_loss: 0.4083 - val_accuracy: 0.8478
Epoch 21/100
54/54 [==============================] - ETA: 0s - loss: 0.2927 - accuracy: 0.8921
Epoch 21: val_loss did not improve from 0.40826
54/54 [==============================] - 18s 325ms/step - loss: 0.2927 - accuracy: 0.8921 - val_loss: 2.9708 - val_accuracy: 0.5543
Epoch 22/100
54/54 [==============================] - ETA: 0s - loss: 0.2830 - accuracy: 0.8997
Epoch 22: val_loss did not improve from 0.40826
54/54 [==============================] - 19s 354ms/step - loss: 0.2830 - accuracy: 0.8997 - val_loss: 0.5690 - val_accuracy: 0.7772
Epoch 23/100
54/54 [==============================] - ETA: 0s - loss: 0.2527 - accuracy: 0.9068
Epoch 23: val_loss did not improve from 0.40826
54/54 [==============================] - 17s 323ms/step - loss: 0.2527 - accuracy: 0.9068 - val_loss: 6.2080 - val_accuracy: 0.4275
Epoch 24/100
54/54 [==============================] - ETA: 0s - loss: 0.2620 - accuracy: 0.9019
Epoch 24: val_loss did not improve from 0.40826
54/54 [==============================] - 17s 320ms/step - loss: 0.2620 - accuracy: 0.9019 - val_loss: 0.4426 - val_accuracy: 0.8514
Epoch 25/100
54/54 [==============================] - ETA: 0s - loss: 0.2730 - accuracy: 0.9003
Epoch 25: val_loss did not improve from 0.40826
54/54 [==============================] - 17s 320ms/step - loss: 0.2730 - accuracy: 0.9003 - val_loss: 0.4247 - val_accuracy: 0.8605
Epoch 26/100
54/54 [==============================] - ETA: 0s - loss: 0.2453 - accuracy: 0.9103
Epoch 26: val_loss did not improve from 0.40826
54/54 [==============================] - 18s 324ms/step - loss: 0.2453 - accuracy: 0.9103 - val_loss: 0.4801 - val_accuracy: 0.8533
Epoch 27/100
54/54 [==============================] - ETA: 0s - loss: 0.2487 - accuracy: 0.9076
Epoch 27: val_loss did not improve from 0.40826
54/54 [==============================] - 18s 324ms/step - loss: 0.2487 - accuracy: 0.9076 - val_loss: 0.6912 - val_accuracy: 0.7989
Epoch 28/100
54/54 [==============================] - ETA: 0s - loss: 0.2254 - accuracy: 0.9192
Epoch 28: val_loss did not improve from 0.40826
54/54 [==============================] - 17s 321ms/step - loss: 0.2254 - accuracy: 0.9192 - val_loss: 1.4465 - val_accuracy: 0.7464
Epoch 29/100
54/54 [==============================] - ETA: 0s - loss: 0.2808 - accuracy: 0.9043
Epoch 29: val_loss did not improve from 0.40826
54/54 [==============================] - 17s 319ms/step - loss: 0.2808 - accuracy: 0.9043 - val_loss: 0.8525 - val_accuracy: 0.7717
Epoch 30/100
54/54 [==============================] - ETA: 0s - loss: 0.2411 - accuracy: 0.9098
Epoch 30: val_loss did not improve from 0.40826
54/54 [==============================] - 18s 337ms/step - loss: 0.2411 - accuracy: 0.9098 - val_loss: 0.7781 - val_accuracy: 0.8116
Epoch 30: early stopping
```

Figure 13. Results of Data Training and Validation of Rice and Chili Plant Diseases

Based on the data training and validation results for rice and chili plants, the number of Epochs =100, and the Batch Size =69. From determining the Batch Size, 69 divides the total number of data training and data validation. The total number of data training is 3759 divided by the number of Batch Sizes of 69, thus obtaining a Batch of 54 and stopping at Epoch 30 from Epoch 100.

The following is in Figure 14. Shows the results curve for data training and validation for rice and chili plant diseases.

