Pomelo Orange Disease Detection Using CNN Based on Digital Image Processing

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Abstract— Pomelo is one of the important fruits in the agricultural industry and has high commercial value. However, pomelos are susceptible to disease. Detecting diseases in pomelos is crucial for maintaining the quality and quantity of production. However, disease symptoms in pomelos are often complex and difficult to accurately detect through human visual observation. Therefore, image processing is a solution for detecting diseases in pomelos. A Convolutional Neural Network (CNN) is a type of artificial neural network architecture that is highly effective in analyzing and predicting diseases. In this study, a model is designed and built to detect and classify diseases in pomelos based on their skin. The study uses a dataset obtained from self-documentation using a digital camera, which includes images of Diplodia/Blondok, Cancer, Fruit Fly, and Healthy pomelos. In the preprocessing stage, the dataset is divided into training, validation, and testing data. Feature extraction is also performed using thresholding, contour detection, and bounding boxes. During the model processing stage, a model is created using training data, validation data, hyperparameters, and transfer learning. Utilizing Convolutional Neural Network (CNN) architecture and advanced image processing techniques, the study achieves a remarkable 92% accuracy in detecting and classifying diseases in pomelos based on their skin. This approach offers a practical solution to the complex and challenging task of accurately identifying diseases in pomelos, which are often difficult to detect through human visual observation. The model's high accuracy rate demonstrates its potential as a reliable tool for pomelo disease detection, which can ultimately aid in maintaining the quality and quantity of pomelo production.

Keywords— Convolutional Neural Network, Orange, Pomelo.

1. Introduction

In recent years, the development of artificial intelligence technology has progressed rapidly. The increasing complexity of human needs has driven experts to continually improve artificial intelligence to provide better assistance than human capabilities. The advancement of artificial intelligence technology has been widely seen in various sectors, such as industry, education, health, and agriculture [1].

Detection of diseases in fruits is crucial in agricultural industries to maintain the quality and quantity of production. However, the symptoms of fruit diseases are often complex and difficult to detect accurately through human visual observation. Therefore, image processing has become a popular solution for detecting fruit diseases [2]. Image-based approaches have advantages such as quick analysis and the ability to detect symptoms that are difficult to see with the naked eye, reducing the cost and time required for manual plant disease detection [3]. The process involves steps like image capture, image processing, segmentation, feature extraction, and classification. However, to improve the accuracy of detection, challenges such as fruit variation, different lighting conditions, and image disturbances need to be addressed. Additionally, collecting a complete and representative dataset of fruit disease images is crucial for training an effective and reliable detection system.

Convolutional Neural Network (CNN) has become a widely used technique in fruit disease detection through image processing. CNN is a type of artificial neural network architecture that is highly effective in analyzing and processing image data. In the context of fruit disease detection, CNN has proven to be a powerful tool for classifying disease symptoms based on fruit images, achieving high levels of accuracy [4]. The main advantage of CNN lies in its ability to automatically learn complex patterns through training with large and diverse image datasets. In fruit disease detection, CNN significantly contributes to helping the general public quickly and accurately recognize diseases, enabling them to take appropriate steps to control disease spread [5].

Pomelo is one of the most important fruits in the agricultural industry with high commercial value. However, pomelo is susceptible to disease attacks that can reduce the quality and productivity of the fruit [6]. Therefore, the detection of diseases in Pomelo is crucial. The use of image processing methods in detecting diseases in Pomelo has shown great potential. Symptoms of diseases in pomelo, such as spots, changes in skin color, and deformations, can be identified through image analysis using image processing techniques [6]. With the help of image processing technology, farmers and the general public can quickly and accurately identify diseases in pomelo, enabling them to take the necessary steps to control disease spread, maintain fruit quality, and improve overall harvest yields.

2. Literature Review

Research conducted [7] "Design and Development of an Android-Based Papaya California Plant Disease Identification Application Using CNN Method with Squeezenet Architecture" shows that the application developed using Convolutional Neural Network (CNN) method and Squeezenet architecture is capable of identifying Anthracnose, Ringspot Virus, and healthy papaya through leaves with an accuracy of 97%, while through fruits, it achieves an accuracy of 70% based on validation results.

Another study [8] "Classification of Rice Plant Diseases Using Convolutional Neural Network Method through Leaf Images (Multilayer Perceptron)" implements the Convolutional Neural Network (CNN) algorithm in the classification of diseased rice leaf images by finding the best architecture design by comparing several parameters such as epochs, optimization types, and dataset scenarios. The best architecture of the Convolutional Neural Network (CNN) is obtained from the comparison of several parameters in the classification of bacterial leaf disease, brown spot, and leaf spot using 100x100 pixel size, 3x3 kernel size, 0.01 learning rate, Adam optimizer type, 150 epochs, 30 batch size, and a dataset comparison scenario of 90%:10% with RGB (color) image type. The accuracy rate obtained from testing data using the best architecture model for classifying rice plant disease images based on leaves is 91.7%.

