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Implementation Of Cnn Mobile Netv2 For Classification And Detection Of Diseases In Banana Plants Through Leaf Images

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Abstract

Banana plants are vulnerable to disease attacks, especially in remote areas with limited access. Banana farmers struggle to identify and classify types of diseases on banana plants early on due to limited information about the types of diseases and the characteristics of diseases that attack bananas.**The purpose** of this study is he development of a CNN model with a MobileNet architecture for the classification and detection of diseases through banana leaf images, which can be implemented in an Android application. **The method** used applies a Convolutional Neural Network (CNN) using the MobileNetV2 architecture that can help classify banana plant diseases. The banana leaf image dataset was obtained independently and additionally from the Kaggle platform up to 4135 images. The images were then divided into 6 classes consisting of healthy leaves, panama disease, moko disease, leaf pests, yellow sigatoka and black sigatoka. The image dataset was then divided again into 3 parts: training data, validation data and test data with a data division of 80:10:10. **The results** showed that CNN with MobileNetV2 architecture can be used for disease classification and detection with an accuracy rate of 87.26% for the test data, 89,59 for validasi and 92.71% for the training data. This model was successfully implemented on the Android platform using Android Studio to detect banana plant diseases in real time without special tools.

Keywords : *CNN, Classification, Image, Banana, Plant Disease*

1. INTRODUCTION

Banana is the world's second largest fruit crop and one of the most traded and consumed fruits according to the Food and Agriculture Organization of the World [1] and it is the most favored fruit by the Indonesian people due to its sweet taste and affordable price [2]. Unfortunately, banana plants are often susceptible to various diseases caused by fungi, bacteria, and viruses, resulting in significant losses for banana farmers [3], [4]. Banana diseases initially attack the banana leaves, and in the early stages it is difficult to distinguish with the naked eye, due to farmers' lack of knowledge about the pathogens and types of diseases that affect bananas [5],[6]. The most common diseases in banana plants are caused by leaf wilt due to Fusarium wilt, Xanthomonas wilt, tip rot, and pest attacks from stem borers. [7],[8].

Banana farmers often face problems in identifying the types of diseases on banana leaves due to a lack of knowledge about the types of banana diseases and the proper ways to handle them. Recent advances in deep learning, especially Convolutional Neural Networks (CNN), are highly trusted in disease identification for agriculture [9],[10],[11],[12]. The use of deep learning technology for classification produces high classification performance results [13],[14], [15], [16]. Deep learning is a subset of machine learning, employs artificial neural network architectures with a large number of processing layers

Early identification of plant diseases can help farmers recover crop yields [4] and minimize financial losses by allowing them to quickly recognize the condition and take necessary action before it worsens [17]. This research aims to build a mobile application that applies the CNN method to identify 6 types of diseases in banana plants, including: *Black Sigatoka* (Sigatoka Hitam), *Yellow Sigatoka (*Sigatoka Kuning), Insect pest disease (Hama Daun), Moko (Moko Disease), and Panama. This research was conducted to support artificial intelligence technology in disease detection in banana plants.

With the advancement of technology, deep learning architectures, particularly Convolutional Neural Networks (CNNs), have increasingly been adopted to improve the accuracy of disease classification in plant leaf images [18], [19]. Syenira Sheila conducted a study titled 'Detection of Rice Leaf Diseases Based on Image Processing Using the CNN Method with the InceptionV3 Base Model,' achieving a test accuracy of 93.75% with a loss value of 0.3076 [20]. Esearch using a different method by Yuliati in 2022 discussed classification using the SVM (Support Vector Machine) Method, with the classification results in that study reaching an accuracy of 89.86% [21]. Esearch related to this was also conducted by Karina Dhena, et al., who implemented the Forward Chaining Algorithm in an Expert System for Diagnosing Pests and Diseases in Banana Plants, which was able to provide accurate results based on the symptoms inputted and could apply existing rules to reach a conclusion [22]. Research using the same method by Sonnya Ghandi, et al. in 2024, entitled 'Application of the Convolutional Neural Network (CNN) Method in an Android-Based Potato Leaf Disease Detection Application,' shows that the CNN method was successfully applied to the Android-based potato leaf disease detection application, achieving effective detection and classification results [23]. Supported by research, Ulfa Khaira conducted detection on corn plants through an Android-based leaf image using the Convolutional Neural Network (CNN) algorithm, employing the MobileNetV2 architecture, achieving an accuracy of 99% for leaf blight disease, 100% for leaf rust disease, and 100% for healthy leaves [24]. In research conducted by Chen et al. (2025) and Dolatabadian et al. (2025), the authors reviewed various literature on image-based plant disease detection using machine learning covering various types of plant diseases [25], [26].

