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Enhancing Papaya Disease Detection using Deep Learning and Data Augmentation Techniques: A Case Study in Sri Lanka

Kosala Kumara, Abishethvarman Vadivel*, Banujan Kuhaneswaran and Samantha Kumara

[1]Faculty of Computing, Sabaragamuwa University of Sri Lanka, Belihul Oya, Sri Lanka

*abishethvarman@gmail.com

Abstract

All farmers, particularly fruit growers, must take plant disease seriously. A significant problem for large farms is the spread of diseases that make the fruits unfit for consumption, thereby negatively impacting the farmer's income. In order to stop the spread of disease, farmers must discover it early in its life cycle. Traditional fruit disease detection and identification rely on a person's ability to see the diseased fruit. Even though this approach may suffice for small-scale farmers, it requires a high skill level for accurate identification. Machine Learning and Image Processing techniques have been used in recent research to develop computerised solutions to this challenge. This study considers Papaya, a popular fruit in Sri Lanka which suffers from a high post-harvest losses. Anthracnose, black spot, powdery mildew, phytophthora, and ringspot were selected among various papaya fruit diseases. They were choosen because they are the most prevalent papaya diseases in Sri Lanka. Data were collected from public image sources from the internet and actual fields. VGG 16, as a Convolutional Neural Network technique, was used to develop a computerised model for detecting papaya diseases. However, due to insufficient data, most image-based disease recognition systems have some limitations. However, novel data augmentation methods have promising advantages in expanding the limited data. This approach used Deep Convolutional Generative Adversarial Network (DCGAN) to expand the data set. The VGG 16 model accuracy was found using the same pre-processed data set with and without subjected to DCGAN. According to the results, the VGG 16 model has shown high accuracy across diseases. The resulting accuracy for Anthracnose, black spot, powdery mildew, phytophthora, and ringspot were 90%, 85%, 70%, 65% and 90%, respectively. The results indicate that the proposed DCGAN model performs better than basic techniques.

Keywords: Papaya diseases, DCGAN, VGG 16, Deep learning

1.Introduction

In Sri Lanka, the agricultural sector plays a critical economic role. From the fast, it has been the main livelihood for the rural population. It contributed 7.3% to the Gross Domestic Production (GDP) in 2020 (Department of Census and Statistics & Ministry-of-Finance-in-Sri-Lanka, 2020). However, the connection between people and the agricultural sector has weakened due to mechanisation and globalisation. Due to lifestyle changes, their preferences have also changed. Therefore, during the last few decades, the growth of the agricultural industry has declined drastically (Rezvi, 2018). The agricultural sector not only provides food but also provides farmers with income. It also contributes to foreign exchange earnings for Sri Lanka. Sri Lanka benefits from optimal climatic conditions for cultivating a wide range of fruits and vegetables, including both indigenous crops and exotic varieties. Besides fruits and vegetables, yams and cereals, like vegetable crops, can be cultivated in many agroclimatic zones with minimum inputs such as fertilisers and irrigation water. During the Yala and Maha seasons, farmers primarily cultivate rice, while fruits, vegetables, and yams are grown as secondary crops in the same fields (K. Perera, 2023) In Sri Lanka, about 80 varieties of fruits and vegetables are available (Industry Capability Report Fresh Fruit & Vegetable, 2016).

As a result of busy life schedules, people in the modern world tend to seek quicker solutions using minimal technology. Therefore, the demand for semi-processed and processed fruits and vegetables remains high on the daily food list (World Health Organization, 2005).

Diseases are a major concern for all farmers, particularly fruit growers. It is a hazard to large farmlands as these diseases can spread rapidly across the area and render the fruits inedible, resulting in a farmer's income loss (Vetal & Khule, 2017). As a result, early disease diagnosis is critical for farmers to prevent or control disease transmission (Dubey & Jalal, 2013). Observation with the naked eye is the traditional way of detecting and identifying fruit diseases. However, some small symptoms cannot be detected by the naked eye. Therefore, novel and advanced technologies have been developed.

