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Research Article

Optimized Fractal Fusion Driven Deep Neural Network: An Efficient Hybrid Methodology for Disease Detection and Classification in Plant Leaves

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Abstract: Plant diseases and pest attacks are among the major issues in agriculture, which have a great impact on crop growth and yield. Early and correct detection of these diseases is vital for effective management and keeping plant health at the desired level. This research proposes a new method for detection and classification of plant diseases, the Optimized Fractional Fusion Deep Neural Network (OFF_DNN) model. The procedure uses a synthetic dataset created by Generative Adversarial Networks (GANs) to enhance the classification results. The OFF_DNN model first enhances low-resolution plant images to produce high-quality images. After this, the enhanced images are GAN-synthesized to create additional data for effective training. After this, two segmentation methods, i.e., Marker-Controlled Region-based Thresholding (MCT) and Active Lesion-based Multilevel Segmentation (ALMS), were performed to segment the regions of interest in the enriched images. Fractal fusionbased feature extraction on these regions was done, and Particle Swarm Optimization was applied for the optimization of the features. The optimized features were then fed into the model as input features for the DNN model for the classification of diseases. The experimentation shows that the OFF_DNN model is effective, achieving average accuracy rates of 98.64, 98.79, 98.6, and 0.9885%, providing an opportunity for utilizing this in automated plant disease detection in agriculture. Hence, incorporation of image enhancement, synthetic data creation, and optimization of features addresses salient challenges in plant disease management, providing a feasible solution to improve yield and quality.

Keywords: Clustering, Deep Neural Network, Image Acquisition, Machine Learning, Optimization, Plant Disease, Segmentation

Introduction

Precision farming comprises, using a variety of digital technologies and data analytics to optimize the cultivation of crops through precise input as stated, by Abbas *et al*. (2021); Salmi *et al*. (2022) detected, this technique tends to help in the improvement of quality and the increase in yield while reducing production costs. Other applications of this computing-based method include disease detection, canopies analysis, and forest safety monitoring. It is a technology-driven system that hence ensures sustainable land use and resource efficiency, as experimented by Zhao *et al*. (2021). Plant pathology involves a study of diseases caused by biotic and abiotic factors that threaten crop productivity and stability of ecosystems. Innovations in image processing and machine learning have completely changed precision farming such that diseases are detected early and farmland management is done in an efficient way by means of various neural network models and analyzing images of the field with algorithms. Such fashions allow sustainable land use and food security Examined by Zhou *et al.* (2021); Cui *et al.* (2021); Li *et al.* (2021).

Gomaa *et al*. (2021) stated that there are two types of plant disease detection systems: they are Visual Examination and Automatic plant disease detection systems. Visual Examination is a challenging task because it needs continuous manual monitoring and a dedicated botanist with good knowledge. The automatic plant disease detection system uses advanced computer vision, and AI techniques for visual monitoring, detecting, and classifying the diseases in plants. The existing automated systems comprise of various steps such as: pre-processing, segmentation, feature extraction, and classification examined by Lu *et al*. (2021); Mzoughi and Yahiaoui (2023).

Numerous conventional automated classification models are available in the literature, for instance, Knearest Neighbors (KNN), Support Vector Machine (SVM), Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN) examined by Chetan *et al*. (2024); Zhang *et al*. (2022); Liu and Wang (2021). The CNN model comprises of different architecture models, viz., Alex Net, Google Net, and VGGNet, etc. by Prasad *et al*. (2021). The SVM model comprises structural risk minimization to reduce regression and classification problems. Mahadevan *et al*. (2024) examined that the k-NN model uses statistical parametric weights associated with the weights for the dynamic classification.

These conventional machine learning approaches provide an effective solution for classification problems. However, their applications are limited to smaller datasets and are not much successful for the bigger datasets. To address the above problems of ML models, artificial intelligence has come up with a new solution, which is named Deep Learning (DL) models. DL models provide an accurate prediction in comparison to traditional ML techniques, which results in an effective decision-making process. Deep Learning (DL) models have great capability to produce the optimal solution even for complex problems, which cannot be easily handled by conventional image processing and ML approaches. Within DL state-ofthe-art architecture, Alex Net and Google Net have exhibited good performance by yielding competent results for general classification problems. However, a major limitation of DL method is that it demands a large amount of data for plant disease detection, which possess several constraints in yielding significant results with higher accuracy. At present, plant disease detection with the DL method requires vast improvement in terms of generating voluminous data that can be obtained by using Generative Adversarial Networks (GANs) used by Zhang *et al.* (2022) to obtain significant results.