From previous research, it can be seen that the CNN model can be used for the process of classification and disease detection in banana plants . Using the same CNN method, but with a larger dataset of 4135 and more diverse classes (6 classes), this study attempts to apply the CNN method with the MobileNetV2 architecture for classification and disease detection in banana plants up to the stage of implementation in an android application. In previous studies, the model classes generally consisted of only 3 or 4 disease classes, with a smaller dataset. This study proposes 6 classes for disease detection in banana plants: 5 disease classes and 1 class for healthy leaves. The application testing was carried out by directly taking pictures of banana leaves in the banana farmers' yards.

By using the lightweight and fast MobileNetV2 architecture, banana leaf disease detection can be carried out in real-time through an Android application without requiring heavy hardware. This is very helpful for farmers or related parties to practically and efficiently use technology without having to rely on special devices or additional tools.

2. METHOD

The research flow designed in this study goes through several stages. These stages are carried out to ensure that the resulting CNN model has optimal performance in terms of accuracy, precision, and computational efficiency. The research stages conducted can be seen in Figure 1.

2.1. Data Colection

The dataset collection process was carried out independently by collecting leaf images directly from farmers' gardens. The independently collected dataset consisted of 2,000 data points, but this was considered insufficient for developing the application, so additional datasets were obtained from the Kaggle platform until reaching 4135 datasets. This dataset was then divided into 6 classes, consisting of 1 class for healthy leaves and 5 classes for leaf diseases. The data exploration process included checking

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image resolution, class balance, and the visual clarity of disease symptoms on the leaves to ensure the data quality was suitable for model training.

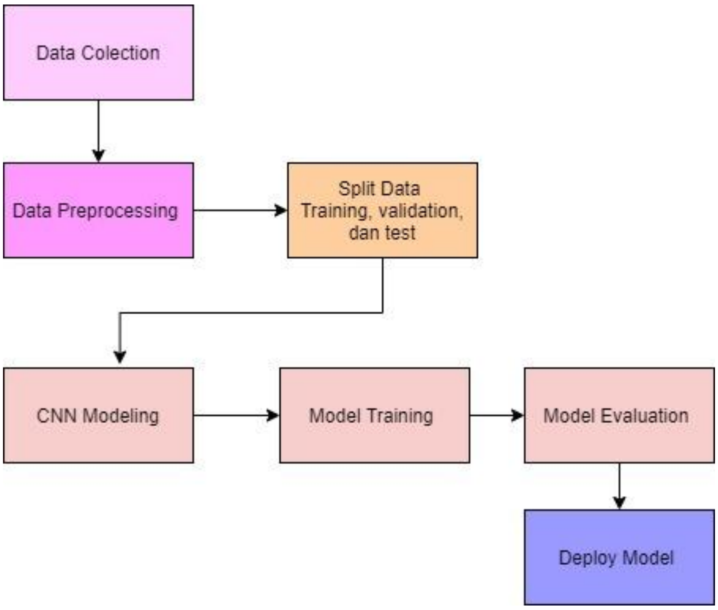

Fig 1. Researh Method

2.2. Data Presprocessing

At this stage, a series of image preprocessing steps are carried out. All images are resized to 224x224 pixels and normalized to a value range between 0 and 1. Class labels are converted into numeric format using LabelEncoder, and then One-hot Encoding is applied to match the model's input format. Next, the dataset is split into training, validation, and testing data with an 80:10:10 ratio in a stratified manner. To address the limited amount of data, image augmentation techniques such as rotation, horizontal flipping, zoom, and positional shifts are applied to increase image variability and improve the model's generalization capability [27]**.** The dataset is divided according to the number of classes, for leaf pest diseases, yellow sigatoka, black sigatoka, Panama disease, moko/banana blood disease, healthy leaves, and leaf pests. The distribution of this dataset by class can be seen in Figure 2.

2.3. CCN Modeling

This study applies CNN with MobileNetV2 architecture designed to recognize visual patterns on banana leaves, both infected and uninfected. The types of diseases detected consist of 5 types of diseases and 1 class for healthy leaves. The classification consists of 6 classes, namely healthy leaves, panama, moko, yellow sigatoka, black sigatoka, and insect pests. The mobile net V2 architecture consists of several convolutional layers that function to extract features from images, pooling layers to reduce dimensions, and fully connected layers that are used to classify images based on features [12], [28]. The use of the MobileNetV2 model will produce image representations related to the types of diseases on banana leaves and provide accurate predictions.

