# Structural Invariant Feature Segmentation Based Apple Fruit Disease Detection Using Deep Spectral Generative Adversarial Networks

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ORIGINAL RESEARCH

# Structural Invariant Feature Segmentation Based Apple Fruit Disease Detection Using Deep Spectral Generative Adversarial Networks

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## Abstract

In Indian economy agriculture, Crop cultivation plays an important role in the fruit production agricultural sector. At present, crop loss is primarily due to infested crops, resulting in reduced production rates for affecting various diseases. Manual monitoring of the disease is very difficult to analyze the type. It requires a huge amount of work, expertise, and excessive processing time.To tackle this problem, we introduce Deep Spectral Generative Adversarial Networks (DSGANs) algorithm to categorize the apple disease. Initially, the preprocessing was carried out through Median and Gabor Filters to enhance the frequency of the Image. Then the boundary regions are adaptively filtered with a canny edge detector. This supports the exact boundary regions of the object to get the affected region. The color variance and the contours are different from the affected and non-effected regions. To optimize this, the Self-Adaptive Plateau Histogram Equalization (SAPHE) technique is applied to find the difference between affected and non-affected regions. Modified Gabor kernels are applied to choose the invariance of the affected region which supports segmentation using Invariant Sliding Window Segmentation (ISWS). This makes optimized segmentation by extracting the features in the affected boundary region. By intent, a ReLu activation for Logical decision to activate the logical decision depends on max successive threshold weights from convoluted margins. The non-linearity substitutive feature margins are extracted to enhance the performance of the output to process the adaptive GAN output layers. Finally, the classification part uses the DSGANs. The gated features get the marginal threshold values based on the feature extraction weights to get trained into classifier layers. This iteratively verifies the feature margins on affected regions get trained in Deep SpectralGenerative Adversarial Networks (DSGANs).


**Keywords** Apple disease · Segmentation · Pre-processing · Segmentation · Histogram · Boundary region · Classification

## Introduction

Today, apples are one of the world's most widely produced, most prolific, and most popular fruits. The quality of the fruit directly specifies the financial development of the apple fruit-growing industry.Nonetheless, diverse types of diseases are always one of the primary reasons for poor apple quality and proceeds, which directly affects agricultural financial development. Diagnosis of most apple diseases always relies on farmers. Yet, due to the similarity of image features in some diseases, there is no clear boundary between different stages of the same disease. Also, some diseases cannot be analyzed in time due to their random affairs.

Therefore, they are unable to utilize the available resources to increase their productivity. The user-friendly software enables farmers to partially detect whether the fruit is diseased. Therefore, deep learning is used for more accurate disease diagnosis. The objective of this research is to provide a cost-effective, real-time solution for fruit disease detection. A deep learning-based optimization algorithm is used for feature extraction and classification. The deep learning concept enables more accurate identification of fruit (apple) diseases. Therefore, through this, diseases can be detected early and treated immediately.

The emergence of new technologies such as digital image processing and image analysis technology has many uses in the biological sector. The image is processed using image

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processing techniques to diagnose the disease. The disease is detected by our image processing software which helps the farmers to take some precautionary measures. This demonstrates the advantages of monitoring a large orchard so that disease can be detected automatically as soon as it appears in the fruit. In this research Deep learning-based image processing analysis is used to identify the Apple fruit disease. This research identifies the problems from the related recent works and its design objectives based on the problem definition to achieve high performance in fruit detection than previous methods.

### Objective of the Research

- The main objective of the research is to improve apple disease prediction accuracy based on optimized deep-learning models.
- To design a Structural invariant feature segmentation based apple fruit detection using Deep Spectral Generative Adversarial Networks (GSANs)
- To design an adaptive Median and Gabor Filter to enhance the frequency of the Image to find the disease-affected region.
- To implement a canny edge detector for enhancing the detection of the affected and non-affected regions.
- To design a Self-Adaptive Plateau Histogram Equalization (SAPHE) is applied to improve the color quantization of balancing affected regions.
- To attain higher sensitivity, specificity, f1-score, classification accuracy, and lower false rate with redundant time complexity.

## Related Work

Shiv Ram Dubey et al. [1], the author discussed a solution to apple fruit disease by using detection and classification. They were using two steps. The first step is K-Means clustering (KMC) and the next step is segmenting the image by features extracted. Finally, Multi-class Support Vector (MSV) Machine is used to classify the image as classes.

Bhavini et al. [2], the author surveys the apple fruit diseases detection of apple fruit diseases, Segmentation of part predicts disease and classifies the diseases by using image processing. It states that different colors different textures different segmentation and different classifiers find benefits and negative marks.

Sivamoorthi et al. [3], the author says that it is not an easy task to find the fruit disease. It requires more knowledge about the fruit disease. So, they have implemented a computer vision-based system to test the affected fruits. To classify the apples by using KMC and Support Vector Machine (SVM).

