Improved inception-V3 model for apple leaf disease classification

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Article Info

Article history:

Received Jan 5, 2024
Revised Mar 22, 2024
Accepted Apr 20, 2024

Keywords:

Apple diseases
Classification
Computer vision
CNN
Improved inception-V3

ABSTRACT

Apple, a nutrient-rich fruit belonging to the genus *Malus*, is recognized for its fiber, vitamins, and antioxidants, giving health benefits such as improved digestion and reduced cardiovascular disease risk. In Indonesia, the soil and climate create favorable conditions for apple cultivation. However, it is essential to prioritize the health of the plant. Biotic factors, such as fungal infections like apple scabs and pests, alongside abiotic factors like temperature and soil moisture, impact the health of apple plants. Computer vision, specifically convolution neural network (CNN) inception-V3, proves effective in aiding farmers in identifying these diseases. The output layer in inception-V3 is essential, generating predictions based on input data. For this reason, in this paper, we add an output layer in inception-V3 architecture to increase the accuracy of apple leaf disease classification. The added output layers are dense, dropout, and batch normalization. Adding a dense layer after flattening typically consolidates the extracted features into a more compact representation. Dropout can help prevent overfitting by randomly deactivating some units during training. Batch normalization helps normalize activations across batches, speeding up training and providing stability to the model. Test results show that the proposed method produced an accuracy of 99.27% and can increase accuracy by 1.85% compared to inception-V3. These enhancements showcase the potential of leveraging computer vision for precise disease diagnosis in apple crops.

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1. INTRODUCTION

Apple is the most popular fruit worldwide [1]. It is favored for its high vitamins and antioxidant content [2]. People who eat apples appropriately can reduce the risk of cardiovascular disease [3]. Simply consuming 25 grams of apples could reduce the risk of heart disease and stroke [4]. This is attributed to apple plants' high fiber content and polyphenolic compounds [5]. Polyphenolic compounds help improve cholesterol levels and reduce inflammation in the walls of blood vessels.

Despite the abundance of antioxidants in apples [6], showcasing their resilience and health benefits, these fruits are not immune to diseases. Apples face various challenges in orchards; diseases can affect their health and yearly yield [7]. The most prominent diseases are apple scab, cedar apple rust, and black rot [8]. Apple scab is an infection brought about by the parasite venturia inaequalis [9]. The natural product becomes distorted and broken, generally lessening market acknowledgment [10]. Cedar apple rust is a disease affecting apple trees caused by a fungus from the genus *Gymnosporangium* [11]. The microorganism prompts critical misfortunes because of untimely decay, decreasing the efficiency of plants [12]. This disease can lead to defoliation of apple trees and declining fruit quality.

In Indonesia, apple plants are among the horticultural crops traded internationally and regionally. These apple orchards are maintained and cared for by local farmers. Local farmers are also required to check for any sick apple plants. However, there is a potential for errors due to the manual nature of the human checking process. Therefore, computer vision can enhance accuracy in classifying apple plant diseases.

The convolutional neural network (CNN) is a popular image classification method. The classification of apple plant diseases using CNN has been previously conducted by Zhong and Zhao [13], resulting in an accuracy as high as 93.71%. In this research, DenseNet architecture was employed with a focal loss function. Additionally, another study by Bansal *et al.* [5] compared the performance of various CNN architectures with a model developed by the researchers [5]. These CNN models were used to classify apple plant diseases based on visual symptoms on their leaves. The researcher-developed model, a combination of DenseNet121, EfficientNetB7, and EfficientNet-NoisyStudent, achieved the highest accuracy at 96.25%.