Papaya fruit has everlasting market demand. It originates from tropical regions of the United States of America. However, papaya cultivation is now common in many tropical countries, including Sri Lanka. It is not a seasonal fruit. It can be harvested, year-round. The largest papaya cultivation can be seen in the Kurunegala district, while papaya cultivation can also be found in other districts such as Gampaha, Kalutara, Galle, Anuradhapura, Puttalam, Badulla, and Hambantota (Abeywickrama, Wijerathna, Rajapaksha, Kannangara, & Sarananda, 2008).

The most commonly detected papaya diseases in Sri Lanka are phytophthora, black spots, powdery mildew, anthracnose, and papaya ringspot (Vidanapathirana, 2019). The quality and quantity of the harvest are both affected by diseases. To combat these problems, farmers increasingly use synthetic chemicals in their farming operations. The freshness of the fruit is harmed by excessive chemical use. As a result, farmers benefit significantly from early detection of the disease.

Among them, image processing techniques are more beneficial in terms of time for detection, and disease detection is based on computer vision techniques (Arunachalam, Kshatriya, & Meena, 2018). In this process, colour images are converted into digital images by means of a series of processing techniques, including image preprocessing filtering. These techniques include segmentation, feature extraction, and classification. The classification can be based on the lesion's shape, colour, texture, and size (Bhargava & Bansal, 2021).

This study used convolutional neural networks as a deep learning approach. In convolutional neural networks, images are used as direct input. Also, it uses automatically learned features for classification purposes instead of handcrafted features. This is achieved by convolving the image with learned filters. A feature map hierarchy is built then (Koushik, 2016). This hierarchical approach enables the learning of distortion and translation invariants and more complex invariant features in the higher layers of CNN.

A large amount of data is required for the training of neural networks. In actuality, limited data hinders the effectiveness of these systems. This is due to underdetermined parameters and poorly generalised networks. In this context, "Generative Adversarial Networks (GAN)" alleviated these problems by using existing datasets (Lata, Dave, & KN, 2019). Various GAN models have been proposed based on specific requirements. Simple GAN, Deep Convolutional GAN (DCGAN), Pix2Pix GAN, Cycle GAN, and Aperture Rendering GAN (AR-GAN) are some of the existing GAN models used in deep learning (Dewi, Chen, Liu, & Yu, 2021; Knyaz, Kniaz, & Remondino, 2018; Plouhinec et al., 2014).

In Sri Lanka, papaya is one of the most widely grown fruits. Papaya is generally preferred by most people. Papaya can also be made into curry. Papaya produces jam, salads, drinks, juices, and flavourings for various cuisine in Sri Lanka. The papain extracted from papaya is employed in various industries, including bubblegum, soap, and pharmaceutical production. Therefore, papaya cultivation contributes to earning foreign exchange for Sri Lanka. However, even in Sri Lanka, papaya production is insufficient to meet local demand (Venkatprahlad, 2018). Therefore, minimising both post-harvest and pre-harvest losses is of paramount importance. Many advanced techniques are used in many developed countries.

VGG 16 is a very deep convolutional network. It is used for large-scale image recognition. It demonstrates high accuracy. For instance, this model could achieve 92.7% (Top 5) accuracy in ImageNet. ImageNet is a dataset containing over 14 million images across 1000 classes. Several empirical studies have already been conducted on image processing-based disease detection in papaya (Habib et al., 2020). However, image processing with GAN augmentation enhances the accuracy of disease decisions using the image processing technique. GAN-based methods can be used with limited datasets (Bi, 2019).

2.Literature Review

Diseases in fruits and vegetables are a significant concern and difficulty in the agricultural industry and a source of financial loss (Arunachalam *et al.*, 2018; Martinelli *et al.*, 2015). When it comes to maximising the export potential of fruits and vegetables, the food's quality must fulfil the requirements of the export market (Bhargava & Bansal, 2021). The number of disease-free fresh fruits and vegetables produced grows for home use and export.

