Machine Learning-Potato Leaf Disease Detection App (MR-PoLoD)

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***Abstract*— Potato production in Indonesia has grown very rapidly, making Indonesia the largest potato producer in Southeast Asia. However, there are challenges for farmers in growing potatoes. Such as treating potatoes for various diseases. 2 diseases will occur in potato plants if not treated quickly, namely early blight disease caused by the fungus Alternaria solani and late blight disease caused by the microorganism Phytophthora infestans. The project "Potato Plant Leaf Disease Detector (MR-PoLod)" aims to design an android application that can classify leaves on potato plants into 3 classifications, namely healthy, early, and late blight disease. This application uses the CNN (Convolutional Neural Network) Machine Learning Algorithm because currently, CNN is recognized as the most efficient and effective model in pattern and image recognition tasks. This application uses the Python programming language which is rich in library and framework availability so that it can meet the needs of machine learning and image classification tasks. The total data used for training data, data validation and data testing is 3165 images. With each division of the data process on the training data of 70%, validation of 15% & testing of 15% to test the effectiveness of the model that has been created. The performance of MR-PoLod for each class, obtained a precision value, recall, and f1-score of 0.99. Likewise, the accuracy value achieved by the model is 0.99 or 99%. Thus, the expected application can facilitate farmers in classifying diseases on potato plant leaves.**

Keywords*— *Accuracy, application, CNN, healthy potatoes

I. Introduction

Indonesia is an agricultural country that has abundant water supplies, vast and fertile land, and produces various agricultural commodities. One of the agricultural commodities in Indonesia is potato farming. Potatoes are the fourth main food in the world, after rice, corn, and wheat. Potatoes are also one of the foods that contain carbohydrates. Potato production in Indonesia has grown very rapidly, making Indonesia the largest potato producer in Southeast Asia. However, there are challenges for farmers in growing potatoes. They face heavy losses every year due to various diseases, pests & extreme weather that attack the potato plants [1]. Recently in September 2023, 6 hectares of potato plants failed to harvest in the Dieng Valley, Central Java. The Head of Dieng Kulon Village, Batur District, Banjarnega Regency, Slamet Budiono said that the failed harvest was caused by the frost phenomenon due to extreme temperatures that occurred there, the temperature in June - September 2023 ranged from 13 ° - 21 ° during the day and 3 ° - 12 ° at night and had frozen 5 times in the morning with temperatures of -1 ° to -3 ° which caused the frost to continue to increase [2]. The average age of their plants is currently between 40 days and -70 days, but the potato plants have not yet borne fruit and most of them are dry which causes material losses of up to hundreds of millions of rupiah [3]. Then, farmers reflected on the previous incident, they continued to replant potatoes on the slopes and covered the potato plants with grass, but this did not rule out the possibility that potatoes planted on the slopes could survive until harvest time due to extreme temperatures [4]. Farmers also said they could not quickly tell whether the potato plant leaves would die due to being attacked by the fungus *Alternaria solani* (Early Blight) which occurs in winter and can infect other leaves through rainwater, dew and direct contact with infected leaves [5].

A similar phenomenon also occurred in the potato plantations of Palelon Village, Makaaroyen and Linelean, Mondoinding District, South Minahasa Regency, North Sulawesi. This potato plantation was attacked by 8 types of pests, namely, Tea Leafhopper (Empoasca sp), Fruit Fly pest (Drosophila sp), Predator Aphid or Predator Aphid (Nesidiocoris sp), Leaf Miner Fly pest (Liriomyza sp), Aphid pest (Lygus sp), Fruit Fly pest (Phtorimaea sp), Antractomorpha sp., and Spider Leaf Beetle Insect (Epilachma sp) [4], which caused a decrease in harvest yields due to attacks by these pests and insects (Late Blight) [6]. Reflecting on this, farmers scheduled pesticide spraying & fertilization using better quality to increase the productivity of potato crop yields assisted by PT *Pupuk Kalimantan Timur* (PKT). The results of the treatment were proven to be able to increase the harvest by 55% with a yield of 15.8 tons/Ha from the previous 9.9 tons/Ha, if seen from the results, the potato harvest increased by 5.9 tons/Ha. From this incident, 2 diseases will be caused in potato plants if they cannot be handled quickly, namely dry spot disease (early blight) caused by the fungus Alternaria solani and late blight disease caused by microorganisms [7]. Early blight disease has symptoms such as dry spots in the form of brown circles on the underside of the leaves and invisible sporulation that looks like white dew [8]. This disease tends to attack early ripening potato varieties more often than medium- or late-ripening potato varieties [9], so that the growing season becomes shorter because the plants die prematurely, producing smaller tubers [10]. Meanwhile, late blight disease caused by the microorganism Phytophthora infestans has early symptoms such as wet spots on the edges of the leaves or in the middle [11]. Then, the spots that appear will widen and the leaves will turn brown/gray [12]. This disease can attack all parts of the leaves or potatoes in just a matter of days [13].