Shiv Ram Dubey et al. [4], the author proposed image segmentation by using KMC unsupervised algorithm. In this, the pixels are clustered based and the clustered blocks are the number of regions. It increases the efficiency of feature extraction.

Similarly, [5], the author proposed KMC approach in three main steps, KMC segmentation algorithm, feature extracted for segmented image, and Learning Vector Quantization Neural Network (LVQNN). Its shows that significantly support accurate detection.

Similarly, Samajpati et al. [6], the author used part of segmentation using KMC. Using this technique classified the feature level fusion of accuracy of the diseases. Similarly, Lv [7], the author discussed that the images were segmented by KMC to obtain segmented images of fruit regions of G and b color channels. Post-processing of different split results. Likewise, Abhijeet et al. [8], the study uses KMC method to segment the images by using color space.

Jagadeesh et al. [9], the author presented a Reduced Feature Set (RFS) approach for identifying the images of fruits are normal or affected. The reduced feature set has a green mean, saturation means, red GLCM (Gray-level Co-occurrence Matrix) summean, and green GLCM summean. In agriculture and horticulture fieldsdeveloping a machine vision system application is used.

Uravashi Solanki et al. [10], the author represents various features, various classifiers for detection, and different segmentation for the fruit grading process. Also gives a summary of color, texture, and classifier all with their merits and demerits.

Padaliya Dharm et al. [11], The author says that the diseases can be identified by some symptoms like gray or brown corky spots, slightly sunken, circular brown or black spots and fungal. So, they have identified the symptoms of the diseases of fruit images by using a computerized system.

Zhang et al. [12], This author using Soluble Solids Content (SSC), Near Infrared (NIR), Competitive Adaptive Reweighted Sampling (CARS), Successive Projections Algorithm (SPA), Random Frog (RF), and CARS-SPA. CARS-RF for evaluating and comparing the wavelengths of apples.

Jiang et al. [13], the author proposes that an improved portion can be detected by using CNNs in real time. The disease can be detected by using INAR-SSD (SSD with Inception module and Rainbow concatenation) model. Similarly, Alharbi et al. [14], the author says thatthe model is based on CNNs to classify healthy apples and diseases apple.Computer vision (CV) and deep learning techniques are given good accuracy in less time.

Liu et al. [15], the novel used to identify diseases based on the deep CNN method. The deep learning model gives a good solution to control diseases with more accuracy and a fast convergence rate. The image generation technique enhances the robustness of CNN.

Sujatha et al. [16], this author's approach was classified with defect segmentations enhanced with a fusion of color, texture, and shape-based features. A histogram of Oriented Gradients (HOG) is used to find the healthy and unhealthy features by using the Decision Trees classifier.

Gaurav Kumar et al. [17] the author discussed the various types of features, and feature extraction techniques. In this, they referto character recognition applications using features and feature extraction methods.

Yogesh et al. [18], the author says that image segmented done by using various method of Otsu, fuzzy c-means, k-means, and watershed segmentation. This is comparatively used to take the disease portion of fruits.

Shiv Ram Dubey et al. [19], the author discussed the methods like KMC for diseases that are classified based on features like color, texture, and shape by using a Multi-Class Support Vector Machine (MCSVM). This is used to find the apples in healthy or unhealthy portions.

Swati Dewliya et al. [20], the author has used shape approximation for extracting features of images. Chain code histogram and pixel density are used for segmenting the image. The images are classified by using a kernel in MCSVM. The SVM with a radial-based kernel achieves better classification accuracy.

Snehal Mahajan et al. [21], the author introduces an SVM and Genetic algorithm (GA). These two algorithms are used for image feature extraction and disease classification. It is improving the accuracy.

Bracino et al. [22], the author used a machine learning model to detect and classify diseases like Venturia inaequalis, Botryosphaeria obtuse, and Gymnosporangium juniperi-virginianae. K-Nearest Neighbors (KNN), Artificial Neural Network (ANN), and Gaussian Process Regression (GPR) algorithms are used to determine the comparison of images.

Khan et al. [23], the author implements a new method for identifying apple disease. This method optimized the result of Expectation Maximization (EM) segmentation and Local Binary Pattern (LBP). It is used to test apple disease by healthy leaves, Blackrot, Rust, and Scab.

Chen et al. [24], the author proposed an improved network namely called arCycleGAN. The attribute registration problem can be solved by the CycleGAN mechanism. Unpaired input source images are transferred by using arCycleGAN.

Ilyas et al. [25], the author proposed to identify the strawberry fruit diseases in a deep learning-based framework. In three classes unripe, partially ripe, and ripe. Encoder-decoder of the network in three modules. Receptive filed controlling, Flow of salient features controlling, and architecture's computational complexity.