Inception-V3 is one of the popular CNN architectures for classification. For example, inception-V3 was used for distinguishing batik and its imitation [14], classification of rice leaf disease [15], classification of jackfruit and cempedak [16], pothole recognition [17], and breast cancer classification [18]. Apart from that, inception-V3 is modified to detect fire symptoms [19]. This research, a modified inception-V3 was compared with other CNN models, such as regular CNN, inception-Resnet-V2, and inception-V3. The modification involved adding a dropout layer with a value of 0.5. These models were employed for fire symptom detection, and the final results proved that the modified inception V3 achieved the highest accuracy at 98.64%. Therefore, this paper proposes the improved inception-V3 model by adding output layers for apple leaf disease classification. The added output layers are dropout, dense, and batch normalization layers. Dropout is used to reduce overfitting [20]. Batch normalization is used to increase the stability of data distribution in training and network convergence by reducing internal covariate shifts [21]. The dense layer transforms data dimensions so that they can be classified linearly. The addition of the output layers to the inception-V3 architecture is expected to increase accuracy compared to the basic architecture for apple leaf disease classification.

2. METHOD

This research is divided into several processes, namely data collection, image resizing, augmentation, classification, and model evaluation, as shown in Figure 1. Data collection is the first process, followed by preprocessing (image resizing and augmentation). The results of the preprocessing process are used for the classification process using the improved inception-V3 model. This model is a development of inception-V3 by adding dropout, dense, and batch normalization layers.

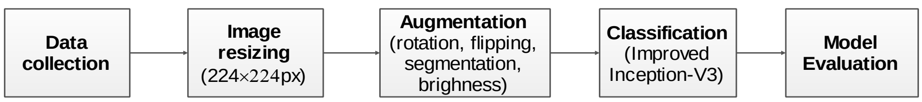

Figure 1. The main steps of the research method

2.1. Data collection

This research utilizes apple leaf image data from the new plant diseases dataset, uploaded on Kaggle [22]. This dataset comprises 87,867 red, green, and blue (RGB) images divided into 38 classes with 14 types. This study focuses only on apple tree diseases, using 3,171 RGB images representing four disease classes. The data distribution is presented in Table 1. Examples of images from each disease class can be seen in Figure 2. Figures 2(a) is apple scab, 2(b) is black rot, 2(c) is cedar apple rust, and 2(d) is healthy leaf image.

Table 1. Dataset class distribution

Classes	Amount
Apple scab	620
Black rot	621
Cedar apple rust	275
Healthy	1,645
Total	3,171

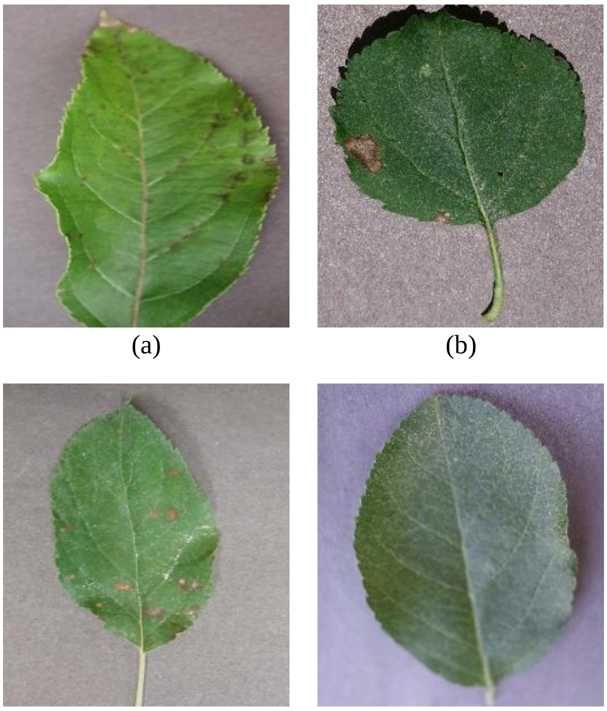

Figure 2. Example of dataset: (a) apple scab, (b) black rot, (c) cedar apple rust, and (d) healthy

2.2. Image resizing

Image resizing is the method involved with changing the info image size. For example, resizing an RGB image of 300×300×3 can transform it into 224×224×3 as in [23]. Resize utilizes the bilinear interpolation algorithm [24]. Bilinear interpolation is a method for filling in values between two points by calculating the weighted average of the four nearest neighbors.

