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Detection of mango leaf disease using the convolution neural network method

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ABSTRACT

Mango trees are a common plant in Indonesia. In 2021, 2.84 million tonnes of mangoes were produced in Indonesia, according to the Central Statistics Agency (BPS). You can eat mangoes either ripe or unripe. Additionally, this fruit can be turned into meals and beverages. Many farmers grow mango plants, however, Some illnesses can infect mangoes and lead to crop failure or poor fruit quality. Fungal infections like anthracnose and black fungus, often known as black fungus, affect mango plants, but many farmers continue to mistakenly believe they are identifying plant illnesses and pests. To the type of disease in mango plants, the Convolutional Neural Network (CNN) method was applied in this study. It has been demonstrated that CNN is a very efficient way of processing images and identifying key elements for intricate pattern recognition. A total of 1,405 leaf photos from three different categories—525 anthracnose images, 656 black sooty mold images, and 224 healthy images—were used as samples for CNN to identify illnesses in mango plants. This image data was taken from the kaggle.com website. The CNN model is trained using distinct datasets into training data and validation data after data collection and preprocessing. On training data, the model is 95% accurate, while on validation data, it is 98% accurate. By feeding photos of mango leaves into the model and evaluating the predictions, the detection is put into practice. Action can be taken to control the illness in these mango trees based on prediction findings showing the presence of disease with a decent amount of confidence.

Keywords: CNN; image; deep learning; detection; mango

1. INTRODUCTION

The Central Statistics Agency (BPS) estimates that the production of mango, one of Indonesia's most popular commodities, will be 2.84 million tons in 2021 [1]. Mangoes serve as a source of vitamins and minerals that are necessary to meet the body's daily nutritional requirements. With a total national production of 2.9 million tons in 2020, mangoes, a popular fruit, come in second position to bananas [1]. Ripe or unripe mangoes can be eaten, and they can also be processed into a variety of dishes and drinks.

Many farmers engage in mango farming, however, the fruit can become infected with some, leading to crop failure or subpar fruit. The fungi Anthracnose and Black Sooty Mold commonly affect mango plants. Leaf spot, curling, and quicker leaf accumulation are all brought on by Anthracnose. Black sooty mold, meanwhile, coats the leaves with a black layer [2]. Some farmers might be able to recognize the many plant diseases and pests, but there are still some farmers that struggle to do so. So that pests can be dealt with effectively, preventive measures must be taken, such as early pest detection.

Identifying the sort of disease that affects mango plants is one of the preventive actions that may be implemented. The purpose of this detection is to pinpoint several diseases that can affect mango plants. The Convolutional Neural Network (CNN) approach is employed, and it uses some photos of mango leaves that have the disease as a source of data [3]. Due to CNN's capability to interpret picture data, it is possible to determine the type of illness in mango plants using this technique. Images of mango leaves can be efficiently used to extract key properties using CNN, which contains a convolution layer that can identify patterns associated with the disease. Additionally, CNN can learn on its own through training using labeled data, enabling it to distinguish diverse patterns of various diseases in mango leaves. The ability to process images has demonstrated that CNN is the best option for identifying diseases in mango trees. Because CNN mimics the image recognition system found in the human visual cortex and can analyze picture data with high accuracy, it is a useful method for recognizing images [4].

Moh Ariei Hasan has research categorizing diseases using the CNN approach on photos of grape leaves. 4,000 photos were used in the test, of which 4,000 were divided into 2800 for training purposes, 800 for validation purposes, and 400 for testing purposes [5]. The accuracy of the test was 99.50% during training and 97.25% during testing [6]. Another study on potato leaves involved testing 5,702 images in three scenarios, with the first scenario using 4860 training data images and 540 data validation images to achieve an accuracy of 91% during training and 99% during validation, the second using 4320 training data images and 1080 validation data images to achieve accuracy of 93% during training and 95% during validation, and the third using 3780 training data images and 1080 validation data images [7]. Additionally, the CNN algorithm was employed in research on the classification of tomato leaf disease by examining 200 leaf photos, 160 of which were used as training data and 40 as test data. The accuracy of the results was 97.5% [8]. Based on some earlier studies that employed the CNN algorithm to look for illnesses in mango leaves. The results of this new study, which employed CNN to specifically identify problems in mango trees, demonstrate how good the algorithm is at classifying images. And it may be said that the Convolution Neural Network (CNN) method is effective in classifying images.