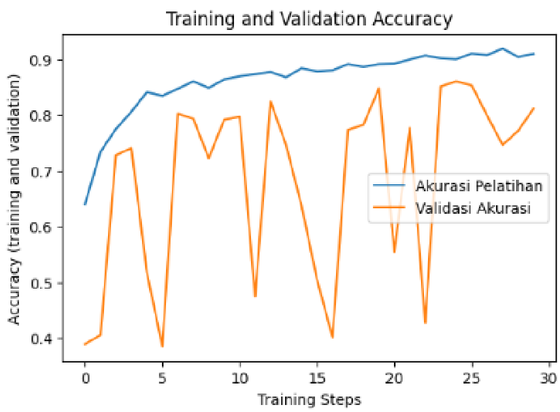

Figure 14. Data Training and Validation Results Curve for Rice and Chili Plant Diseases

From the results of the data training that has been carried out, training accuracy and validation accuracy have been obtained, with the level of training accuracy increasing significantly. In contrast, the validation accuracy obtained from training has varied validation. The accuracy values at the last epoch (30th), namely the training accuracy and validation accuracy values, were 0.9098 and 0.8116. The blue curve line is training accuracy, and the orange curve is validation accuracy. Because the accuracy curve achieved accuracy close to 1, the training and validation were declared successful in classifying rice and chili plant diseases.

Then, the training and validation errors on the data training have a training error approaching 0 as the epoch increases, both on the training and validation datasets. The loss value in the last epoch with a training error of 0.2411, while a validation error of 0.7781. Because the curve reached an error value approaching 0, the training and validation process was declared victorious in classifying rice and chilli plant diseases. The following is in Figure 15. shows the training and validation error curves.

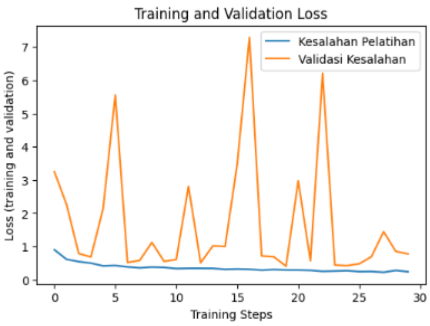

Figure 15. Training and Validation Error Curves

Then, test the Mobile Net version 1 and Sequential CNN models for rice and chili plant diseases via Google Colab. Random testing is carried out in Figure 16.

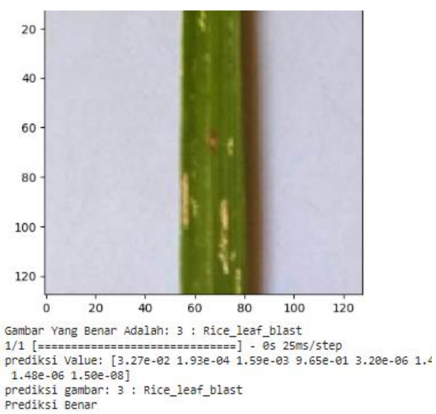

Figure 16. Results of Rice Plant Disease Testing Experiments via Google Colab

In Figure 16. Explain the rice plant disease testing results, which correctly predicted Rice Leaf Blast disease.

Then, training, validation, and testing evaluation were carried out on the Mobile Net version 1 and Sequential CNN models for rice and chili plant diseases, getting a training accuracy value of 0.8827 with a loss of 0.3467, a validation accuracy value of 0.8493 with a loss of 0.4027 and a testing accuracy value of 0.8678 with a loss of 0.4350. Because the accuracy results were close to 1, the training, validation, and testing were declared successful in classifying rice and chilli plant diseases. The following figure 17. shows the results of training evaluation, validation, and testing on rice and chilli plant diseases

```
['loss', 'accuracy']
118/118 [==============================] - 3s 19ms/step - loss: 0.3467 - accuracy: 0.8827
[0.34666264057159424, 0.8826815485954285]
18/18 [==============================] - 1s 32ms/step - loss: 0.4027 - accuracy: 0.8493
[0.4027107357978821, 0.8492907881736755]
12/12 [==============================] - 1s 43ms/step - loss: 0.4350 - accuracy: 0.8678
[0.43504568934440613, 0.8670212626457214]
```

Figure 17. Results of Training Evaluation, Validation, and Testing on Rice and Chili Plant Diseases

Confusion matrix is used to determine the level of success and failure in testing. Correct and prediction labels are displayed in the confusion matrix, each containing the name of the rice and chili plant disease. The mobile net version 1 model and the CNN sequential model test results produced an excellent confusion matrix with the highest value of 1 and the lowest value of 0.71. The following is in Figure 18. the confusion matrix on training and validation data for rice and chili plant diseases is shown.

