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Development of a Mobile Application for Plant Disease Detection using Parameter Optimization Method in Convolutional Neural Networks Algorithm

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Abstract

Plant diseases are a serious problem in agriculture that affects both the quantity and quality of the harvest. To address this issue, authors developed a mobile software capable of detecting diseases in plants by analyzing their leaves using a smartphone camera. This research used the Convolutional Neural Networks (CNN) method for this purpose. In the initial experiments, authors compared the performance of four deep learning architectures: VGG-19, Xception, ResNet-50, and InceptionV3. Based on the results of the experiments, authors decided to use the CNN Xception as it yielded good performance. However, the CNN algorithm does not attain its maximum potential when using default parameters. Hence, authors goal is to enhance its performance by implementing parameter optimization using the grid search algorithm to determine the optimal combination of learning rate and epoch values. The experimental results demonstrated that the implementation of parameter optimization in CNN significantly improved accuracy in potato plants from 96.3% to 97.9% and in maize plants from 87.6% to 93.4%.

Keywords: convolutional neural networks, deep learning, parameter optimization, grid search

1. INTRODUCTION

Plant diseases are one of the factors that greatly affect the quantity and quality of crop yields in the agricultural sector [1]. In Indonesia, the majority of the population works as farmers. Aside from cultivating rice, Indonesian farmers also grow crops such as potatoes and maize. Therefore, handling plant diseases is crucial to improving productivity and the quality of crop yields in the agricultural sector.

Potatoes and maize are important food commodities that serve as a source of carbohydrates for people in Indonesia and around the world. Diseases in potato and maize plants can cause significant economic losses, especially if they are not promptly identified and properly managed. Plant disease detection technology using Convolutional Neural Networks (CNN) is one solution that can assist farmers and agricultural experts in quickly and accurately identifying plant diseases. CNNs are the top choice for plant disease detection because they are excellent at handling plant images, automatically learning important features without manual tweaking. Their strong track record in image classification means they are accurate and reliable, crucial for identifying diseases quickly and helping farmers.

Detecting plant diseases late or mishandling them can be disastrous for farmers and consumers. Quick identification is vital for food security, crop health, and farmers' livelihoods. Therefore, this research aims to develop a CNN-based mobile application that can be used by farmers to detect diseases easily and effectively in potato plants.

2. RELATED WORKS

Elhassouny et al. [2] utilized the MobileNet architecture to classify 10 types of diseases in tomato plants. Several optimization algorithms were applied, and it was concluded that Proximal Gradient Descent achieved the highest accuracy of 89.2%. Parameter optimization using grid search showed that a learning rate of 0.001 resulted in the highest accuracy of 90.3%. Furthermore, plant disease classification technology was also implemented on smartphones.

Meeradevi et al. [3] employed the VGG16 architecture and a tomato dataset with five labels. They also utilized the train-test split technique with a ratio of 0.75 for training and 0.25 for validation. The research results showed that the application of feature extraction and transfer learning significantly improved accuracy.

Gehlot et al. [4] tested various Convolutional Neural Network (CNN) architectures for classifying 10 types of diseases on tomato leaves using the PlantVillage dataset. Out of 14,529 images, the data was divided into 11,623 for training and 2,905 for testing. To reduce memory utilization, a data generator was used due to the large image sizes. The results demonstrated that DenseNet-121 achieved the highest performance with an accuracy of 99.68% and a file size of 89.6 MB. This study is significant as tomato production in India ranks third globally, and this method can assist farmers in quickly and accurately identifying plant diseases.

Mokhtar et al. [5] conducted experiments using SVM for tomato leaf disease detection with a dataset of 200 images and 2 labels. Features were extracted using Gabor wavelet transformation, and grid search and n-fold cross-validation were used for performance evaluation. The results showed that the Cauchy kernel and Laplacian kernel achieved the highest performance with accuracies of 100% and 98%, respectively, while the Invmult kernel reached only 78%. SVM is a powerful classification technique for small datasets with binary features.

Al-Tuwaijari et al. [6] compared the performance of Convolutional Neural Network (CNN) and Support Vector Machine (SVM) on the

PlantVillage dataset, which consisted of 20,636 images from three different plant types: bell pepper, potato, and tomato, each with different labels. The SVM pipeline involved image preprocessing, segmentation, post-processing, feature extraction, and classification, while the CNN pipeline included image preprocessing, CNN structure design, training, testing, and CNN classification. The results showed that the CNN performance achieved an accuracy of 98.029%, while SVM only reached 57.11% as it performed optimally for binary classification. Based on these findings, it can be concluded that the CNN method produces better performance in this case.