In this investigation, three different mango leaf images—two with the illness and one without—were used for the detection process. It is hoped that this research will be quite accurate.

2. METHOD

This study was conducted in multiple stages, as the accompanying picture illustrates.

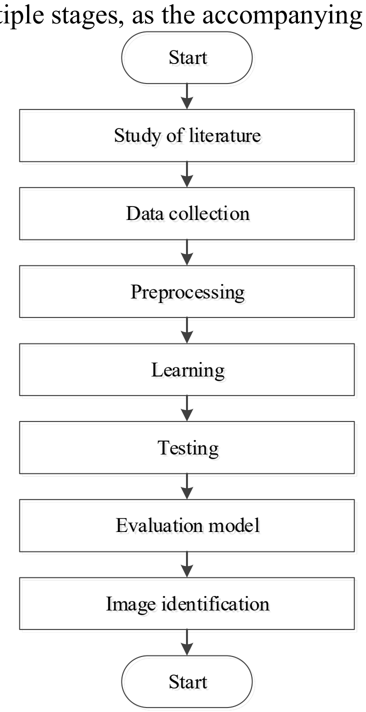

Figure 1. Chart of research stages

According to the research stages chart in Figure 1, there are some actions must that must be taken during the image recognition process to get good findings. Before beginning the investigation, the researcher must first complete the basic preparation process. After that, a literature review was done to look at picture recognition algorithms already in use. The next step is to gather pertinent data for research purposes. Preparing the data for machine learning requires performing some changes during the preprocessing stage. During the learning phase, machine learning algorithms like deep learning are used to train the image recognition model. Testing model performance is done with test data that isn't used for training. To analyze test results and assess model performance using the proper evaluation measures, model evaluation is done. Finally, the trained and assessed model can be applied to identify objects, patterns, or characteristics in a picture.

2.1 Data collection

In this study, a total of 1.405 cars were used as samples, each of which came from a different category. There are 525 cars affected by anthracnose, 656 cars affected by black sooty mold, and 224 cars in healthy condition. This data was obtained from the website kaggle.com, a portal that provides data for research and app development needs. This website serves as a resource for data that can be made available to researchers interested in studying illness and Hama in the plant, including in the case of the current study's connection to the detection of illness in the mangga daunt. Utilizing a dataset from the website kaggle.com that provides information on illness and death in the field is highly pertinent to the issues with the study's design that will be resolved. The data set in question contains numerous images of mangy animals that fall into three distinct categories: healthy conditions and two types of illnesses, namely anthracnose and black sooty mold [9]. With this dataset, researchers have access to a large number of sample images that may be used to enhance and refine a model for detecting illness in mangga using the Convolutional Neural Network (CNN) algorithm [10].

2.2 Preprocessing

Raw data is prepared using the preprocessing procedure so that the system can process it. Resizing the image to 256256 pixels with three RGB (Red, Green, and Blue) channels is the first step in preprocessing. Furthermore, oversampling is done to prevent the model from being overfited due to the imbalanced distribution of the data used [11]. Using a data augmentation technique, the author oversamples the data by randomly rotating and flipping the image's position, either horizontally or vertically [12].

Additionally, the input, which takes the form of color coefficients, is rescaled. The range of values for this color coefficient is 0 to 255. In order to alter the color coefficient value to a range between 0 and 1, the input computation is multiplied by 1/255 in this step. For data normalization, a color coefficient is changed from a range of 0-255 to a range of 0-1 [13]. To modify the range of pixel values to match the range requested by the algorithm or model to be employed, normalization is a general image processing technique. The normalization procedure is used to transform the color coefficient value in the image to a range of 0–1. The normalization procedure is typically as straightforward as dividing each pixel value by the highest value in the range prior to normalization. The maximum value in this situation is 255. In order to obtain values in the range of 0 to 1, the image's pixel values are divided by 255 [14].