2.4. Model Training

This training phase uses the MobileNetV2 architecture to detect diseases in banana plants through images of banana leaves. The dataset consists of images of banana leaves labeled according to categories, namely healthy leaves, moko disease, Panama disease, leaf pests, black sigatoka, and yellow sigatoka. During training, the model learns the unique patterns and specific visual features of each category [27]. During the training process, metrics monitored include accuracy and loss to regulate

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training and validation. However, for better analysis of multi-class (6-class) problems and synchronization, precision, recall, and F1-score per class are also calculated, as well as a confusion matrix to see patterns of misclassification between categories (e.g., whether yellow sigatoka is often confused with black sigatoka or whether moko disease is the same as Panama). Interpretation of the complexity matrix helps identify visually similar class pairs that require data enrichment, additional features, or preprocessing adjustments.

2.5. Model Evaluation

The next stage is model evaluation to assess its performance in identifying banana leaf diseases. Evaluation is carried out using an accuracy metric to measure the percentage of correct classifications [29]. Accuracy is calculated based on the number of correct predictions divided by the total number of samples tested. This evaluation is carried out on test data separate from the training data, to ensure that the model is able to generalize well on data that has not been seen before. The evaluation results in this study will produce a percentage that indicates good performance in identifying banana leaf diseases. The following (1) is the formula used to calculate accuracy

$$\textbf{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

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

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

$$\textbf{F1 Score} = 2\,\frac{Precision.Recall}{Precession+Recall}$$

2.6. Deploy Model

The final stage is the model that has gone through the evaluation stage and then implemented into the system. The trained MobileNetV2 model is saved in .h5 format and then converted to tflow format using Google Colabs. The model is then integrated into an Android-based mobile application with the Tensor Flow framework and application development using Android Studio. Once the model is successfully implemented, users can upload an image of a banana leaf via smartphone and the system will run the classification model, then display the detection results on the application's display page in real-time. This entire process is done locally without the help of additional tools, so users in areas with limited internet connections can still benefit from AI-based disease detection technology.

3. RESULT

This study used the MobileNetV2 architecture as the base model for developing a banana plant disease classification and detection application. The initial research process involved grouping the dataset, which had been divided into disease and healthy leaf classes. The dataset was divided into three parts: training data, validation data, and test data, divided in an 80:10:10 ratio. The appropriate proportions between training, validation, and test data were used to ensure balance and diversity in the learning model. This dataset division was performed using Python code with the help of Google Colabs to randomly separate the data based on its class. After the model was completed, the android application and its features were developed

3.1. Data Collection

The dataset used in this study was taken from images of banana leaves directly in farmers' gardens and approximately 2000 additional datasets were taken from several sources on the Kaggle platform. This

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dataset is divided into 6 classes, namely healthy leaves, Panama, Moko, leaf pests, black sigatoka disease, and yellow sigatoka. The collected dataset of 4135 that has been collected is divided again into folders based on predetermined classes. This dataset is further divided into three subsets, 80% for training, 10% for validation, and 10% for testing to support the optimal model process. Dataset details are presented in Table 1.

Table 1. Dataset Division Results

Disease Name	Training	Validation	Test
Healty Leaf	619	77	78
Insect Pest	669	84	84
Moko Disease	143	18	18
Panama	666	83	84
Yelow Sigatoka	481	60	61
Black Sigatoka	728	91	91

3.2. Data Preprocessing

The preprocessing stage is carried out to identify the images in the dataset and initialize the ImageDataGenerator as part of data preprocessing for model training preparation. The first step is to specify the location of the folder containing the image dataset, which will be used in model training. The divided image dataset folder is then stored on Google Drive. After that, the ImageDataGenerator is initialized, which is used to perform image processing techniques. Normalization is done by changing the pixel values of the images from the range 0-255 to 0-1 using the parameter rescale=1./255, which aims to allow the model to process data more efficiently to prevent overfitting. Meanwhile, augmentation, which includes operations such as rotation, zoom, and horizontal flipping, aims to create image variations so that the model can learn from a wider range of conditions.

The segmented images are then resized to 224x224 pixels and grouped by class category, according to a predefined folder structure. This process ensures that the dataset is ready for model training, with the data having been processed through normalization and augmentation to enable the model to learn better. The following is a breakdown of the data preprocessing process, as seen in figure 1

Figure 2. Visualisasion dataset image

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3.3. CNN Modeling

The implementation of the MobileNetV2 architecture for recognizing input images involves a series of feature extraction and visual analysis processes. The initial process is carried out with an initial convolutional layer, which is responsible for capturing the basic patterns of an image, such as texture, color, and edges. The model uses inverted residual blocks with shortcut connections, allowing the model to retain important information from the input image while reducing the number of parameters used. The depthwise separable convolution layers applied in this architecture help improve efficiency by separating spatial convolution and channel convolution processes, so the model remains lightweight yet still capable of capturing intricate feature details. In the final convolutional layer, the Softmax activation function is used to generate probabilities for each class [30], such as healthy leaves, Panama, moko, leaf pests, yellow sigatoka, and black sigatoka.

