Mobile-Driven Disease Identification System for Rice Plants Using ResNet

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ABSTRACT

Rice is one of the staple food sources of the Indonesian people. Rice is one of the staple food sources of the Indonesian people. However, rice production in Indonesia has decreased significantly. This has led to more rice imports in Indonesia. It makes Indonesia more dependent on other countries. The main factor in the crop failure of rice is disease. Agricultural experts are still lacking in Indonesia. This makes the problem of crop failure persist. Therefore, we developed a mobile-based system to identify rice plant diseases. It provides treatment advice for infected plants. This system works in reference to one of the artificial intelligence methods, namely convolutional neural networks. The system is programmed to learn and recognize interconnected networks that form a pattern. So that it can understand similar patterns in different images. In this study, we used the ResNet-50 model with Adamax optimization. It got a training accuracy of 99.94%. To use this application, users only need a smartphone and do not need any internet access. The app has high mobility and easy access for farmers during fieldwork activities. It can solve the problem of crop failure. It's especially helpful in rice fields.

INTRODUCTION

Rice is a staple food in many parts of the world, especially in Asian countries. According to statista.com, as of 2022, China has the most rice. It produces 208.49 million tons. India is in second with 196.25 million tons. Through this data, rice production in Indonesia in 2022 is 54.75 million metric tons. It ranks fourth in the world (Shahbandeh, 2022). Low production in 2023 and export limits from producing countries threaten national food security. According to the Institute for Development of Economics and Finance (InDEF), countries that do not have sufficient food security will have difficulty controlling inflation. Poor food security will make it difficult for the country to have good stability, it involves high inflation rates.

The unmet need for food is a big problem. It causes more hunger and malnutrition. It can also harm the country's economy. Based on the Area Sampling Frame survey (KSA) BPS-STATISTICS INDONESIA data, the harvest area in February 2023 was only 940 thousand ha. Indeed, it increased from the position in January 2023 which was only 448,000 ha and jumped from February 2022 which was recorded at only 767,000 ha. Thus, national rice production in February 2023 was only 2.86 million tons. While January 2023 was only 1.33 million tons. This means that there is a shrinkage of around 802,000 tons from the government's estimate of around 3.68 million tons.

One of the reasons is flooding due to high rainfall in February 2023. Where the BMKG analysis states normal to above normal rainfall. As a result, 31 thousand ha of paddy fields experienced crop failure. While the projected national monthly consumption reached 2.54 million tons, in January 2023 RI experienced a rice deficit of 1.2 million tons and in February 2023 a rice surplus of 320 thousand tons (Pertanian, 2016). The high number of crop failures in Indonesia has increased the number of rice imports. To overcome this, rice productivity must be increased immediately. Such as increasing farmer education about technological innovations in agriculture, which can be applied in optimizing plant and animal production, managing resources efficiently, and improving the quality of agricultural products.

Rice has the scientific name Oryza sativa L. is a cultivated plant that is easily found in agrarian countries such as Indonesia. Although a cultivated plant, rice also has plant species that can live wildly in nature. Based on the variety, rice in Indonesia is divided into three varieties, namely hybrids which are single-plant rice, superior varieties are rice that can be planted many times with the same quality as its derivatives, and local varieties are rice with special types that can only breed in certain areas (Tonael, Kaesmetan, & Lamabelawa, 2021). Common rice plant diseases in Indonesian agriculture include tungro, blast, bacterial leaf blight, sheath blight, and brown spot, each with varying degrees of severity, requiring prompt and accurate identification (Rani & Singh, 2022). Rice plants often face issues like pest or disease attacks, leading to plant death and harvest failure. Therefore, proper handling is essential to address these issues. One approach is to detect diseases in rice plants, enabling farmers to take appropriate action (Santosa, Fu'adah, & Rizal, 2023).

