OPTIMIZATION OF POTATO LEAF DISEASE IDENTIFICATION WITH TRANSFER LEARNING APPROACH USING MOBILENETV1 ARCHITECTURE

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Abstract—*Diseases affecting potato leaves frequently lead to significant setbacks for farmers, reducing the overall harvest and the quality of the potatoes. Given the critical need for prompt disease detection, this research introduces the use of the MobileNet framework grounded in the Convolutional Neural Network (CNN) for adept detection of potato leaf ailments. During the research, potato leaf images undergo processing, and their distinct features are gleaned using CNN. Then, harnessing the MobileNet framework, these images undergo classification to ascertain the existence of diseases. The aspiration is that the formulated model can pinpoint diseases with notable precision, rapid feedback, and enhanced computational adeptness. Initial findings underscore the potential of this methodology in discerning potato leaf diseases, providing renewed optimism for farmers grappling with plant health issues. Experiments using the Transfer Learning approach showed good performance in classification and displayed a high accuracy rate of 99.2%.*

Keywords: *CNN, disease classification, mobilenet architecture, potato leaf disease, transfer learning.*

Abstrak—*Penyakit yang menyerang daun kentang kerap menyebabkan dampak negatif bagi petani, menurunkan jumlah dan mutu hasil panen. Menyadari urgensi deteksi dini terhadap penyakit ini, studi ini merekomendasikan penggunaan arsitektur MobileNetV1 yang berlandaskan Convolutional Neural Network (CNN) sebagai solusi cekatan dalam identifikasi penyakit daun kentang. Selama proses penelitian, citra daun kentang diolah dan karakteristiknya dianalisa melalui CNN. Berikutnya, dengan bantuan arsitektur MobileNetV1, citra-citra tersebut dikelompokkan untuk konfirmasi keberadaan penyakit. Tujuan dari penelitian ini adalah menciptakan model yang dapat mengidentifikasi penyakit dengan presisi yang tinggi, kecepatan tanggap, dan keefisienan komputasi. Temuan pendahuluan menegaskan bahwa metode ini berpotensi dalam identifikasi penyakit daun kentang, memberikan optimisme bagi petani yang berhadapan dengan masalah penyakit pada tanamannya. Dengan percobaan menggunakan pendekatan Transfer Learning menunjukkan hasil performa yang baik dalam klasifikasi dan menampilkan nilai akurasi yang cukup tinggi, yaitu 99.2%.*

Kata Kunci: CNN, klasifikasi penyakit, mobilenet arsitektur, penyakit daun kentang, *transfer learning.*

INTRODUCTION

Potatoes are known as a type of tuber rich in carbohydrates. In addition, potatoes also contain good nutrients for the body, ranging from antioxidants, vitamins, and minerals (Lesmana et al., 2022). In terms of growth, potatoes are one of the food crops that grow well in the mountainous areas of Indonesia. These factors drive the high production of potatoes in the country, reaching millions of tons. In fact, according to data from the Central Bureau of Statistics (BPS), potato production in Indonesia continues to increase year by year. This was shown in 2022, with potato production in Indonesia amounting to 1.42 million tons. This number increased by 4.21% compared to the previous year's production of 1.36 million tons.

In the cultivation process, there are several aspects that need to be considered so that crop production can run smoothly, including when planting potatoes (Gaikwad & Musande, 2023; Jaya & Sahlinal, 2022). However, in the cultivation process, there are often problems with disease attacks on potato plants, one of which is diseases on potato leaves. If farmers are not careful in monitoring the symptoms of disease on potato leaves, the disease can be a major factor affecting the decline in the quality and quantity of potato crop production.

Early pattern recognition of potato leaf diseases is crucial; an effective approach is needed to detect these diseases to improve production and plant quality. Farmers often face difficulties in identifying diseases in the early stages through traditional methods, especially novice farmers. The ability to detect diseases in the early stage will give farmers an advantage in increasing their harvest. The success of the search and identification process highly depends on the appropriate and accurate keywords in assisting disease recognition through digital searches. Keyword mismatches will result in inappropriate search results. Diagnosing potato leaf diseases in traditional ways is not only at risk of error but also requires slow time. On the other hand, systems supported by technology tend to be faster and more cost-efficient. The development of the industrial revolution 4.0 has had many impacts on various sectors, including agriculture. In the agricultural sector, the existence of digital technology offers various solutions, such as automatic detection of diseases on potato leaves.