The research titled "Implementation of Disease Detector on Avocado Leaves Using CNN Method" [9] utilizes the Convolutional Neural Network (CNN) method in the process of identifying diseases in avocado leaf images. CNN works by processing avocado leaf images gradually through several layers to recognize specific patterns in the images. In each layer, CNN performs convolution operations to generate more complex features. Then, the results from each layer are processed by the next layer until finally producing an output in the form of disease classification on avocado leaves. In the study conducted by the authors, test results show that Convolutional Neural Network (CNN) can identify diseases in avocado leaf images with an accuracy rate of up to 80%.

Based on related research results, before the model is constructed, feature extraction is performed with thresholding, contouring, and a bounding box. The CNN model to be built uses the DensNet121 architecture with 2 convolution layers, 2 pooling layers, and 1 dense layer with ReLU activation to obtain disease predictions from pomelo fruit.

3. Research Methodology

The data collection techniques used are divided into two methods, namely interviews and documentation. The interview method is used to obtain details about the application requirements, while the documentation method is used to gather the data needed for application development.

a. Interviews

The interview process is conducted to gather the specifications for the application's requirements. The author interviewed one of the farmers and owners of the Pomelo orchard Mr. Sukur, who resides in the village of Japan, Dawe, Kudus.

b. Documentation

Documentation process is carried out to obtain the dataset requirements used for the processing and development of the application. Digital images are captured from the skin of infected pomelo fruits, such as skin cancer disease, fruit fly pests, Diplodia, and healthy pomelo skin. These images will be captured using a digital mobile camera with quality image capture capabilities.

3.1. Data Acquisition

Data acquisition stage is a crucial initial step in the development of the CNN model. This process involves gathering raw data from infected pomelo fruits affected by Diplodia, cancer, fruit flies, and healthy conditions, which will be used for training and testing the model. The research methodology overview depicted in Figure 1 is as follows:

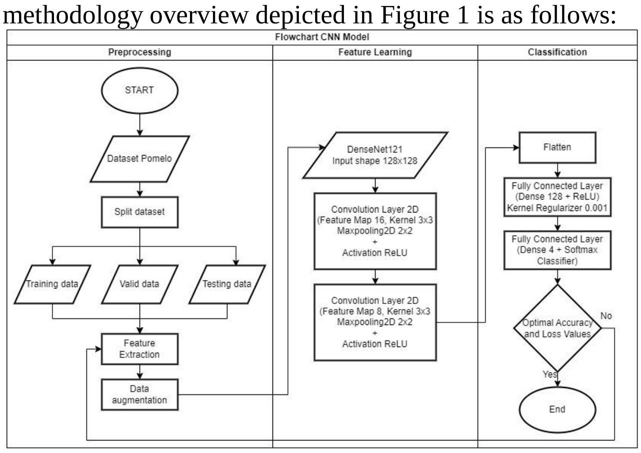

Figure 1 Flowchart CNN Model

3.2. Split Data

Data will be divided into three separate sets: training data, validation data, and test data. The training data is used to train the model, the validation data is used for parameter tuning, and the test data is used to evaluate the model's performance. This is done to measure, evaluate, and optimize the model's performance [10].

3.3. Data Preprocessing

The appropriate preprocessing of data is crucial for enhancing the performance of a model. Through preprocessing, the desired features in the image are emphasized, leading to more prominent features [11]. This stage in Convolutional Neural Network (CNN) involves a series of steps necessary to convert raw data into a format suitable for training a CNN model. Here are the steps:

3.3.1. Feature Extraction

Feature Extraction is an important step aimed at extracting relevant features from images that will be used as input for a CNN model. Typically, feature extraction is done using filters or convolution kernels that can extract visual patterns such as edges, corners, and textures from the image.

3.3.2. Image Resizing

Before being used for training, the images need to be resized to a consistent size. The images will be resized to 128x128 pixels. This ensures that all images have uniform dimensions.

3.3.3. Data Normalization

Normalization is the process of converting pixel values in an image to a consistent scale. Generally, pixel values are normalized to the range [0, 1] or [-1, 1]. Normalization helps in faster convergence of the training model and avoids numerical issues.

3.3.4. Data Augmentation

Data Augmentation is a technique used to generate additional variations in training data by applying transformations such as rotation, shifting, flipping, and color changes to the images. This helps the model learn variations in the data and improves the model's robustness [12].