Janarthan et al. [26], the author used machine learning-based approaches. This method is used to give accurate disease detection of deep metric learning-based architecture. This is available for citrus fruits and leaf datasets, and detecting the different disease from the images are very efficient and accurate.

Zhang et al. [27], the author designed an Automated Robot (AuRo) that works in real time with accuracy. The parameters of neural networks and samples of dataset relationships can be evaluated.

Chouhan et al. [28], the author proposed a bacterial foraging optimization-based Radial Basis Function Neural Network (BRBFNN) to identify the disease automatically. It increases the speed and accuracy to find the disease.

Aiadi et al. [29], the author proposed a method to classify fruit disease. To use Discriminant Correlation Analysis (DCA) algorithm for features learning. DCA is used to reduce the complexity to find out the disease.

Luo et al. [30], the author used multi-scale feature fusion to classify the disease. In this, they used two techniques called Residual Network (ResNet) and Rectified Linear Unit (ReLU). This two are used to classify the information flow and efficient information. It differentiates the accuracy of the original data set and the proposed data set.

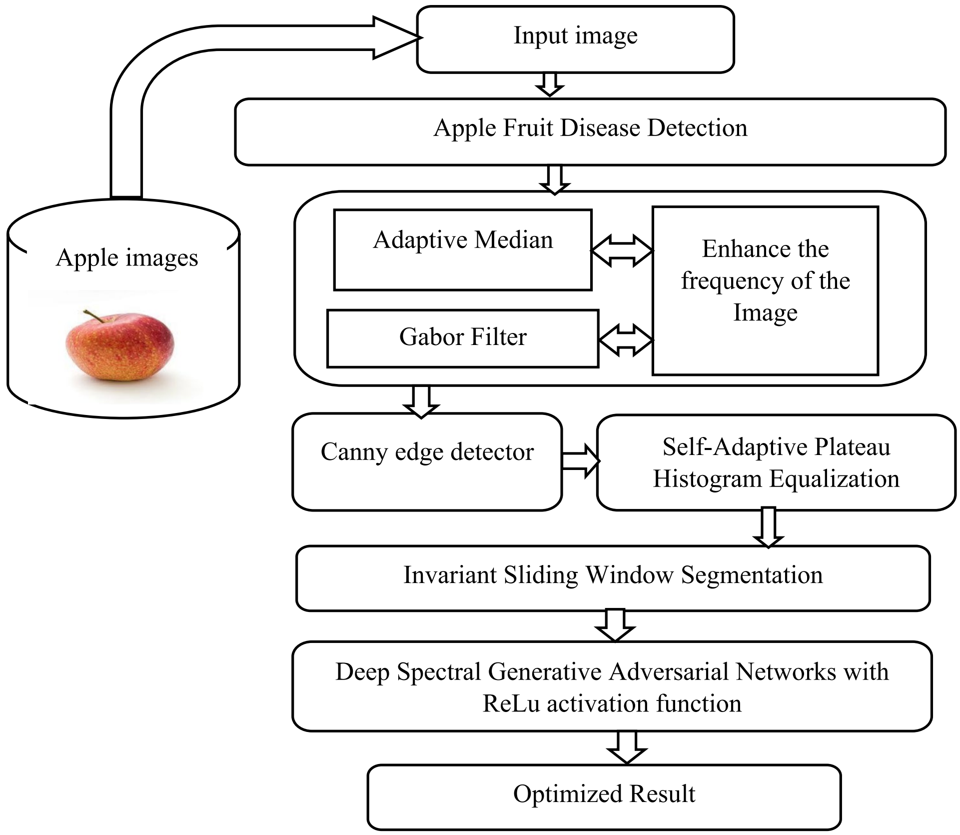
## Problem Identification Factors

- The regular changes in skin color are very difficult to detect the infection of the fruit product utilizing images.
- The existing study's image segmentation technique is not able to categorize the image is not clear gray level histogram peek and segmentation image affected regions is not ensured.
- Apple disease diagnoses are conducted by visual observation of the experts, in that subjective perceptions are very risky due to error.
- In the previous studies, image segmentation takes more time because of data limitations and also having imbalanced distribution. The learning process has more samples.
- Most of the existing systems provide less sensitivity, septicity, and disease classification accuracy results.

## Proposed Methodology for Apple Fruit Disease Detection

This section explains the Deep learning based Deep Spectral Generative Adversarial Networks (DSGANs)with ReLu activation to detect apple fruit disease. Figure 1 illustrates

**Fig. 1** Architecture diagram for apple disease detection




the proposed workflow of apple disease detection. Initially, we gather images of healthy and unhealthy apples from the Internet Kaggle repository and apply a Median and Gabor Filter to enhance the input image, suppress unwanted distortions, improve image features, and produce them more suitable for processing.The next step is to apply the canny edge detector technique to identify the affected non-affected boundary region of the preprocessing apple image.

