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Application of the Mobilenet Model for Pest Detection in Mustard Plants Based on Leaf Imagery

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Abstract

Student mental health is a crucial issue that requires effective and responsive self-monitoring systems. This study aims to develop "LacakJiwa," an Android-based mobile application designed to monitor student mental health through the analysis of daily activity patterns. The method employed is the Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel to classify mental health risks into low and high categories. Input data includes sleep duration, daily step count, gadget usage, and social interaction duration collected from 146 student data entries. The SVM model is integrated into the application using TensorFlow Lite to enable on-device classification, ensuring user privacy through SQLite local database storage. Testing results on 44 test samples showed an accuracy rate of 52.27%, precision of 36.36%, and recall of 22.22%. While the system was successfully implemented technically, the low recall value indicates significant challenges in detecting complex non-linear behavioral patterns in students. This research provides a foundation for developing digital self-control instruments that are adaptive to Indonesian local culture. Mustard greens (*Brassica rapa*) are one of the most widely cultivated vegetables in Indonesia due to their high economic value and nutritional content. However, the productivity of mustard plants often decreases because of pest attacks such as armyworms (*Spodoptera litura*) and diamondback moth caterpillars (*Plutella xylostella*). The process of pest identification that is still performed manually is considered inefficient and prone to human error. Therefore, a technology-based system is needed to automatically and accurately detect pests. This study aims to develop an Android-based pest detection application for mustard plants by implementing the MobileNet model based on leaf images. The method used in this research is Convolutional Neural Network (CNN) with the MobileNet architecture because it is lightweight and efficient for mobile devices. The dataset used consists of 1,380 mustard leaf images, including 1,241 training data and 139 testing data. The research stages include data collection, image preprocessing, MobileNet model training, and model evaluation using a confusion matrix. The results of this study show that the developed application is capable of detecting the condition of mustard leaves, whether healthy or infected by pests. The MobileNet model achieved a training accuracy of 97% and a validation accuracy of 95%–98%, indicating that the model can effectively recognize leaf damage patterns. In addition, the application was successfully implemented on Android devices with gallery, camera, cropping, and automatic detection features, making it easier for users to identify pests on mustard plants quickly and practically.

***Keywords**: Mobilenet, Convolutional Neural Network, Pest Detection, Mustard Plant, Leaf Image, Android*

1. Introduction

The development of agriculture in Indonesia makes Indonesia have many varieties of vegetables, one of which is a vegetable that is in great demand among the community, namely mustard greens. In addition, knowledge about the health benefits of eating mustard greens makes mustard greens an *important export* for Indonesia. According to horticultural statistical data of the Special Region of Yogyakarta, the potential vegetable harvest area of mustard plants in 2016 was 539 hectares and in 2017 it was 438 hectares, meaning that the mustard harvest area decreased by 101 hectares (18.74%). Meanwhile, in 2018 it became 397 hectares, which means that the mustard harvest area decreased again by 41 hectares (9.36%). In 2017, in general, the production of vegetable crops experienced a very significant decline. Among them are mustard greens from the total production in 2016 of 39,105, in 2017 it dropped to 36,305, and in 2018 it dropped to 32,047. The condition where agricultural land is decreasing, especially in urban areas, encourages various kinds of technology and innovation and in developing the agricultural sector [1].

Mustard (*Brassica rapa*) is a popular vegetable in Indonesia. Pest attacks often hamper its productivity, reducing the quality and quantity of the harvest. Accurate identification of pests is essential for effective control. Conventional methods with *observation b* are prone to human error, hence the need for technology to increase efficiency in pest control. However, conventional methods that involve *visual* observation are often less efficient and prone to human error [2]. Mustard leaves have various benefits and uses in daily activities. In addition to vegetable foodstuffs, mustard greens can also be used as a means of treatment. There are several types of mustard vegetable pests that are most commonly found, namely armyworm pests (*Spodoptera litura*), and tritip caterpillars *(Plutela xylostella*) where the damage rate produced by these pests is between 10 to 25%, and some even fail to harvest [3].