Deep learning methods are currently a good solution in the ability to recognize complex patterns and automate the process of image classification (Wani et al., 2022). Using image data from an object to be recognized, it is very possible to use deep learning methods in the training process of pattern recognition on potato leaves. The system will be able to recognize diseases on potato leaves based on the given image data. The Convolutional Neural Network (CNN) is the most efficient part of the Deep Learning method in its ability to select features in images (Anim-Ayeko et al., 2023; Gao et al., 2021; Sharma et al., 2020).

Research on potato leaf diseases has been widely carried out before, and this research is aimed at classifying diseases on potato leaves. Currently, deep learning methods are considered the most appropriate method to develop algorithms capable of categorizing various diseases on an object, including potato leaves (Dasgupta et al., 2020; Saputra et al., 2021). This adopted approach is expected to provide high-accuracy classification results for potato leaf diseases. This CNN model applies multi-layered convolution in extracting and integrating a very large dataset, which distinguishes the CNN model from conventional image classification methods (Khan et al., 2023; Rashid et al., 2021). One of the challenges with using this CNN model is that the data available for image classification is not always abundant. There will be a possibility of imbalance in the number of samples from each class, which can affect accuracy in classification. During the classification process, the application of the transfer learning model can also be used as the basis for a previously trained model, which will facilitate the classification process compared to doing the process raw or from a model that has not been trained before (Akther et al., 2021; Islam et al., 2019; Sagar & Jacob, 2020).

Regarding the research that has been conducted by various researchers, studies related to potato leaf diseases have been conducted by several researchers using different methods and results presented. A study by (M & Kristiyanti, 2023) researched potato leaves using the CNN method and the MobileNetV2 architecture. In their study, due to the unbalanced and limited data amounting to 2,152 colored potato leaf images obtained from the Kaggle repository, the researchers applied a data augmentation technique to address this issue. Thus, in the classification process, the researchers compared results without performing data augmentation and with data augmentation, and also conducted experiments using several Transfer Learning methods, namely InceptionV3, VGG16, InceptionResNetV2, and MobileNetV2. From the results using MobilenetV2 without data augmentation, an accuracy rate of 97.6% was achieved, and by performing data augmentation, an accuracy of 99.6% was achieved. A study by (Arshad et al., 2023) on various objects such as tomatoes, apples, and potato leaves from PlantVillage (Kaggle) yielded an accuracy rate of 94.25% using the PDDPNet method. Research by (Nishad et al., 2022) on potato leaf objects used the CNN algorithm with the VGG16 architecture and a dataset obtained from PlantVillage (Kaggle) and Mendeley totaling 2,580 images, split in an 80:20 ratio for training and testing data. By performing data augmentation, an accuracy rate of 97% was achieved. A study by (Rozaqi et al., 2021a) classified potato leaves with a dataset of 450 images obtained from PlantVillage (Kaggle). By testing several methods, accuracy results were obtained as follows: InceptionV3 78%, VGG16 95%, and ResNet-50 at 78%. Research by (Tiwari et al., 2020) used potato leaf images totaling 2,152 images obtained from PlantVillage (Kaggle).

Using the VGG19 architecture, they achieved an accuracy rate of 97.8%.

After reviewing several previous studies, it was decided that this research would use the Convolutional Neural Network model with the MobileNetV1 architecture to classify potato leaf diseases. The reason for using the Convolutional Neural Network (CNN) method in this research is its efficiency in recognizing complex patterns and automating the process of image classification. Deep learning methods, particularly CNN, are highly effective in utilizing image data for the training process of pattern recognition. In the context of potato leaf disease detection, the CNN model is capable of accurately recognizing diseases based on the provided image data, making it a suitable and powerful tool for this application. In our research, the choice of MobileNetV1 architecture as the foundation of our deep learning model for identifying potato leaf diseases was driven by considerations of computational efficiency, inference speed, and high accuracy (Sharma et al., 2021). With its lightweight design, MobileNetV1 offers significant advantages in terms of computational efficiency and inference spee factors that are crucial for field applications where computational resources are limited and response speed is critical (Howard et al., 2017). Furthermore, in our evaluation of various CNN architectures using the same dataset, we observed that research with MobileNetV2 achieved an accuracy of 99.6% after data augmentation (M & Kristiyanti, 2023). Although this result is similar to our achievement, we assessed that MobileNetV1 provides an optimal balance between accuracy and computational efficiency a crucial quality for implementation on edge devices. The use of the MobileNetV1 architecture in image classification can also be explored in terms of its efficiency in extracting features and optimizing the model size for environments with limited resources, especially when compared to other CNN-based architectures such as VGG16, AlexNet, and others (Suganthi & Sathiaseelan, 2020). This underscores the strategic thinking behind the selection of MobileNetV1, affirming its superiority for field applications of potato leaf disease detection.