Based on the boundary region SAPHE technique to improve the affected non-affected color region. After the histogram, segment to detect the affected region using the Self-Adaptive Plateau Histogram Equalization (SAPHE) algorithm. Based on the segmentation, the proposed DSGAN algorithm and ReLu activation function are used to classify the apple fruit disease. The apple fruit disease dataset consists of images of healthy and unhealthy apples, and the confusion matrix used to validate the proposed algorithm. Finally, results are generated in the form of disease classification accuracy, sensitivity, specificity, F1-score, and time complexity.

## Median and Gabor Filter

In this stage, the proposed Median and Gabor Filter (MGF) are used for the reduction of low-frequency image components, noise reduction, sharpening, and edge enhancement. This filter consists of various transforms, image properties, operators, frequencies, and multiplicative transformation properties of detected edges. This method first enhances the brightness of the input apple image as described by Eq. 1,

$$B_T(a,b) = \frac{1}{p_x} \sum_{a=1,b=1}^{p_x} I(a,b) \tag{1}$$

Let us assume $B_T$ brightness transformation of image coordination points (a, b), $p_x$ is the number of pixels in the RGB color image and I is the input image. As shown in expression (2) calculate the standard deviation $S_{td}$

$$S_{td} = \left[ \frac{1}{p_x} \sum_{a=1,b=1}^{p_x} \left( I(a,b) - B_T(a,b) \right)^2 \right]^{\frac{1}{2}} \tag{2}$$

The standard deviation value reflects the amount of apple color variation.

$$Noise_{free} = Mn_{(a,b)}\{I(a,b)\} \tag{3}$$

As shown in Eq. (3) estimated the noise-free apple image $Noise_{free}$ of the input apple image. Let us assume $Noise_{free}$ is a noise-free image and $Mn$ denotes the median.

$$G_f(a,b) = \exp\left(\frac{a'^2 + \Upsilon^2 b'^2}{2{S_{td}}^2}\right) \times \exp\left(2\pi\frac{a'}{\omega} + \psi\right) \tag{4}$$

In Eq. (3) is used to estimate enhance the frequency of image edges $G_f(a,b)$. Here, $\Upsilon$ is an aspect ratio, $\omega$ described the wavelength of the sinusoidal factor and $\psi$ is a central frequency.

Where,

$$a' = acos\theta + bsin\theta \tag{5}$$

$$b' = -asin\theta + bcos\theta \tag{6}$$

Let us assume $\theta$ is anangle of the apple disease. The disease direction $\theta$ estimated by,

$$\theta = \frac{\pi}{D} * (i-1) \tag{7}$$

$i = 1,2 \ldots D$, D $\in i$ where D denotes the number of directions.

$$\Upsilon = \frac{S_{td}(a)}{S_{td}(b)} \tag{8}$$

Equation (6) is used to find the aspect ratio based on the standard deviation $S_{td}$ image coordination points (a, b).

This section proficiently analysis the noise-free apple image and enhance the frequency of image edges. RGB apple images are transformed quality-enhanced images in the preprocessing stage. At this point, an 8-bit pixel size is fixed and the size is between 0 and 255.Thus, the proposed MGF is a linear filter used to enhanceedge and noise reduction.

## Canny Edge Detector

In this stage, the canny edge detector technique is applied to improve the affected and non-affected regions of the pre-processed image.Edges have the most vital information in a disease apple image, representing the location information of the entity. This method identifies the disease apple image smoothness, extract boundary, skewness, intensity gradient, and edge direction. As defined in Eq. (9) to evaluate the apple image smoothness,

$$C(s) = exp\frac{\left(\frac{G_f(a,b)}{2\sigma^2}\right)}{2\pi\sigma^2} \tag{9}$$

Let us assume $C(s)$ is an image smoothness of the pre-processed image $G_f(a,b)$ coordination points a, b.

$$E_b = C(s) - \left(C(s) \ominus S_E\right) \tag{10}$$

Equation (10) is used to estimate the extracted boundary $E_b$ of the smoothness image $C(s)$. Where $S_E$ is the structuring element of the disease apple image.

$$S_K = \sum_{a=1,b=1}^{p_x} (a-b)^3 E_b(a,b) \tag{11}$$

Equation (11) is used to identify the disease skewness $S_K$ from boundary extraction image $E_b$.

$$G_{\text{scale}}(a,b) = \sqrt{{S_{K_x}}^2(a,b) + {S_{K_y}}^2(a,b)} \tag{12}$$

$$G_{direction}(a,b) = tan^{-1}\left(\frac{{S_{K_y}}^2(a,b)}{{S_{K_x}}^2(a,b)}\right) \tag{13}$$

As shown expression (12 and 13) is calculated for the apple disease gradient scale and edge direction. Let us assume x and y is the directions of the disease apple image. The proposed canny edge detector technique efficiently identifies the affected and non-affected regions based on image smoothness, boundary extraction, skewness, gradient scale, and direction.