2.3. Augmentation

Image augmentation is a technique for adding data by creating new variations of existing images. We use rotation, flipping, segmentation, and brightness enhancement techniques. Image rotation is the process of rotating an image either clockwise or counterclockwise. Rotation can be performed between 1° and 360° [25]. The flipping process is carried out by exchanging elements in the columns or rows of the input matrix [26]. Image segmentation is identifying objects or essential parts of an image. The segmentation used in this work is grayscale [27]. Image brightness is the process of increasing or reducing the overall brightness level of an image. The total data after augmentation is 9,714 images, as indicated in Table 2.

Table 2. The total data after augmentation

Augmentation	Apple scab	Black rot	Cedar apple rust	Healthy
Default	630	621	275	1,645
Rotation -90˚	630	621	275	0
Rotation -180˚	0	0	275	0
Rotation -270˚	630	621	275	0
Rotation 30˚ vertical flip	630	621	275	0
Rotation 30˚ horizontal flip	0	0	275	0
Horizontal flip	0	0	0	865
Segmentation	0	0	275	0
Brightness	0	0	275	0
Total	2,520	2,484	2,200	2,510

2.4. Classification (improved inception-V3)

The classification process for apple leaf diseases uses the improved inception-V3 model, as shown in Figure 3. This model is a development of inception-V3 proposed by Szegedy *et al.* [21]. We added output layers, namely dense, dropout, and batch normalization. Adding a dense layer after flattening typically consolidates the extracted features into a more compact representation [28]. Dropout can help prevent overfitting by randomly deactivating some units during training [20]. Batch normalization helps normalize activations across batches, speeding up training and providing stability to the model [29].

The development of inception V3 aimed to overcome computing time problems and improve accuracy [21]. Previously, CNN had a reasonably deep kernel size, which could cause a model to be susceptible to overfitting. Inception V3 addressed this problem by operating the filters in parallel. Inception operated multiple filters and measured in parallel.

The RGB image is received and proceeded to a collection of convolutional layers of small size to extract low-level features. The next step is concatenating Inception modules. Each module has 1×1, 3×3, and 5×5 convolution layers running parallel. The network is optimized during training using appropriate loss functions and backpropagation to update model parameters. Overall, the inception V3 architecture leverages parallel branches with different filter sizes, dimensionality reduction modules, additional classifiers, and global average pooling to extract and combine features at multiple scales and dimensions.

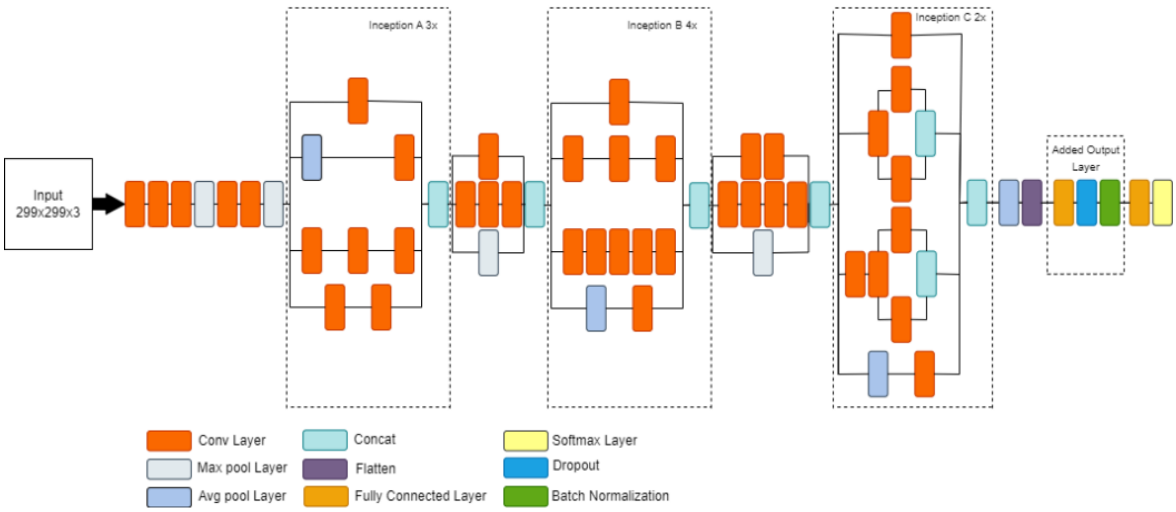

Figure 3. The improved inception-V3 architecture

2.5. Model evaluation

We use accuracy to evaluate the proposed method, as in (1). True positive (TP) is the sum of instances correctly predicted as positive. True negative (TN) is the sum of instances correctly predicted as negative. False positive (FP) is the sum of instances incorrectly predicted as positive. False negative (FN) is the sum of instances incorrectly predicted as negative.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