MATERIALS AND METHODS

The research method carried out in this study includes several stages, namely, the preparation of the dataset used, the division of training data, test data, and validation data, the design of the classification process architecture, followed by the creation of a model for the classification process.

Datasets

The data used in this study come from a public dataset sourced from Kaggle (https://www.kaggle.com/datasets/rizwan123456789/potato-disease-leaf-datasetpld). The image data utilized consists of 4,072 colored leaf images with a resolution of 256x256 pixels, encompassing three disease classes: EarlyBlight, Healthy, and LateBlight.

Data Split

Once the data was compiled, it was divided into two groups for classification: training data and testing data. The data division ratio adopted is 90:10, where 90% is used for training and 10% for testing. The data breakdown can be seen in table 1.

Table 1. Dataset Distribution

No	Class	Training (90%)	Testing (10%)	Total
1	EarlyBlight	1.465	163	1.628
2	Healthy	918	102	1.020
3	LateBlight	1.282	142	1.424
	Total	3.665	407	4.072

Source :(Rashid et al., 2021)

For validation data, 100 images per class were used or 7.3% of the total images. In this study, data was used without any modifications or augmentation. This decision was made to maintain the integrity of the original data, facilitate the replication of research by other researchers using the same dataset, and evaluate the model under conditions that resemble real-world scenarios, including facing the imbalance in the number of samples among classes that often occurs in application settings. We chose not to implement techniques such as oversampling or undersampling because we wanted to assess the efficiency and effectiveness of the MobileNetV1 architecture in classifying potato leaf diseases under as-is conditions.

Classification Design

After the data division phase, the next step involves the design of the architecture for image classification. The design process begins with the preparation of the dataset as input data, the division of training and test data, followed by the creation of a model using a transfer learning scheme up to the classification results. The scheme of the process can be viewed in figure 1.

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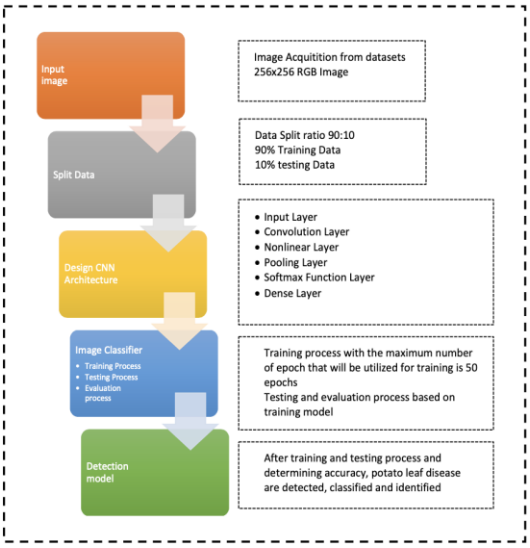


Source : (Research Results, 2023)

Figure 1. General Scheme for Image Classification

The CNN architecture was created using the MobileNetV1 design. Using an image input resolution of 224x224 pixels (Saputra et al., 2021). This resolution choice aligns with the standard resolution of MobileNetV1. The model was developed by running tests using a Conv2D with 32 Kernels and 3 classes. The activation function employed is the Rectified Linear Unit (ReLU), with the Adam compiler, and a loss function using categorical_crossentropy. The results of the classification process will be saved as a model checkpoint, as illustrated in Table 2.

Table 2. MobileNetV1 and Sequential model

Model: "sequential"		
Layer (type)	Output Shape	Param #
Mobilenet_1.00_224 (Functional)	(None, 7, 7, 1024)	3228864
conv2d (Conv2D)	(None, 5, 5, 32)	294944
Global_average_pooling2d (GlobalAveragePooling2D)	(None, 32)	0
dense (Dense)	(None, 3)	99
Total params: 3523907 (13.44 MB)		
Trainable params: 295043 (1.13 MB)		
Non-trainable params: 3228864 (12.32 MB)		