Farisi et al. [7] introduced a system for detecting and classifying diseases in tobacco leaves using the Gray Level Co-Occurrence Matrix (GLCM) technique and Support Vector Machine (SVM). The system performed preprocessing to clean and enhance image quality, feature extraction using GLCM to obtain four features, and outlier detection using the IQR method. SVM was used for classification with an accuracy of 74%. This research demonstrated that GLCM and SVM can be used to detect and classify diseases in tobacco leaves with good results.

Irmak et al. [8] classified tomato leaf diseases using deep learning techniques. The authors used a dataset from Kaggle consisting of a total of 18,345 tomato leaf images, which were divided into training and test sets with an 80:20 ratio. They achieved an accuracy of 97.05% on the test set using their own custom CNN architecture. Although the validation loss fluctuated during training, the training and testing accuracies were nearly the same. This study highlights the effectiveness of using CNN for detecting and classifying tomato leaf diseases with high accuracy.

Rocha et al. [9] explored the use of deep learning technology to address the problem of increasing diseases in maize plants. The authors employed CNN architectures such as AlexNet, ResNet-50, and SqueezeNet, with hyperparameter fine-tuning using Bayesian optimization techniques on batch size, learning rate, and momentum. The research results showed that the ResNet-50 and SqueezeNet models achieved the highest accuracy, reaching 96%. This study highlights the potential use of CNN and Bayesian optimization as a solution to address the issue of increasing diseases in maize plants.

Shah et al. [10] conducted a survey on classification techniques for detecting diseases in rice plants. Two approaches discussed were image processing and deep learning, with classification techniques including SVM, KNN, ANN, and various other techniques. The results showed that the CNN classification technique excelled in pattern recognition problems and achieved a high accuracy of 96%. The authors concluded that deep learning, particularly CNN, is the most effective approach for identifying plant diseases in rice.

Al-Amin et al. [11] developed a prediction system for diseases in potato plants to assist farmers in taking necessary actions. Using the PlantVillage dataset, this research employed a CNN model with their own architecture and achieved an accuracy of 98.33%. The developed system is cost-effective, requires less time, and efficiently predicts plant diseases.

Tiwari et al. [12] used the PlantVillage dataset and a pretrained VGG19 model to develop a plant disease detection system. The developed system achieved an accuracy of 97.8%.

Abbas et al. [13] used Conditional Generative Adversarial Networks (C-GAN) to create synthetic tomato leaf images and applying transfer learning with a DenseNet121 model. They achieved remarkable classification accuracies. Extensively evaluated on the PlantVillage dataset, the method reached 99.51%, 98.65%, and 97.11% accuracy for categorizing tomato leaf images into 5, 7, and 10 disease classes, respectively. This research underscores the effectiveness of their approach in early disease detection, surpassing existing methods.

Agarwal M et al. [14] employed a deep learning technique known as Convolutional Neural Network (CNN). Their CNN model, featuring 3 convolution and 3 max-pooling layers, followed by 2 fully connected layers, outperforms pre-trained models like VGG16, InceptionV3, and MobileNet. It achieves an accuracy ranging from 76% to 100% across different classes and maintains an average accuracy of 91.2% for 9 disease classes and 1 healthy class.

Anandhakrishnan T et al. [15] developed a Deep Convolutional Neural Network (DCNN) model using 18,160 tomato leaf disease images, achieving an accuracy of 98.40% in disease identification. This DCNN approach outperforms traditional methods and contributes to faster and more accurate disease detection in agriculture.

Gonzalez-Huitron V et al. [16] trained and evaluated four Convolutional Neural Network models with 18,160 tomato leaf images, aiming for low-power device compatibility. The research includes quantitative and qualitative analysis with quality metrics and saliency maps, and it implements the models on a Raspberry Pi 4 microcomputer with a user-friendly interface.

Kaur P et al. [17] uses 1610 tomato leaf images from PlantVillage to develop a memory-efficient Deep Learning model, based on Mask R-CNN, for autonomous disease segmentation and detection. By optimizing anchor proportions and feature extraction, they improve detection accuracy. The proposed technique outperforms existing models with an mAP of 0.88, F1-score of 0.912, and accuracy of 0.98 while reducing detection time by half.

Karthik R et al. [18] uses Convolutional Neural Networks (CNN) to learn features. Two deep architectures are used to detect tomato leaf diseases. The first applies residual learning, and the second adds an attention mechanism. Experiments use the Plant Village Dataset with three diseases. The approach uses CNN-learned features with attention and achieves 98% accuracy in 5-fold cross-validation.

Rangarajan AK et al. [19] uses tomato leaf images (6 diseases and a healthy class) from the PlantVillage dataset. They employ two deep learning models, AlexNet and VGG16 net, to examine the impact of image quantity and hyperparameters (minibatch size, learning rates for weight and bias) on classification accuracy and execution time.