The development of a mobile-based rice plant disease identification system is very important in providing a quick and effective solution to detect plant diseases early, especially for farmers. Considering that sometimes farmers in Indonesia still need experts in the process of identifying rice plant diseases, whose availability is not always certain so that it can hamper agricultural activities, a system is needed that can replace the role of an expert to facilitate agricultural activities. With a system that can be accessed via smartphone without an internet connection, farmers can periodically check the condition of their crops. This makes it possible to detect diseases early and take timely preventive or treatment measures, thereby reducing crop losses. By utilizing the Transfer learning method, which is an approach that allows the reuse of knowledge that has been learned by the model from previous tasks, it is hoped that this system can provide maximum benefits. In this context, the model used is ResNet, a convolutional neural network (CNN) architecture that has proven effective in a variety of computer vision tasks, including object identification in images.

By using transfer learning, we can utilize the knowledge that the ResNet model has acquired from training on large and varied datasets. The ResNet model has successfully extracted useful features from complex images, including images of rice plants. Then, this acquired knowledge can be used to speed up the training process of the rice plant disease identification model. In addition to providing solutions for farmers, the development of this system is also expected to support the growth of the agricultural sector in Indonesia. By utilizing easily accessible technology such as smartphones, it is expected that this system can be widely applied by farmers in all regions of Indonesia, even in remote areas. This will help increase productivity and efficiency in the agricultural sector, as well as contribute to the country's food security.

1.1 Convolutional Neural Network

As we know the development of Artificial Intelligence (AI) is now increasingly widespread. By utilizing AI in one of its researches called deep learning, which allows computer programs to learn data without human intervention in making accurate predictions. In this research we use the Convolutional Neural Network (CNN) is one of the deep learning methods that teach computers to process data in a way inspired by the human brain. The computer will learn to form a pattern from each connected network from large amounts of data. The pattern that has been learned is called a model. The model is used over the object to be recognized (Via, et al., 2023). as illustrated in Figure 1

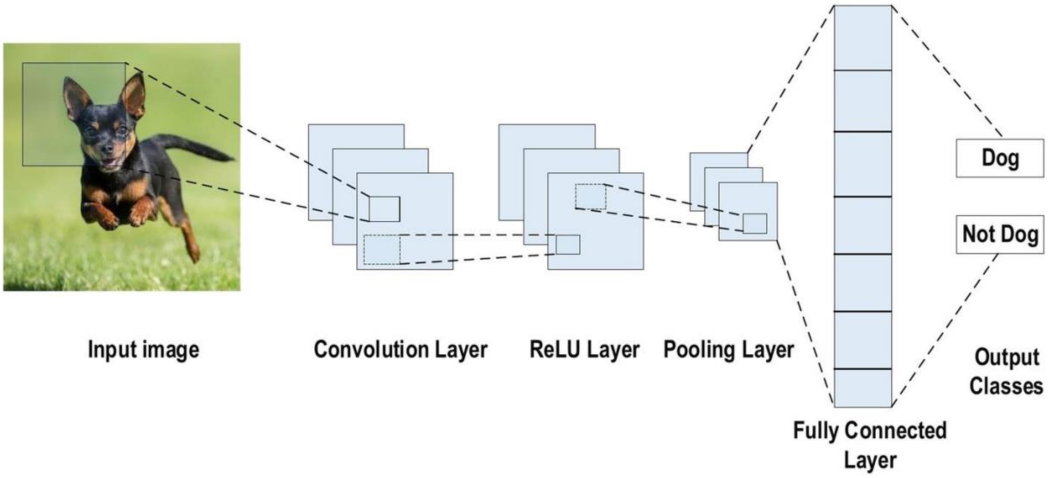

Figure 1. CNN Architecture

Source: (Alzubaidi, et al., 2012)

1.2 ResNet-50

ResNet (Residual Networks) is one of CNN (Convolutional Neural Network) architecture. There is 4 Key Components of Resnet Architecture. The first key is residual block, in residual block the inputs to the block are added to the outputs of the block creating a residual connection. The second key is Skip connection, consists of the residual block's input. It passes through the convolutional layer and is added to the residual block's output. The third key is stacked layers, the ResNet architecture forms by stacking multiple residual blocks together. And the last key is global average pooling (GAP) is the last layer before the fully connected leyer. GAP reduces spatial dimensions to a single value per feature map providing a compact representation of the entire feature map (Azeem-I, 2023). In this research we use ResNet-50. It has 50 bottleneck residual blocks, which are stacked. The initial layer of the network features a conventional convolution layer and a pooling layer to perform image preprocessing before undergoing further processing by the residual blocks. Finally, a fully connected layer positioned at the top of the structure utilizes the enhanced data to categorize the image with precision (Shah, Qadri, Shah, Sharif, & Marinello, 2023). An illustration of the Resnet 50 architecture can be seen in Figure 2.