Usually, this normalizing step is completed before the image is provided to the CNN model as input. After normalization, the image can be subjected to feature extraction and classification using the CNN model's convolution layer and other layers. This normalization limits the CNN model to the 0–1 range and enables it to learn significant patterns in images with a consistent scale. This is accomplished in order to scale the input to meet the requirements of the algorithm that will be applied during further processing.

2.3 Learning

The suggested CNN model design uses TensorFlow to categorize photos of mango leaves. This model has numerous layers that were created specifically to analyze and extract significant characteristics from photos of leaves.

Convolution layers are used by the CNN model to mix the source image and the filter to create pertinent features. A max-pooling layer is added after each convolution layer to minimize the size of the convolution-generated features [15].

Three fully connected layers follow the convolution and max-pooling layers [16]. Neurons that connect the preceding layer and the following layer completely make up the fully connected layer. These layers seek to merge data obtained from features that the convolution layers have discovered.

The ReLU activation function is applied at each hidden layer, including fully connected and convolutional layers. ReLU (Rectified Linear Unit) is a function that converts negative signals to zero

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while allowing positive signals to pass through unaltered. This activation mechanism aids in the learning of increasingly intricate data representations [17].

The softmax layer, which is the final layer, creates probability distributions for each potential class. Based on the examined features, the model uses the softmax function to deliver the most likely class predictions Figure 2.

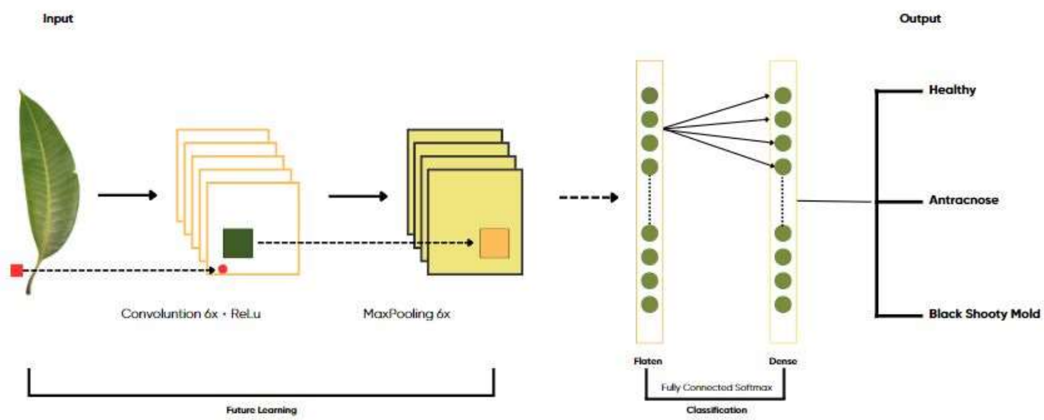

Figure 2. Model schematic

Some preprocessed mango leaf image datasets will be sent to the model during the training process. The model will develop the ability to spot significant patterns in photos and group them into the proper classes. Table 1 has further details.

Table 1. CNN network architecture

Layer(type)	***Output Shape***	***Param#***
Sequential (Sequential)	(32, 256, 256, 3)	0
Conv2d (Conv2D)	(32, 256, 256, 32)	896
Max_pooling2d (MaxPooling2D)	(32, 127, 127, 3)	0
Conv2d_1 (Conv2D)	(32, 125, 125, 64)	18496
Max_pooling2d_1 (MaxPooling2D)	(32, 62, 62, 64)	0
Conv2d_2 (Conv2D)	(32, 60, 60, 64)	36928
Max_pooling2d_2 (MaxPooling2D)	(32, 30, 30, 64)	0
Conv2d_3 (Conv2D)	(32, 28, 28, 64)	36928
Max_pooling2d_3 (MaxPooling2D)	(32, 14, 14, 64)	0
Conv2d_4 (Conv2D)	(32, 12, 12, 64)	36928
Max_pooling2d_4 (MaxPooling2D)	(32, 6, 6, 64)	0
Conv2d_5 (Conv2D)	(32, 4, 4, 64)	36928
Max_pooling2d_5 (MaxPooling2D)	(32, 2, 2, 64)	0
Latten (Flatten)	(32, 256)	0
Dense (Dense)	(32, 256)	16448
Dense_1 (Dense)	(32, 3)	195
Total params: 183,747		
Trainable params: 183,747		
Non-trainable params: 0		