Divyanth *et al*. (2022); Cap *et al*. (2021) showed that the currently available traditional methods do not detect multiple diseases within a single image, as stated by Subash *et al*. (2021), these methods have encountered persistent difficulties with optimization, global search, and pattern matching problems, and requires a high-quality image. The usage of endangered pesticides harms plant growth that leads to an inappropriate estimation of the severity of the infection and hence impacts further vegetation. To deal with the above problems, numerous researchers have proposed enhanced computational methods to automatically detect the damage or strain of the pathogen on any part of the multiple plant species by training the individuals to perfectly tag according to the severity to ensure an accurate result. Rajalaxmi *et al*. (2021) in their research they found that Generative Adversarial Networks (GANs) train two neural networks, the generator and the discriminator, in an adversarial setup. The generator creates synthetic images, while the discriminator evaluates whether the images are real or generated. Through iterative training, the generator improves its ability to produce images that increasingly resemble real ones, as it learns to deceive the discriminator more effectively.

In this direction, we also tried to develop Adaptive Equalization and Clustering Optimization based deep learning (AECO_DNN) model for plant disease detection and classification. The AECO_DNN model uses the GAN to generate image augmentation to produce better classification results. With ALMS and MCT clustering, the threshold value is computed to reduce misclassification with an estimation of lesions. The normalized feature vector of EFT is stored in the serial codebook for effective recognition. The features normalized with EFT are Scale Invariant Feature Transform (SIFT), Color features using Hue Saturation Value (HSV) color model, Fractal Dimension of texture features using Wavelet-based Segmented Fractal Texture Analysis (WSFTA), and Texture features using Gray Level Co-occurrence Matrix (GLCM). Subsequently, the network layer weights were optimized to perform the recursive operation during backpropagation to identify the presence of error in each layer to stabilize the network for a better classification rate with the Levenberg-Marquardt (LM) Genetic Algorithm and finally, plant diseases were classified by using a deep learning network.

Literature Survey

In recent years, numerous techniques based on image processing, ML and deep learning have been proposed by different researchers for detection and classification of diseases in various plants. For instance, in research by Agarwal *et al*. (2021), authors proposed a system to classify and estimate the infected areas of soybean diseases like Frogeye, Downy Mildew, and Bacterial Pustule. The work was carried out by segmenting the image based on K Means segmentation and subsequently required attributes were obtained using Grey Level Co-occurrence Matrix (GLCM). The extracted attributes were used to train the Back Propagation Neural Network (BPNN) with 20 hidden neurons. The proposed system obtained an accuracy of 93.3% with the test images that had the resolution of 768×512 pixels.

Pahurkar and Deshmukh (2022) proposed a method to perform the quantitative analysis of soybean rust disease using various image processing techniques. The developed system was specialized in detecting the disease during its early stage starting from day 1 to day 25. They have collected images captured using DXC-3000A, Sony, Tokyo, Japan with the focal length of 72mm, and 10220mm of zoom. The images were captured with the resolution of 1920 x 1080 pixels, which were then resized to 400x400 pixels. Percentage Disease Index (PDI) of 95.5% was observed on the 25th day and a minimum PDI of 0.2% was seen on the 6th day.

Liang *et al*. (2021) suggested a method to detect three types of diseases like Rust-Tan, Mildew, and Rust using local descriptors. The system was designed to perform early detection of diseases using Image Local Descriptor - Bag of Visual Words (BOVW) merged with Pyramid Histograms of Visual Words (PHOW). It was also tested with other local descriptors like SURF, DSIFT, and SIFT using a scanned image dataset of 1200 healthy and unhealthy Images. Finally, SVM was employed as a classifier and obtained an accuracy of 98%. In their study, the average time taken to process per image was 0.1 second.