With the latest technology, image processing methods and *machine learning* are used to improve accuracy and efficiency in pest identification in agriculture. *Convolutional Neural Network (*CNN) has successfully identified plant diseases and pests [4]. *CNN* is one of

the *machine learning methods* , namely *Multi Layer Perceptron (MLP)* which was developed again. *CNN* is designed to process data from two dimensions. Because *CNN* has a network level and many applications are made in the image, *it* falls into one type of *Deep Neural Network method. CNN* itself has two methods, namely classification with *feedforward* and *backpropogation* for the learning stage [5].
In the field of image processing, the use of *CNN* has proven to be very effective. *CNNs* are a type of neural network that has special convolutional layers that can automatically extract important features from images. *MobileNet* is one of the *CNN* architectures developed by Google. The advantage *of MobileNet* lies in its efficiency in terms of the use of computing resources. This architecture is designed to run well on devices with limited resources, such as smartphones or *Internet of Things (*IoT*)*-related devices. Thus, a technology with an intelligent system designed to be able to automatically identify mango plant diseases and how to deal with them based on *visual* symptoms using *the digital imaging* method [6] *is needed.*
Digital imagery is an image consisting of a two-dimensional matrix that can be processed by a computer consisting of dots called pixels. Each pixel is depicted as a small box on an image. Pixels are a form of reflection of the interstitial of light in the image. In the mathematical relationship between image matrices, it can be written as f(x,y) which will further define the coordinate system in an image. For a structured implementation process, a method is needed as a guide for each process carried out [7].
For this reason, the researcher used a digital imaging method with *the SVM* algorithm, *Convolutional Neural Network (*CNN) as a stage to gain an understanding of disease identification techniques in mustard leaves. The *digital imaging* methods that can be used in disease identification in mustard plants are *the stages of Image Acquisition*, *Preprocessing*, *Segmentation*, Feature Extraction and Feature Selection [8]. Based On The Above Background, The Researcher Is Interested In Conducting Research Entitled "Application Of *Mobilenet* Model For Pest Detection In Mustard Plants Based On Leaf Image"

2. Literature Review

2.1 . Machine Learning

Machine learning is a branch of artificial intelligence (AI) that focuses on developing algorithms that allow computers to learn from data and make predictions or decisions without being explicitly programmed. The main concept is that the model can improve its performance as the trained data increases. One of the key approaches in machine learning is *supervised learning*, where models are trained using labeled data to perform tasks such as classification [10].
Deep learning is a sub-field or branch of *machine learning* that uses artificial neural *networks* with many *hidden layers*. The name "*deep*" refers to the depth of these layers. Deep artificial neural networks mimic how the human brain processes information.
Deep learning is part of *machine learning*. The difference is that *deep learning* can automatically retrieve important traits from data, while ordinary machine learning needs those traits to be determined manually by humans. Therefore, *deep learning* is better used for complex tasks, such as recognizing images or processing large amounts of data. This capability makes *deep learning* particularly effective for complex tasks such as image recognition and analysis of large, unstructured data [11].

2.2. Convulutional Neural Network (CNN)

CNN is a type of *deep learning* architecture that is specifically designed to process image data. The main advantage of CNN lies in its ability to automatically extract important features from *visual* data through a series of layers, so it does not require manual feature extraction.

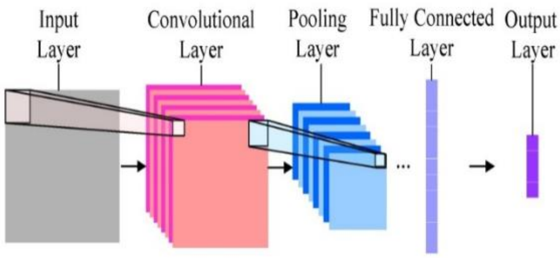

Fig. 1: Algoritma CNN

Figure 1 above shows that CNN is made up of several *different layers, including a convolutional layer*, a pooling layer*, and a fully connected layer.* In the convolution layer, convolution filters are used to extract features from images, i.e. identify patterns or features in the image, such as more complex lines, angles, or shapes. *The Convolutional Layer* is the core layer of CNN where most of the convolutional processes are done here. At this layer, a convolutional mathematical operation is performed between the image input and *a filter* of a certain size. In *the pooling layer*, the data generated on the convolution layer is compressed to reduce the dimensions of the data and speed up processing. On the *fully connected layer*, data that has gone through the convolution and *pooling* layers is further processed to perform classification or regression. CNN has become one of the most popular techniques in *deep learning*, and has been used in many applications such as image classification, image segmentation, facial recognition, and so on [12].