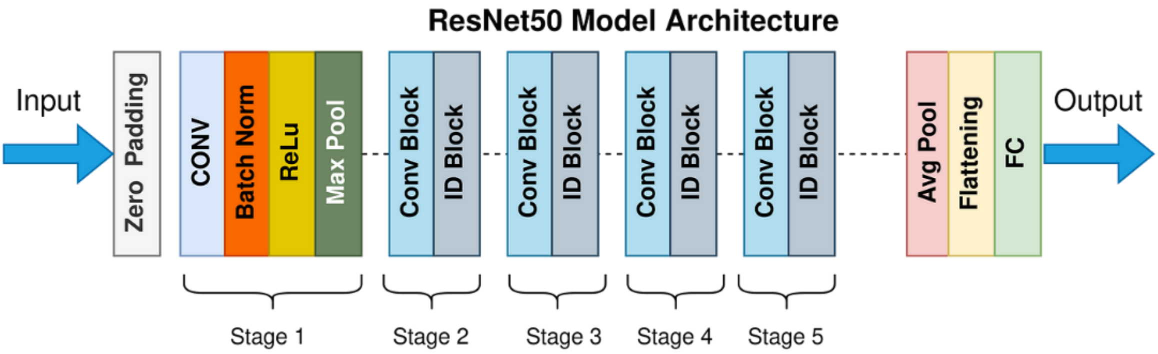

Figure 2. ResNet-50 Architecture

Source: (Mukherjee, 2022)

RESEARCH METHOD

This research was designed through several stages obtained through adaptation of two methodologies, namely IBM Data Science Methodology as a reference analysis method and Waterfall Methodology as a reference method for application development. as illustrated in Figure 3.

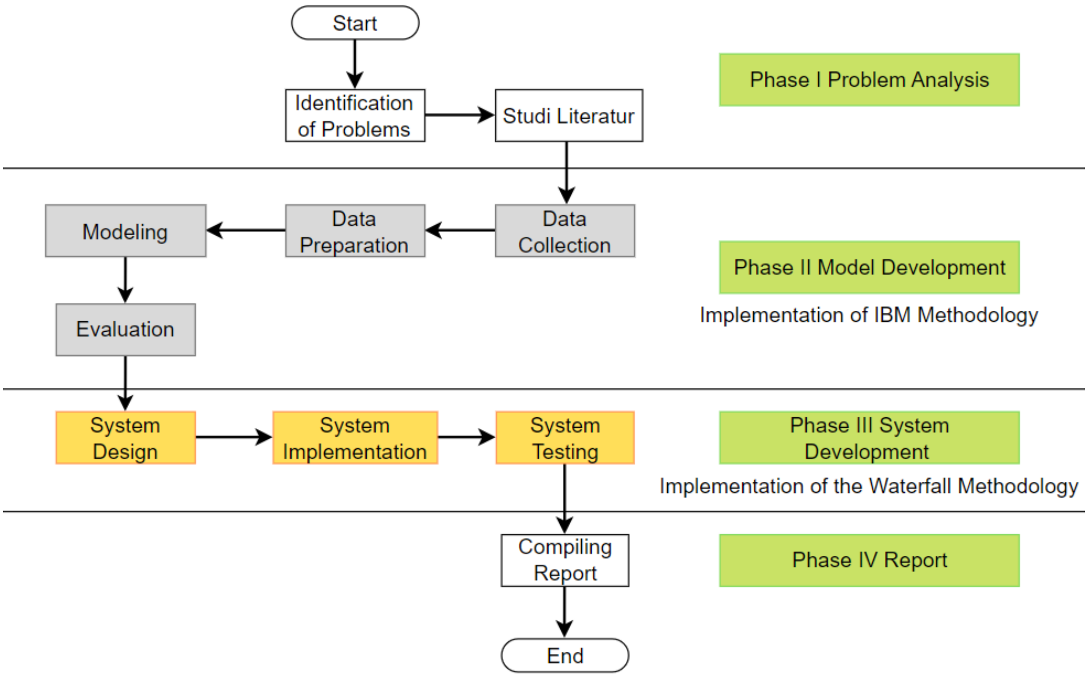

Figure 3. Research Flow

2.1 Phase I Problem Analysis

The This research was designed through several stages obtained through adaptation of two methodologies, namely IBM Data Science Methodology as a reference analysis method and Waterfall Methodology as a reference method for application development.