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Farmers can detect both diseases quickly and apply the right treatment, so they can save a lot of waste and prevent economic losses [14]. Because the treatment of leaf diseases caused by fungi or microorganisms has only a slight difference [15]. So, it is important to be able to detect it accurately. Handling the problem of identifying leaf diseases in potato plants has been carried out in previous studies such as identifying leaf diseases in potato plants through texture and color features using the *Support Vector Machine* (SVM) method with the RBF kernel [16]. The study aims to be able to identify symptoms of disease in potato plants earlier and to be able to determine the type of disease in the potato plant [17]. However, the results of the study produced an accuracy value of 87% which was caused by the characteristics or texture of a diseased leaf greatly affecting the process of identifying the type of disease [9]. In addition, farmers also carry out the process of identifying leaf diseases in potato plants traditionally, but this has shortcomings because human nature has weaknesses such as lack of accuracy, so the results obtained are ineffective and less accurate for large quantities [18]. Therefore, in this study, the handling of the problem of identifying leaf diseases in potato plants uses the utilization of informatics using the *Convolutional Neural Network* (CNN) algorithm which is one of the Deep Learning methods [19]. The data used is data obtained from primary data obtained directly from potato gardens by taking photos with potato farmers as experts and secondary data through the kaggle website which contains data in the form of images of diseases on potato plant leaves [20]. Referring to this, it is necessary to create a system in the form of this application so that it can help farmers or agricultural managers in identifying diseases on potato plant leaves by taking pictures of potato leaves through the android application.

The novelty of the MR-PoLoD lies in its unique combination of cutting-edge machine-learning techniques and real-world agricultural applications. Unlike existing plant disease detection methods, MR-PoLoD integrates advanced image processing algorithms with a mobile platform to provide real-time disease diagnosis specifically tailored to potato crops. This focus on a single crop, along with its incorporation of disease-specific models, sets it apart from more generalized plant health apps. The app's ability to perform precise detection across multiple disease types, even in varying environmental conditions, enhances its practical utility, offering a fresh, innovative solution to the agricultural community. The originality of MR-PoLoD also stems from its emphasis on accessibility and scalability. While many machine learning models require high computational power, MR-PoLoD is designed to operate efficiently on mobile devices, making it accessible to farmers in rural or resource-limited areas. Additionally, the app integrates user-friendly features such as disease history tracking and growth monitoring, allowing users to manage and respond to plant health over time. This approach is not only original in its technical execution but also in its potential impact on small-scale farming, democratizing the use of advanced technologies in agriculture and empowering farmers to adopt precision farming practices with minimal technological barriers.

II. RESEARCH METHODS

In this study using android application-based software has several stages in its creation, which can be seen in Figure 1. Based on this flowchart, it begins with collecting datasets (data collection) related to leaf disease image data on potato plants. Where the leaf classification is divided into 3, namely healthy leaves, leaves that are rotten due to fungus (early blight) and leaves that are rotten due to microorganisms (late blight) which are taken from the Kaggle site with a total data of 3000 images and also taking data on potato plant leaf images to the potato garden with potato farmers with a total data of 165 images evenly distributed for each classification [21]. Additionally, the data is pre-processed by importing the data and downsizing the dataset image from a random pixel size to a 256 × 256 pixel image [22]. Additionally, carrying out data cleansing, also referred to as data scrubbing or data cleaning. This procedure, which involves finding and fixing mistakes in the data set and eliminating inaccurate data from the dataset, is crucial for preparing data before moving on to the data analysis or machine learning modeling stage [23]. As a result, the data will be high-quality, clean, and ideal.

