Analysis for Detecting Banana Leaf Disease Using the CNN Method

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Abstract - Banana farmers face major challenges due to banana leaf diseases such as Cordana, Pestalotiopsis and Sigatoka, which severely affect the quality and quantity of the crop. Early detection of these diseases is particularly challenging as the initial symptoms are often similar to other disorders. To solve this problem, fast and accurate automated detection is needed to help farmers effectively identify diseases on banana leaves. This research focuses on developing a banana leaf disease detection model using Convolutional Neural Network (CNN) method with MobileNetV2 architecture. The dataset used consists of 937 images of both infected and healthy banana leaves. These images were collected under various lighting conditions and viewing angles to simulate real field situations. The dataset was divided into 70% for training, 20% for validation, and 10% for testing, to ensure robust model evaluation. The CNN model was trained to recognize important visual features on banana leaves that indicate disease infection. The results showed that the model was able to detect banana leaf diseases with an accuracy of 90.62%, indicating high effectiveness. This accuracy confirms the potential of CNN in significantly improving the disease detection process on banana plants. This research is expected to help farmers identify diseases more quickly and accurately, thereby minimizing yield losses and increasing productivity. In addition, this research provides valuable insights into the application of technology in agriculture, particularly in plant disease detection which opens up opportunities for further advancements in this sector.

Key words: agricultural sector; banana leaf disease detection; CNN model.

I. INTRODUCTION

Banana plants are an important sector in the global economy, especially in tropical countries such as Indonesia, which is one of the largest banana producers in the world. Bananas are the main source of income for many farmers and are also an important food ingredient for society. However, this sector faces serious challenges, especially from attacks by leaf diseases such as Cordana, Pestalotiopsis and Sigatoka. These diseases can reduce the quality and quantity of crops, as well as increase production costs due to the intensive care required for control. Another challenge in controlling banana leaf disease is the difficulty of detecting the initial symptoms, because the signs that appear are often similar to symptoms of environmental stress or other disorders. Early identification is very important so that farmers can take quick preventive action to minimize further losses. Therefore, automatic, fast and accurate banana leaf disease detection technology is urgently needed.

Various digital image processing models can be applied to identify types of banana leaf diseases, including K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree, Random Forest, as well as deep learning models such as Convolutional Neural Network (CNN), YOLO , Efficient Net, and MobileNet. CNN models, in particular, have an advantage in terms of accuracy in image classification, due to their ability to handle high-resolution imagery while preserving important details [1], [2], [3]. This makes it ideal for disease detection applications that require high accuracy and fast identification processes. CNN works through convolutional layers to extract visual features from images, pooling layers to reduce data dimensionality, and fully connected layers to interpret the features in the form of a final classification[4]. By using CNN, this model is expected to be able to identify banana leaf diseases precisely by utilizing large amounts of image data, thereby increasing classification accuracy. In addition, CNN has proven effective in recognizing complex visual patterns on leaves that are indicative of disease[5], [6].

There are several similar studies related to the detection and classification of banana leaf diseases using image processing approaches, although there are significant differences in the methodology and datasets used. Research by [7] menggunakan Knowledge Embedded-Graph Convolutional Neural Network (KEGCNN) to process banana images and achieve an average accuracy of 98%. The use of random sampling techniques that ensure unbiased representation of the dataset also makes an important contribution to the accuracy of their model. Meanwhile, research by [8], [9] used a computer vision system to analyze physical and chemical changes in bananas during storage and showed the relationship between banana peel color and quality, which is different from the focus of this research which focuses more on banana leaf diseases. Other research by [10] focused on sampling banana leaves and stems in Tanzania to detect Black Sigatoka and Fusarium Wilt diseases, using imagery acquired over six months under varying farming conditions. This approach provides insight into how variations in field conditions can affect detection accuracy, which is also of interest in this study, considering that the dataset used involves images taken under various lighting conditions and viewing angles. Meanwhile, research conducted by [11] using UAV and satellites for large-scale banana plant detection with 97% accuracy using the Random Forest model. The use of remote sensing technology is different from the direct image processing approach applied in this research. In addition, research by [12] which combines the HOG + LBP + SVM method, which achieves a precision and recall rate of 100% under varying lighting conditions, showing that the combination technique can also provide excellent results in detecting plant diseases, an approach that is also interesting to apply in this research in future.