2.2.1 Identification of Problems

This research begins with the problem analysis stage, which is the first step in the research process. This analysis includes topic selection, determining the problem formulation, and determining research objectives, which will be supported by literature studies related to the topic of disease identification in rice plants using the ResNet model. This problem analysis stage is an important foundation that will guide the next steps in this research.

2.2.2 Study Literature

The next step is a literature study, where researchers search for references and literature related to the research topic, such as books, journals, articles and other online sources. The aim is to understand theoretical concepts, research methodology, as well as relevant findings related to research subjects, such as types of rice plant diseases, the use of deep learning technology in identifying rice plant diseases, and the application of the ResNet model.

2.2 Phase II Model Development

The second stage is model development. The steps in this stage adopt an approach from IBM Data Science Methodology, especially in data processing and solution creation. There are four main steps taken in this stage, namely:

2.2.1 Data Collection

Data collection carried out in this research was divided into 2 stages, namely by collecting images of rice plant leaves as material for system experiments. And collecting data sets to carry out model training which can be accessed on the kaggle.com website with the title "Rice Leaf Disease Detection".

2.2.2 Data Preparation

After The data preparation process is the stage of preparing the data after it has been collected and then processed using a predetermined model. This process goes through 3 stages, namely cleaning data, where the collected image will be adjusted by cropping the background, increasing contrast, or adjusting color to increase sharpness of detail. Data augmentation, where variations are added to the resulting training dataset by carrying out transformations such as rotation, shift, shear, zoom and horizontal flip on the image. Annotation, which is the stage of giving labels or other information to certain objects or areas in the image. This entire preprocessing process is an important step in preparing the dataset for model training.

2.2.3 Modelling

The model development in this research was carried out using Google Colab, the following are the stages of model development. Start by selecting the ResNet model to use. This algorithm consists of several layers of stages, namely pre-trained model, feature extraction model, and fully connected layer. Optimize the model with the Adam Optimizer algorithm to train the model and adjust parameters such as learning rate according to needs. Then train the model using the previous training data, and set hyperparameters such as learning rate, number of epochs, and size. Then the model will be saved in tflite format which can be integrated with the Flutter framework.

2.2.4 Evaluation

After all stages are trained, evaluate the performance of the model to ensure good performance in detecting objects in various image conditions. In this study, the evaluation is carried out using the Confusion Matrix method using several equations presented by (Kundu, 2022) as follows:

1. Accuracy, describes how accurately the model can classify correctly.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

2. Precision (Positive Predictive Value), describes the level of accuracy between the requested data and the prediction results provided by the model.

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

3. Recall or Sensitivity (True Positive Rate), describes the success of the model in retrieving information.

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

4. F1 describes the balance between Precision and Sensitivity (Recall) which provides information on how well the model has been created.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

2.3 Phase III System Development

After building the model using the Python programming language. At this stage of development of this mobile information system, the language used is Dart in the Flutter framework. This difference in the programming languages used can be overcome by using the Tensorflow library. Where the output of the model created in the form of an h5 file will be converted into tensorflow's tflite which can be read by the flutter framework. In this stage, the waterfall model is used as a system development model.