3.4. Data Generator

During training, a data generator is employed to load and process data in batches, which helps overcome memory limitations and optimize computing time. This approach enhances data diversity and improves the model's ability to generalize patterns [13].

3.4. Training Model

After the data is prepared, the CNN model is trained using the training data. This involves a series of iterations (epochs) where the model's weights are updated based on the comparison between the model's predictions and the actual labels.

3.4. Model Evaluation

After training, the CNN model is evaluated using validation and test data. Metrics such as confusion matrix, accuracy, F1-score, and others are used to measure the model's performance.

4. Results and Discussion

Research results provide an elaboration on the selection and testing of the proposed CNN model based on the research methodology that has been developed. From the obtained test results, a discussion and analysis of each test are conducted to obtain research findings that can be used as the basis for conclusions in further discussions.

4.1. Dataset

The dataset used in this study was obtained from documentation using a digital camera, consisting of 1200 images with each class comprising 300 images. This dataset consists of images of pomelo fruits categorized into 4 classes: diplodia/blondok, cancer, fruit flies, and healthy, each with a size of 128x128 pixels. An example of the dataset can be seen in Table 1 below.

Table 1 Dataset

Class Names	Image	Total
Diplodia		300
Skin Cancer		300
Fruit flies		300
Health		300

4.2. Split Dataset

In this stage of the dataset split, the dataset is divided into training, testing, and validation subsets. First, the original dataset is divided into two main parts: the training subset (x_train and y_train) and the remaining dataset, which consists of the testing and validation subsets (x_test and y_test). The size of the testing subset is set to 20%. Then, the testing subset is further divided into separate testing and validation subsets (x_test, y_test, x_valid, and y_valid), each with a size of 50%. This process results in three main subsets: training, testing, and validation. The results can be seen in Table 2 below.

Table 2 Split Dataset

Subset	Total
Training Dataset	960
Testing Dataset	120
Validation Dataset	120

4.3. Feature Extraction

In this feature extraction stage, thresholding, contouring, and bounding box techniques are used. Thresholding is used to identify the regions containing objects to be extracted from the image, the contour with the largest area is identified, and its bounding box is extracted. Figure 2 is an example of feature extraction results.

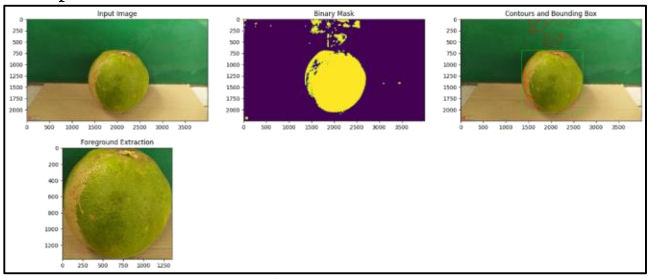

Figure 2 Result of Contour and Bounding Box

4.4. Preprocessing

In this stage, data augmentation is performed for the training subset. This augmentation process helps increase the variation and diversity of the dataset, allowing the model to learn more general patterns and have good generalization capabilities.

This augmentation technique is done using several techniques such as rotation_range, width_shift_range, height_shift_range, shear_range, zoom_range, horizontal_flip, fill_mode, and rescale. The results of the augmentation can be seen in Figure 3 below.

Figure 3 Augmentation Result

4.5. CNN Model

In this process, a basic model for the Convolutional Neural Network (CNN) is constructed using the DenseNet121 architecture. Then, convolution layers, ReLU activation functions, and L2 regularization are applied. Pooling layers are also included to perform subsampling. Figure 4 illustrates the CNN network model.

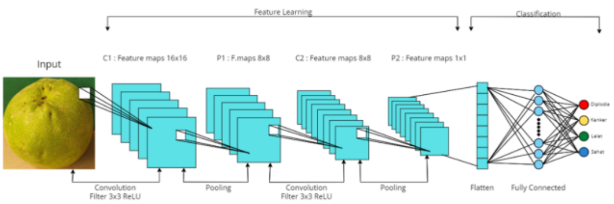

Figure 4 Illustration of the CNN Model

Next, the hyperparameters are set. This process involves configuring several important parameters for the model training process. The model's optimizer is determined using Adam and a learning rate. The optimizer is utilized not only to enhance the model's training accuracy but also to minimize overfitting during the training process [14]. It is responsible for optimizing the model's weights to minimize the loss function.

Furthermore, the 'categorical_crossentropy' function is selected, which is suitable for multi-class classification tasks like in this research. This function measures how well the model's predictions match the actual class labels.

Finally, the evaluation metric used to monitor the model's performance during training is 'accuracy'. This metric indicates of how well the model can classify the data correctly.