The basic structure of CNN consists of several key layers:
1. The Convolution layer filters the image with a filter so that it can
   Find important features, such as edges, textures, or shapes.
2. The *Pooling layer* functions to shrink the data size so that the calculation is lighter and the model is not easily *overfitting.*

The *Fully Connected layer* works to combine all the features that have already been processed to perform the classification and determine the type of object.

2.3. Mobile Net *Model*

The MobileNet model is an efficient CNN architecture , designed specifically for computer vision applications on devices with limited resources, such as smartphones. It offers high performance with a small file size and low compute requirements, making it ideal for implementation on on-device applications [13].
The advantage of MobileNet lies in the use of depthwise separable convolution. This technique separates standard convolution operations into two lighter steps: depthwise convolution, which applies a single filter per channel, and pointwise convolution, which combines results through 1x1 convolution. This separation drastically reduces the number of parameters and operations, so that the model becomes very fast without sacrificing accuracy significantly [14].

2.4. Mustard Plants

Mustard Plant (*Brassica juncea L.*) is a type of vegetable from the Brassicaceae family that is widely cultivated in Indonesia. Mustard greens are known for their economic value and high nutritional content. In the context of modern agriculture, accurate and rapid identification and monitoring of mustard crop conditions is essential to maintain the quality and productivity of crops. Planting mustard greens (*Brassica juncea L.*) can be done all year round in both cold and hot areas, and are best planted in loose soil with a lot of organic matter content and good irrigation. Mustard greens (*Brasicca juncea L.*) have a lot of content including protein, potassium, carbohydrates, Ca, P, Fe, vitamin K, vitamin A, vitamin B, vitamin C and can live in various places, either in high or low altitudes. However, mustard greens (Brasicca juncea L.) are mostly cultivated in lowlands with an altitude between 5-1200 meters above sea level, both in rice fields, fields, and yard yards.
Mustard greens have specific morphological characteristics, such as oval, notched leaf shapes, and a distinctive green color. However, there are various varieties of mustard greens that have *visual* differences, such as mustard greens and mustard pakcoy. This diversity, coupled with environmental conditions that affect growth and possible diseases, creates challenges in manual *visual* identification , which can be overcome with AI-based recognition systems [15].

2.5 . Confusion Matrix

Confusion matrix is also often called *error matrix.* Basically, *the confusion matrix* provides information on the comparison of the classification results carried out by the system (model) with the actual classification results. *Confusion matrix* is in the form of a matrix table that describes the performance of the classification model on a series of test data whose actual values are known. *Confusion Matrix* to obtain *Accuracy*, *Precision*, *Recall*, and F1 *Score values*. The calculation in *the Confusion Matrix* pays attention to *the values of true positive* (TP), *true negative* (TN), *false positive* (FP) and *false negative* (FN) [16].
Accuracy describes the percentage of all data that is classified as correct in the positive and negative classes so that the calculation process is carried out by dividing all the prediction data that has a correct value with all available data.

	Prediksi Positif	**Prediksi Negatif**
Aktual Positif	TP (Benar Positif)	FN (Salah Negatif)
Aktual Negatif	FP (Salah Positif)	TN (Benar Negatif)

Fig. 2: *Confusion Matrix*

The formula for calculating accuracy based on *the confusion matrix* is:

$$Akurasi = \frac{TP+TN}{TP+FP+TN+FN}$$

$$Recall = \frac{TP}{TP+FN}$$

$$Precision = \frac{TP}{TP+FP}$$

$$F1\ Score = \frac{2\ x\ Recall\ x\ Precision}{Recall\ x\ Precision}$$

3. Research Methods

3.1. Problem Analysis

The following is a *flowchart* of the research procedure carried out can be seen in the following figure 3.1:

Fig. 3: *Flowchart* Research

Procedure Stages The procedure in the research conducted can be seen below:

1. Preliminary study
   The initial stage was carried out to understand the basic concepts related to the research, including the characteristics of mustard plants and pest types, the basic concepts of digital image processing and *the architecture of the Convolutional Neural Network* (CNN), The study also included an in-depth review of *the MobileNet* Model and relevant previous research research.
   Dataset Collection
2. The data used is in the form of mustard leaf images with the name Data Mustard Jirifarm. This dataset is collected from sources derived from https://www.kaggle.com.The *dataset* is downloaded directly through the Kaggle page and contains images of mustard leaves that have been grouped according to their condition, both pest-infected and healthy.
3. Image data analysis
   At this stage, an analysis of the structure, size, and complexity of mustard leaf imagery is carried out to determine *the right preprocessing* technique .
4. *Data Pre-processing*
   The collected image data will go through several initial processes to be ready for use by *the MobileNet* model, including:
   a. Resize the image, so that all images have uniform dimensions.
   b. Normalize, to adjust the range of pixel values to make the model easier to learn.
5. *MobileNet*