## Self-Adaptive Plateau Histogram Equalization

After the canny edge detector, this phase uses the Self-Adaptive Plateau Histogram Equalization (SAPHE) technique to improve the color quantization of balancing affected regions. This proposed method enhances the color quality based on the affected region object grey level and enhances brightness intensity level using threshold values. This method first identifies the affected region grey level $(H_g)$ is defined by expression (14),

$$H_g = \sum_{(a,b)\in o_j} \frac{G_{direction}(a,b)}{p_x} \tag{14}$$

Let us assume $o_j$ is the object, $p_x$ is the number of pixels in the image.

$$C_{range} = M_x\left(C_{range}\right) - M_n\left(C_{range}\right) \tag{15}$$

The above equation is used to find the color ranges of the edge detection apple image based on a maximum color rant and minimum color ranges.

$$BI_{i,r} = \sum_{p_x} H_g\left(n_v - c_p\right) \tag{16}$$

The above equation is used to calculate the brightness intensity $BI$ using values of neighbors $n_v$ and central pixel $c_p$ values. Let us assume i is the total amount of neighbors and r is the radius of the neighborhood.

$$h_s(a,b) = \begin{cases} g_v(a,b),\ for\ g_v(a,b) \le th \\ th,\ otherwise \end{cases} \tag{17}$$

The above equation is used to estimate the affected region contrast level to easily segment the diseased part. Let us assume $g_v$ presents global maximum values in the image, $andth$ is the threshold value.

## Invariant Sliding Window Segmentation (ISWS)

After Histogram Equalization, this stage uses the Invariant Sliding Window Segmentation (ISWS) method for segregating the affected part. In this stage, analysis of the upper and lower bound scaling, entropy, local homogeneity, energy, and irregular objects.

$$\frac{\partial \varnothing}{\partial T} + S_v\left|\nabla_{\varnothing}\right| = 0 \tag{18}$$

The above equation is used to calculate the level set (L) function $\varnothing(L,T)$ at time T-dependent quantity for disease shape. Here, $S_v$ is the boundary of the shape.

$$B_{scale}(ub) = M\left(\frac{maximum(\varnothing(L)) - minimum(\varnothing(L))}{\Delta L}\right) \tag{19}$$

$$B_{scale}(Lb) = M\left(\frac{maximum(\Omega(L)) - minimum(\Omega(L))}{\Delta L}\right) \tag{20}$$

Expressions(19) and (20) are used to analyze the upper bound $B_{scale}(ub)$ and lower bound $B_{scale}(Lb)$ scaling. Let us assume M is the control of the level set boundary of the histogram image.

$$E^{gy} = \sum_{a,b=0} h_s(a,b)^2 \tag{21}$$

As shown in expression (21)is used to estimate the energy $E^{gy}$ level of energy of apple disease image.

$$E^{py} = -\sum_{a,b=0} h_s(a,b)\ln 2 h_s(a,b) \tag{22}$$

$$L^{hy} = \sum_{a,b=0} \frac{h_s(a,b)}{1 + \left((a,b)^2\right)} \tag{23}$$

As described in expressions (22) and (23) estimate the entropy $E^{py}$ and local homogeneity $L^{hy}$.

$$IR_o = \int \frac{\ln p_x(h_s(a,b),w)}{\ln w} \tag{24}$$

The above equation is used to identify the disease irregular objects $IR_o$ in the image based on width w and $h_s(a,b)$ histogram image. This stage proficiently segments the affected region to classify the apple diseases.

## Deep Spectral Generative Adversarial Networks

After segmentation, this phase applied Deep Spectral Generative Adversarial Networks (DSGANs) algorithm and ReLu activation function to identify the apple disease. A DSGANs algorithm can detect apple fruit disease based on varying sizes and colors. The proposed method has three neurons there is input, hidden and output neurons to classify the diseases. The first one is the input neuron to choose features of disease from the segmented image, and the second layer hidden process is responsible for extracting features map using matrices of the image to reduce the dimension. An output layer is connected to the output of the previous layer with the ReLu activation function. This connected input layer transforms the output generated by the prior layer into a vector. An output neuron applies significance to the outputs yielded from prior neurons to predict apple disease.

$$C_e = P\left(IR_o\right) * Di^{h,w}{}_{truth} \tag{25}$$

The above equation is used to analyze the actual bonding box confidence score $C_e$. Let us assume P refers to probability, $IR_o$ is irregular objects $Di$ affected region truth with height and width.

