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Implementation of Convolutional Neural Network (CNN) for Image Classification of Leaf Disease In Mango Plants Using Deep Learning Approach

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Abstract

Plant diseases pose a serious threat to a country's economy and food security. One way to identify diseases in plants is through the visible features on their leaves. Farmers need to conduct an active examination of the condition of the leaves of plants to eradicate this disease. In this case, automatic recognition and classification of diseases of leaf crops is required in order to obtain an accurate identification. Digital image processing technology can be used to solve this problem. One effective approach is the Convolutional Neural Network (CNN). The trial image used a dataset consisting of 4000 images of mango leaf disease, namely Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, and Sooty Mould. This study aims to compare the accuracy of CNN, VGG16 and InceptionV3. Architectural modeling uses these drawings to train and test models in recognizing and classifying mango leaf diseases. The results of modeling trials in the three scenarios were most optimally obtained by VGG16 with an accuracy of 96.87%, then InceptionV3 with an acquisition of 96.50% and CNN by 81%.

Keyword: Convolutional Neural Network, InceptionV3, Mango, Tranfer Learning, VGG16

1. INTRODUCTION

Mango (Magnifera Indica L.) is a fruit commonly grown in tropical countries [1]. Mango is also known as the "king of fruits" and is one of the most important fruit crops worldwide. About 40% of the world's mango production is estimated to suffer damage caused by diseases and insect pests [2][3]. Plant diseases pose a serious threat to a country's economy and food security [3]. One way to identify diseases in plants is through the visible features on their leaves. Diseases affecting the leaves can inhibit the process of photosynthesis and negatively affect plant growth. Farmers need to conduct an active examination of the condition of the leaves of plants to eradicate this disease. Therefore, careful monitoring is required in each stage of leaf growth so that the disease can be precisely identified at the appropriate time. However, observation using only the human eye may not be enough and can sometimes be confusing. In this case, automatic recognition and classification of foliar plant diseases is required to obtain accurate identification [4].

Digital image processing technology can be used to solve this problem. Image processing can help in image-based data recognition and classification [5]. One effective approach is the Convolutional Neural Network (CNN). CNN is a type of artificial neural network that is very good at processing images [6]. CNNs involve convolution operations that combine multiple processing layers using elements operating in parallel, inspired by the biological nervous system. Processing in CNNs relies on kernel multiplication of 3D weights and 3D input features. However, CNN has characteristics that require high computing power and large bandwidth [7].

CNN has been widely applied to research using image classification data. one of them is in research conducted by Samala, et al by identifying diseases in tomato leaves using InceptionV3 architecture which produces an accuracy rate of 99% [8]. His further research was conducted by Kusrini, et al by comparing the architecture of VVG16, ResNet50, Inception ResNet-V2, Inception-V3 and DenseNet to identify pests and diseases in mangoes, it was found that the accuracy results using the VVG16 model achieved top validation with accuracy of 89% and 90% respectively [9]. Another study conducted by Tsabitah Ayu, et al using a model (CNN) to classify the types of mango leaves affected by pests and healthy obtained accuracy results of 0.96% [10].

Based on previous research, image classification of mango leaf disease was carried out using deep learning with the Convolutional Neural Network (CNN) method. One of the tests conducted using this deep learning algorithm model aims to classify types of diseases quickly, easily, and efficiently through processing large amounts of image data. In this study, classification was carried out using the Convolutional Neural Network (CNN) method which became the main topic to deal with the problem. The classification of diseases in mango leaves is carried out based on physical images from image data involving 7 types of diseases, namely anthracnose, bacterial canker, cutting weevil, die back, gall midge, powdery mildew, and sooty mould. The comparison method of 3 CNN architectures was used to design a model capable of classifying diseases and producing a high degree of accuracy.

This study aims to classify diseased (pest attacked) and healthy mango leaf types based on leaf shape and texture using a comparison of 3 CNN model architectures. CNN has proven to have excellent performance in the field of image classification. The CNN model was chosen because previous studies, especially in the detection of mango types in India, showed that the CNN model was able to classify different types of mangoes with satisfactory success rates. Through this research, it is expected to produce accurate results in classifying mango leaves based on their shape and texture. The results of this study are expected to have significant benefits in the future, especially in understanding and overcoming disease problems in mango plants.