The CNN model in Table 1 consists of 183,747 parameters and includes six convolutional layers with a very small receptive field of 3 x 3, six max-pooling layers with a size of 2 x 2, and three fully connected layers as the next to the last layers. The final layer is the softmax layer

2.4 *Testing*

Testing on the Convolutional Neural Network (CNN) using TensorFlow as the primary library for CNN model construction is the last procedure. Additionally, Jupyter Notebook or the Python Console are utilized as code execution environments, while Numpy and Matplotlib are used for manipulating numerical data and visualizing images, respectively. To test the effectiveness of the CNN model, we first create test data. The test data are then preprocessed like how the training data were preprocessed. The pre-trained CNN model is loaded following that. Making inferences from test data, or feeding test data into a model to derive predictions, is the first step in the testing process. Figure 3 shows it in further depth.

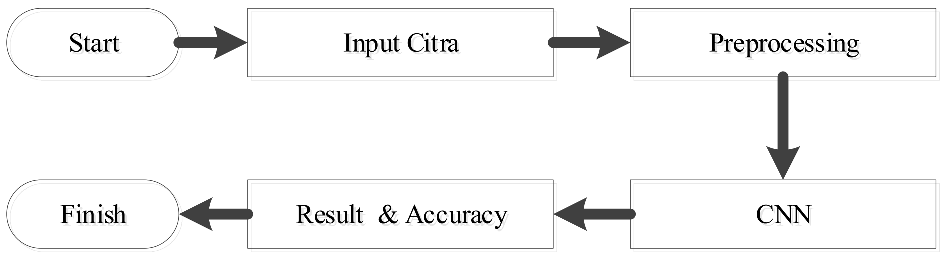

Figure 3. The flow of the testing process

2.5 Evaluation Model

The dataset is divided into subsets for training, validation, and testing during the model evaluation process. To guarantee the stability of the model's accuracy, the author additionally uses the cross-validation method. Cross-validation's major objectives are to acquire a more accurate estimate of the overall model performance and to prevent bias that could arise from using only one test set. Tools like TensorFlow, Scikit-Learn, and Keras are employed in the evaluation. Accuracy, one of the metrics for evaluating the classification model, is one of the evaluation outcomes that are presented. The study is over at this point. The outcome employed in this study to assess the efficacy of the CNN model in identifying mango leaf photos is accuracy. The equation displays the correctness of the calculation

$$accuracy = \frac{correct\ amount\ of\ data}{amount\ of\ test\ data} x\ 100\% \tag{1}$$

3. RESULTS AND DISCUSSION

The data is split into three subgroups with a ratio of 80:10:10 to ensure that there is enough dataset to train, test, and evaluate disease detection models in mango leaves. A ratio of 80:10:10 separates the data into three equal sections, namely:

- 80% of the research data were used to train the model. This aids the model's internal parameters and weights in being updated to produce precise predictions.
- 10% of the validation data were used as such. During training, it is used to monitor model performance and improve parameter values.
- 10% of theist data will be utilized as test data after the model has been trained. This was utilized to evaluate the finished model's performance and confirm its potency in spotting illnesses in mango leaves.

In the Convolutional Neural Network (CNN) algorithm, dividing the data into training (80%), validation (10%), and test (10%) subsets has several benefits, including allowing the model to learn more effectively, lowering the risk of overfitting, and enhancing generalizability. Smaller validation and test subsets are still crucial for effective and unbiased model tuning and assessment.