MobileNet is the CNN architecture chosen in this study because of its lightweight and efficient nature. This model is specifically designed to run well on devices with computing limitations, such as *smartphones*, while still delivering accurate results.

a. Main Techniques
   MobileNet uses *the depthwise separable convolution technique*, which separates the standard convolution process into two stages, namely *depthwise convolution* and *pointwise convolution.* This separation makes *MobileNet* faster and more resource-efficient without sacrificing accuracy significantly.
b. Research Limitations
   This research is only focused on pest detection in mustard plants (*Brasicca rapa*), and does not include other plants.

6. Model evaluation with *the Confusion Matrix*

Model evaluation is a crucial stage in *Deep Learning* research to measure how well classification models (such as *MobileNet*) can make correct predictions.
The Confusion Matrix is a table-shaped tool used by researchers to display and analyze the performance of classification models in detail. The main functions *of the Confusion Matrix* are as follows:

a. Displaying Predicted Results, this matrix compares the actual class (actual leaf condition, e.g. Healthy or Pest) with the class predicted by the model.
b. Tracking Errors, the matrix not only shows the correct predictions, but more importantly, it details the types of errors the model makes, so that researchers can understand the model's weaknesses specifically.

3.2. Research Instruments and Variable Measurement

The image data used in this study is sourced from https://www.kaggle.com/datasets/bintangpratomo/data-sawi-jirifarm under the name Data Sawi Jirifarm. The dataset is downloaded directly through the Kaggle page and contains images of mustard leaves that have been grouped according to their condition, both pest-infected and healthy.

The dataset used in this study amounted to 1,380 image images with 1241 *training data* and 139 *testing data* used for the model training process and can be obtained through direct scanning or uploading from the gallery application. All of these images are images of mustard leaves which are grouped into two main categories, namely:

1. Mustard Images with Caterpillar Pests
   In this category, the mustard leaf imagery used shows the presence of pests in the form of caterpillars, especially armyworms (*Spodoptera litura*) and tritip caterpillars (*Plutella xylostella*), which are the main focus in the detection process.
2. A Picture of a Mustard Without Worm Pests
   This category includes images of mustard leaves that do not show any pest infestation and are considered to be in good health.

This stage is known as *Image Acquisition*, which is the process of taking and collecting mustard leaf images that will be used as input data in research
this.

The data source was obtained through two methods, namely:
1. The Observation Method, is carried out to determine and select *the dataset* to be used. The process is not in the form of direct physical observation in the field, but rather observation and evaluation of various *publicly available dataset* sources , which is often referred to as a dataset *repository survey*.
2. Literature Study Method, which refers to journal articles and research documents related to the application of the MobileNet model for pest detection in mustard plants based on leaf imagery..

3.3. Developed Methods

The main parameters to be measured and tested in this study are the accuracy of measuring the proportion of correct predictions, both pests and non-pests to the total prediction, the time it takes for the model to provide a prediction of a single image of a mustard leaf, and the classification level of *the MobileNet* model, including:

1. The Depthwise Separable Convolution *action parameter* relates to *the MobileNet* model used to reduce the number of parameters and computation compared to standard full convolution, making the model lightweight and efficient to implement on limited devices.
   a. Number of convolution and *pooling layers.*
   b. Convolutional *kernel* size 3 x 3.
   c. ReLU6 activation function.

2. Training Parameter, this parameter is used to organize the learning process of the model with the data provided.
   a. *Epochs* (number of training iterations).
   b. *Batch Size* (the number of data samples per training iteration).
   c. *Optimizer* : to update the weight of the model.
   d. *Learning Rate*: the amount of steps to change the weight during training.