Mishra S et al. [20] uses deep neural networks to recognize corn leaf diseases. They enhance the network's performance through hyper-parameter tuning and pooling adjustments, making it efficient for real-time use. The model is optimized for Raspberry Pi 3 with Intel Movidius Neural Compute Stick, achieving 88.46% accuracy. This model can run on standalone devices like Raspberry Pi, smartphones, and drones, aiding in disease recognition.

D. J. M. Bonifacio et al. [21] addresses the challenge of maize diseases in the Philippines by proposing an image processing solution. Utilizing Gray-Level Segmentation and Edge-Detection techniques processed with TensorFlow and Keras, a Convolutional Neural Network identifies common maize diseases. Implemented on a portable Raspberry Pi 3B, the system achieves a remarkable 92.50% overall accuracy and precision rate, providing an efficient method for timely maize disease detection.

A. Yadav et al. [22] proposes an automated image processing method to identify and quantify rust-affected maize leaves. Using morphological operations and area-based thresholding, the algorithm ensures computational efficiency in measuring the degree of crop disease damage. The results show promise for real-time disease detection in the agricultural industry, contributing to the preservation of crop productivity.

M. V. Overbeek et al. [23] propose a system for accurate detection of fungal diseases in maize leaves. Utilizing digital image processing, the Sobel operator extracts shape features, and a multiclass Support Vector Machine with a Radial Basis Function kernel ensures effective detection. The system achieves an impressive identification accuracy of 92.225%.

M. J. Hasan et al. [24] introduces a hybrid CNN-BiLSTM model for early detection and classification of nine prevalent maize diseases. Leveraging a dataset of 29,065 images, with 80% used for training, the model achieves an outstanding 99.02% accuracy. The proposed system ensures reliable AI-based disease recognition, potentially enhancing crop productivity.

Numerous studies have established the pivotal role of Convolutional Neural Networks (CNNs) in plant disease detection. They've shown the power of CNN architectures like MobileNet, VGG16, and DenseNet in achieving high accuracy for identifying diseases in crops like tomatoes, maize, and rice. Some studies compared CNNs to other methods like SVM, concluding CNNs' superior performance. Additionally, innovative approaches like Conditional Generative Adversarial Networks (C-GAN), memory-efficient models, and hybrid CNN-BiLSTM, have been introduced, further advancing disease detection. All these findings underscore the importance of CNNs in this research, where author aim to optimize CNN parameters for mobile-based plant disease detection, addressing a critical agricultural challenge.

3. ORIGINALITY

This research compares the performance of four different deep learning architectures in detecting plant diseases in a mobile application, namely VGG-19, Xception, ResNet-50, and InceptionV3 architectures. The analysis includes validation accuracy and validation loss.

Through grid search method, this study performs parameter optimization on CNN for plant disease detection. The optimized parameters include learning rate and epochs. The experimental results demonstrate a significant improvement in the accuracy of plant disease detection when utilizing parameter optimization with grid search algorithm on CNN.

4. SYSTEM DESIGN

The system design involves three main phases: training, testing, and classification, as illustrated in Figure 1. These phases ensure a structured approach to developing and using the mobile application for plant disease detection.

The training phase involves preparing the dataset, which will be labeled images. Data augmentation is then performed to increase the number of images, followed by image preprocessing to generate images suitable for classification.

In the testing phase, plant images are captured using a smartphone to obtain images of the plants, which will later be sent to the server. Image preprocessing is applied to prepare the images for further processing.

The classification phase consists of the classification using CNN, which will provide the results of the classification of plant diseases and recommendations for addressing those diseases. It is important to note that parameter optimization is performed during this phase.