Post-harvest losses of fruits and vegetables are estimated at 30-40% of total production (Vidanapathirana, 2019). Fruit post-harvest losses are esimated at 20-40%, with papaya experiencing, the largest loss, while vegetable post-harvest losses range from 20-46%, with okra being the most affected. These losses are primarily caused by, poor handling and inadequate plant care both before and after harvesting.

Stem-end rot, anthracnose, water blister, and interior browning of fruits are the most common post-harvest diseases and disorders in Sri Lanka. For efficient implementation of control and management measures, accurate diagnosis of causal agents for plant disease and disorders is essential (Arunachalam *et al.* , 2018). In Sri Lanka, the minimum intervention required to ensure the fresh produce's quality and safety at the growing and production stages has been identified. Limited technological improvement in disease identification and a lack of knowledge about fruit and vegetable diseases in Sri Lanka are major problems in quality inspection and disease detection of fruits and vegetables.

Anthracnose, a major crop disease that causes significant economic losses when present in fruits, is considered the most common. Around 90% of papaya loss can be attributed to anthracnose (dos Santos Vieria *et al.*, 2020). Sunken necrotic tissue characterises anthracnose caused by Colletotrichum species. Orange conidial masses appear when the disease is at its most severe (Lata *et al.*, 2019). Before and after harvest, the pathogen can attack immature and mature fruit (Udayanga, Manamgoda, Liu, Chukeatirote, & Hyde, 2013). With high humidity and rain, anthracnose is prevalent in tropical and subtropical regions (Maeda & Nelson, 2014). The papaya fruit is far more severely affected by anthracnose than papaya leaves. Small, light-coloured spots appear as the fruit reaches the end of its growth cycle. As the spots grow larger, they sink in and appear soggy. Spots on a fruit can grow up to 5 cm in diameter or merge and destroy it. Cordial masses" of *Colletotrichum gloeosporioides* form concentric rings in the sunken lesions as the fruit ripens and the disease progresses. "Chocolate spot lesions" are another common symptom. These reddish-brown, irregular or circular spots measure between 1 and 10 millimetres—circular, sunken lesions up to 20 millimetres in diameter form as the fruit ripens. There is no known explanation for why the same pathogen causes two distinct symptoms (Maeda & Nelson, 2014).

Zhang (Zhang, Rao, Man, Jiang, & Li, 2021) has proposed a method for identifying cucumber leaf diseases using deep learning and a small sample size for agricultural Internet of Things (IoT). This approach involved extracting disease spots from cucumber leaves, and employed a two-stage segmentation process to acquire lesion images was reported. When applied to data sets of lesion and raw field diseased leaf images with three distinct illnesses of anthracnose, downy mildew, and powdery mildew, the average detection accuracy was 96.11% and 90.67%, respectively. Both AR-GAN and DC-GAN were employed.

Three approaches, including data augmentation, generative adversarial network, and label smoothing regularisation, were developed and applied in the study proposed by (Bi, 2019) to increase the prediction accuracy of CNN in recognising plant diseases using a limited training dataset. The GAN was trained regularly using real images. The trained GAN was then utilised to generate more labelled pictures. The produced images were combined with genuine photographs before being enhanced using data augmentation. Finally, the dataset was employed in the CNN training.

Tian, Li, and Liang (2021) proposed a method for diagnosing typical apple diseases using a deep learning method based on a multi-scale dense classification network. In that study, Cycle-GAN was used for data augmentation. Multi-scale connections were also used to develop two models, Multi-scale Dense Inception-V4 and Multi-scale Dense Inception-Resnet-V2, that allowed image data from the bottom layers to be reused in classification neural networks. Both algorithms were successful at identifying 11 different image categories. The classification accuracies were 94.31% and 94.74%, respectively.