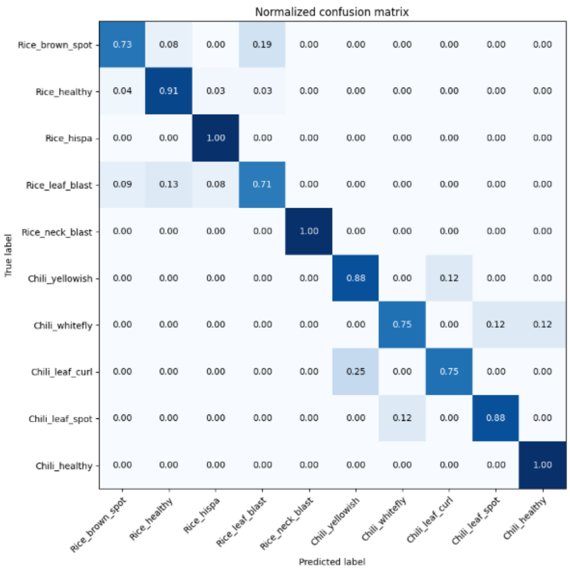

Figure 18. Confusion Matrix on Data Training and Validation for Rice and Chili Plant Diseases

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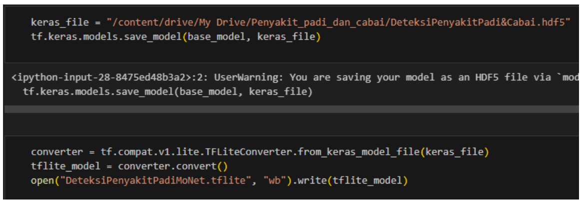
After gaining Learning or knowledge from images of rice and chili plant diseases through the training and validation data process using the CNN method with the Mobile Net version 1 model and the Sequential CNN model, the training results are converted into Tensor Flow Lite format, which will later be used in developing Android-based applications. Below is Figure 19. shows the conversion process into Tensor Flow Lite format.



```
keras_file = "/content/drive/My Drive/Penyakit_padi_dan_cabai/DeteksiPenyakitPadi&Cabai.hdf5"
tf.keras.models.save_model(base_model, keras_file)

<ipython-input-28-8475ed48b3a2>:2: UserWarning: You are saving your model as an HDF5 file via `mod
  tf.keras.models.save_model(base_model, keras_file)

converter = tf.compat.v1.lite.TFLiteConverter.from_keras_model_file(keras_file)
tflite_model = converter.convert()
open("DeteksiPenyakitPadiMoNet.tflite", "wb").write(tflite_model)
```

Figure 19. Conversion process into Tensor Flow Lite format

Figure 19. explains that the CNN model that was created previously was taken and then converted into Tensor Flow Lite format. Tensor Flow Lite is a machine-learning library for running CNN models of rice and chili plant diseases on Android devices.

System Development

The system development in this research uses the Rapid Application Development (RAD) software development method, starting from Requirements Planning, RAD Design Workshop, and Implementation (Kendall, 2010) Below in Figure 20. shows the RAD method.

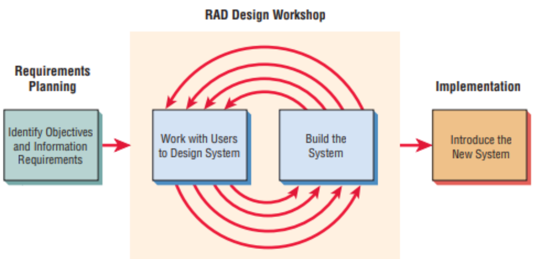


Figure 20. RAD Method

Requirements Planning, in this stage, identifies the system objectives and needs for a disease detection system for rice and chili plants.