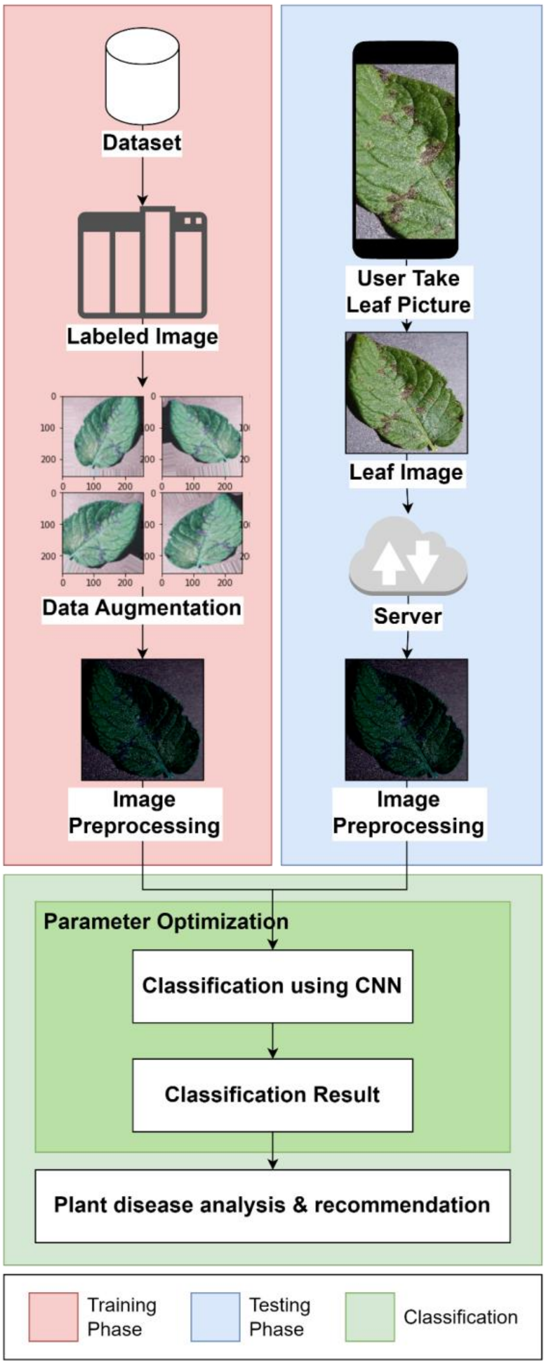

Figure 1. System design

4.1 Training Phase

Before the classification model can be used to classify plant diseases, a training phase is required. These datasets come pre-labeled, providing the necessary information for training the model. You can find detailed specifications for each plant dataset in Table 1.

Table 1. Plant dataset specification

Name	N-Data	N-Classes	Data per Classes
Potato	2152	3	 Early blight (1000),  Late blight (1000),  Healthy (152)
Maize	4188	4	 Blight (1146),

Name	N-Data	N-Classes	Data per Classes
			 Common Rust (1306),  Gray Leaf Spot (574),  Healthy (1162)

The dataset employed in this study was obtained from publicly available sources, namely Kaggle. It is worth noting that this dataset has also been utilized in prior research endeavors, specifically in the research conducted by Al-Amin et al. [11] for potato plants and by Rocha et al. [9] and Mishra et al. [20] for maize plants.

Due to the limited number of images, applying data augmentation to the image data can enhance the model's performance and reduce the chances of overfitting and underfitting. We utilize the ImageDataGenerator library, and the parameters for image augmentation used in the training and testing data are shown in Table 2 and Table 3.

Table 2. Image augmentation parameter for training

Number	Parameter Name	Value
1	rotation_range	25
2	width_shift_range	0.1
3	height_shift_range	0.1
4	shear_range	0.2
5	zoom_range	0.2
6	horizontal_flip	TRUE
7	fill_mode	nearest

Table 3. Image augmentation parameter for testing

Number	Parameter Name	Value
1	Rescale	1./255

Image Augmentation transforms images into multiple variations, effectively expanding the dataset. This process generates several distinct images, each featuring different conditions, as shown in Figure 2. This augmentation technique contributes to a more diverse and robust dataset for model training.

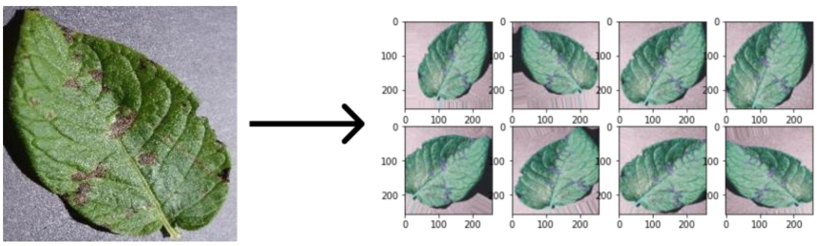

Figure 2. Data after augmentation

After that, image preprocessing is performed on the images to enhance the clarity of disease context in the plant images, reduce noise, and create adjustments so that the images can be accepted as input in the CNN. The results of the preprocessing are shown in Figure 3.

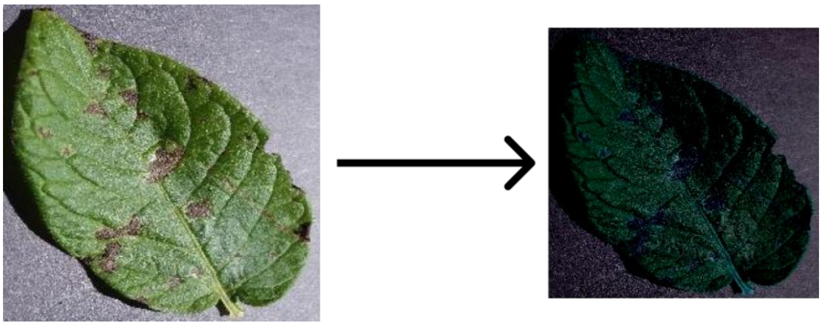

Figure 3. Data before and after preprocessing

4.2 Testing Phase

In the testing phase, the user needs to capture images of diseased plants using a smartphone. The images of the diseased plants are then taken and sent to the server for further processing, as depicted in Figure 4.