3.4 System Planning

The analysis methods used in this study include:

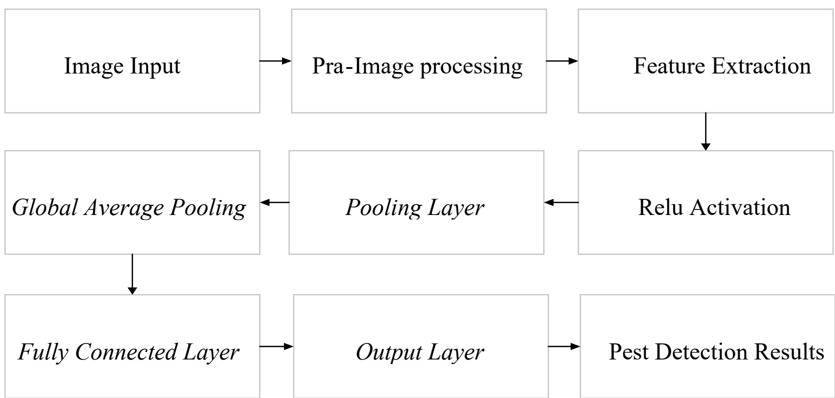

Fig.4: Stages of Analysis

4. Result and Discussion.

4.1. Result

In this chapter, the author discusses the results of the application of the method used in this study, namely the MobileNet model to detect pests in mustard plants based on leaf images. At this stage, the author explained the results of the implementation of the mustard plant pest detection system that has been built in the form of an Android-based application:

4.1.1. Splashscreen Display

The *splashscreen display* is the first page that appears when the user opens the pest detection application on mustard plants

Fig. 5: Splashscreen Preview

4.1.2. Main View

The main display is the main page of the Android-based mustard plant pest detection application. This view serves as a navigation center that makes it easier for users to access the main features of the app.

Fig. 5: Main Display

4.1.3. Gallery View

The Gallery view is a display that functions to allow users to select mustard leaf images stored on the device. By pressing the Gallery button, the application will open the device's gallery so that users can select the mustard leaf image they want to detect.

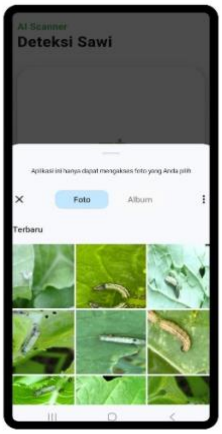

Fig. 7: Gallery View

4.1.4. Cropping Display

After the image of the mustard leaf is taken through the camera, the user can crop the image to adjust the area of the leaf to be analyzed. This feature aims to focus the detection process only on the part of the mustard leaf that is indicated by pests and eliminate unnecessary parts of the image.

Fig. 8: Cropping Display

4.1.5. Results Display

The results button is the main button in this application that is used to display the results of pest detection on mustard plants.

Fig. 9: Results Display

4.2. Discussion

This section discusses the results of a study that found pests on mustard plants based on leaf images taken using the MobileNet model. The discussion was carried out based on the criteria and references that have been set in the previous chapter, which include the pest detection process, ease of use of the application, and the ability of the system to automatically display the results of the detection of mustard leaf conditions.

Users can use this application to find out the condition of mustard leaves, such as healthy leaves or those attacked by pests such as armyworms and tritip caterpillars. In addition, it is hoped that this Android-based application will facilitate a fast and efficient pest detection process

4.2.1. Model Evaluation with *Confusion Matrix*

The model accuracy graph shows that the accuracy of *the* MobileNet model training and validation process is increasing all the time. At the beginning of training, the accuracy of training was still quite low, but after several *epoches* of training, its value increased considerably. The value of training and validation accuracy increases with the number of *epochs*, showing stable results and approaching maximum values. The 97% training accuracy and 95%–98% validation accuracy demonstrate the ability of the MobileNet model to study mustard leaf image patterns in the leaf condition classification process.

In addition, it can be concluded that the model did not suffer *significant overfitting* due to a fairly small difference seen between the training precision value and the validation accuracy value. Therefore, the model is excellent at recognizing new information. Thus, the model has a good ability to recognize new data outside of training data. Figure 4.5 shows a graph of the model's accuracy results.

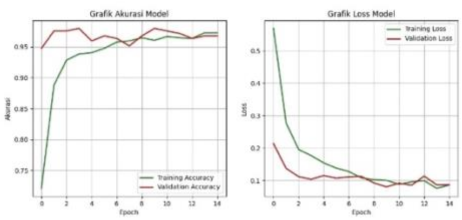

Fig. 10: Graph of the model's accuracy results.

4.2.2 . System Testing with *Black Box Testing*

Black Box *testing* is carried out to verify the functionality of the application from the user side. The purpose of this test is to ensure that each button or feature of the application runs properly and produces outputs that match the design of the interface that has been created.