2. MATERIAL AND METHOD

The flow of research methods can be seen in Figure 1.

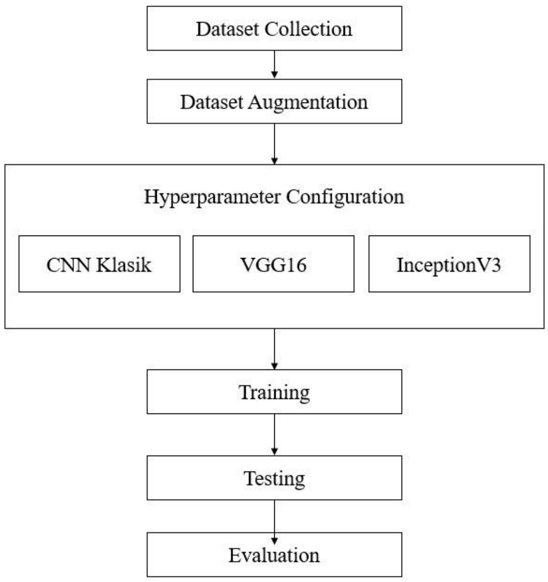

Figure 1. Research Methodology

In this study, three Convolution Neural Network (CNN) architectures were tested to evaluate their performance in image classification. By comparing these three CNN architectures, specifically designed for classifying diseases on mango leaves, we can gain a deeper insight into their performance. This insight has the potential to contribute to the development of superior technology and methods in the future. The models were trained using Google Colab, employing 100 epochs, images measuring 255x255 pixels, and batch sizes of 64. The difference in training between the Classic CNN model and VGG16 lies in the utilization of optimizers and learning rates. The Classic CNN model utilizes an RMSprop optimizer with a learning rate of 0.001, while in the VGG16 model, an Adam optimizer is employed with a learning rate of 0.0001.

2.1 Dataset Collection

The dataset used in this study consisted of 4000 images of mango leaf disease derived from the Kaggle database (https://www.kaggle.com/datasets/aryashah2k/mango-leaf-disease-dataset). This image data has been divided into 7 (seven) categories, each category consisting of 500 images, namely Anthracnose, Bacterial Canker, Cutting Weevil, Die Back, Gall Midge, Powdery Mildew, and Sooty Mould. Each image has been manually labeled and has dimensions of 2x320 pixels. This study used these images to train and test models in recognizing and classifying mango leaf disease. In Figure 2 in the study, several sample images from each of the different disease categories are shown, providing a visual picture of the variations and differences in characteristics between these diseases.

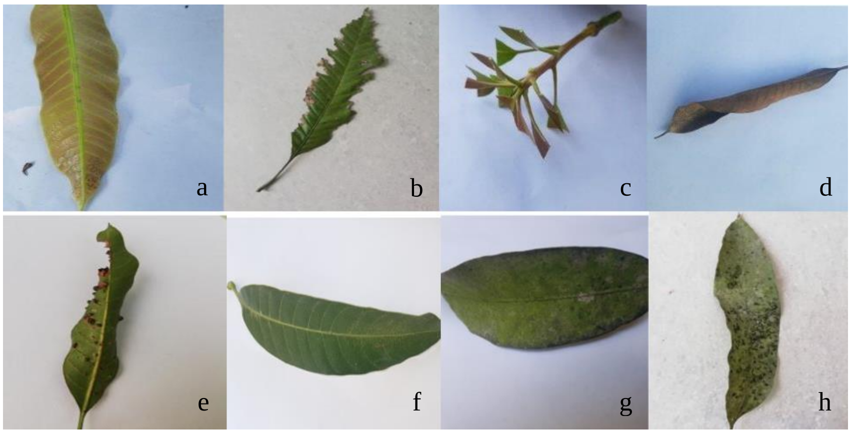

Figure 2. Dataset Visualization. (a) Anthracnose (b) Bacterial Canker (c) Cutting Weevil (d) Die Back (e) Gall Midge (f) Healthy (g) Powdery Mildew (h) Sooty Mould