2.7. Data Training

The training dataset is used in the model training process to introduce data patterns such as texture, color, and edges of an image so that the model can understand the relevant features to make predictions. In this study, the training dataset contains images of banana leaves categorized into six classes, namely 1 for healthy leaves and 5 for disease classes.

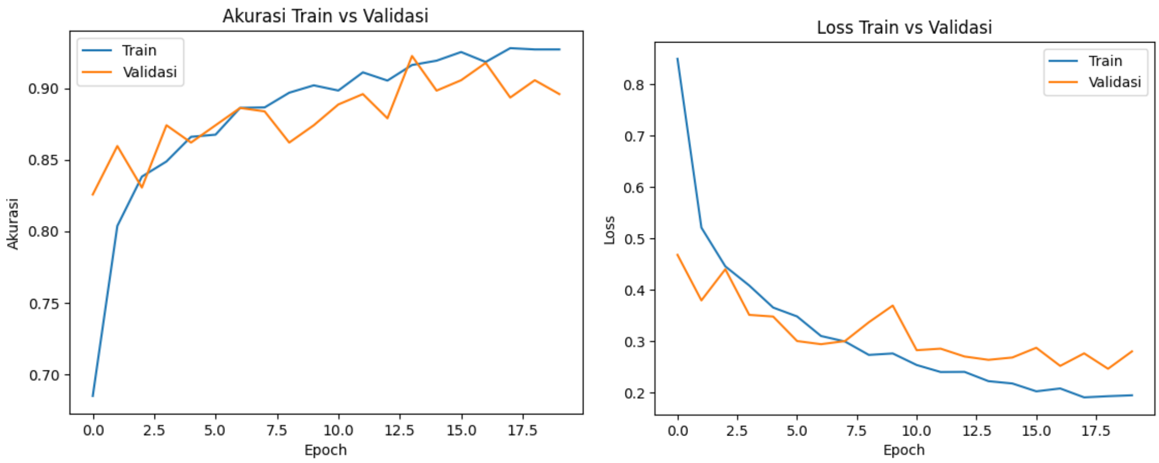

Fig. 3 Akurasi Train and validasi

Figure 3 is a graph showing the changes in accuracy and loss during model training, providing an overview of the learning process occurring in the MobileNetV2 used. In the first epoch, accuracy started at around 51.3%, indicating that the model was still in the early stages of learning and not yet capable of effectively identifying data patterns. As the epochs progressed, accuracy gradually increased, reaching about 91.78% in the 20th epoch, showing that the model became increasingly capable of recognizing patterns in the data and producing more accurate predictions. This steady increase in accuracy indicates an effective training process. Meanwhile, the loss value decreased from 1.33 in the first epoch to 0.2067 in the 20th epoch. This decrease in loss demonstrates that the model became more efficient at reducing prediction errors, indicating that the model was successfully optimized to minimize errors on the training data.

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3.5. Model Evaluation

A Convolutional Neural Network (CNN)-based classification model using the MobileNetV2 architecture was evaluated using validation and test data to measure the model's generalization performance. During the training process, the accuracy and loss values showed a steady upward and downward trend, indicating that the model was able to effectively learn feature representations. On the validation data, the model recorded high accuracy values 0,9278 (92, 78 %) and relatively low val_loss 0,27899 values, indicating that the MobileNetV2 architecture is suitable for use in the visual feature extraction process on the used dataset.

Further evaluation using test data shows that the model has good generalization ability, with accuracy values consistent with the performance on the validation data. The resulting confusion matrix shows that most classes can be predicted correctly, although there are still some misclassifications in classes with high visual similarity such as black sigatoka and yellow sigatoka. The precision, recall, and F1-score values obtained for each class also show balanced performance, and prove that MobileNetV2 is able to identify objects optimally in the banana leaf image recognition scenario. Overall, these evaluation results indicate that the MobileNetV2 model is an efficient and effective architecture for image classification tasks with varying visual complexity. The results of the classification report to see the model's capabilities per class can be seen in Figure 4.

```
Confusion Matrix
[[64  0  0  9  1  4]
 [ 1 83  0  0  0  0]
 [ 0  0 17  1  0  0]
 [ 0  0  1 82  0  1]
 [ 0  1  0  5 45 10]
 [ 1  0  0  3 15 72]]

Classification Report
                  precision    recall  f1-score   support

     Daun Sehat       0.97      0.82      0.89        78
      Hama Daun       0.99      0.99      0.99        84
  Penyakit Moko       0.94      0.94      0.94        18
Penyakit Panama       0.82      0.98      0.89        84
  Sigatoka Hitam      0.74      0.74      0.74        61
Sigatoka Kuning       0.83      0.79      0.81        91

       accuracy                           0.87       416
      macro avg       0.88      0.88      0.88       416
   weighted avg       0.88      0.87      0.87       416
```