2.3.1 System Design

This step involves designing the system based on the needs analysis that has been carried out previously. In this research, the system will be designed using the mobile-based Flutter framework as an application that will be used by users. In the application, users can input images using a camera or select images stored in the gallery. Then the image will be analyzed using the model that has been created, which outputs the identification of rice plant diseases and how to overcome them. Illustration of the workflow can be seen in Figure 4

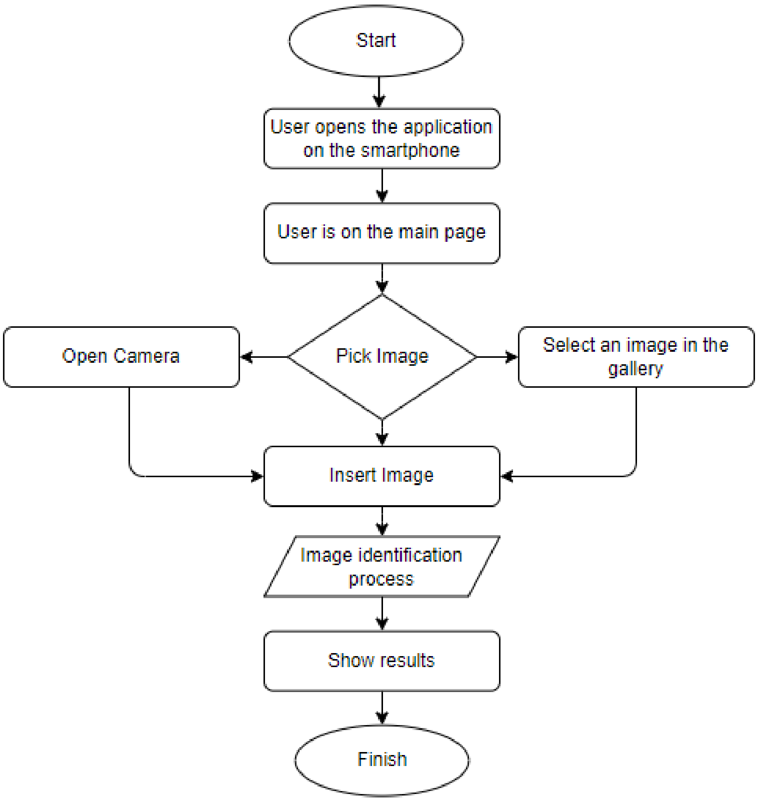

Figure 4. Workflow Diagram

2.3.2 System Implementation

This stage is the implementation of the system based on the previously created design which involves the process of compiling mobile application code using the flutter framework. This application is intended for users to input which then the image will be analyzed using a model that has been stored in *.tflite format and the results of the analysis are issued along with suggestions for actions that must be taken.

2.3.3 System Testing

After the implementation is complete, the system will be tested to ensure that all features function properly and in accordance with the system design that has been made. In this stage we use 2 tests, Black Box testing and model testing. Testing is done by observing the input and output results. Furthermore, the system testing stage is carried out on the disease identification system in rice plants to test the model in detecting diseases in rice plants.

2.4 Phase IV Reporting

The final stage of this research is the preparation of the report. After the application development stage is complete, the final step is stage IV, namely Reporting, where the results of research and system implementation will be compiled in the form of a complete and structured report for documentation and publication purposes.

RESULTS AND DISCUSSION

Model development is made through the google collab application with data collection from Kaggle. Website development is made through the vscode application with the flask framework for website display and integration with data analysis modeling. The following is an explanation of both points: Data collection, model development, system implementation, and evaluation.

3.1 Data Collection

Data collection carried out in this study is divided into 2 stages: collecting images of rice plant leaves as material for system experiments and collecting data sets to perform model training that can be accessed on the kaggle.com website with the title "Rice Leaf Disease Detection".

Table 1. Dataset

No.	Class	Number of Images
1	Bacterial Leaf Blight	1.386
2	Rice Hispa	1.464
3	Brown Spot	1.480
4	Neck Blast	993
5	Healthy Rice Leaf	1.491
6	Narrow Brown Leaf Spot	1.416
7	Leaf Blast	1.639
8	Sheath Blight	1.578
9	Tungro	1.690
Total		13.135

3.2 Model Development

We develop the model using ResNet 50 structure, we trained the model for 20 epochs which lasted for 1 hour 19 seconds, with the best results obtained at the 17th epoch with an accuracy value of 99.948 and a loss value of 0.265, To determine the performance of the model that has been trained previously, it is necessary to evaluate the model by displaying the overall model performance graph and visualizing the model training data. The learning progress of the model on the training dataset is visualized by a line graph. The figure 5 is for loss value and figure 6 is for accuracy value.