1. The test was conducted on an Android device. The process includes opening the application, selecting images from a gallery or camera, processing leaf images using the MobileNet model, and displaying the results of the mustard leaf condition detection by the system.
2. Black Box *Test Results Table*
   Table 4.1 Here are the key feature testing details on the app:

Tabel 1: ***Black Box* Testing**

No	Features or Buttons	*Test Case* (Aksi)	The results Expect	Results Testing	Conclusion
1	*Splashhcreen*	Open First application Time	Displays the logo and app name for a few seconds and then moves to the main menu automatically	Conform Hope	Valid
2	Buttons *Gallery*	Press the "Gallery" button in the main menu	The app manages to enter the phone's gallery storage to select a mustard leaf image	Conform Hope	Valid
3	Camera Button	Press the "Camera" button in the main menu	The camera is active and can be used to take pictures of mustard leaves directly	Conform Hope	Valid
4	Cropping Button	Choosing a mustard leaf area after selecting a photo	The image was successfully cropped according to the area of the box that the user chose to focus on.	As Expected	Valid
5	Results	Performing the mustard leaf detection process	The system displays the results of the classification of leaf conditions, such as healthy leaves or pest infested	As Expected	Valid

4.2.3. Advantages and Disadvantages of the Application

The advantages of the application built are:

1. Using a lightweight and efficient MobileNet model in performing the image detection process on Android devices. This model is able to automatically recognize the pattern of damage to mustard leaves based on the texture, color, and shape of damage caused by pest attacks.
2. Able to detect the condition of mustard leaves from images entered by users, either through *the Gallery* and *Camera* features directly.
3. Displays the results of the classification of leaf conditions, such as healthy leaves or pest-infested leaves, so users can easily identify pests.
4. The implementation of the system in the form of an Android application makes it easy for users to access and use the application practically through a mobile device anytime and anywhere.
5. The app is very easy to use. The user only needs to select or take a picture of the mustard leaves, and the system will automatically detect them. Interface aplikasi dirancang So it is easy to understand by people without special technical knowledge of artificial intelligence or digital image processing.

The weaknesses of the application built are:

1. Image preprocessing is still not optimal, so some leaf images have *poor noise* and lighting that can affect the accuracy of pest detection.
2. The number of mustard leaf imagery datasets used is still limited, both from the variety of leaf conditions and pest types, so that the performance of the MobileNet model in the classification process has not been maximized.
3. The method used is still limited to one deep learning approach, so the system's ability to recognize leaf damage patterns due to pests still has limited accuracy.
4. The classification system in the application is still limited to the detection of armyworms and tritip caterpillars, so it cannot recognize other types of pests and diseases of mustard plants more broadly.
5. The available application features are still simple and not equipped with pest handling information, plant care tips, and detection history, so the benefits of the application for users are still limited.

5. Conlusions and Suggestions

5.1. Conclusion

The conclusions of this study are as follows: The conclusions of this study are as follows:

1. An Android-based mustard plant pest detection application using the MobileNet model has been successfully designed and can be used to detect pests on mustard leaves based on leaf imagery with detection results in the form of detected pests and healthy mustard greens.
2. The use of the MobileNet model has been proven to be able to recognize patterns of damage to mustard leaves based on the texture, color, and shape of damage caused by pest attacks. This model is able to efficiently perform the leaf image classification process on Android devices, although the detection success rate is still affected by the quality of the image entered by the user.

5.2. Suggestion

Although the application of pest detection on mustard plants has been running well, there are still several aspects that can be further developed to make the system more optimal. Some suggestions that can be given for further research and development are as follows:

1. Optimization is needed at the image preprocessing stage, such as improving image quality and reducing noise, so that pest detection results become more accurate.
2. It is necessary to increase the number of mustard leaf imagery datasets with a greater variety of leaf conditions and pest types so that the MobileNet model can produce more optimal classification performance.
3. It is necessary to develop methods using *transfer learning* techniques or a combination of other deep learning models to improve the accuracy of the system in recognizing leaf damage patterns due to pests.
4. It is necessary to add other types of classification of pests and plant diseases so that the application not only detects armyworms and tritip caterpillars, but can also be used to detect various disturbances in mustard plants.
5. It is necessary to develop additional features in the application, such as providing pest management information, plant care tips, and detection results history so that the application becomes more informative and useful for users.application are aligned with applicable clinical diagnosis standards sentence use, is needed.

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