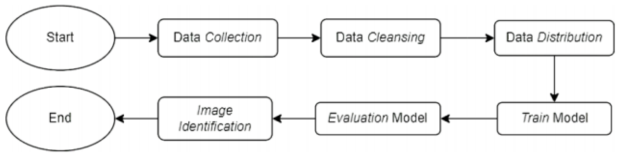

Fig 1. Research Block Diagram

Inaccurate, redundant, inconsistent, misformatted, and other flaws in the cleaned data may hinder data analysis or subsequent machine learning modeling. Errors in the image classification process may arise from the vast number of unclear photos and the unequal distribution of data in each category. These issues can be resolved by selecting ambiguous data for each category and distributing the data equally. The next step is data distribution, which involves splitting the data into two categories: training data, which is used to train the model, and validation data, which is used to confirm the model after testing. To train the model that will be used for image classification, training data must be separated from validation data, and testing data is required to evaluate the machine learning model's performance [24]. Following data distribution, the CNN model architecture will be developed. The model should then be trained. CNN, a machine learning algorithm, is used in this design to detect diseases in the leaves of potato plants. The next step is to evaluate the model to make sure the obtained image categorization meets the required level of accuracy. Next, move a filter of a specific size into a picture to carry out image identification that makes use of the convolution layer. Next, CNN will use the same convolution to split the image into several little pieces[25]. Next, the value of the convolution is put into a new array, where the array will be used by the neural network to identify an image.

Furthermore, as seen in Figure 2 about the block diagram for the deployment model to Android Studio software. The model that has been constructed can then be optimized using methods like hyperparameter tuning, which involves attempting to alter the parameters of the number of epochs or

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iterations in the training process in order to obtain the optimal model, following image identification. When the training accuracy and validation accuracy values are at their maximum and the training loss and validation loss values are at their lowest, the optimal model will be produced [26]. Additionally, to enable immediate deployment to Android Studio software, the model is saved in tensor flow light format. After that, the user's smartphone can execute and install the created Android application..

Fig 2. Deployment Model

III. RESULTS AND DISCUSSION

The application's two screens are the first one for starting, and the second one serves as a classification feature with buttons for retrieving data via the gallery and the camera, respectively. Each leaf condition's confidence value and the type of leaf condition classified according to the highest confidence value may be seen in the classification feature's findings. The Java programming language and Android Studio software were used to create this application. Figure 3 illustrates how the Android application's display is created.

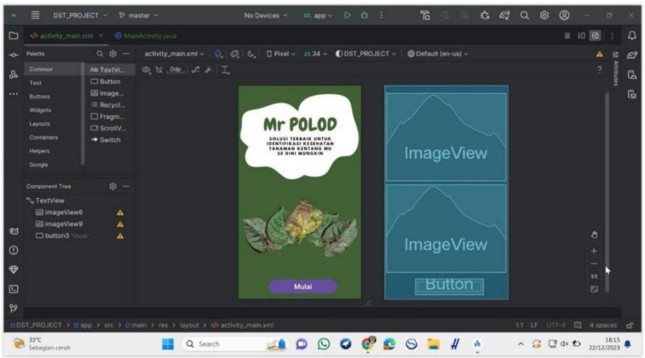

Fig 3. Application View on Android

This application must be installed first on the user's mobile phone by running the main program of the Android Studio software so that the application can be installed using a USB cable connection. The user can follow the application's workflow after it has been installed. When the application is first launched, the start button will be visible on the first screen. After that, the start button is pressed to switch to the second screen. The user has a choice between two buttons on the second display for the image data retrieval process: obtaining data from the user's gallery or from the camera. A classification model that has been developed and implemented in the application will then be used to examine the image[27]. The confidence value section will show the classification analysis's findings, and the image will be categorized based on whether it belongs to the early blight, late blight, or healthy leaf condition. Figure 4 shows the system's mechanism and the framework of the installed Android application.

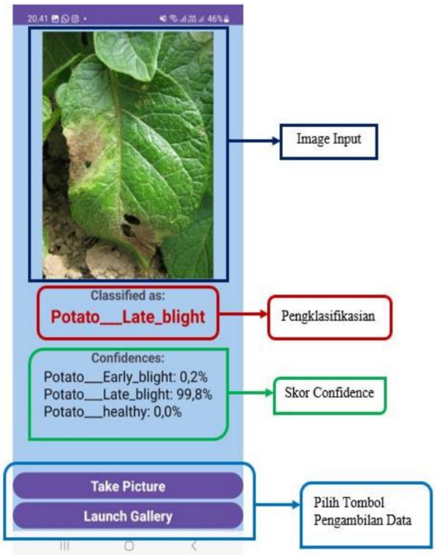

Fig 4. MR-PoLoS Android Application Framework

The Python programming language, which has a wealth of libraries and frameworks to fulfill the demands of machine learning and image classification tasks, is used in this project's CNN-based image classification model. A machine learning framework called TensorFlow offers a comprehensive architecture for creating and refining models. An interface for creating, training, and assessing neural network models is offered by the high-level neural networks API Keras [28]. frequently employed as a tensor-flow front end. A multidimensional array data structure (numpy array) and strong mathematical functions are provided by Numpy, a core Python library for numerical computation, to make processing and manipulating numerical data easier. The output is in the form of model results that may be utilized in the following step, and the input data is a dataset of potato plant leaf kinds that will subsequently be classified [29]. This system's primary feature is a classification model that takes the shape of different potato plant illnesses. 3165 photos in all were used as training, validation, and testing data. The effectiveness of the developed model is tested by dividing the process data into three categories: 70% for training data, 15% for validation, and 15% for testing.