3.Methodology

3.1.Overview

After reviewing previous research, some research gaps in image processing technology for disease identification, especially for papaya fruit, were identified, and to address these gaps, new image processing techniques incorporating generative adversarial networks were employed. This chapter explains the step-by-step implementation and technologies used in this study.

3.2.Technologies

Deep Neural Networks (DNN), Artificial Neural Networks (ANN), Autoencoders, Restricted Boltzmann machines, and Convolutional Neural Networks (CNN). CNN is the best deep-learning approach for image-based pattern identification applications. It functions similarly to a multi-layer perception network. The use of appropriate filters can capture the temporal and spatial dependencies of an image. Convolutional, fully connected, normalisation, and pooling layers are some types found in CNN. Compared with other classification algorithms, CNN requires less image pre-processing. This is considered one of CNN's main advantages. The following libraries were used to implement the algorithms in the model.

i. TensorFlow

ii. Keras

iii. OpenCV

iv. NumPy

v. Sklearn

3.3.Model development

The research consists of five main steps. This process includes acquisition, pre-processing, DC-GAN augmentation, training, and validation of images. The overall methodology is shown in Figure 1.

3.3.1.Image acquisition and pre-processing

Raw images of diseased papaya fruit were collected during the image acquisition stage. The information was gathered from both online and local sources. In order to categorise the images of diseased papaya fruits, diseases like anthracnose, powdery mildew, ringspot virus, black spot, and phytophthora-like diseases were selected.

The pre-processing of the images was the next step. All images that are not in the.jpg, the formats were first converted to.jpg. Next, the images were subjected to basic augmentation and cropped to highlight disease-affected areas. Adobe Photoshop was used to rotate the images in the following order: flipped horizontally, rotated counter-clockwise, flipped counter-clockwise. Anthracnose, black spot, Phytophthora, powdery mildew, and Ringspot were all included in the dataset of 3500 images. Each category contained 700 images. All images were saved in Google Drive. The images were fed into the VGG 16 model. For training, 60% of the images were allocated, while 20% of the images were allocated for validation, and the remaining 20% of the images were allocated for testing. The sample images are shown in Figure 2.

3.3.2.Data set augmentation with DC-GAN

Generative Adversarial Networks is a framework for training a deep learning model to capture the distribution of training data such that fresh data can be generated from the same distribution. A generator and a discriminator are the two models in DC-GAN. The generator creates fake images that resemble the training images. The discriminator examines an image and determines whether it is a true training image or a fake image generated by the generator. During training, the generator tries to outsmart the discriminator by creating increasingly better fakes, while the discriminator functions to improve as a detective and accurately categorise real and fake images. The task reaches equilibrium when the generator generates perfect fakes that appear to have come directly from the training data, and the discriminator is left to anticipate whether the generator output is real or fake with a 50% confidence level.

Many existing GANs and their variation models, such as DCGAN and SinGAN, are successful in visually producing a more realistic and attractive composite image by retaining the semantic identity and properties of the objects in the input mask in the recently suggested DC-GAN.

A DCGAN is an extension of the GAN, except that the discriminator and generator layers are explicitly convolutional and convolutional-transpose layers. Stride convolution layers, batch norm layers, and LeakyReLU activations make up the discriminator. The output is a scalar probability that the input is from the genuine data distribution, and the input is a 5x64x64 input image. The generator comprises convolutional-transpose layers, batch norm layers, and ReLU activations. The input is a 5x64x64 RGB image, and the output is a latent vector, space vector (ZZ), derived from a typical normal distribution. The latent vector can be turned into a region with