In recent years, artificial intelligence (AI) technology, especially in image processing, has shown rapid progress [13], [14] Deep learning with the CNN model is widely applied to detect plant diseases, including banana leaves. CNN has the ability to extract relevant visual features from banana leaf images, such as different spot patterns, colors and textures between healthy and infected leaves [15-17]. CNN studies these patterns to classify banana leaves as healthy or infected with certain diseases. Even so, CNN training requires considerable computing time and is often sensitive to variations in environmental conditions, such as lighting or different viewing angles [1], [11]. This research aims to develop a CNN model to detect banana leaf diseases, focusing on the four main categories of Cordana, Pestalotiopsis, Sigatoka and Healthy leaves. The dataset used includes 937 images of infected banana leaves and healthy leaves as controls. Images are taken in various lighting conditions and viewing angles to represent real situations in the field. Pre-processing is performed to improve image quality and ensure data consistency. The CNN model was trained to recognize important features on banana leaves that indicate disease infection. It is hoped that this model can help farmers detect banana leaf diseases early, which in turn improves the quality and quantity of harvests and reduces economic losses. Apart from that, this research is also expected to contribute to the application of AI in the agricultural sector, which supports sustainable agriculture in the future.

II. METHOD

The research stages carried out were designed to ensure that the resulting CNN model had optimal performance in terms of accuracy, precision and computational efficiency. The following is a picture of the research carried out which can be seen in Fig. 1.

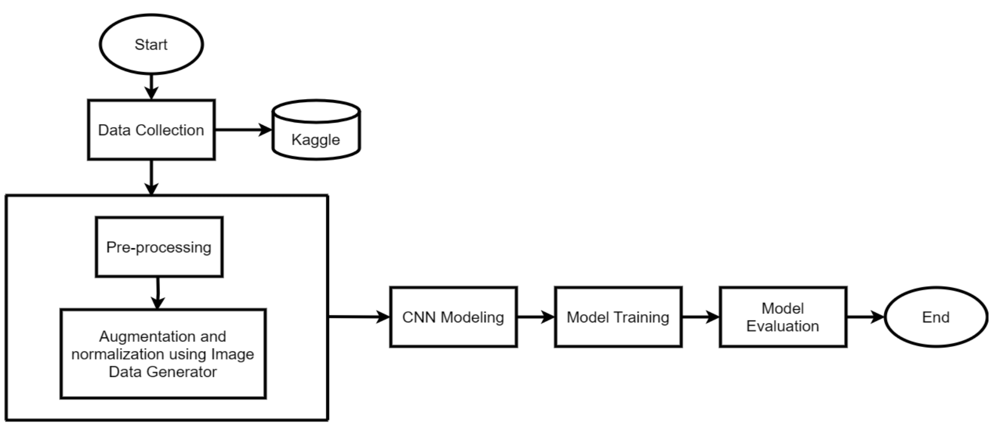


Fig. 1 Research method

This research aims to analyze the performance of the CNN model in detecting diseases on banana leaves. The stages of this research method are described as follows:

A. Data Collection

The first step taken in this research was collecting dataset in the form of pictures of banana leaves infected with various diseases and healthy ones. This data was obtained from the Kaggle platform, which provides a dataset of banana leaf images with various disease categories such as Cordana, Pestalotiopsis, Sigatoka and Healthy leaves. After the data is downloaded, each image is grouped into folders based on the type of disease, so that the dataset structure is more organized and makes the analysis and model training process easier. With this dataset, the model will be trained to recognize visual patterns and specific characteristics found on banana leaves infected with Cordana, Pestalotiopsis and Sigatoka diseases and differentiate them from healthy leaves. This dataset is an important element in developing accurate and efficient detection models.

B. Preprocessing

At the data pre-processing stage, image normalization and augmentation is carried out to ensure the quality and consistency of the dataset before being used in model training. Normalization is carried out by adjusting the pixel values in the banana leaf image using ImageDataGenerator with the parameter rescale=1./255, which changes the pixel value range to between 0 and 1 [18]. This process is important to avoid differences in pixel value scales which can affect model performance. Apart from that, image augmentation is also applied with techniques such as shear, zoom, and horizontal flip, which aim to increase dataset variation and make the model more robust to variations in image conditions. With this normalization and augmentation, it is hoped that the model can be trained with a more consistent and diverse dataset, so that it can recognize banana leaf disease patterns more accurately.