2.2 Data Augmentation

Data Augmentation is a technique used to enrich training data to avoid overfitting. In this study, data augmentation was done using the Keras library. The data augmentation process involves several operations, such as horizontal flip, shear range, and zoom range. The shear range and zoom range values used are 0.2. The horizontal flip operation serves to generate variations in training data by rotating the image horizontally by 90 degrees. This is done to increase the variety of data and prevent the model from recognizing objects in only one orientation. Shear range applies the shear transformation method to the image by rotating the image by a certain degree. This operation aims to add variety to the image and provide variation in the angle of view of the object. The zoom range enlarges the image by a certain scale from the original image. The purpose of this operation is to create variations in the scale of objects in the image, so that the model can learn to recognize objects of various sizes. By applying these operations, data augmentation can effectively enrich the training dataset, so that the model can learn from wider variation and reduce the possibility of overfitting. The data generated from this augmentation will be divided into two categories, namely 80% training datasets and 20% test datasets.

2.3 Deep Learning

The learning method that involves multilayered representations in artificial neural networks is known as Deep Learning [11]. In agriculture, Deep Learning uses many Convolutional Neural Networks (CNN) in detecting diseases in plants. CNN is a type of Deep Neural Network (DNN) consisting of different types of layers that create different data representations as the layers become deeper [12]. One of the techniques used in CNN is transfer learning. By using transfer learning, models can leverage knowledge learned from large datasets to speed up the training process and improve disease detection performance in plant leaves to be more accurate. CNN with the application of transfer learning, can identify and detect diseases in plant leaves with high accuracy [13].

2.4 Convolutional Neural Network Model

The classic CNN model is used to perform image recognition and classification [14]. This model consists of several types layers, namely Convolutional Layer, Pooling Layer, and Fully Connected Layer [11].

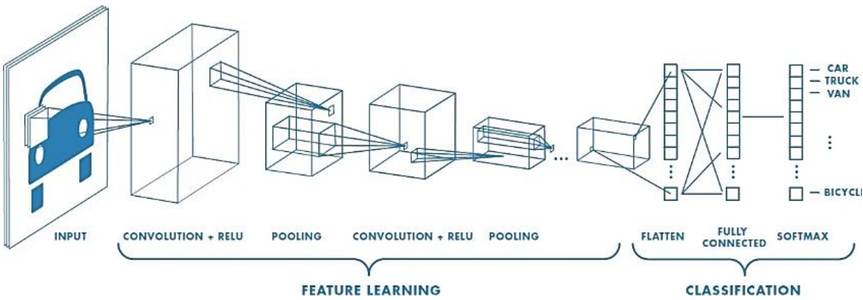

Figure 3. CNN Architecture

1. Convolutional Layer
   Plays an important role in the extraction of image features. In this layer, various kernel sizes are used to extract features from the image. By applying convolution layers repeatedly, a map of different features is formed. The feature map (f) of the i-th layer in CNN can be expressed using equation 2. Using the Convolutional Layer, the CNN model can recognize important patterns in images and form representations—features relevant to further classification tasks. Here, wi is the weight and bi is the offset used in the i-th layer.

$$f = \varphi(f_i - \times\, \omega_i + b_i) \tag{1}$$

2. Pooling Layer
   Pooling Layer is used to reduce the spatial dimension and complexity of calculations in the model. This coating has a significant impact on the risk of overfitting the model. In this layer, the output feature map is calculated using equation 3, where the variable s indicates the pooling size, and xl−1 j is the feature vector of the previous pixels in the layer.

$$x_j^l = down\left(x_j^{l-1}, \theta\right) \tag{2}$$

3. Fully Connected
   A Fully Connected Layer, also known as a fully connected layer, takes the value of the extracted feature from the previous layer and converts it into a vector. This layer aims to categorize the input image into appropriate classes. For this purpose, softmax activation is used, which is written in equation 4

$$softmax\left(z_j\right) = \frac{e^{zj}}{\sum {k}_{k=1e^k}} forj = 1{,}2..k \tag{3}$$

