Grapevine Disease Identification Using Resnet−50

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Abstract. Visual identification of diseases in grapevines can be a difficult task for growers. The importance of farmers in the identification of grape diseases due to control the spread of disease and lower agricultural yield losses. In this study developed a disease identification system in plants using image processing. Images of leaves on grapevines infected with the disease were taken, extracted features from the images and applied the ResNet-50 algorithm. The dataset of grape leaf images taken was 200 images for four classes, including 3 classes of leaves identified as diseased and 1 class of healthy leaves. The experimental results show that the image processing system for identifying diseases in grapes identifies the types of disease in grapevines. This research has the potential to be implemented in a farm automation system to detect early diseases in grapevines and take appropriate preventive measures to increase productivity and crop quality.

1 Introduction

Grapes have a high market value, making them profitable in the economic sector [1]. Additionally, grapes contain antioxidants that are beneficial to human health [2]. Due to the numerous benefits of grapes, the demand for them continues to increase. Identifying plant diseases in grapevines is crucial for improving grape harvests. It is important to do this early and accurately [3]. In addition, grape growth requires just the right amount of sunlight to prevent the grape skin from becoming wrinkled [4]. Viruses also have a significant impact on the growth of grape leaves [5]. Most growers diagnose diseases manually by observing plants with identified diseases only by naked eye. Timely disease identification is very important as a small number of diseased leaves can transmit the disease to other leaves and even to the grapes [6-7]. If growers want a good harvest, then it is very important to detect vine diseases at an early stage to recommend treatment to prevent heavy losses.

Although many agricultural experts are skilled in identifying diseases, they also have shortcomings such as losing focus, resulting in decreased accuracy in disease identification. Therefore, an automated system with precise accuracy is needed. The combination of image processing, pattern recognition, and classification technology can help to overcome or at least reduce the problem of disease identification [8-10]. The aim of this research is to use digital image processing to detect and characterize diseases in grape plants.

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Identifying diseases in grape plants is a crucial aspect of agriculture as it can aid farmers or agricultural experts in controlling and preventing the spread of diseases. Conventional identification methods such as visual observation can be time-consuming and not always accurate [11-12]. Therefore, image processing techniques have been proposed as an alternative solution for quickly and accurately identifying diseases in grape plants [13-14].

Previous studies have tested the effectiveness of image processing techniques in identifying diseases in grape plants. For example, a study used color segmentation technique to identify leaves of grape plants infected with diseases. The study showed that the color segmentation technique successfully separated infected leaves from healthy ones with a high level of accuracy [15-16].

In addition, research has been conducted using climate-based techniques to identify Downy Mildew and Powdery Mildew. By observing the existing climate conditions, timely diagnosis and accurate detection of plant diseases can be achieved [17]. Other studies have utilized Ghost convolution and Transformer networks to diagnose grape leaves [18], while CNN architecture has been used to identify diseases such as black rot, esca, and isariopsis leaf spot on healthy grape leaves [19].

ResNet-50 (Residual Network-50) is one of the most popular and effective convolutional neural network (CNN) model architectures for image processing tasks, including identifying diseases in grape plants. These blocks allow the network to 'learn' residual information (differences) between the input and output of a layer, enabling deeper and better network training. The main advantage of the ResNet architecture is the use of residual blocks.

2 Research Method

Image processing is a technique used to analyze digital or photographic images. In the context of identifying diseases on grape vines, images of infected leaves are captured using a smartphone camera. The image will then undergo several images processing techniques, including segmentation, which aims to separate the object area from the background, extraction, which is the process of extracting features including color, texture, shape, and size of the object, and classification, which is the process of determining a specific class label for each object in the image.

The image processing method used in this study involves data collection, modeling, and detection (Figure 1). Data was collected through existing datasets on Kaggle, and the identified plant diseases were based on three sets of diseased leaf datasets and one set of healthy leaf dataset, each containing fifty images for each type of disease.

The modeling technique used in this study is thresholding, which is a type of image processing technique used to convert grayscale or color images into binary (black and white) images with the aim of separating objects from the background. The method compares the pixel intensity values with a certain threshold value and converts them into black or white pixels.

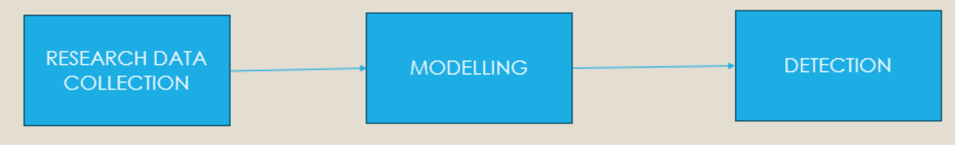


Fig. 1. Methods in image processing

2.1 Dataset

This study will only identify common grape diseases in Indonesia, such as Black Rot, Esca, and Leaf Blight. The research revealed several types of grape diseases, including: Rare grape diseases will not be the focus:

2.1.1 Black Rot

Black rot: brown lesions on leaves that develop black spots (Figure 2). This disease affects leaves, stems, flowers, and fruit. All new growth on the plant is prone to attack during the growing season. Fungicides, such as Dithane, can be used to treat this disease.