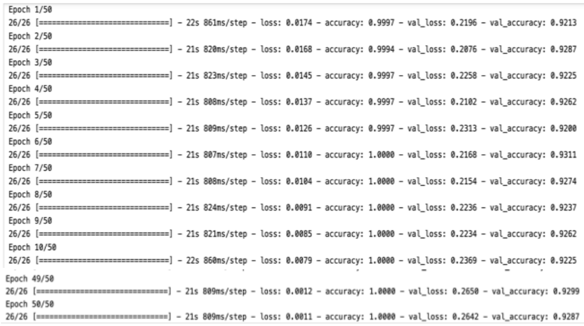
Source : (Research Results, 2023)

RESULTS AND DISCUSSION

The experiments in this study were conducted using Python programming and the Tensorflow framework, supported by the Apple Silicon M1 Pro processor and 16 GB RAM. The training and testing data processes were conducted in two trials. The first trial used an epoch setting of 50, while the second involved hyperparameter tuning.

Training and Testing Results

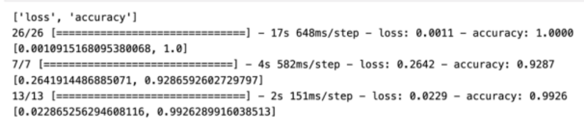
In the first trial, an epoch of 50 was set. An epoch is a specific parameter that describes how many times the entire dataset runs through the CNN model. The classification process's performance on training and validation data using the transfer learning model and an epoch setting of 50 was quite satisfactory.



Source : (Research Results, 2023)

Figure 2. First Experiment Process

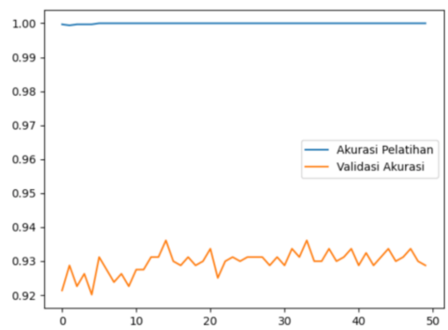
Referring to figure 2, the first trial using an epoch of 50 displayed good training and validation accuracy values. Training accuracy increased to 1.0000 and validation accuracy rose to 0.9287. Similarly, training error dropped to 0.0011, and validation error reached 0.2642. The model evaluation process in Figure 3 showed a final accuracy value of 0.9926 or 99.26%.



Source : (Research Results, 2023)

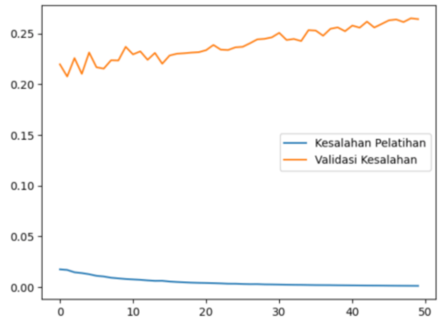
Figure 3. Model Experiment Result (First Experiment)

In Figure 4, the obtained accuracy values showed regular training and testing accuracy values, although the increase wasn't significant. In Figure 5, validation loss appeared stable without significant fluctuations.



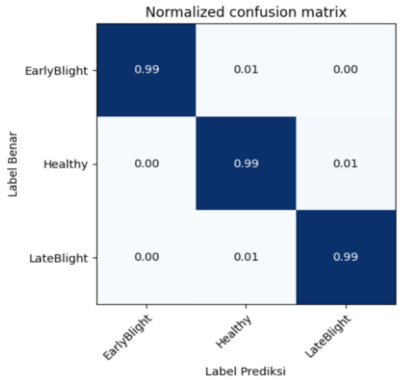
Source : (Research Results, 2023)

Figure 4. Accuracy Value Graph (First Experiment)



Source : (Research Results, 2023)
Figure 5. Loss Value Graph (First Experiment)

Additionally, the evaluation results and confusion matrix from the first trial can be seen in figure 6.



Source : (Research Results, 2023)
Figure 6. Confussion Matrix First Experiment

Considering the confusion matrix in figure 6, an accuracy of 99.2% was achieved. Predicted and actual values can be seen in table 3.