$$ReLu = Maximum(0,x) \tag{26}$$

Expression (26) is used to estimate the apple disease category. This activation function works between the hidden neuron and the output neuron transforming all negative values to zero. However, this activation function does not impact image dimensions from the hidden layer. This proposed method proficiently identifies the apple disease using GANs and ReLu activation function. This algorithm's first step is to extract the feature in the first layer of input, next step is to extract the feature maps to reduce dimension from the input layer. After that third step is to evaluate the output layer performance to identify the apple disease using the ReLu activation function. Finally, calculate loss rate performance based on irregular objects' true class and predicted values. Let us assume $x$, y is the direction in the image, $b_s$ is the bias values, $t_c$ is a true class, n is the number of pixels, and $p_v$ predicted value.

Algorithm 1

**Input:** Affected region segmentation image $IR_o$

**Output:** Categorize the apple disease

Begin

Initialization segmentation $IR_o$(a,b)

For each i in $p_x$ do

Estimate the input layer performance $I^{Layer}$

$$I^{Layer} = \sum_a^i \sum_b^i IR_o(a,b).(x-a, y-b)$$

Estimate hidden layer process $H^{Layer}$

$$H^{Layer} = \emptyset\left(\sum_a^{p_x}\sum_b^{p_x} I^{Layer}(a,b) + b_s\right)$$

Estimate Output layer process $O^{layer}$

$$O^{layer} = ReLu\left(\sum_a^{p_x}\sum_b^{p_x} H^{Layer}_{(n-a)(n-b)} + b_s\right) * C_e$$

Compute loss rate $L_{rate}$

$$L_{rate} = \sum_{a=0,b=0} IR_o(a,b) \sum \left(t_c - p_v(O^{layer})\right)^2$$

End for

Return ← apple disease

Stop

**Table 1** Simulation parameters for apple fruit disease detection

| Parameter name | Parameter value |
|---|---|
| Language | Python |
| Tool | Anaconda |
| Dataset name | Apple fruit disease |
| Number of images | 506 |
| Training image | 382 |
| Testing image | 124 |

## Experiment Setup and Results Analyses

In this phase, we present all the test details and analyze the results with comparison methods. First, we describe the environmental setup for apple disease classification, then illustrates the comparison performance result.

### Experimental Setup

The simulation software is using a windows 10, 64-bit OS using python language as a Deep Learning (DL) technique. The hardware setup includes 8 GB of memory and an Intel i5-2.40 GHz.

Table 1 depicts details of simulation parameters names and values described for apple fruit disease detection.During the experiment, 80% dataset was used for training and the remaining 20% was used for testing the proposed algorithm.

### Description of Dataset

In this simulation experiment, we used the apple fruit disease collected from the online Kaggle website. https://www.kaggle.com/datasets/kaivalyashah/apple-disease-detection here in this link is used to download the dataset.

Figure 2 illustrates the sample of normal apple images from the collected dataset. This dataset has split into training and testing images. Therefore 24 normal apple images were for testing and 67 normal images for training.

Figure 3 depicts the sample images of apple disease images like Blotch, Rot, and Scab. Hence, 94 diseased apple images were for testing and 315 images for the training set. Here, these images have.jpg format, apple disease symptoms are usually circular, vary in size, and can be seen through changes in the shape of the disease.

### Performance Model

The Confusion Matrix (CM) provides an efficient result of the proposed algorithm. It demonstrates how well the model performs on the processed empirical dataset.