C. CNN Modeling

In this study, disease detection on banana leaves was carried out using MobileNetV2 who were trained to recognize visual patterns on banana leaves infected with various types of Cordana, Pestalotiopsis, Sigatoka diseases and healthy banana leaves[19]. This architecture consists of several convolution layers which function to extract features from images, pooling layers to reduce dimensions, and fully connected layers which are used to classify images based on features [20], [21]. Using the MobileNetV2 model will produce image representations related to the type of disease on banana leaves and provide accurate predictions.

D. Model Training

The training stage is carried out to train the model MobileNetV2 CNN-based in detecting diseases on banana leaves. This dataset consists of images of banana leaves that have been labeled according to disease categories, namely Cordana, Pestalotiopsis, Sigatoka, and Healthy. During training, the model learns unique patterns and specific visual features of each category[22]. To increase data variation and prevent overfitting, augmentation techniques are applied to the images. The training process involves a forward pass, where the image passes through each layer in the model architecture to extract visual features, and loss calculations. After that, backpropagation was carried out to update the weights and biases in the model using the Adam optimization algorithm. Training is carried out in several epochs, with each epoch representing one full cycle of training on the entire dataset. The model is also evaluated using the validation dataset during training to monitor performance and avoid overfitting. With this process, the model MobileNetV2 can recognize visual patterns well, so as to provide accurate predictions.

E. Model Evaluation

The next stage is model evaluation to assess performance in identifying banana leaf diseases. Evaluation is carried out using accuracy metrics to measure the percentage of correct classifications. Accuracy is calculated based on the number of correct predictions divided by the total samples tested [23], [24]. This evaluation is carried out on testing data separate from the training data, to ensure that the model is able to generalize well on data that has never been seen before. The evaluation results in this research will produce a percentage that shows good performance in identifying banana leaf diseases. The following (1) is the formula used to calculate accuracy.

$$Accuracy = \frac{Correct\ Prediction}{Total\ Sample} \tag{1}$$

In equation (1) the number of correct predictions is the number of classifications carried out correctly by the model, while the total number of samples is the total amount of data used for testing.

III. RESULTS AND DISCUSSION

In this study, a detailed discussion is presented regarding the results of banana leaf disease analysis which was carried out using the CNN method. This discussion covers every stage of the research process, from data collection to model evaluation to provide a comprehensive picture of the effectiveness of the CNN approach on banana leaf diseases.

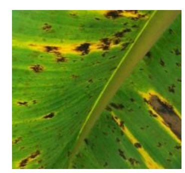
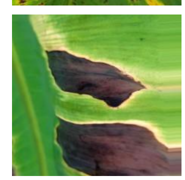
A. Data Collection

The dataset used in this research consists of images of banana leaves which are classified into four main categories, namely healthy leaves and three types of banana leaf diseases, namely Sigatoka, Cordana, and Pestalotiopsis diseases. This dataset is sourced from the open platform Kaggle and has been organized in folders based on disease type to simplify the classification process. The total number of images in this dataset is 937, consisting of 473 images of banana leaves infected with Sigatoka disease, 173 images infected with Pestalotiopsis disease, 162 images infected with Cordana disease, and 129 images of healthy banana leaves. This dataset is further divided into three subsets, 70% for training, 20% for validation, and 10% for testing to support the model process optimally. Details of the dataset are presented in Table I.

B. Preprocessing

At this preprocessing stage, it is carried out for specifying the path to the dataset, initializing the ImageDataGenerator, and loading the data using flow_from_directory is part of data pre-processing in preparation for model training. The first step is to determine the path or location of the folder containing the image dataset, which will be used in model training. In this case, the folder containing the banana leaf images is stored in Google Drive. After that, the ImageDataGenerator is initialized, which is used to carry out image processing techniques. Normalization is carried out by changing the image pixel value from the range 0-255 to 0-1 using the parameter rescale=1./255, which aims to make the model able to process data more efficiently. Meanwhile, augmentation, which includes operations such as rotation, zoom, and horizontal flip, aims to enrich the dataset with image variations, so that the model can learn from a wider variety of conditions and avoid overfitting. The final stage is loading data using the method flow_from_directory, which converts images from a folder into a format that the model can process. These images are resized to 150x150 pixels and grouped by class category, according to the existing folder structure. This process ensures that the dataset is ready to be used to train the model, with data that has been processed through normalization and augmentation so that the model can learn better and more robustly. The following are the results of image preprocessing which can be seen in Fig. 2.