Table 3. First Experiment Classification Performance

	EarlyBlight	Healthy	LateBlight
EarlyBlight	162	1	0
Healthy	0	101	1
LateBlight	0	1	141

Source : (Research Results, 2023)

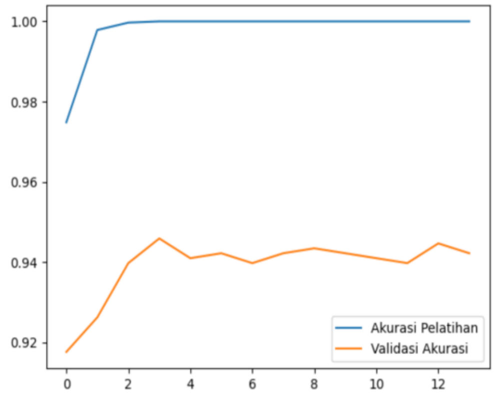
From table 3, it's inferred that the classification results from the first trial were satisfactory, with one error in each class, totaling three errors.

In the second trial, hyperparameter tuning was performed with settings of epoch 50, batch size 64, optimization using the Adam optimizer, setting Categorical Cross Entropy as the loss function, and using "save best" in model checkpoint and early stopping focusing on validation loss, patience 10, and verbose 1. The results are shown in figure 8, where there was no improvement in accuracy and loss on epoch 14, with training accuracy reaching 1.000 and validation accuracy 0.9422, training error 0.0013, and validation error 0.2443.

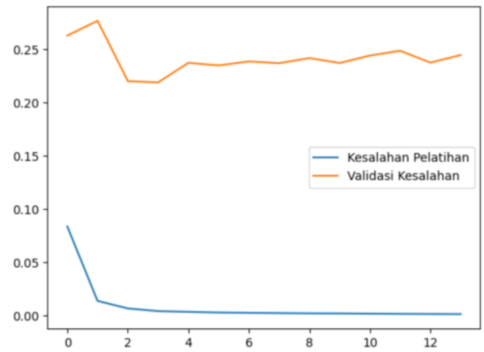
```
Epoch 1/50
26/26 [==============================] - ETA: 0s - loss: 0.0835 - accuracy: 0.9748
Epoch 1: val_loss improved from inf to 0.26252, saving model to best_model.h5
26/26 [==============================] - 22s 830ms/step - loss: 0.0835 - accuracy: 0.9748 - val_loss: 0.2625 - val_accuracy: 0.9176
Epoch 2/50
26/26 [==============================] - ETA: 0s - loss: 0.0136 - accuracy: 0.9979
Epoch 2: val_loss did not improve from 0.26252
26/26 [==============================] - 21s 826ms/step - loss: 0.0136 - accuracy: 0.9979 - val_loss: 0.2765 - val_accuracy: 0.9262
Epoch 3/50
26/26 [==============================] - ETA: 0s - loss: 0.0066 - accuracy: 0.9997
Epoch 3: val_loss improved from 0.26252 to 0.21991, saving model to best_model.h5
26/26 [==============================] - 21s 810ms/step - loss: 0.0066 - accuracy: 0.9997 - val_loss: 0.2199 - val_accuracy: 0.9397
Epoch 4/50
26/26 [==============================] - ETA: 0s - loss: 0.0041 - accuracy: 1.0000
Epoch 4: val_loss improved from 0.21991 to 0.21859, saving model to best_model.h5
26/26 [==============================] - 21s 831ms/step - loss: 0.0041 - accuracy: 1.0000 - val_loss: 0.2186 - val_accuracy: 0.9459
Epoch 5/50
26/26 [==============================] - ETA: 0s - loss: 0.0034 - accuracy: 1.0000
Epoch 5: val_loss did not improve from 0.21859
26/26 [==============================] - 22s 829ms/step - loss: 0.0034 - accuracy: 1.0000 - val_loss: 0.2370 - val_accuracy: 0.9410
Epoch 6/50
26/26 [==============================] - ETA: 0s - loss: 0.0027 - accuracy: 1.0000
Epoch 6: val_loss did not improve from 0.21859
26/26 [==============================] - 21s 820ms/step - loss: 0.0027 - accuracy: 1.0000 - val_loss: 0.2346 - val_accuracy: 0.9422
Epoch 7/50
26/26 [==============================] - ETA: 0s - loss: 0.0025 - accuracy: 1.0000
Epoch 7: val_loss did not improve from 0.21859
26/26 [==============================] - 21s 809ms/step - loss: 0.0025 - accuracy: 1.0000 - val_loss: 0.2383 - val_accuracy: 0.9397

Epoch 13/50
26/26 [==============================] - ETA: 0s - loss: 0.0013 - accuracy: 1.0000
Epoch 13: val_loss did not improve from 0.21859
26/26 [==============================] - 21s 810ms/step - loss: 0.0013 - accuracy: 1.0000 - val_loss: 0.2372 - val_accuracy: 0.9446
Epoch 14/50
26/26 [==============================] - ETA: 0s - loss: 0.0013 - accuracy: 1.0000
Epoch 14: val_loss did not improve from 0.21859
26/26 [==============================] - 21s 812ms/step - loss: 0.0013 - accuracy: 1.0000 - val_loss: 0.2443 - val_accuracy: 0.9422
Epoch 14: early stopping
```