A number of factors need to be checked, and each one yields numbers for training accuracy, validation accuracy, training loss, and validation loss. When creating the model layer with the relu activation function, the first fixed parameter is the kind of activation function. The Adam optimizer is the second fixed parameter. The level of tuning or altering the number of epochs employed in the training process is the third parameter [30]. The parameter with the highest value in this instance is the one with the highest training accuracy and validation accuracy parameters and the lowest training loss and validation loss parameters. A graph of the Hyperparameter tuning model's 50 epoch outcomes in the MR-PoLoD application is displayed in Figure 5.

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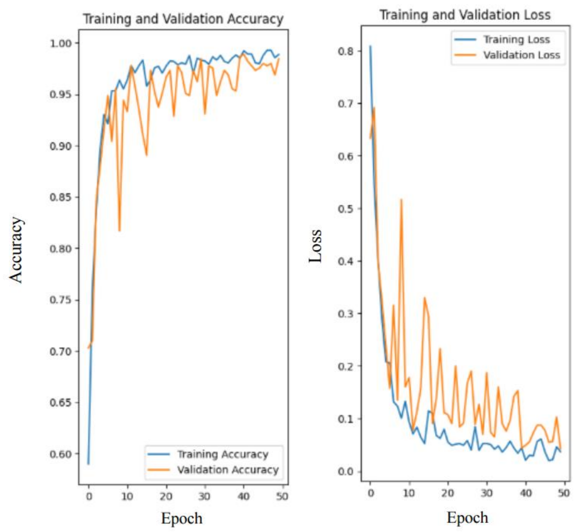

Fig 5. Training and Validation Accuracy and Loss Graphs

The final model's performance was evaluated using 509 picture data that the model had never seen before. The process of testing the model's performance involves analyzing the test results. Figure 6 displays the model's test results that have been compiled into the confusion matrix graph.

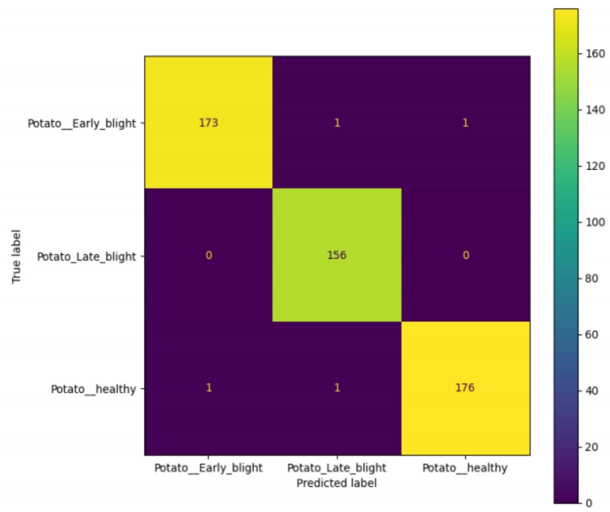

Fig 6. Confusion Matrix Graph

The next step after creating the confusion matrix is to assess and examine the values that are present in each class. The model's accuracy, f1-score, precision, and recall are the parameters that must be assessed. The values of each parameter range from 0 (minimum) to 1 (maximum). The model performs better at classifying detected items when the parameter value is larger. Table 1 displays the findings of the model's precision, recall, f1-score, and accuracy analysis.