Kohli *et al*. (2022) developed a system to identify leaf diseases and grade them using computer vision and fuzzy logic techniques. The developed system comprises of preprocessing and image denoising step followed by K-means segmentation. The segmented region of leaf images was utilized to calculate the GLCM features where various attributes such as contrast, energy, correlation, and homogeneity were computed. Based on the computed attributes, ANN and Fuzzy classifier was trained to determine the severity of disease in Leaf Scorch of Hydrangea and Leaf Spot.

Padmanabhuni and Gera (2022) and Mohammelad Baljon (2023) developed a disease detection system utilizing a multiple linear regression method combined with an enhanced histogram segmentation technique. Their model was trained on a limited dataset of just 60 images. The preprocessing phase involved isolating leaf structures from complex backgrounds, followed by image denoising using median filtering. Subsequently, an improved histogram segmentation was applied, using a minimum peak interval of 10 pixels to reduce histogram fluctuations. This effectively distinguished between healthy and diseased areas of the leaf. The disease detection achieved an accuracy of 96.3% on the training set. However, when tested with external images, the accuracy dropped to 90%

Vasudevan and Karthick (2022) developed an automatic detection system to identify 12 nutrient deficiencies on tomato leaves using texture feature and Fuzzy Artificial Neural Network. The high-quality images were utilized to compute GLCM features. Based on computation of GLCM parameters, various attributes like Pixel Brightness Mean, Variance, Skewness, Standard deviation, Contrast, and Entropy were calculated as mentioned in Chetan *et al*. (2024). The obtained were finally utilized to train the developed machine learning model. To minimize the error rate and adjust with the membership function Artificial Neural Network fuzzy inference system (ANFIS) was adopted as a classifier tool to overcome the capability issues of Artificial Neural Network.

Wang *et al*. (2022) developed a system to detect Bacterial Blight, Leaf Spot, Leaf Smut diseases in paddy using dataset of 120 sample images. In their study, color features were extracted by applying nonzero values and the mean function of RGB. The same mathematical operations were used for HSV and LAB color space. Afterwards, texture features viz., cluster shade, homogeneity, correlation, contrast, cluster prominence, and energy were extracted using block size of 8 x 8 pixels. Subsequently, extracted features were fed as an input to SVM to classify the diseases. The developed system obtained an average accuracy of 92.7% based on the above-mentioned attributes.

Gangadharan *et al*. (2020), using Radial Basic Function Neural Network (RB-FNN) model, proposed a leaf spot disease detection system by taking the plant village dataset of 326 sample images. The system used a morphological operation to enhance the image by removing the noise. Moreover, Fussy CMeans segmentation was applied over the resulting images to spot the lesion region. The applied method differentiated between the diseased region and the background with 12 attributes, which were obtained from the segmented samples using Radial Basic Function. The developed RB-FNN model achieved an accuracy of 96% when it was trained using 300 sample images with an average training time of 14.0 seconds.

The literature survey article, Baljon (2023), is about various plant diseases like bacterial, fungal, viral, deficiencies, etc., based on manual or visual analysis and an automatic disease detection system. The studies referred by the authors were on multiple plant species such as Corn, Peanut, Grape leaves, Paddy, Banana, Soybean, Mango, Chili, Lemon, Tomato, Wheat, Passion Fruit, Sugarcane, Hydrangea, Cotton, Pomegranate, etc., for the estimation of the image processing methods and diseases performed to detect the contamination. From the evaluation, it is observed that the researchers have not considered pest attacks, unlike infectious diseases. Pest attack is also more susceptible like infectious diseases and pests may tend to spread infectious diseases to the plants that grow in the group. Plants destruction due to diseases and pest attacks had drawn the researchers towards this research. Image processing and Neural Network techniques have overcome the disadvantages of the high-definition tools for disease detection.

Based on the literature survey, some of the research gaps observed are accuracy that relies on the image capturing techniques under different lighting

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conditions, resolution, position, and complex background. Noise elimination and feature optimization is also a big challenge that creates a big hindrance for developing an efficient computer aided diagnosis tool for plant disease detection. As feature optimization is a complex task and dense feature vectors lead to higher computational cost. Hence, in this study, we considered all the above-mentioned constraints to develop an efficient computer-aided diagnosis system for plant disease detection.

The objective is to create an efficient plant disease detection system that enables early diagnosis, accurate multi-class classification, optimized computation, realworld adaptability, and includes pest detection.