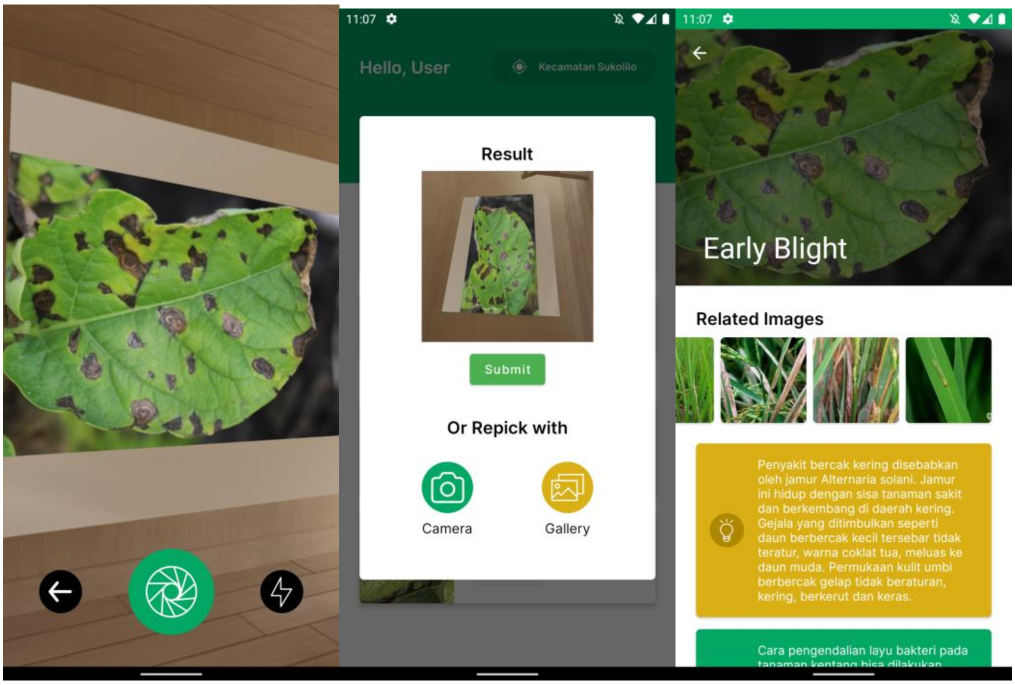

Figure 4. Flow of capturing plant image

Once the images are transmitted to the server, they undergo a crucial preprocessing step. This preprocessing phase is essential for adapting the images to meet the specific input requirements of the Convolutional Neural Network (CNN).

4.3 Classification

In the classification phase, the processed images from the training and testing phases are classified using the CNN model. To divide the dataset during classification, k-fold cross-validation is used.

In this study, four CNN architectures were tested: VGG-19, Xception, ResNet-50, and InceptionV3. After evaluating their performance based on validation accuracy and validation loss, it was found that Xception had the best performance. Therefore, the Xception architecture was used in this research.

Xception is a convolutional neural network (CNN) architecture developed by Francois Chollet in 2016 [25]. It is based on the popular Inception architecture but introduces a new concept called "depthwise separable convolution."

Depthwise separable convolution separates the convolution operation into two separate operations: depthwise convolution and pointwise convolution as depicted in Figure 5. The depthwise convolution applies filters independently to each channel, while the pointwise convolution applies filters to the result of the depthwise convolution.

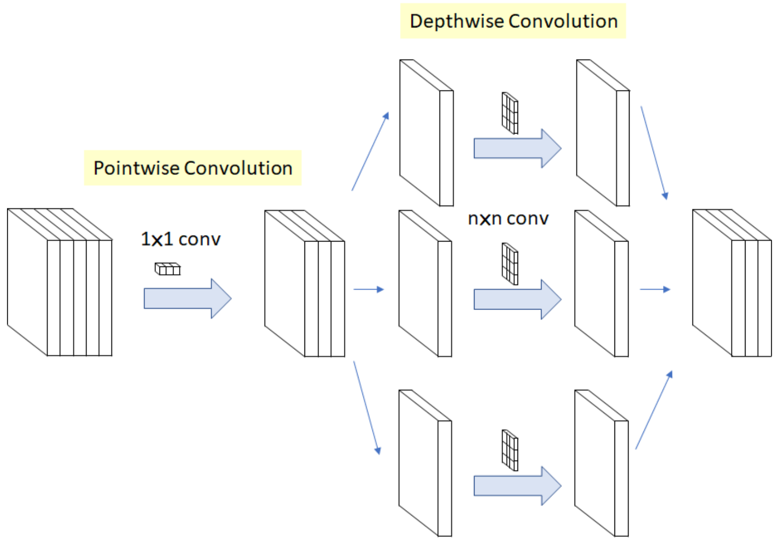

Figure 5. Xception architecture[1]

By separating the convolution operations, Xception achieves higher computational efficiency and reduces the number of parameters required. Additionally, Xception incorporates residual connections, which allow the model to learn more complex features more effectively.