4.6. Model Evaluation

4.6.1 Accuracy and Loss

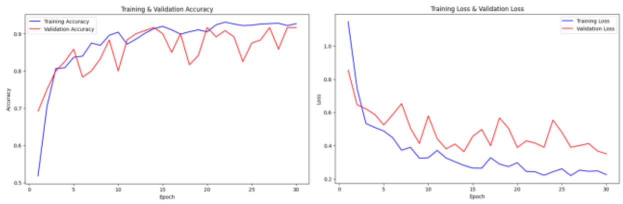

Figure 5 Graphic Accuracy and Loss

Graphic in Figure 5 displays the accuracy curve (blue) and the validation data (red). It can be concluded that the training data experiences an increase but is not very stable, starting from the first epoch with an accuracy value of 0.517 up to the eighth epoch, which experiences a decrease with an accuracy value of 0.8687. Despite some fluctuations, the overall accuracy value shows an increase. This indicates that the higher the accuracy value achieved, the better the resulting model. Additionally, the loss for each epoch decreases, but there are instances where it increases, starting from the first epoch with a value of 1.1459, which decreases until the eighth epoch but then increases by 0.3896. This means that the smaller the loss value, the lower the error rate experienced.

4.6.1 Classification Report

Classification Report:

	precision	recall	f1-score	support
blondok	0.94	0.97	0.96	33
kanker	0.85	0.93	0.89	30
lalat	0.96	0.82	0.88	28
sehat	0.93	0.93	0.93	29
accuracy			0.92	120
macro avg	0.92	0.91	0.91	120
weighted avg	0.92	0.92	0.92	120

Figure 6 Classification Report

In Figure 6, the classification report provides a detailed overview of the CNN model's performance on the four identified classes: Diplodia, cancer, fruit flies, and healthy. The precision values for all classes have an average of 0.92, while the recall and f1-score values have an average of 0.91. The accuracy value is 0.92.

4.6.1 Confusion Matrix

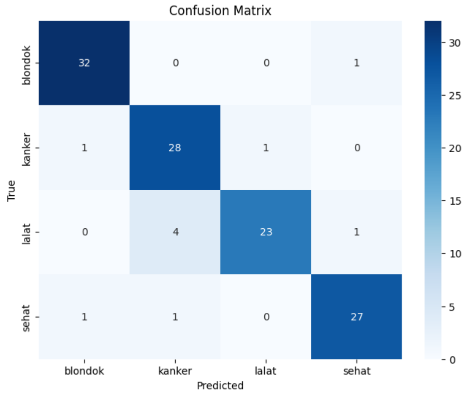

Figure 7 Confusion Matrix

Confusion Matrix graph in Figure 7 provides a visualization of the correct and incorrect predictions [15] made by the classification algorithm for the four classes: blondok, cancer, fruit flies, and healthy. Correct predictions for Diplodia/blondok occurred 28 times, while 1 image was predicted as healthy. Correct predictions for cancer occurred 28 times, while 1 image was predicted as blondok and 1 image as fruit flies. Correct predictions for fruit flies occurred 23 times, while 4 images were predicted as cancer and 1 image as healthy. Correct predictions for healthy occurred 27 times, while 1 image was predicted as blondok and 1 image as cancer.

4.6.1 Prediction Results

To view the prediction results obtained, Figure 8 below shows several images obtained from the test data that were then predicted using the DenseNet121 model. The results indicate that out of 25 predicted images, only 2 were incorrectly predicted, while 23 images were correctly predicted according to the specified labels.

Figure 8 Prediction Results

5. Conclusion

Based on the research results, it can be concluded that the developed model demonstrates notable performance compared to previous studies. The model, utilizing DenseNet121 architecture, achieves an accuracy of 92.50% on the test dataset after being trained for 30 epochs. This surpasses the accuracy rates reported in prior research, such as the 80% accuracy in the avocado leaf disease identification application and the 91.7% accuracy in the classification of rice plant diseases without using pre trained model architecture.

Furthermore, the utilization of DenseNet121 architecture in this study enhances the model's ability to extract features effectively from the images, as evidenced by the comprehensive feature extraction methods employed, including thresholding, contouring, and bounding box techniques. These advanced feature extraction methods contribute to the model's high accuracy in identifying diseases in pomelo fruit.

In conclusion, the developed model showcases significant advancements in disease identification in pomelo fruit, offering higher accuracy and robust feature extraction capabilities compared to previous studies. For future research, it is recommended to consider increasing the quantity and diversity of training data. A larger and more varied dataset can significantly benefit the model, especially in the context of multi-class classification. Additionally, evaluating the model on external, independent datasets to test its generalization and ability to handle a wider range of data variations is advised.

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