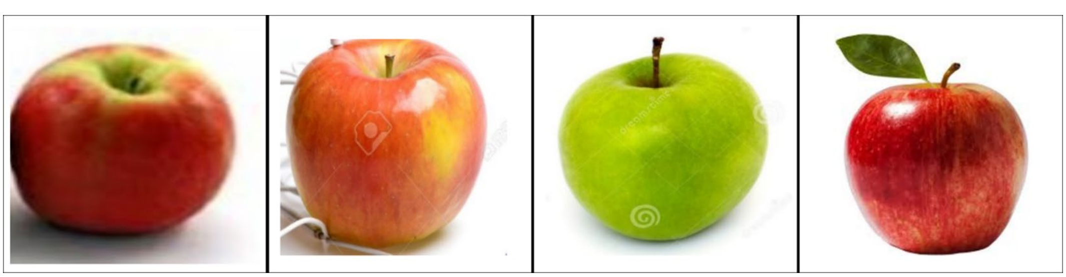


**Fig. 2** Sample of normal apple images

**Fig. 3** Sample of apple disease images

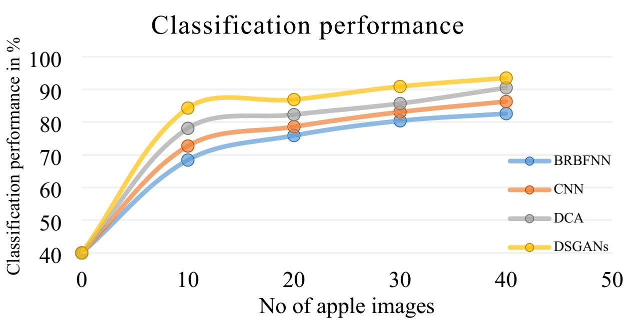



**Fig. 4** Classification result for the proposed and previous methods performance

**Table 2** Classification result for the proposed and previous methods performance

| Classification performance in % | | | | |
|---|---|---|---|---|
| No of apple images/methods | BRBFNN | CNN | DCA | DSGANs |
| 10 | 68.4 | 72.7 | 78.1 | 84.3 |
| 20 | 75.9 | 78.6 | 82.3 | 86.9 |
| 30 | 80.4 | 83.1 | 85.7 | 90.9 |
| 40 | 82.6 | 86.3 | 90.5 | 93.5 |

$$\text{Sensitivity } = \sum \frac{T_p}{T_p + F_n} * 100 \tag{27}$$

$$\text{Specificity} = \sum \frac{T_n}{F_p + T_n} * 100 \tag{28}$$

$$\text{Accuracy} = \sum \frac{T_p + T_n}{T_p + F_n + F_p + T_n} * 100 \tag{29}$$

$$\text{F1} - \text{score} = \sum 2 * \frac{\text{Sensitivity} * \text{Specificity}}{\text{Sensitivity} + \text{Specificity}} * 100 \tag{30}$$

## Comparative Result Analysis for Apple Disease Identification

To estimate the efficiency of the proposed algorithm, we compare it with recently designed techniques (*i*) Convolutional Neural Network (CNN) Alharbi et al. [14], (ii) Radial Basis Function Neural Network (BRBFNN) Chouhan et al. [28], and (iii) Discriminant Correlation Analysis (DCA) O. Aiadi et al. [29].

Figure 4 and Table 2 depicts Apple fruit disease classification result for the proposed and previous methods

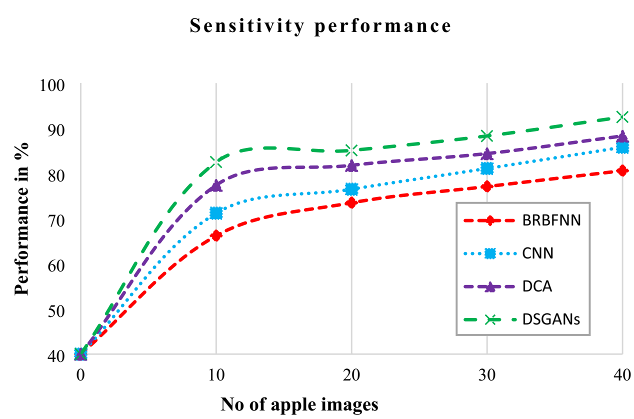



**Fig. 5** Sensitivity performance for apple disease detection

**Table 3** Sensitivity performance for Apple disease detection

| Sensitivity performance in % | | | | |
|---|---|---|---|---|
| No of apple images/methods | BRBFNN | CNN | DCA | DSGANs |
| 10 | 66.2 | 71.2 | 77.4 | 82.5 |
| 20 | 73.5 | 76.5 | 81.8 | 85.1 |
| 30 | 77.1 | 81.1 | 84.4 | 88.3 |
| 40 | 80.6 | 85.8 | 88.3 | 92.5 |

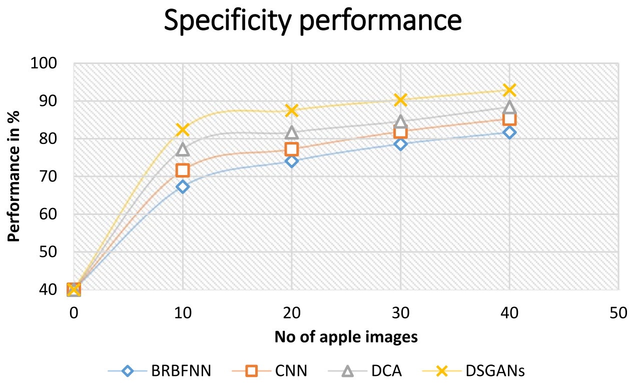



**Fig. 6** Specificity performance for apple fruit disease detection

**Table 4** Specificity performance for apple fruit disease detection

| Specificity performance in % | | | | |
|---|---|---|---|---|
| No of apple images/methods | BRBFNN | CNN | DCA | DSGANs |
| 10 | 67.3 | 71.6 | 77.2 | 82.4 |
| 20 | 74.1 | 77.2 | 81.7 | 87.5 |
| 30 | 78.6 | 81.9 | 84.6 | 90.3 |
| 40 | 81.7 | 85.3 | 88.4 | 92.9 |