Based on the literature survey, the proposed system the table describes the comparison with the previous work and helps emphasize the novelty of research.

Table 1 clearly describes the contributions of previous works in terms of plant type considering the Broadspectrum model tested on multiple crops, disease type including pest attack, Feature extraction including optimized texture, color, and shape descriptors with PCAbased reduction and novel including adaptive preprocessing and feature selection with reduced cost.

Table 1: Proposed system aspects and description in comparison with previous work

Aspect	Description
Plant Type	Broad-spectrum model tested on multiple crops
Disease Types	Includes infectious diseases and pest attack also
Techniques	Advanced denoising, hybrid segmentation
Feature Extraction	Optimized texture, color, and shape descriptors with PCA-based reduction
Classifier	Ensemble-based Deep Neural Network with optimization
Dataset	Custom dataset with diverse lighting, backgrounds, and resolutions
Accuracy	>98.5% - (with cross-validation)
Novel Contributions	Adaptive preprocessing for lighting/complex backgrounds
	- Optimized feature selection to reduce computational cost

Materials and Methods

In this study, a small section of the "Plant Village Dataset", which is available on Kaggle, is used. The Plant Village dataset contains a total of 54,303 images. Divided into 38 distinct classes. Comprising 14 different species of crops, namely apple, blueberry, cherry, grape, orange, peach, pepper, potato, raspberry, soy, squash, strawberry, and tomato.

In this section, to perform effective plant disease detection and classification, the proposed OFF_DNN model uses a plant image datas*et al*ong with the augmented images generated by GAN. The simulation is performed in MATLAB with i7 9th-generation PC with 16GB RAM and Nvidia graphics card. The detailed analysis of the performance of the proposed model is presented.

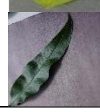
Dataset

To evaluate the performance of plant diseases classification model, we utilized the Plant Village dataset which is available on Kaggle. The plant village dataset comprises of 14 leaf directories. The leaf considered for the analysis is Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, Pepper, Potato, Raspberry, Soybean, Squash, Strawberry, and Tomato.

Each fruit or vegetable leaf is observed based on a healthy leaf and infection in the leaf. However, the acquired images' angles vary at the different intensities of light, inconsistent backgrounds, and some other noises that affect the accuracy of disease detection.

The image class information and description is presented in Table 2. Based on the collected sample for each class, sub-classes are created with consideration of the disease in the plant. This image dataset is being used for training and testing purposes. After going through each phase of methodology, there some result produced.

Table 2: Classes in dataset

Plant Sample No	Name	Sample Images	Plant Sample No	Name	Sample Images
1	Apple		8	Pepper Bell	
2	Blue Berry		9	Potato	
3	Cherry		10	Rasp berry	
4	Corn		11	Soy bean	
	Grape		12	Squash	
6	Orange		13	Strawberry	
7	Peach		14	Tomato	

Methodology for Plant Diseases Detection

To mitigate the limitations discussed earlier, this section presents a refined and effective approach for plant disease detection, illustrated in Figure 1.

Before implementing the proposed OFF_DNN algorithm, standard preprocessing steps are applied to the input images. The initial step involves resizing the images using the seam method, standardizing them to a resolution of 640×480 pixels. To enhance image quality, median filtering is employed, where the center value of each pixel window is replaced with the median value of its neighboring pixels.

Next, a Generative Adversarial Network (GAN) architecture is implemented to generate synthetic plant images. The GAN utilizes discriminator data to create augmented images at 90°, 270°, and 30° rotations with a right-to-left flip. These synthetic images (Figure 2) are then used for training, significantly enhancing the dataset quality to improve model performance.