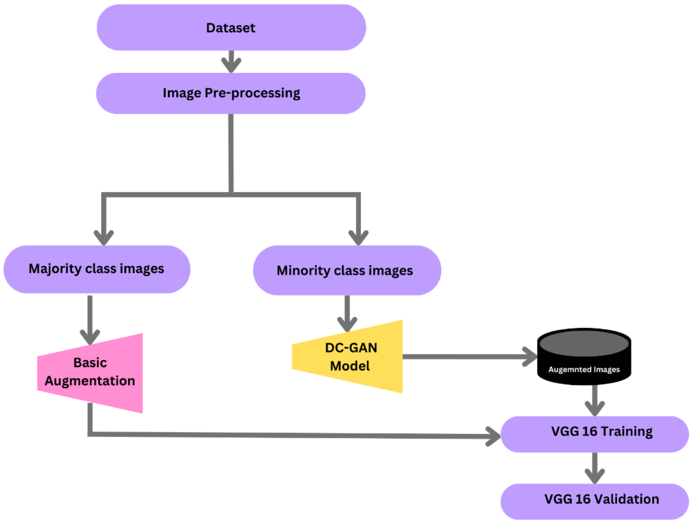

Figure 7: Proposed model for disease identification of papaya fruit

Figure 8: Sample images for papaya diseases. (A) Anthracnose. (B) Black spot. (C) Phytophthora. (D) Powdery mildew. (E) Ring spot.

the same shape as an image using the stridden Conv-transpose layers. All the layers are displayed in Figure 3.

The model was run, and then the data set subjected to basic augmentation in Google Drive was linked. A deep learning package called Keras is utilised to build the DC-GAN model on top of the TensorFlow GPU backend. TensorFlow is the backend framework that supports the deep learning model by providing both high and low-level APIs. Keras is an open library that gives high-level APIs.

The generator maps the latent ZZ to the data space. Because data was in the form of images, transforming ZZ to data space entails constructing an RGB image of the same size as the training images (5x64x64). A succession of stridden two-dimensional convolutional transpose layers, each paired with a 2d batch norm layer and a ReLu activation, is used to achieve this. The generator's output was sent through a function to return it to the [-1,1] input data range. The existence of batch norm functions after the conv-transpose layers was noteworthy. These layers aid in the gradient flow during training.

A discriminator is a binary classification platform that receives an image as input and returns a scalar probability that the image is real. The discriminator takes a 5x64x64 input image, runs it through a succession of Conv2d, BatchNorm2d, and LeakyReLU layers, and then uses a Sigmoid activation function to output the final result. If more layers are required for the problem, this architecture can be expanded, but the employment of stridden convolution, BatchNorm, and LeakyReLUs is essential. The batch norm and leaky ReLu functions support a good gradient flow, essential for generator and discriminator training processes.

3.3.3.DC-GAN model training

First, create a batch of original samples from the training set, then forward pass through the discriminator, calculate the loss (log(D(x))), and backward pass to get the gradients. Second, using the current

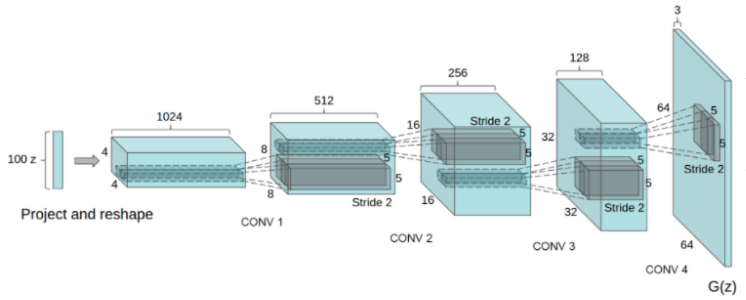

Figure 9: Generator of DC-GAN

generator, create a batch of fake samples, forward run them through the discriminator, and compute the loss (log(1-D(G(z)))). The discriminator was optimised using the gradients obtained from the all-real and fake batches.

In order to create better fake images, the generator was trained by minimising log(1-D(G(z))). The approach included classifying the discriminator's output, computing the generator's loss using real labels as GT, computing the generator's gradients in a backward pass, and finally updating the generator parameters.