Source : (Research Results, 2023)
Figure 7. Second Experiment Process

In this trial, error values and accuracy can be seen in Figures 8 and 9. Figures 8 and 9 indicate a slight increase in accuracy and a decrease in error values, although not significantly.



Source : (Research Results, 2023)
Figure 8.Accuracy Value Graph (Second Experiment)



Source : (Research Results, 2023)
Figure 9. Loss Value Graph (Second Experiment)

The confusion matrix in the second trial showed improved results compared to the first trial with an accuracy of 99.51%, as seen in Figure 10.

```
['loss', 'accuracy']
26/26 [==============================] - 17s 642ms/step - loss: 0.0011 - accuracy: 1.0000
[0.0011103596771135926, 1.0]
7/7 [==============================] - 4s 568ms/step - loss: 0.2443 - accuracy: 0.9422
[0.2442903220653534, 0.9421893954277039]
13/13 [==============================] - 2s 158ms/step - loss: 0.0281 - accuracy: 0.9951
[0.028144290670752525, 0.9950860142707825]
```

Source : (Research Results, 2023)
Figure 10. Model Experiment Result (Second Experiment)

Predicted and actual values are shown in table 4.

Table 4. Second Experiment Classification Performance

	EarlyBlight	Healthy	LateBlight
EarlyBlight	162	1	0
Healthy	0	102	0
LateBlight	0	1	141

Source : (Research Results, 2023)

In table 4, the confusion matrix classification performance showed reduced errors, with two mistakes found in the EarlyBlight and LateBlight classes.

From the two trials conducted, performance metrics like precision, recall, and f1-score can also be observed in table 5.

Table 5. Classification Validation Performance Metrics

	Class	Precision	Recall	F1-Score
Experiment 1	EarlyBlight	1.00	0.99	1.00
	Healthy	0.98	0.99	0.99
	LateBlight	0.99	0,99	0.99
Experiment 2	EarlyBlight	1.00	0.99	1.00
	Healthy	0.98	1.00	0.99
	LateBlight	1.00	0.99	1,00

Source : (Research Results, 2023)

Performance Comparison

Table 6 displays a performance results comparison between the proposed CNN model and models from previous studies.

Table 6. Comparison between the proposed model and previous studies

Author(s), Year	Algoritma	Dataset	Accuracy
(M & Kristiyanti, 2023)	CNN – MobileNetV2	Kaggle (2.152 Images)	97.6% (without Augmentation), 99.6% (with augmentation)
(Arshad et al., 2023)	PLDPNet	Kaggle (2.152 Images)	94.25%
(Nishad et al., 2022)	CNN - VGG16	Kaggle (2.580 Images)	97%
(Rozaqi at al., 2021b)	CNN – VGG16	Kaggle (450 Images)	95%
(Tiwari et al., 2020)	CNN _ VGG19	Kaggle (2.152 Images)	97.8%
Our proposed work	**CNN – MobileNet V1**	**Kaggle (4. 072 Images)**	**99.5%**

Source : (Research Results, 2023)

CONCLUSION

Considering the importance of agriculture and crops in Indonesia, and given the various plant diseases currently, especially in potato plants, a reliable approach to detecting and classifying diseases in potato leaves can produce accurate results. This research contributes to the field of agricultural technology by developing a highly accurate and efficient model for the detection and classification of potato leaf diseases using the Convolutional Neural Network (CNN) with the MobileNetV1 architecture. With the aid of computer technology and deep learning, this research, utilizing the CNN algorithm with a simple MobileNetV1 architecture, managed to achieve a satisfactory accuracy of 99.5%. This value demonstrates a highly accurate and rapid detection capability against types of diseases in potato leaves. Various trial levels and optimization methods can also be considered for further research with the proposed system. Furthermore, there's hope to develop the proposed model by building an expert system for identification and classification of diseases in potato leaves.

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