2.5 VGG16 Model

VGG16 is a model developed by the Vision Geometry Group at Oxford University [15]. This model managed to win the Imagenet competition in 2014 [9]. The VGG16 architecture consists of a series of uniform convolution blocks followed by an integrated pooling layer. Each convolution layer uses filters with kernel sizes 3 × 3 and step 1 (stride 1), with padding using the same values as stride. While each pooling layer uses pool sizes 2 × 2 and step 2 (stride 2) [16]. The next layers after the convolution block are the classification layers, which consist of the fully connected and softmax layers [17]. Three fully connected (FC) layers are used in this model: the first two layers have 4096 channels, while the third layer has 1000 channels which are used to classify ILSVRC with 1000 classes. The configuration of the fully connected layer in the VGG16 model is uniform across all networks, meaning that the number of channels at each FC layer is the same. All hidden layers in this model use the Rectified Non-Linear Unit (ReLU) activation function. With the architecture mentioned above, VGG16 can process and classify images with a high degree of accuracy, making it one of the popular models in image recognition and image classification competitions such as Imagenet.

2.6 InceptionV3

InceptionV3 is one of the modified variants of the initial generation that was done with several improvements. These improvements include improved Label Smoothing, 7x7 factor convolution, and the use of additional classifications to disseminate label information into the network at the bottom. In addition, batch normalization is used on side-head layers. InceptionV3 is specifically used for image analysis and object detection [18]. Efficient decomposition of the InceptionV3 network involves the use of small convolution kernels, which significantly reduces the number of parameters in the model and reduces the risk of overfitting. In addition, this approach also enhances the network's ability to express non-linearity by extracting features at various levels of abstraction and encoding them into high-level features [19] [20].

3. RESULTS AND DISCUSSION

3.1 Convolutional Neural Network Model

The results of this study involved the training and testing stage of mango leaf disease classification using convolutional neural network. The architecture of the model consists of several types of layers, including Conv2D (convolution layer), MaxPooling2D (pooling layer), Flatten (flatten layer), and Dense (dense layer). The activation function used is ReLU. In this study, the kernel or filter size used for each convolution layer was 3x3. As for the pooling layer, the size used is 2x2. The number of filters or kernels used varies, with 128 filters for convolution layer 1, 128 filters for convolution layer 2, 256 filters for convolution layer 3, and 256 filters for convolution layer 4.

The number of parameters studied in this model is 7,463,560 parameters. The ReLU activation function is used at the convolution layer, while at the dense output layer, 8 filters are used because the dataset has 8 classes. The optimizer used is RMSprop with learning_rate=0.0001. The training process was carried out with 100 epochs and an early stopping function was applied to monitor changes in the validation loss value during the training. The training process stopped at the 19th epoch with a training accuracy of 81%. The results of the model test are shown in figure 2.