Xception is recognized as a highly efficient Convolutional Neural Network (CNN) model. It boasts impressive performance metrics, making it well-suited for a wide range of tasks, including image recognition and object detection. This versatility and robustness position Xception as a valuable tool in the field of deep learning and computer vision.

It should be noted that during the classification with CNN, there is parameter optimization involving multiple iterations to test the model's

[1]https://towardsdatascience.com/review-xception-with-depthwise-separable-convolution-better-than-inception-v3-image-dc967dd42568

performance. From this series of iterations, the model with the best performance is selected and used.

After the classification is performed, the model returns the disease type and corresponding measures for the input image. These results are then sent back to the user's Android application through the server intermediary.

4.4 Mobile Application

To obtain plant disease classification results, users must utilize the Android application. This app is divided into three screens: the home screen, which appears upon opening the app, the detail screen, which displays disease classification details and recommended solutions, and the camera screen, used for capturing plant images as data for disease classification.

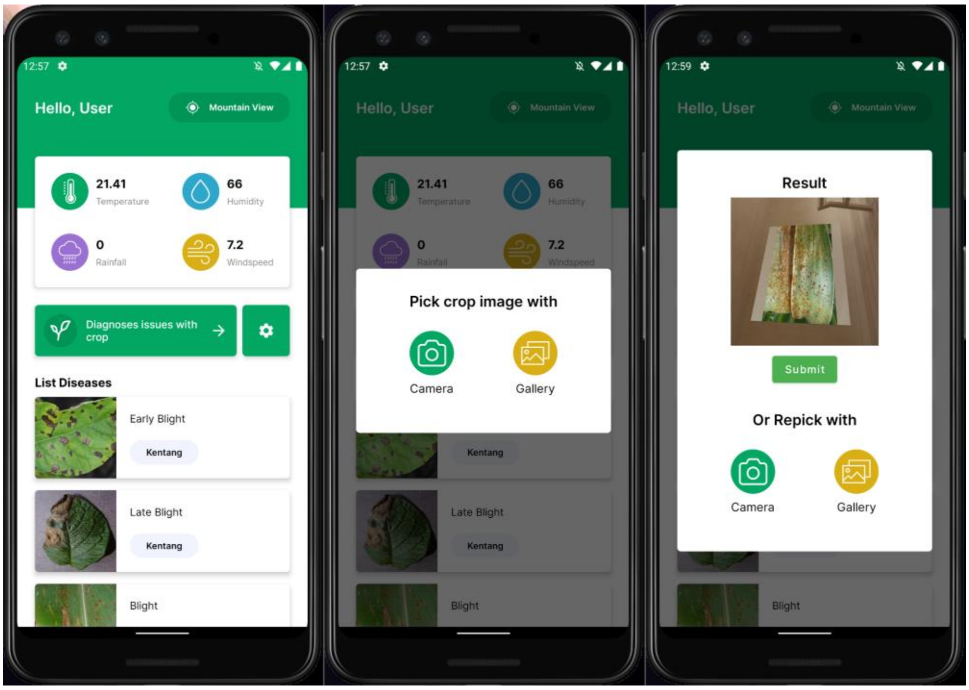

Figure 6. Home screen

On the home screen, as shown in Figure 6, users can access weather and environmental information for their current location, use buttons for disease detection via the camera or gallery, and view a list of available diseases within the app.

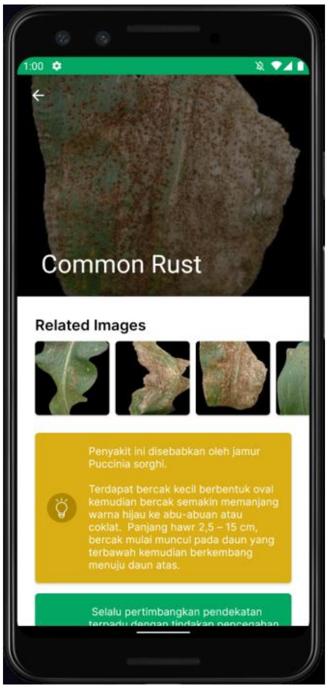

Figure 7. Disease detail screen

In the disease detail screen, as seen in Figure 7, users can access information about the disease's name, view related images, understand its causes, and find suggested remedies. Users will be directed to this screen after the image preprocessing is completed.