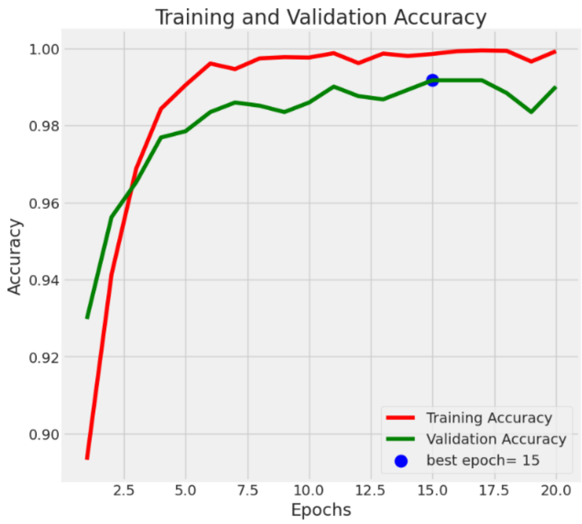

Figure 5. Training and Validation Accuracy

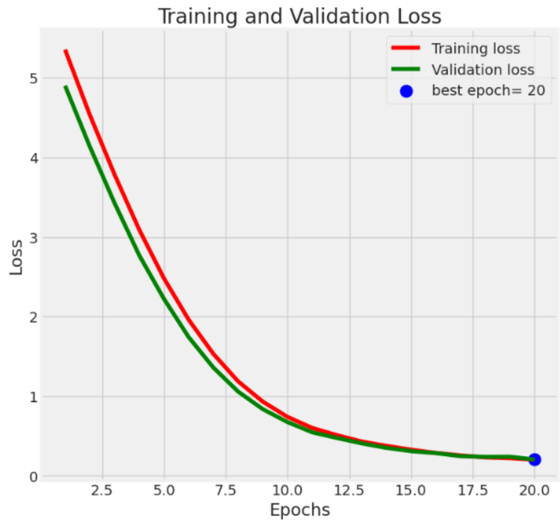

Figure 6. Training and Validation Loss

After modeling, an evaluation of the model is carried out using confusion matrix calculations for each class in the dataset. Which can be seen in the classification report in fig 7. The calculation such as precision, recall, f1-score, and support refer to the basis of the calculation of evaluation matrix. The highest value obtained is 100% and the lowest value obtained is 99%.

	precision	recall	f1-score	support
Bacterial Leaf Blight	1.00	0.99	1.00	119
Brown Spot	1.00	0.99	1.00	155
Healthy Rice Leaf	1.00	1.00	1.00	109
Leaf Blast	0.99	0.99	0.99	175
Leaf scald	0.99	0.99	0.99	133
Narrow Brown Leaf Spot	1.00	1.00	1.00	95
Neck_Blast	1.00	1.00	1.00	100
Rice Hispa	1.00	1.00	1.00	130
Sheath Blight	0.99	1.00	1.00	163
Tungro	1.00	1.00	1.00	31
accuracy			1.00	1210
macro avg	1.00	1.00	1.00	1210
weighted avg	1.00	1.00	1.00	1210

Figure 7. Classification Report

Then a confusion matrix diagram is needed to evaluate the performance of the model by running the model on the testing dataset which can be seen in Figure 8

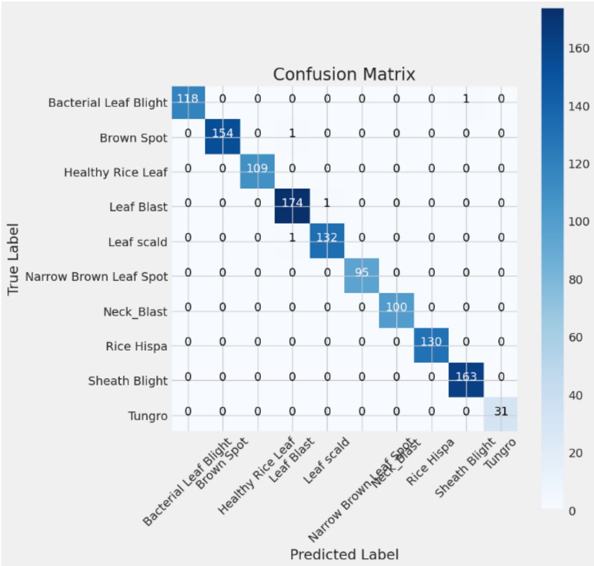

Figure 8. Confussion Mattrix

In the diagram above the true label takes data from the training dataset, and the predicted label takes data from the testing dataset. from the diagram there is a loss in 1 rice hispa data detected as bacterial leaf blight, 1 leaf scald data detected as brown spot, 1 leaf scald data detected as leaf blast, and 1 leaf blast data detected as leaf scald.