3. RESULTS AND DISCUSSION

The experiments determine the best combination of parameters for the output layer in classifying images of apple leaf diseases. The experiments are divided into three parts: variation of dense, dropout, and batch normalization parameters. Each experiment is executed with 80% training data, 10% validation data, and 10% test data. Each experiment runs for 30 epochs, uses a learning rate of 0.001, a batch size of 64, and uses the Adam optimizer.

3.1. Experiment result of dense layer variations

The first experiment uses the dense parameter variations, namely 512; 1,024; 2,048; and 4,096 values. These parameters are selected based on the research conducted by Basha *et al.* [30]. The experiment results can be seen in Table 3. The highest experiment accuracy reached 99.17%. The 512 dense can provide the best results because of its fewer parameters. It reduces the risk of overfitting while allowing the model to understand complex patterns in the training data.

Table 3. Experiment result of dense layer variations

Dense	Training accuracy (%)	Validation accuracy (%)	Testing accuracy (%)
512	**99.43**	**99.06**	**99.17**
1,024	99.27	98.15	98.97
2,048	98.75	98.04	98.45
4,096	99.15	98.76	98.87

3.2. Experiment result of dropout layer variation

The second experiment uses the dropout parameter variation, namely ratios of 0.25, 0.5, 0.7, 0.75, and 0.9. These parameters are determined based on the research conducted by Srivastava *et al.* [20]. The result of this experiment is shown in Table 4. The highest testing accuracy reached 98.86% using a dropout of 0.75. Dropout of 0.25 yields good results as it reduces overfitting by deactivating a small percentage of neurons.

Table 4. Experiment result of dropout layer variation

Dropout	Training accuracy (%)	Validation accuracy (%)	Testing accuracy (%)
0.25	99.78	99.18	98.35
0.50	98.25	98.66	98.14
0.70	95.24	99.07	98.25
0.75	**89.64**	**98.87**	**98.86**
0.90	60.79	97.53	96.91

3.3 Experiment result of a batch normalization layer

The batch normalization parameter is used with the options of on and off. The results of this experiment are shown in Table 5. The highest testing accuracy reached 99.27% using batch normalization. The reason is that data distribution can be maintained, and the network can adjust weights effectively.

Table 5. The experiment result of on and off-batch normalization

Batch normalization	Training accuracy (%)	Validation accuracy (%)	Testing accuracy (%)
on	**99.65**	**99.49**	**99.27**
off	99.78	99.18	98.35

Finally, we compared the proposed method with previous research, namely the DenseNet-128 [13] and the basic inception-V3, as shown in Table 6. This table shows that the proposed method produces higher accuracy than previous research. In addition, the proposed method can improve the accuracy by 1.85% of inception-V3. For this reason, it can be concluded that adding dense, dropout, and batch normalization layers to the inception-V3 architecture can improve the model's performance.

Table 6. Comparison between the proposed method with previous research and inception-V3

Methode	Accuracy (%)
DenseNet-128 [13]	97.73
Inception-V3	97.43
Improved inception-V3 (proposed)	**99.27**

4. CONCLUSION

This research has developed the inception-V3 method by adding dense, dropout, and batch normalization layers to classify apple leaf diseases. An experiment was done with dense, dropout, and batch normalization parameter variations. The experiment results show that the proposed method can achieve an accuracy of 99.27%. Adding these layers can increase the accuracy of inception-V3 by 1.85%. These enhancements showcase the potential of leveraging computer vision for precise disease diagnosis in apple crops.

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