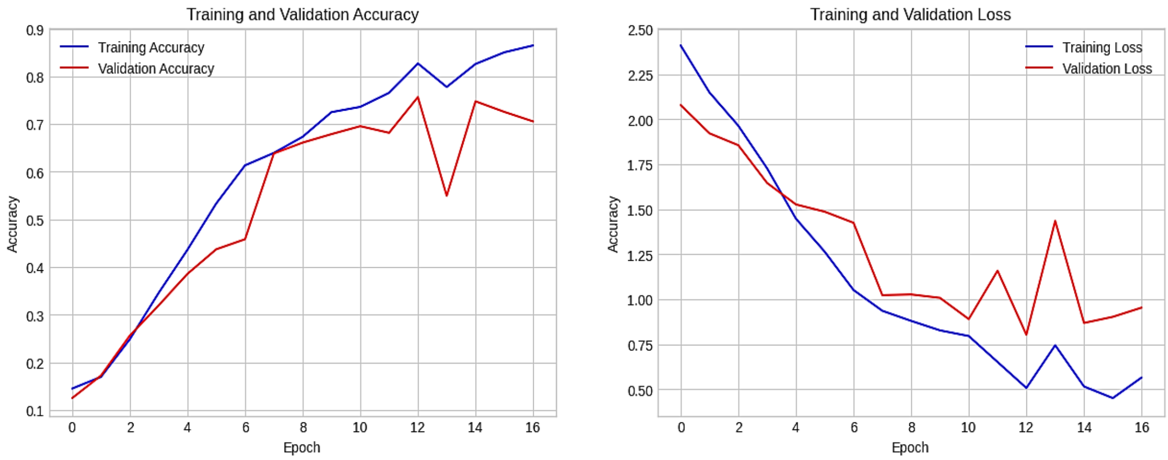

Figure 4. Training and Loss CNN

3.2 VGG16

Further testing was conducted with VGG16 transfer learning previously trained on the ImageNet dataset. This model has an input shape (224, 224, 3). In the process, a Dense layer with 256 units is added and uses the ReLU activation function. A Dropout layer is also added with a dropout value of 0.2. This Dropout layer serves to prevent overfitting by randomly ignoring a portion of the unit in the previous layer during the testing process. Next, a final Dense layer with 8 units is added, which corresponds to the number of classes you want to classify. The activation function used in the last Dense layer is softmax, which is useful for generating the probability of class distribution at the model output. In the testing process, Adam optimizer was used with a learning rate of 0.0001. The results of model training are shown in Figure 5.

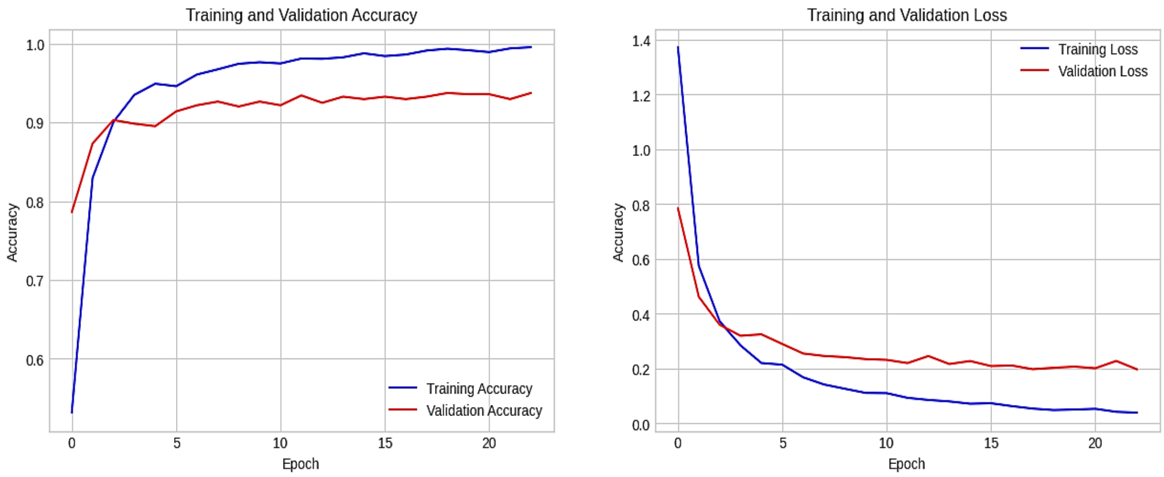

Figure 5. Training and Loss VGG16

Training is carried out with 100 epochs, but an early stopping function is also applied that monitors changes in validation loss values during training. The training process stopped at the 23rd epoch with a training accuracy of 96,87%. The figure shows the accuracy value of training increases significantly, while the loss value decreases as the number of epochs increases.

3.3 InceptionV3

Furthermore, testing was carried out using InceptionV3 Architecture transfer learning by setting the input_shape parameter to (224, 224, 3). This parameter specifies the form of image input to be used in the model. Next add a Dense layer with 128 units and a ReLU activation function to learn more complex features.

In the testing process, Adam optimizer was used with a learning rate of 0.001. The results of model training are shown in Figure 6.