3.3.4.Deep learning model VGG 16

Google Collaboratory was used to develop and train the model. It made it easier to use the cloud's processing and storage capabilities. Training a model in the Google Colaboratory environment is also faster because it requires less computing power. VGG16 is a regularised version of the multilayer perceptron used in this study. The author used the TensorFlow backend to build the model. The Keras model is used to create the model.

VGG16 convolution layers of 3x3 filter with a stride one always use identical padding and maxpool layer of 2x2 filter of stride 2. It follows the configuration of convolution and max pool layers uniformly throughout the complete design. Ultimately, it contains two fully connected layers and a softmax for output. The 16 in VGG16 refers to it containing 16 layers that have weights. This network is huge, and it has roughly 138 million parameters. These conv layers and specifications for VGG16 are displayed in Figure 4.

Training and validation losses and accuracy were analysed and visualised after training the model. All diseases were included in the new dataset created for this study's testing. Based on the results of testing, a confusion matrix was created.

All of the libraries required to implement VGG16 were added to the project. Layers were arranged in a sequential order using a sequential model. Keras' ImageDataGenerator was imported. ImageDataGenerator aims to simplify importing data with labels into the VGG 16 model. It can rescale, zoom, rotate, and flip images. When applying the data to the model, this generator might change it on the run. Then, the image folder was created for ImageDataGenerator.

The folder with train data was passed to the object training data, and the folder with test data was passed to the object testing data. Image Generator can automatically label images according to the type of Papaya disease. Then, the model was started as follows. After that model, the summary was generated, and the model was validated. It is shown in Table 1.

4.Results and Findings

The field data sets are stored in Google Drive, and Images are visualised using Google Collaborator. Pre-processed photos are cropped to highlight only the diseased parts, using Photoshop are stored in Google Drive and visualised using Google Collaborator. Those images are set to be inserted into DC-GAN and fed to the VGG 16 model. Then, the epochs were increased to 1000, and the generator loss was reduced for all diseases. The generator loss was minimal for papaya ringspots, among other diseases.

There is a possibility of a gap between the discriminator and the generator loss. That implies that more than 1000 epochs are needed to equilibrate the DC-GAN model. Both data sets from basic augmentation and DC-GAN were fed into VGG 16. The VGG 16 model was trained using both data sets. Eventually, it can be seen

Table 14: Structure of VGG 16 Layers

Layer		Feature Map	Size	Kernel Size	Stride	Activation
Input	Image	1	224 x 224 x 3	-	-	-
1	2 x Convolution	64	224 x 224 x 64	3x3	1	ReLu
	Max Pooling	64	112 x 112 x 64	3x3	2	ReLu
3	2 x Convolution	128	112 x 112 x 128	3x3	1	ReLu
	Max Pooling	128	56 x 56 x 128	3x3	2	ReLu
5	2 x Convolution	256	56 x 56 x 256	3x3	1	ReLu
	Max Pooling	256	28 x 28 x 256	3x3	2	ReLu
7	3 x Convolution	512	28 x 28 x 512	3x3	1	ReLu
	Max Pooling	512	14 x 14 x 512	3x3	2	ReLu
10	3 x Convolution	512	14 x 14 x 512	3x3	1	ReLu
	Max Pooling	512	7 x 7 x 512	3x3	2	ReLu
13	FC	-	25088	-	-	ReLu
14	FC	-	4096	-	-	ReLu
15	FC	-	4096	-	-	ReLu
Output	FC	-	1000	-	-	Softmax