We will have 1124 data for training, 140 data for validation, and 140 data for testing in cross-validation with an 80:10:10 divide. It initially resizes the mango leaf image to the required size before processing it into the model and verifying its predictions. It is also required to normalize the image pixel values (in the range of 0 and 1 by dividing by 256) to enhance the model's performance. This should take place during model testing and training. As a result, we may add it to our Seiquencial Model as a layer. Before putting a picture into the CNN model, resizing is used to resize the image to the appropriate size, whilst rescaling normalizes pixel values into a range of 0 to 1.

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3.1 Test results

Training a Convolutional Neural Network (CNN) model with TensorFlow's fit() function. The CNN model will process an image and label the training dataset throughout the training phase. The number of samples to employ in each training iteration is determined by the provided batch size. To reduce errors between predictions and labels during training, the model will optimize parameters using the backpropagation technique. To keep track of a model's performance on novel data, validation datasets are also employed. The model learns and enhances its capability to categorize photos by running the code for 50 epochs. To assess the model's performance, we will be able to determine the training's status at each epoch from the output. According to the test results, training data accuracy was 95% and validation data accuracy was 98%. Figure 4 shows it clearly. Figure 5 displays the model's accuracy graph created during the model testing phase.

```
Epoch 42/50
30/30 [==============================] - 116s 4s/step - loss: 0.2166 - accuracy: 0.9137 - val_loss: 0.1890 - val_accuracy: 0.9167
Epoch 43/50
30/30 [==============================] - 116s 4s/step - loss: 0.1400 - accuracy: 0.9495 - val_loss: 0.1039 - val_accuracy: 0.9583
Epoch 44/50
30/30 [==============================] - 115s 4s/step - loss: 0.1398 - accuracy: 0.9589 - val_loss: 0.0767 - val_accuracy: 0.9792
Epoch 45/50
30/30 [==============================] - 116s 4s/step - loss: 0.1285 - accuracy: 0.9495 - val_loss: 0.0935 - val_accuracy: 0.9688
Epoch 46/50
30/30 [==============================] - 115s 4s/step - loss: 0.1217 - accuracy: 0.9568 - val_loss: 0.0899 - val_accuracy: 0.9792
Epoch 47/50
30/30 [==============================] - 113s 4s/step - loss: 0.1420 - accuracy: 0.9432 - val_loss: 0.0694 - val_accuracy: 0.9896
Epoch 48/50
30/30 [==============================] - 114s 4s/step - loss: 0.1278 - accuracy: 0.9484 - val_loss: 0.1062 - val_accuracy: 0.9583
Epoch 49/50
30/30 [==============================] - 116s 4s/step - loss: 0.1159 - accuracy: 0.9611 - val_loss: 0.0846 - val_accuracy: 0.9688
Epoch 50/50
30/30 [==============================] - 116s 4s/step - loss: 0.1143 - accuracy: 0.9568 - val_loss: 0.0342 - val_accuracy: 0.9896
```

Figure 4. Model test results

Positive signals for model training include the training and validation accuracy graph's upward trend and the training and validation loss graph's downward trend. When the accuracy of graph training improves, it signifies that the model is gradually learning the patterns in the training dataset and improving over time at accurately classifying images. The graph of improved validation accuracy demonstrates the model's ability to generalize effectively to validation data that has never been seen before.

On the other hand, a decreasing training loss graph indicates that the model was successful in lowering the error during each training cycle. The model becomes better over time at correctly predicting labels for the photos in the training dataset. The model can reduce mistakes in validation data that have never been observed previously, as seen by the decreasing validation loss graph.