Fig. 2. Shows Black Rot

2.1.2 Esca

Esca: is marked by a 'tiger stripe' pattern on the leaves (Figure 3). Esca is also known as 'silent disease', meaning that its symptoms often go unnoticed and can lead to sudden death of the plant. This symptom is caused by toxins produced by *Phaeomoniella, Phaeoacremonium,* and *Cylindrocarpon* spp. Esca can occur as a chronic disease or suddenly during hot and dry summers. Controlling or preventing this disease involves the use of healthy materials, pruning, removal, and burning of diseased plants.

Fig. 3. Shows Esca

2.1.3 LeafBlight

Leaf Blight: Leaf blight is a disease that can infect plants at all growth stages (Figure 4). The cause of this disease is when the leaves are injured or have natural holes such as stomata, which damages the chlorophyll in the leaves and disrupts the photosynthesis process, resulting in the death of the leaves. In addition, environmental factors such as high humidity can also lead to the emergence of this disease. To control it, prune the affected leaves, improve plant sanitation, and spray with bactericide.

Fig. 4. Shows LeafBlight

2.1.4 Healthy

Healthy leaves were used as a control and reference for the images in the dataset (Figure 5).

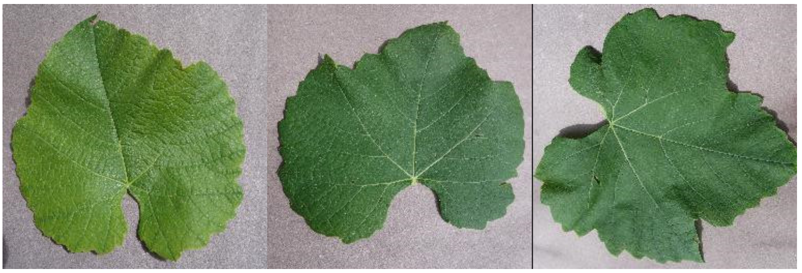


Fig. 5. Shows Healthy leaves

2.2 Preprocessing

Table 1 displays the number of datasets to be trained, which greatly affects the model's performance on image processing and retrieval. The number of images in the dataset and their quality are influenced by several factors, including the complexity of the disease, the required level of accuracy, and the difficulty of identification. In image processing, we must consider the image resolution, which refers to the number of pixels in the image, and the image quality, which includes sharpness, contrast, and detail. By converting the input into images of infected or healthy vine leaves, the model can learn to recognize the characteristic patterns that indicate disease in the vine leaves. The dataset of leaf images is randomly separated into train and test folders with a ratio of 8:2. The source code generated on Google Collaboratory will be used to test the image files.

Table 1. Grapes leaf dataset

Type	Class	Number of Images
Black Rot	0	50
Esca	1	50
LeafBlight	2	50
Healthy	3	50

ResNet-50 was used to train the dataset using the TensorFlow and PyTorch libraries. The top layer of ResNet-50 employs a dense (fully connected) layer and softmax. The dataset consists of three infected classes and one healthy class. An iterative process is used to minimize the loss function by updating the weights in the model. To ensure color consistency in grape plant leaves, white balance correction technique is used to normalize colors, along with preprocessing techniques such as resizing and cropping. The use of ReLU (Rectified

Linear Unit) function in ResNet-50 convolutional layers helps introduce non-linearity into the model, allowing the neural network to learn complex patterns in grape plant image data. This can assist the model in understanding and distinguishing relevant features for identifying diseases in grape plants and learning more abstract representations of grape plant images, enabling the model to make accurate predictions about infected or healthy plants (Figure 6).

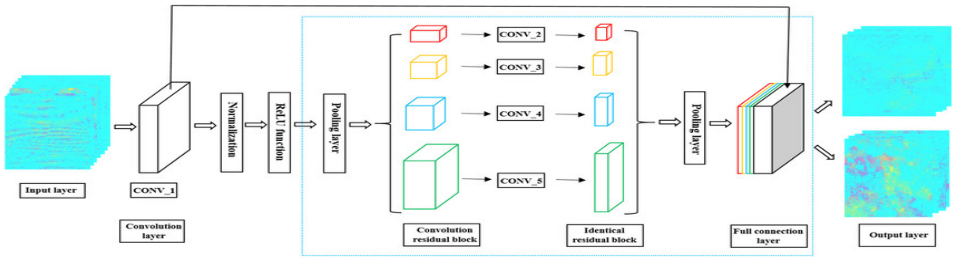


Fig. 6. ResNet-50

After completing the training, evaluate the model on the test dataset using metrics such as accuracy, precision, recall, F1-score, and confusion matrix to measure its performance. Precision is a useful measure to determine the accuracy of the model in classifying positive instances (Eq. 1). Recall provides information about the model's ability to identify all relevant positive examples (Eq. 2). The F1 score is a harmonic measure of precision and recall (Eq. 3). It differs from the regular arithmetic mean in that it places more weight on the lower value of the two metrics [20].