Fig 4. Clasification Report

3.6. Deploy Model

The trained MobileNetV2 model, saved in .h5 format, is integrated into the Android platform using Android Studio. The system workflow is as follows:

1. The user uploads an image of a banana leaf via smartphone or can also take an image already available on the mobile device.
2. The Flask API processes the image using the MobileNetV2 model.
3. The prediction results can be viewed in real time.

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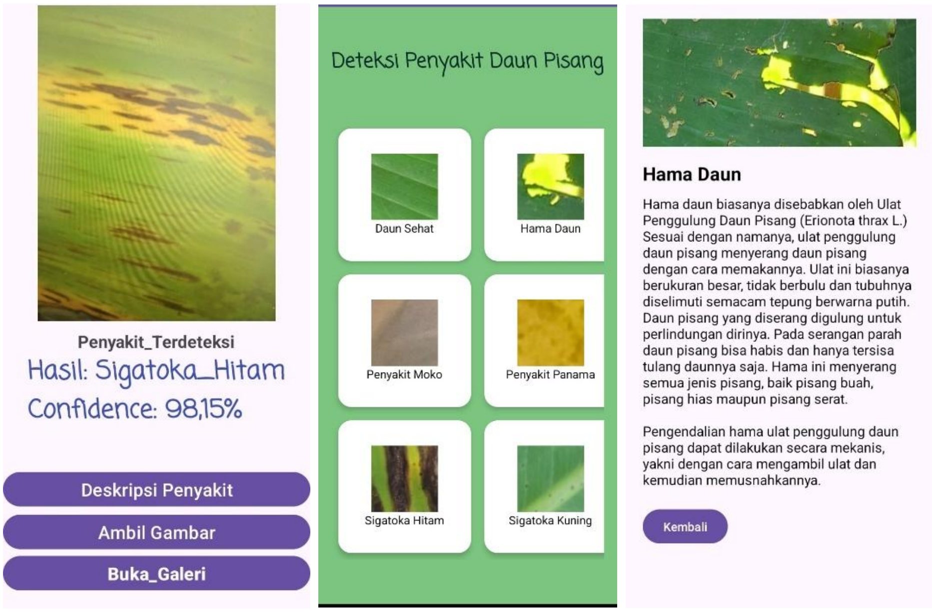

Fig. 5 Aplication Mobile

The model was successfully implemented into the application system using the android platform. The model successfully read the data correctly.

Figure 5 shows the application display, which includes the initial menu for disease detection. When the user presses the "Open Camera" button, they will be prompted to go to the gallery menu and select the banana leaf image they want to detect. Once the image is selected, the detection results will appear in real time in the application. After knowing the detection results, the user can proceed to the next menu, the "Check Disease" page, to learn more about the disease and its treatment.

3. CONCLUSION

This research aims to develop a CNN model with the MobileNetV2 architecture implemented on the Android platform. The CNN Mobile Net V2 model was successfully implemented on an Android device with an accuracy rate of 87.26% for test data, 89.59% for validation and 92.71% for training data. This approach emphasizes computational efficiency, ease of access, and classification accuracy, so that the application can be used directly in the field by farmers and agricultural managers. This approach emphasizes computational efficiency, ease of access, and classification accuracy, enabling the application to be used directly in the field by farmers and agricultural managers. Therefore, this research is expected to make a significant contribution to strengthening national food security through effective and accessible early detection of banana plant diseases. This application not only detects banana plant diseases but also includes features for identifying preventive and treatment measures. This study supports the transformative potential of deep learning in advancing agriculture, serving as a vital tool for early disease detection, and contributing to food security in banana-growing regions, particularly smallholder farming systems.

However, despite the promising results, significant challenges still exist in developing a reliable mobile net CNN model for leaf disease detection, including the limited availability of labeled data, class imbalance, and environmental variations. Future research should address dataset limitations by integrating advanced data augmentation techniques, including additional plant diseases, and leveraging smart agriculture technologies to enhance real-world applications. By overcoming these challenges, deep learning-based disease detection models can strengthen agriculture and contribute to sustainable farming practices.

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