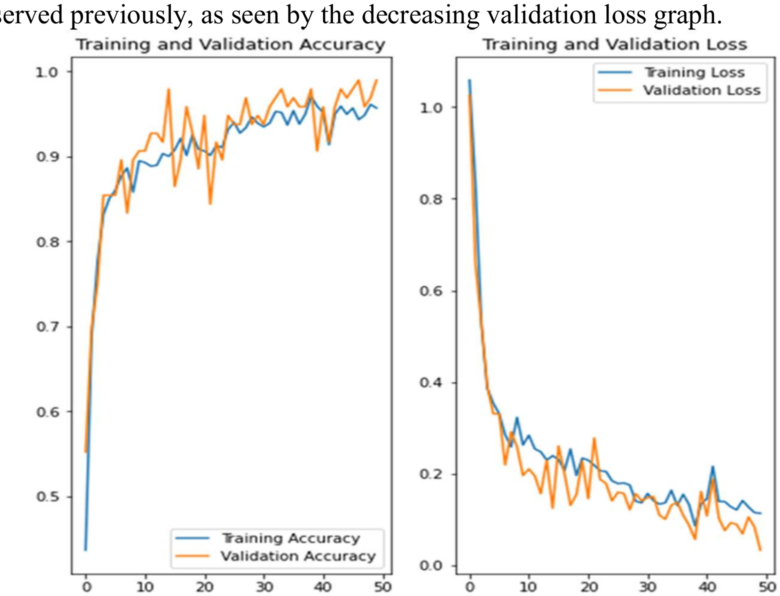

Figure 5. Graph of model test results

Training graphs and validation accuracy go up, and training graphs and validation loss go down, showing that the model is improving and getting better at classifying things. This suggests that model training has been successful and that the model's capacity to recognize patterns in images has grown.

3.2 Image identification

To split an image into smaller pieces while still using the convolution layer, the CNN approach moves a fine-sized filter into the image. The convolution value is then added to a new array that will be utilized by the neural network to identify an image. This approach is used to draw out crucial details from an image of mango leaves in the context of mango leaf identification. For instance, a filter can identify patterns such as edges, textures, or distinctive areas of a mango leaf. The array holding the convolution values will be given to the following layers of the neural network for the classification step after the convolution procedure is finished. Figure 5 displays the outcomes of the mango leaf image's identification.

Table 2. Image identification results

Figure	Actual	Predicted	Confidence
	Healthy	Healthy	100,0%
	Anthracnose	Anthracnose	99,34%
	Black Sooty Mold	Black Sooty Mold	100,0%

Figure	Actual	Predicted	Confidence
	Black Sooty Mold	Anthracnose	84,15%

Table 2 after the CNN has been trained, the model's performance and accuracy are evaluated using different datasets during the testing and validation stage. It is evident in the model-generated labels and the presentation of the projected results. These findings reveal how well the model performs at identifying disease in leaf photos and how successful it is at accurately classifying different disease categories.

The CNN approach can be used to carry out the picture recognition process more efficiently and accurately. CNN has been demonstrated to be efficient in a variety of image recognition tasks, such as object detection and picture classification, therefore this approach can produce accurate results when identifying photographs of mango leaves.

4. SIMPULAN

Several significant conclusions were drawn from research employing the Convolutional Neural Network (CNN) approach on photos of mango leaves. The research data included 1,405 photographs of mango leaves that were classified into three groups: 525 photographs of leaves with anthracnose illness, 656 photographs of leaves with black sooty mold disease, and 224 photographs of leaves in good health. Data are divided into three groups for the training process: 80% for training data, 10% for validation data, and 10% for test data. On this sample of data, training, and evaluation were done, and extremely good accuracy results were obtained. The accuracy score during testing reached 95%, demonstrating that the CNN model is capable of correctly identifying and differentiating the different types of illnesses on mango leaves. Additionally, the validation procedure evaluation findings reveal an accuracy rate of 98%, demonstrating that the CNN model is highly accurate at identifying illnesses in mango leaves. Thus, it can be concluded that the Convolutional Neural Network (CNN) algorithm used in this study was successful in detecting disease in mango leaves with high accuracy. As a result, it can significantly contribute to the development of disease detection techniques in plants using artificial intelligence technology, which can aid in efforts to manage and defend mango plants from disease attacks.

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