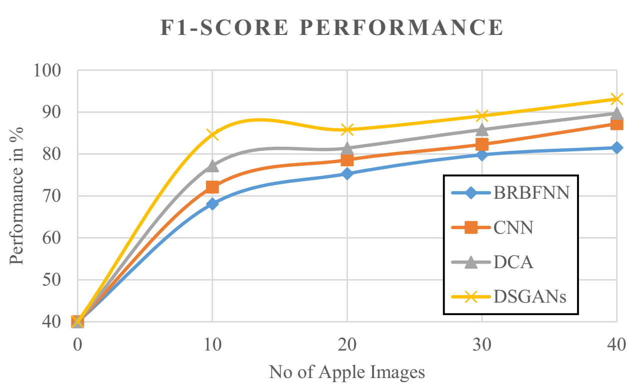



**Fig. 7** F-measure performance for apple fruit disease

performance. The proposed method attained 93.5% of apple fruit disease prediction classification performance also DCA method attained 90.5% of classification performance, the CNN method attained 86.3% of classification performance and BRBFNN attained 82.6% of classification performance.

Figure 5 and Table 3 demonstrate the proposed and existing algorithm performance of sensitivity performance. The proposed method has produced a 92.5% of sensitivity performance than the previous method namely, BRBFNN, CNN, and DCA techniques.

Figure 6 and Table 4 describe the proposed and existing techniques for specificity performance in apple fruit disease

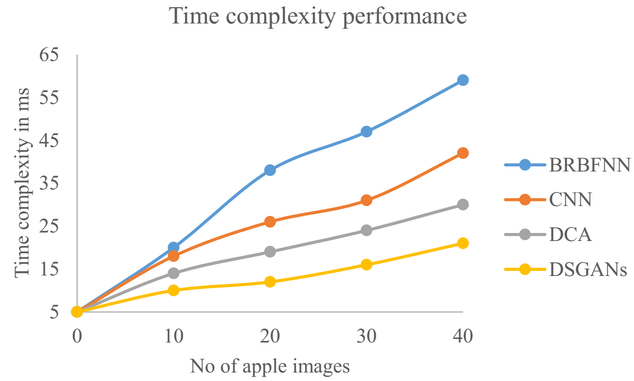



**Fig. 8** Time complexity for apple fruit disease detection

detection. The proposed method achieved a specificity performance has 92.9% than previous methods, BRBFNN, CNN, and DCA techniques.

Figure 7 F-measure performance for apple fruit disease detection based on Invariant Sliding Window Segmentation (ISWS). The proposed method gives 93.1% of F-measure performance also the existing methods are the CNN method produced 87.2% of F-measure, and the DCA method produced 89.7% of F-measure performance. However, the proposed method achieves high performance than other methods

Figure 8 shows the proposed and existing methods for disease identification time complexity for apple fruit disease detection. The proposed method produces a time complexity result is 21 ms for apple fruit disease classification, but the existing techniques produce high time complexity performance.

## Discussion

This novel explores deep-learning-based Deep Spectral Generative Adversarial Networks (DSGANs) for apple fruit disease detection from the collected dataset. The apple disease detection results of the proposed algorithm are vital to the analysis of the size, and shape of disease symptoms, which is apt of capturing the latent features of disease signs. Hence, the simulation demonstrates to show that the proposed algorithm can detect diseases in apple fruit images with high accuracy.

The existing CNN algorithm attained an apple disease classification performance had 86.3%, a sensitivity of 85.8%, a specificity has 85.3%, f1-score had 87.2%, and a time complexity performance had 42 ms for disease classification. However, the proposed DSGANs algorithm achieved a better result than other techniques.

## Conclusion

In this paper, we introduced Deep Spectral Generative Adversarial Networks (DSGANs) technique to identify the apple fruit disease. This proposed algorithm uses a Median and Gabor Filter to enhance the frequency of the Image at pre-processing phase. The next stage is the canny edge detector is used to identify the boundary region. Based on the boundary find the affected and non-affected regions using Self-Adaptive Plateau Histogram Equalization (SAPHE). Then Invariant Sliding Window Segmentation (ISWS) method is used to extract the affected boundary region. Later the proposed DSGANs algorithm is used to classify the apple fruit disease. The proposed method produces the optimal result in terms of disease classification accuracy performance, sensitivity, specificity, and F1-score performance. The proposed algorithm provides an accurate and robust diagnosis that surpasses the existing state-of-the-art apple disease detection approaches. Comparative experiments confirmed the significance and usefulness of the improvement in disease classification.

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**Data Availability** The dataset generated and analyzed during the current study are available from the corresponding author on reasonable request.

## Declarations

**Conflict of Interest** No conflict of interest.

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