RAD Design Workshop: this stage involves designing an application prototype by communicating with users. From the results of the prototype agreement, application development is carried out, and intensive communication with users so that the application developed adapts to user needs. In this case, researchers communicated directly with rice and chilli farmers.

Implementation, this stage discusses and agrees on business and non-technical aspects, and then the system built is refined and tested. Next, it is introduced to users.

Requirements Planning

The results obtained from identifying the system objectives and system needs for detecting rice and chilli diseases can be seen in Table 1.

Table 1. System Requirements for Rice and Chili Plant Diseases

No	System Requirements
1	Camera Identification
2	Gallery Identification
3	Help

RAD Design Workshop

1. Flowchart System

The Flowchart System is a diagram of the built rice and chili disease detection application. Figure 21. shows the Flowchart of the rice and chili disease detection system.

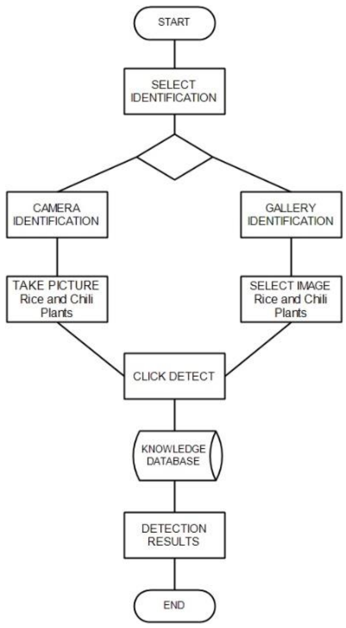


Figure 21. Flowchart of the Rice and Chili Plant Disease Detection System

2. System Creation

After the system design is complete, the application is developed. Application development using the Android platform with the Kotlin programming language. Below is Figure 22. shows the main page of the rice and chili disease detection application.

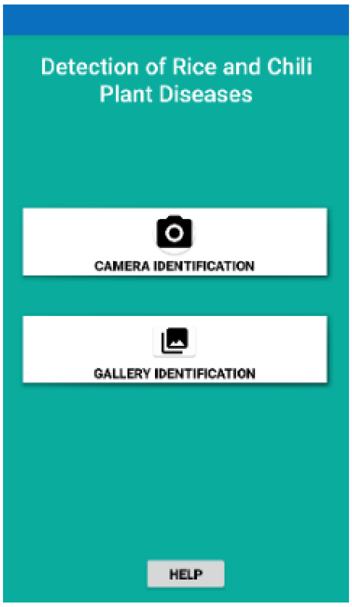


Figure 22. The Main Page of the Rice and Chili Plant Disease Detection Application

Testing and Evaluation

At this stage, application testing was carried out using Black Box and Probability testing to detect rice and chilli plant diseases. Testing was carried out directly in the field by taking test data in rice and chilli farmers' fields by selecting rice and chilli plants that had experienced damage caused by disease. The test data taken was 20 pictures of rice and chilli plants. The following are the results of field tests that have been carried out.

Figure 23. Test 1 on Rice Plants

The results of test 1 on rice plants were successfully carried out by detecting Rice Neck Blast disease with a probability of 98%.

Figure 24. Test 2 on Rice Plants

The results of test 2 on rice plants were successfully carried out by detecting Rice Neck Blast disease with a probability of 99%.

Figure 25. Test 3 on Chili Plants

The results of test 3 on chilli plants were successfully carried out by detecting Chili Yellowish disease with a probability of 83%.

Figure 26. Test 4 on Chili Plants

The results of test 4 on chilli plants were successfully carried out by detecting Chile Leaf Spot disease with a probability of 99%.vComplete field test results can be seen in Table 2.