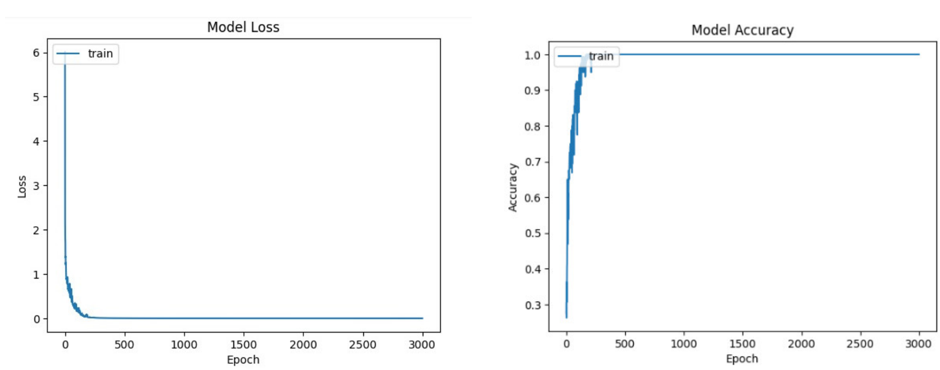
$$Precision = \frac{\mathrm{TP}}{TP+FP} \tag{1}$$

$$Recall = \frac{\mathrm{TP}}{TP+FN} \tag{2}$$

$$F1\ Score = 2 \times \frac{(P \times R)}{P+R} \tag{3}$$

3 Results and discussion

The trial loss measures how well the model performs on the trial data, while the validation loss measures performance on data that the model has not seen during trial. When trial a model, a measure is used to indicate how well or poorly the model predicts the true target from the trial data to minimize the loss value (Figure 7).



(a) **(b)**

Fig. 7. Diagram (a) Loss Data Model (b) Accuracy Data Model

```
5/5 [==============================] - 1s 113ms/step - loss: 1.5281e-06 - accuracy: 1.0000 - val_loss: 1.4636 - val_accuracy: 0.687
Epoch 2993/3000
5/5 [==============================] - 1s 111ms/step - loss: 1.5512e-06 - accuracy: 1.0000 - val_loss: 1.4960 - val_accuracy: 0.6562
Epoch 2994/3000
5/5 [==============================] - 1s 112ms/step - loss: 1.4886e-06 - accuracy: 1.0000 - val_loss: 1.7091 - val_accuracy: 0.6875
Epoch 2995/3000
5/5 [==============================] - 1s 111ms/step - loss: 1.4819e-06 - accuracy: 1.0000 - val_loss: 1.6875 - val_accuracy: 0.7188
Epoch 2996/3000
5/5 [==============================] - 1s 114ms/step - loss: 1.4856e-06 - accuracy: 1.0000 - val_loss: 1.7189 - val_accuracy: 0.6875
Epoch 2997/3000
5/5 [==============================] - 1s 119ms/step - loss: 1.4581e-06 - accuracy: 1.0000 - val_loss: 1.3369 - val_accuracy: 0.7188
Epoch 2998/3000
5/5 [==============================] - 1s 117ms/step - loss: 1.4588e-06 - accuracy: 1.0000 - val_loss: 1.7219 - val_accuracy: 0.6562
Epoch 2999/3000
5/5 [==============================] - 1s 114ms/step - loss: 1.4491e-06 - accuracy: 1.0000 - val_loss: 1.5451 - val_accuracy: 0.6875
Epoch 3000/3000
5/5 [==============================] - 1s 119ms/step - loss: 1.4693e-06 - accuracy: 1.0000 - val_loss: 1.5154 - val_accuracy: 0.6875
7/7 [==============================] - 1s 147ms/step - loss: 2.0592 - accuracy: 0.7450
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3000: UserWarning: You are saving your model as an HDF5 file via `model.save()`.
  saving_api.save_model(
Test accuracy: 0.7450000047683716
```

Fig. 8. Image an accuracy test results on Google Colaboratory

The Figure 8 illustrates the loss incurred during the modeling process in Google Colaboratory over time or epochs during the model training, specifically 3000 epochs with an accuracy of 0.75%.

During the testing phase of grape leaf disease detection with a dataset of 200 images, the parameters used will be TP (True Positive), which represents the number of blocks that correspond to grape leaves and are detected as such, FP (False Positive), which represents the number of blocks that are detected as grape leaves but are not, and FN (False Negative), which represents the number of blocks that are detected as non-grape leaves but are and the detection results based on the program run on Google Collaboratory are in Figure 9.

	precision	recall	f1-score	support
Black_Rot	1.00	0.97	0.99	36
Esca	0.97	1.00	0.99	33
Healthy	1.00	1.00	1.00	30
Leaf_Blight	1.00	1.00	1.00	29
accuracy			0.99	128
macro avg	0.99	0.99	0.99	128
weighted avg	0.99	0.99	0.99	128

Fig. 9. Image the detection results in Google Collaboratory

4 Conclusion

This article discusses the use of ResNet-50 for classifying grape leaf images into four categories: three different symptom images, namely BlackRot, Esca, LeafBlight, and one healthy leaf image. The experimental results show that ResNet-50 can achieve 99% accuracy, making it a reliable tool for assisting farmers in identifying grape plant diseases.

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