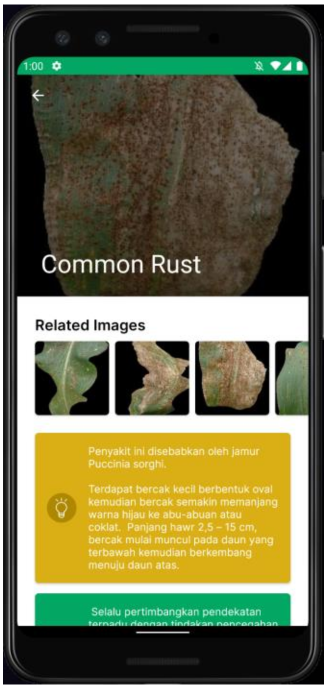

Figure 8. Camera screen

On the camera screen, depicted in Figure 8, users can capture images of diseased plants. These images will then undergo processing to determine the disease type and provide recommended solutions.

5. EXPERIMENT AND ANALYSIS

This section aims to analyze the performance of the CNN model using four different architectures. Additionally, the performance of the trained CNN model will be evaluated by applying transfer learning with Xception, K-fold cross-validation, and parameter optimization such as learning rate and epochs.

The first step is to analyze the performance of the CNN model using four different architectures with default parameters that have been predefined. The purpose is to select the architecture with the best performance. The parameters used are as follows, as shown in Table 4.

Table 4. Default parameter

Number	Parameter	Value
1	Learning Rate	1.00E-06
2	Epoch	15
3	Batch Size	64
4	K-fold N Splits	5
3	Seed	13

The performance results of the CNN architecture comparison are presented in Table 5, which includes validation accuracy values for each architecture. This table serves as a valuable reference for evaluating the effectiveness of the different CNN models in the context of the study.

Table 5. Model performance results for each architecture

CNN Architecture	Best Validation Accuracy	
	Potato Dataset	Maize Dataset
VGG-19	0.937355	0.869928
Xception	0.962791	0.875895
ResNet-50	0.811628	0.830346
InceptionV3	0.763341	0.824373

Based on the analysis, it can be observed that the Xception architecture outperforms the other architectures. Therefore, we have decided to use the Xception architecture for this research.

After selecting the architecture, the next step is to train the CNN model. Here, we compare the performance results of training using default parameters and optimized parameters. The performance results of the model trained with default parameters are shown in Table 6.

Table 6. Model performance result for each dataset

Dataset	Validation Accuracy	Validation Loss
Potato	0.962791	0.175818
Maize	0.875895	0.362875

Table 7 provides the configuration details for training, incorporating the optimized parameters. These settings are instrumental in achieving the improved performance observed in the study's results.

Table 7. Parameter optimization configuration

Number	Parameter	Value
1	Learning Rate	1.00E-4 1,00E-5 1,00E-6
2	Epoch	30 40 50

To determine the most suitable parameters for optimization, the study employed the grid search algorithm, a comprehensive approach to parameter tuning. The results of this iterative process, highlighting the selected parameters, are presented in Table 8.

The training results of the CNN when applying the optimized parameter configuration for the potato dataset are shown in Table 9. We can see that the best model performance is achieved at the 7th iteration with a validation accuracy of 97.9%.

Table 8. List iteration of parameter optimization

Iteration	Learning Rate	Epoch
1	1.00E-04	30
2	1.00E-05	30
3	1.00E-06	30
4	1.00E-04	40
5	1.00E-05	40
6	1.00E-06	40
7	1.00E-04	50
8	1.00E-05	50
9	1.00E-06	50

Table 9. Potato dataset model performance with parameter optimization

Iteration	Learning Rate	Epochs	Validation Accuracy	Validation Loss
1	1.00E-04	30	0.976744	0.071441
2	1.00E-05	30	0.951163	0.139866
3	1.00E-06	30	0.862791	0.508284
4	1.00E-04	40	0.97907	0.068839
5	1.00E-05	40	0.95814	0.135588
6	1.00E-06	40	0.869767	0.439888
7	1.00E-04	50	0.97907	0.070187
8	1.00E-05	50	0.962791	0.121576
9	1.00E-06	50	0.872093	0.428334

Similarly, for the maize dataset, the training results of the CNN with optimized parameters are shown in Table 10, where the best model performance is obtained at the 7th iteration with a validation accuracy of 93.4%.