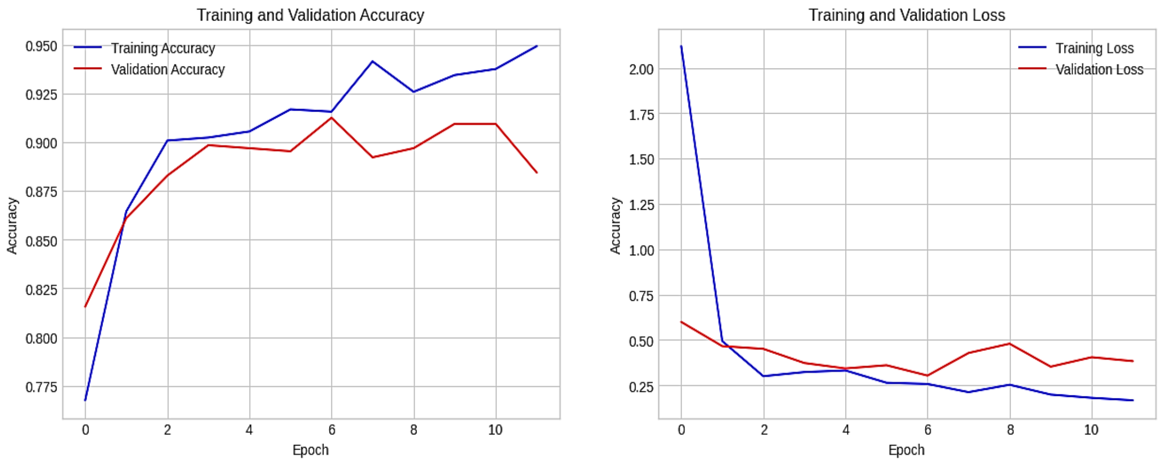

Figure 6. Training and Loss InceptionV3

Training is carried out with 100 epochs, but an early stopping function is also applied that monitors changes in validation loss values during training. The training process stopped at the 12th epoch with a training accuracy of 96.50%. Based on the tests that have been done, then a comparison of accuracy is carried out on validation and testing data to determine the best model performance. The results of the accuracy comparison are shown in figure 7.

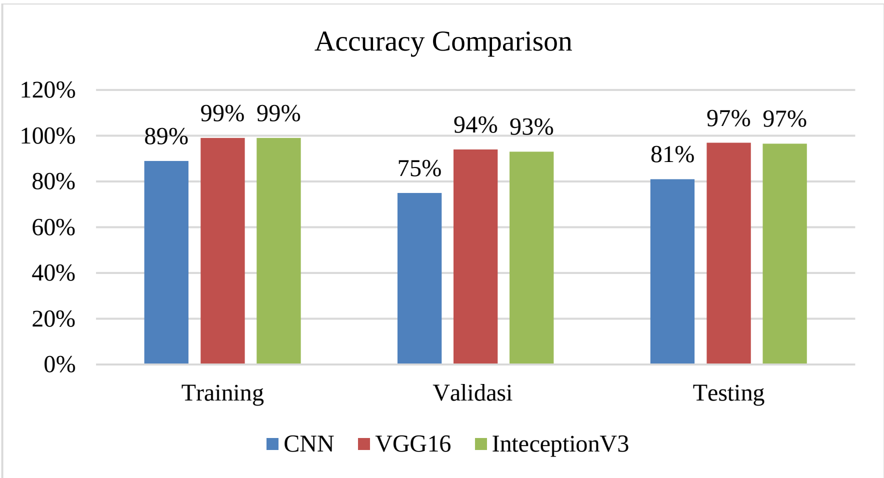

Figure 7. Accuracy Comparison

Based on figure 7, the best training accuracy is obtained on VGG16 and InceptionV3. While the best accuracy validation data is VGG16. Based on these comparisons, VGG16 and InceptionV3 are the best models in solving the problem of classification of leaf diseases in mango plants.

4. CONCLUSION

The study aimed to classify mango leaf diseases using CNN, transfer learning VGG16, and InceptionV3. The dataset used in this research comprised 4000 images categorized into 8 classes. The training process utilized distinct data sharing techniques, employing CNN and transfer learning, which resulted in optimal accuracy. The tests conducted in this study showed that transfer learning performed better than CNN, with an average accuracy of 90%. Moreover, the tests conducted with three different CNN architectures successfully classified diseases in mango leaves. The comparative method used in designing the model for classifying diseases in mango leaves using the three CNN architectures can provide deeper insights into model performance, leading to better methods in the future. Future research should focus on improving the dataset of mango leaf diseases to enhance model accuracy and real-world implementation. Additionally, collaboration with experts in the field, such as plant pathologists and agricultural scientists, could validat

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