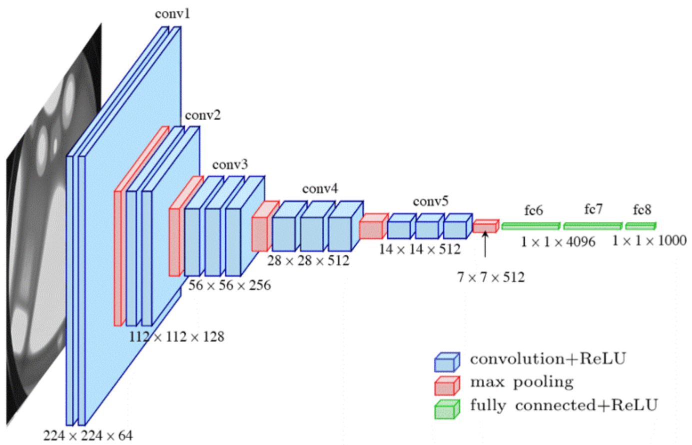

Figure 10: Standard VGG 16 architectures

Table 14: Classification accuracy of the VGG 16 model with DC-GAN augmentation and basic data augmentation

Disease	**Classification Accuracy with GAN Augmentation (%)**	**Classification Accuracy with Basic Augmentation (%)**
Anthracnose	90	80
Black Spot	85	85
Phytophthora	70	65
Powdery Mildew	65	65
Ringspot	90	80

that DC-GAN has increased the model's accuracy and reduced the model loss.

As mentioned earlier, Agriculture is the most important means of providing food to people. Fruit production is a significant component of agriculture. Papaya is a tasty fruit that is grown in a variety of nations throughout the world. It is also a commonly grown crop in Sri Lanka. Diseases pose a significant challenge in papaya farming, as in many other crops. Early disease detection is critical for farmers who want to avoid or limit the effects of these illnesses. Traditional disease detection methods, such as naked eye monitoring, are often ineffective. Various digitalised disease identification approaches have been developed to address this problem. The overall purpose of this study is to develop an improved computational model for detecting papaya diseases. Anthracnose, Black Spot, Phytophthora, Powdery mildew, and ringspot were the five most frequent papaya diseases in Sri Lanka included in the study. A VGG 16 Convolutional Neural Network was used to classify the images. In addition, the study was divided into five stages: picture acquisition, image pre-processing, training, and validation. This study aimed to improve the effectiveness of automatic fruit disease detection. The size of the dataset determines the model's accuracy. The suggested model accuracy can be enhanced by using image pre-processing. The implemented model successfully detected papaya diseases with a high degree of accuracy. The results reveal that colour images achieved a higher classification accuracy.

Table 2 shows the VGG 16 model accuracy for both data sets. According to the results, the model trained with DC-GAN shows higher accuracy than the model trained with images not subjected to DC-GAN. Because the data set is large in the model training phase with DCGAN. Additionally, the test results indicate that the number of epochs influences the model's accuracy. When the number of epochs is low, there is a huge gap between G and D loss. But when the number of epochs increases, the G and D loss becomes low and equilibrate. Therefore, there should be a sufficient epoch to generate an accurate model.

When considering the overall model accuracy with both data sets subjected to DCGAN and without being subjected to DCGAN, the model accuracy was increased, and model loss was decreased with epochs with the data set subject to DCGAN.

5.Conclusion

According to the test results, it can be concluded that the proposed model for papaya disease identification could increase the accuracy of the detection of papaya diseases because the detection accuracy for all diseases is higher in the data set from DCGAN compared to the data set with basic augmentation. Therefore, the proposed method is beneficial for situations with limited data sets. With 8000 epochs, DCGAN can efficiently equilibrate discriminator and generator losses. All accuracies are different, where anthracnose and ring spot diseases showed high detection accuracy, whereas powdery mildew showed the least accuracy. Therefore, the proposed method is particularly effective for detecting anthracnose and ring spot diseases.

This approach can be extended to develop a model with DCGAN with other neural network methods and a method with different GAN models to find the best pair with the highest accuracy for papaya disease detection. It is suggested to develop a generalised model for disease detection for all fruits and vegetables by using GAN and deep learning approaches.

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