TABLE I
BANANA LEAF DISEASES DATASET

Disease Name	Number of Datasets	Picture
Sigatoka	473	
Pestalotiopsis	173	
Cordana	162	
Healthy	129	

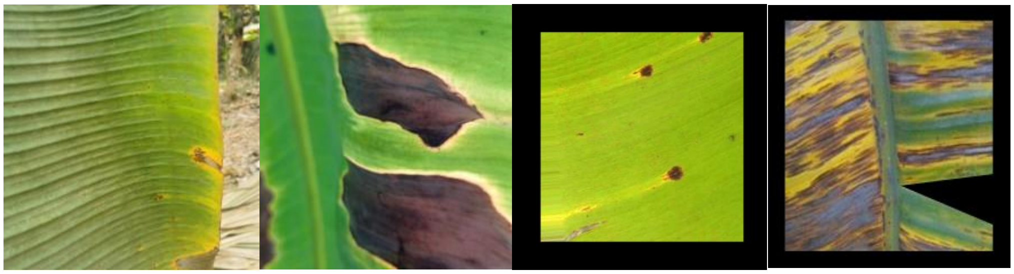


Fig. 2 Example of preprocessing result

C. CNN Model

Architecture MobileNetV2 is designed to recognize input images through a series of complex visual feature extraction and analysis processes. This process starts with an initial convolution layer whose job is to capture basic patterns of the image, such as edges, texture and color. MobileNetV2 uses a block of inverted residuals with shortcut connections, which allows the model to retain important information from the input image while reducing the number of parameters used. The depthwise separable convolution layer applied to this architecture helps increase efficiency by separating the spatial convolution and channel convolution processes, so that the model remains lightweight but is still able to capture complex feature details. In the final layer, the Softmax activation function is used to generate probabilities for each class, such as Cordana, Pestalotiopsis, Sigatoka, or healthy banana leaves. With this approach, the architecture on MobileNetV2 able to recognize visual patterns from input images and use them for accurate classification. Results from model implementation MobileNetV2 can be seen in Table II.

Table II starting with MobileNetV2 as a base model, which produces an output of the form (None, 5, 5, 1280), which indicates the size of the feature map after the feature extraction process from the image. Next, Global Average Pooling is carried out on the layer global_average_pooling2d, which flattens the output into a 1280-dimensional vector. The next layer is Dense with 512 hidden units and a ReLU activation function, which is used to capture more complex patterns in the data. The final layer is the Dense layer with 4 output units and a softmax activation function, which functions for multi-class classification. This model has a total of 2,915,908 parameters, with 657,924 trainable parameters, which include additional layers added for classification tasks, and 2,257,984 non-trainable parameters, which come from the base model MobileNetV2 which has been pre-trained with the ImageNet dataset.

D. Model Training

Training datasets are used in the model training process to introduce data patterns so that the model can understand the relevant features for making predictions [25-27]. In this research, the training dataset contains images of banana leaves which are categorized into four. To find out the results of model training, you can see in Fig. 3.

TABLE II
CNN MODEL

Layer (Type)	**Output Shape**	**Param #**
mobilenetv2_1.00_224	(None, 5, 5, 1280)	2,257,984
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1280)	0
dense	(None, 512)	655,872
dense_1 (dense)	(None, 4)	2,052
Total params		2,915,908
Trainable params		657,924
Non-trainable params		2,257,984