3.3 System Implementation

System implementation is carried out after the system design is made for reference. Which in this study the design of a mobile information system is made using the Flutter framework, consists of 4 pages. As shown in the picture below which is the first and second onboarding is a page that used as a brief introduction to the application to users

Figure 9. onboarding 1

Figure 10. onboarding 2

Furthermore, there is a homepage, on this page users can input images by opening the camera and taking pictures directly or selecting images in the gallery. and the last is the detection result display, on this display the user gets the detection results of the image that has been entered. There is a back button on the top right and bottom center which functions to return the display to the homepage so that users can repeat the image capture process.

Figure 11. homepage

Figure 12. resultpage

After implementing the system and modeling, the model was integrated into the system using the tflite package, the following tests were carried out after system integration.

Figure 13. the prediction result is correct

Figure 14. the prediction result is correct

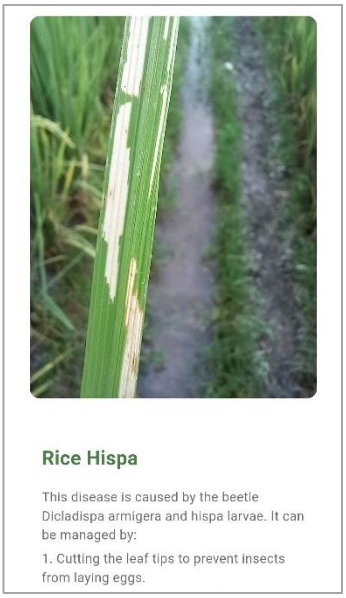

Figure 15. the prediction result is correct

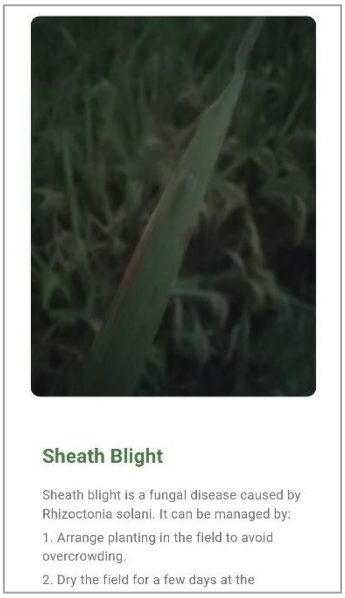

Figure 16. the prediction result is not correct

From 4 final product tests that have been carried out show that the prediction results run well, but there is 1 that is not correct, this is because the quality of the input image is not good, in this case the image is experiencing a lack of light so that the identification process is not correct.

CONCLUSION

This research uses deep learning as the main method in machine learning to recognize objects in the form of images, by utilizing the ResNet-50 model as the foundation in developing deep learning structures. In the development of this model, the Adamax optimization algorithm was also used to improve the overall performance, which resulted in a significant improvement in the accuracy of the model to reach 99.95% and the lowest loss value reached 0.265. The developed model was successful in the task of disease detection in rice plants, demonstrating its ability to provide consistent and reliable results in visually analyzing plant conditions. Thus, the implementation of deep learning with ResNet-50 and the application of Adamax optimization algorithm become an effective foundation in providing smart solutions to support the success of agriculture through technology. The development of this rice plant disease identification system was carried out using the Flutter framework for the Android mobile platform. This process involved the design and development stages of the system as a whole, where model integration became a crucial part of the development process. Model integrity in the system is done through conversion to the TFLite format, which allows the model to be optimized for performance on mobile devices. During this process, the model was properly annotated in order to be implemented in the rice plant disease detection system. The result of successful integration is a system that is able to produce outputs in accordance with the application requirements, providing users with accurate and reliable information regarding the health condition of rice plants.

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