Table 2. Field Test Results

No	Testing of Rice and Chili Plants	Disease and Probability	Test results
1	Test 1, on rice plants	Rice Neck Blast = 98%	Succeed
2	Test 2, on rice plants	Rice Neck Blast = 99%	Succeed
3	Test 3, on chilli plants	Chili Yellowish = 83%	Succeed
4	Test 4, on chilli plants	Chili Leaf Spot = 99%	Succeed
5	Tets 5, on rice plants	Rice Neck Blast = 99%	Succeed
6	Test 6, on rice plants	Rice Neck Blast = 99%	Succeed
7	Test 7, on rice plants	Chili Healthy = 63%	Failed
8	Test 8, on rice plants	Rice Hispa = 100%	Succeed
9	Test 9, on rice plants	Rice Hispa = 97%	Succeed
10	Test 10, on rice plants	Rice Neck Blast = 94%	Succeed
11	Test 11, on rice plants	Rice Hispa = 98%	Succeed
12	Test 12, on rice plants	Rice Neck Blast = 100%	Succeed
13	Test 13, on rice plants	Rice Hispa = 97%	Succeed
14	Test 14, on chilli plants	Chili Whitefly = 95%	Succeed
15	Test 15, on chilli plants	Chili Whitefly = 91%	Succeed
16	Test 16, on chilli plants	Chili Healthy = 81%	Succeed
17	Test 17, on chilli plants	Chili Healthy = 78%	Succeed
18	Test 18, on chilli plants	Chili Healthy = 99%	Succeed
19	Test 19, on chilli plants	Chili Leaf Curl = 75%	Succeed
20	Test 20 on chili plants	Chili Leaf Curl = 76%	Succeed

In Table 2. Results of field tests on the functions of the rice and chilli disease detection application, from 20 field tests consisting of 11 tests on rice plants and nine on chilli plants. Relatively good test results were obtained by correctly detecting rice and chili plant diseases, and there was one prediction error in Test 7, rice plants. Prediction errors are possible because the pictures were not taken correctly or well enough. The following are the results of calculating accuracy and loss values with the following equation.

From the results of these calculations, a good accuracy percentage of 95% was obtained, and a prediction error of 5% was received. These results indicate that the CNN method uses the Mobile Net. Version 1 model and sequential CNN can carry out classification well.

$$\%\ accuracy = \frac{\text{number of correct predictions}}{\text{amount of test data}} \times 100\%$$

$$\%\ accuracy = \frac{19}{20} \times 100\% = 95\%$$

$$\%\ loss = \frac{\text{number of correct predictions}}{\text{amount of test data}} \times 100\%$$

$$\%\ loss = \frac{1}{20} \times 100\% = 5\%$$

CONCLUSION

From the research that has been carried out, it can be concluded that the results of training, validation, and testing evaluations in the training and validation data process using the Mobile Net version 1 and Sequential CNN models for rice and chilli plant diseases obtained a training accuracy value of 0.8827 with a Loss of 0.3467, validation accuracy value amounting to 0.8493 with a loss of 0.4027 and a testing accuracy value of 0.8678 with a loss of 0.4350. It also produces a suitable confusion matrix with the highest value of 1 and the lowest value of 0.71. Because the accuracy value is close to 1, the training, validation, and testing were declared successful in classifying rice and chilli plant diseases. Developing a disease detection system for rice and chilli plants based on Android-based image classification using the Convolutional Neural Network (CNN) method with the Mobile Net version 1 model combined with the Sequential CNN and Tensor Flow Lite models has been successfully built. The results of field tests have been carried out on 20 images of rice and chilli plants, consisting of 11 tests on rice plants and nine tests on chilli plants. Relatively good test results were obtained by correctly detecting rice and chilli plant diseases with a reasonable accuracy percentage of 95% and a prediction error of 5%. The effects of development Farmers can use an Android-based rice and chili plant disease detection system to determine what type of disease their rice and chilli plants are affected by. So it can make it easier for farmers to deal with conditions that attack their plants. Future researchers can compare versions of the mobile net model by looking at the best accuracy results from the mobile net version. You can conduct research using datasets of rice and chilli plants with better image quality. And can research other disease datasets using the same or different models.

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