TABLE 1. Classification results of precision, recall, f1-score, and accuracy values

No	Leaf Condition	Precision	Recall	F1-Score
1	*Early blight*	0.99	0.99	0.99
2	*Late blight*	0.99	1.00	0.99
3	*Healthy*	0.99	0.99	0.99
Average		0.99	0.99	0.99
Accuracy		0.99	0.99	0.99

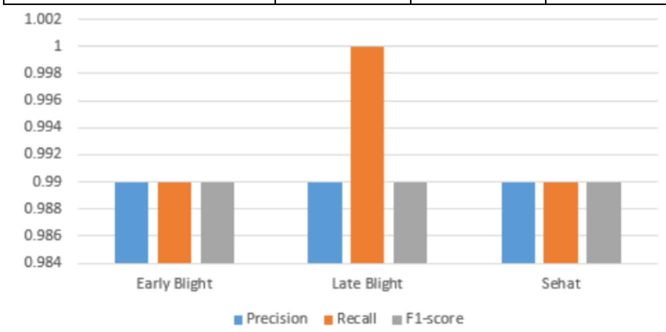

Fig 7. Classification Model Performance Results per Class

According to Table 1, the average precision, recall, and f1-score of 0.99 are the same for the three classes (healthy leaves, late blight, and early blight). Similarly, the model's accuracy rating for identifying potato plant leaf diseases is 0.99, or 99%. Figure 7 displays the assessment graph for each class as well as the average evaluation based on the analysis results. The author used 30 data samples to test the MR-PoLoD application in order to ascertain its accuracy performance. Due to the restrictions of having actual leaf samples, this sample was taken from doing "take pictures" and identifying potato leaves on the internet or Google for each of the following classifications: Early Blight Disease (10 samples), Late Blight Disease (10 samples), and Healthy (10 samples). Determining the proportion of accurate and inaccurate predictions from the complete trial sample requires this level of precision. The graph of the MR-PoLoD application's trial results in Figure 8 shows that leaves that are successfully recognized correctly receive a score of 1, while leaves that are incorrectly detected receive a score of 0.

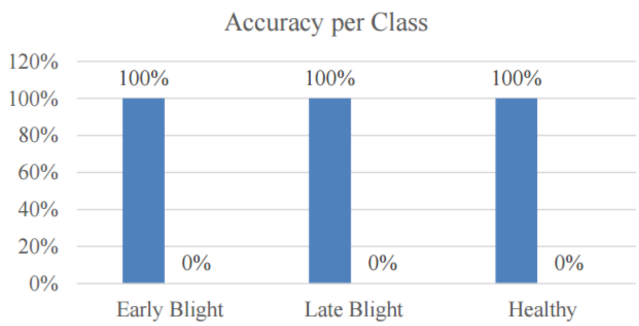

Fig 8. Accuracy Results per Class with 30 Potato Leaf Samples

With the help of the MR-PoLoD application's user-friendly interface, farmers or other users can quickly get a diagnosis by snapping a photo of the potato leaf they want to analyze. According to user interface discussions, a responsive and straightforward design was necessary to guarantee that users with different levels of technological proficiency could utilize the application. A small sample of users with an agricultural background were used to test the interface [31], and they largely expressed satisfaction with the application's usability [32].

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However, a number of technical issues were discovered throughout the application's development and testing.. Because the machine learning model is housed in the cloud, one of the primary obstacles was the requirement for consistent internet access in order to process photos and acquire diagnosis results [33]. Additionally, although though the application's accuracy was fairly high, it might still be improved, particularly when handling low-quality photographs or in dimly illuminated environments [34]. As a result of these conversations, a more reliable and resource-efficient mechanism to support offline functionality has to be created[35].

Overall, the outcomes of the creation of the MR-PoLoD application demonstrate that machine learning technology can offer a workable and effective way to identify potato leaf disease. In the agricultural industry, this application has a lot of promise for broad adoption, particularly in assisting with early disease identification that can preserve crop harvests. To overcome current technical obstacles and enhance the application's precision and functionality, particularly in more diverse field situations, more research is necessary. In order to provide a more comprehensive and sustainable solution, future advancements may potentially involve integration with other smart agricultural systems. Furthermore, by providing farmers with a mobile app for disease diagnosis, MR-PoLoD advances the integration of technology in agricultural practices. In rural locations where access to sophisticated diagnostic equipment may be limited, the development of this app increases the potential for machine learning applications. MR-PoLoD encourages data-driven agricultural methods by giving farmers an easy-to-use platform to diagnose and track plant health, which helps with disease control, crop yields, and resource efficiency.

IV. Conclusion

In summary, the results of testing and analysis that have been carried out in system design, the MR-PoLod application can work well to identify and classify leaf diseases on potato plants and display detection results and confidence values on the interface. The performance of MR-PoLod has a precision, recall, f1-score value for each class of 0.99. The trial results of the MR-PoLod application obtained an accuracy value of 0.99 or 99%. Thus, this application is expected to make it easier for farmers to classify diseases in potato plant leaves. We believe that by adding classes or types of leaves that can be detected, the detected leaves are more diverse and can develop the design of this system if the author has deficiencies or errors either in writing or in the system.

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