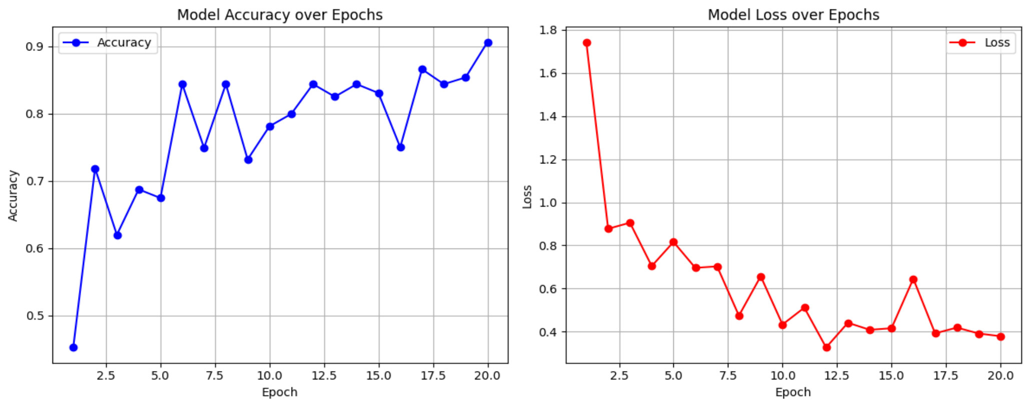


Fig. 3 Model accuracy and loss over epochs

Fig. 3 is a graph changes in accuracy and loss during model training provide an overview of the learning process that occurs on the MobileNetV2 used. In the first epoch, accuracy started at around 45.26%, which shows that the model is still in the early stages of learning and is not yet able to identify data patterns well. As time goes by, accuracy increases gradually, reaching about 90.62% at the 20th epoch, indicating that the model is increasingly able to identify patterns in the data and make more accurate predictions. This steady increase in accuracy indicates an effective training process. On the other hand, the loss value showed a significant decline from 1.7421 in the first epoch to 0.3792 in the 20th epoch. This decrease in loss value shows that the model is becoming more efficient in reducing prediction errors, indicating that the model's internal parameters have been successfully adjusted to minimize errors in the training data. Overall, these accuracy and loss graphs show that the model learns progressively and achieves better performance over time.

E. Model Evaluation

After training the model, the next stage is model evaluation to measure and assess how well the trained model predicts new data or data that was not seen before. In this research, accuracy indicates the percentage of correct predictions from the total data tested to show that the model can identify correctly. The results of this model evaluation show an accuracy of around 90.62% of the total predicted data, which means the model is quite effective in recognizing patterns in the data. The number of correct predictions is 906 and the total number of samples is 1000, accuracy can be calculated using (1), producing a value of 0.9062 or 90.62%. Thus, the model accuracy on the test data is 90.62%, which shows the model's success rate in identifying the correct pattern. The model accuracy graph can be seen in Fig. 4.

IV. CONCLUSION

This research succeeded in developing and testing a CNN model to detect diseases on banana leaves with a focus on four main categories, namely Sigatoka, Pestalotiopsis, Cordana, and healthy leaves. The CNN model was applied to a dataset consisting of 937 banana leaf images, covering various disease states. The preprocessing process involves image normalization and augmentation to increase dataset variation and ensure data quality before training. This model shows excellent ability to recognize visual patterns on disease-infected banana leaves, thanks to the CNN's ability to extract

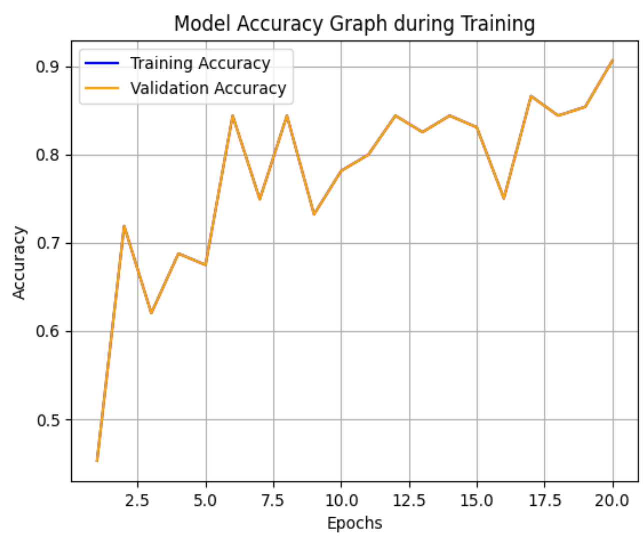


Fig. 4 Graph of model accuracy during training

features from high-resolution images. The model evaluation results show that CNN can identify banana leaf disease with an accuracy rate of 90.62% which has the potential to be applied in an early detection system for banana leaf disease in the field. This approach not only increases the efficiency of disease detection, but also helps farmers in reducing economic losses caused by banana leaf disease. In addition, this research also shows the potential for using AI technology in the agricultural sector to support sustainable agriculture and increase crop yields. Future research is recommended to use the CNN model with the Support Vector Machine (SVM) model to increase the robustness of the model to variations in environmental conditions that can affect image quality and diversity. In addition, this approach is expected to speed up the model training process, considering SVM is known to be effective in handling high-dimensional data and can reduce the computational time needed to achieve convergence on large datasets. Future researchers are also advised to conduct further research using the CNN model but with different datasets, to test the generalizability of the model on various types of data and increase the sustainability of the research in a broader application context.

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