Table 10. Maize dataset model performance with parameter optimization

Iteration	Learning Rate	Epochs	Validation Accuracy	Validation Loss
1	1.00E-04	30	0.926014	0.176007
2	1.00E-05	30	0.903341	0.2472
3	1.00E-06	30	0.787589	0.549295
4	1.00E-04	40	0.929594	0.176246
5	1.00E-05	40	0.910501	0.230025
6	1.00E-06	40	0.793556	0.518487
7	1.00E-04	50	0.934368	0.16605
8	1.00E-05	50	0.912784	0.237452
9	1.00E-06	50	0.816229	0.463769

From Tables 9 and 10, it can be observed that overall, the generated models have good performance with an average accuracy above 90%. Additionally, it is evident that the learning rate and epochs parameters each have an impact on the resulting CNN model's performance. Based on these results, we can conclude that a learning rate value of 1e-4 and an epoch value of 50 are the optimal parameters for this research.

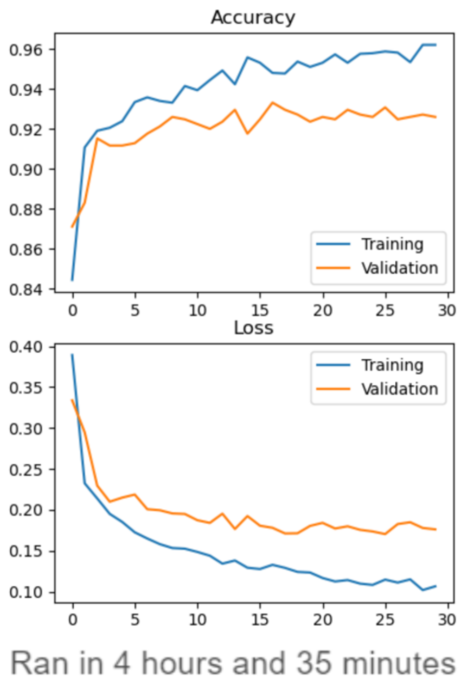

Figure 9. Maize dataset model metrics with parameters 1e-4, 30

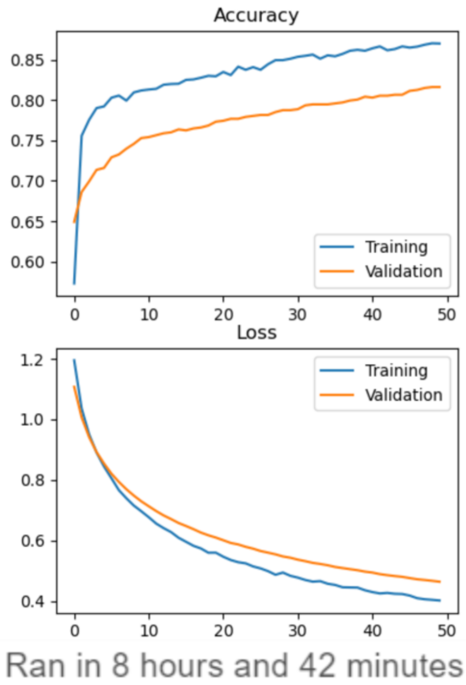

Figure 10. Maize dataset model metrics with parameters 1e-6, 50

In Figure 9 and Figure 10, it can be observed that the values of the learning rate and epochs parameters have an impact on the model's performance. Changing the learning rate affects the convergence speed of the model and the resulting performance. In this case, a larger learning rate will make the model converge faster and provide better performance. However, increasing the learning rate can also lead to higher fluctuations in the metric graphs, as seen in Figure 9 and Figure 10.

On the other hand, changing the value of epochs also influences the model's performance. A larger value of epochs tends to improve the model's performance and reduce fluctuations in the metric graphs, as shown in Figure 10. However, increasing the value of epochs also means an increase in resource usage, such as longer training time. Therefore, when choosing the value of epochs, it is necessary to consider the trade-off between the desired performance and the resource cost involved.

6. CONCLUSION

This research successfully proposed an efficient and accurate disease detection system for potato plants. The generated model is capable to identify the different types of diseases in both potato and maize plants with high accuracy. This detection system has been implemented on a server and Android smartphones, enabling wider and practical usage.

In the model development, we applied transfer learning techniques using the Xception architecture, k-fold cross-validation, and parameter optimization. Through experiments, the performed parameter optimization successfully improved the performance of the generated model. By employing grid search, optimal parameters were found, namely a learning rate of 1e-4 and 50 epochs. As a result, the model's performance on the potato dataset increased from 96.3% to 97.9%, while on the maize dataset, it increased from 87.6% to 93.4%.

The findings of this research demonstrate the high potential of the disease detection system for potato plants to be implemented in agricultural practices. However, there are still opportunities for further development by incorporating additional optimized parameters, such as batch_size, momentum, and the number of folds. By pursuing such advancements, it is expected to yield a better model and strengthen this potato plant disease detection system.

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