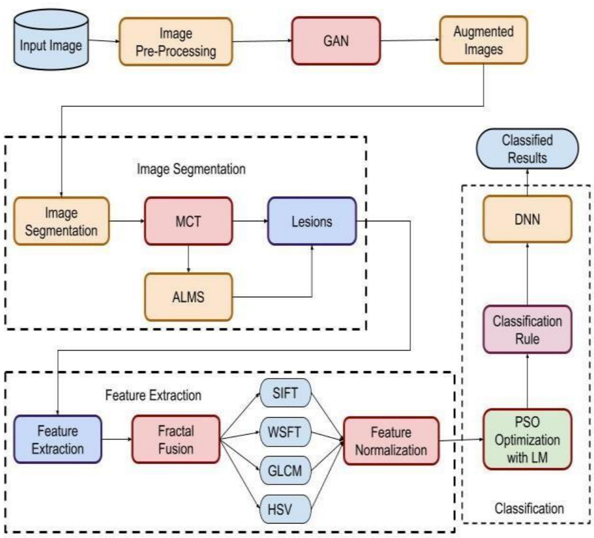


Fig. 1: Proposed plant disease detection system

Fig. 2: Apple Leaf Augmentation

(i) Actual input image
(ii) 900 right to left flip
(iii) 2700 right to left flip
(iv) 300 right to left flip

Furthermore, segmentation of synthetic plant images was performed using a combined approach of Marker-Controlled Thresholding (MCT) and Active Lesion-based Multilevel System (ALMS). MCT computes an optimal threshold by minimizing intraclass variance through recursive iterations, distinguishing foreground (plant regions) from background. This process categorizes pixels into two classes: within-class (foreground) and between-class (background) variance, as defined by Equation 1 (30):

$$\sigma_i^2\,(T) = P_A(T) + P_B(T)\sigma_B^2(T) \tag{1}$$

Where, $P_A\ nd\ P_B$ are probabilities $\sigma_A{}^2(T)$ is the variance of foreground and $\sigma_B{}^2(T)$ is the variance of the background. We then set the sub-range boundaries $L1$, $L2$, … L for calculating available multiple thresholds based on the variable intensity range in the lesion area [31]. The pixel intensities are assigned to the levels by evaluating the range at which the contrast levels are visible in the lesion area. The computed threshold is computed as in Equation (2):

$$T = [[a{:}\,T_1 * 256]/2 \tag{2}$$

Following thresholding, the ALMS model evaluates disease-affected regions using a clustering-based segmentation process. Clusters are formed by grouping pixels with similar intensities, and the average distance (AvgD) between individual data points (Dis) is calculated to determine cluster centers. The dissimilarity matrix pairs data points based on their differences, ensuring similar points are grouped together. The Probability Density Function (Equation 3 (32)) is then used to refine cluster center estimation. This integrated MCT-ALMS approach enables precise segmentation and accurate disease quantification, providing a robust framework for automated plant disease analysis.

Additionally, to improve disease detection accuracy in plants, this study employs multiple feature extraction methods Scale Invariant Feature Transform (SIFT), Wavelet-based Segmented Fractal Texture Analysis (WSFTA), Gray Level Co-occurrence Matrix (GLCM), and Hue Saturation Value (HSV). as stated by Mehmood *et al*. (2023).

These methods extract key-points, fractal dimensions, statistical texture features, and color attributes, which are normalized to ensure consistency and concatenated into a unified feature vector through the algorithm 1 given:

The fused features are stored in a high-dimensional codebook, addressing the limitations of individual extraction techniques and providing a comprehensive representation of lesion regions while minimizing intra-class variability experimental analysis.

Algorithm 1.1: Creating a feature vector of extracted features

STEP 1: Feature Extraction from Segmented Region
1.1 SIFT Features

Detect keypoints and descriptors using SIFT → SIFT_Features
1.2 WSFT Features
Apply 2D wavelet transform on the segmented region
Extract coefficients → WSFT_Features

1.3 GLCM Features
Compute Gray-Level Co-occurrence Matrix (offset = [1, 0], [0, 1], etc.)
Extract texture descriptors: contrast, homogeneity, entropy, etc. → GLCM_Features

1.4 HSV Color Features
Convert Segmented region to HSV
Compute mean and std of H, S, V channels → HSV_Features

STEP 2: Feature Vector Construction
FeatureVector ← [SIFT_Features, WSFT_Features, GLCM_Features, HSV_Features]

Output: Feature Vector for classification

Results and Discussion

Collected sample shown in Table 1 for each class, subclasses are created based on the consideration of infection in the plant. This image dataset is being used for the training and testing purposes. After going through each phase of methodology there some result produced.

The resulting images, which were obtained after applying various steps viz., plant image processing, segmentation, feature extraction using (SIFT, Key points, WSFTA, hue saturation) and classification are presented in Figure 3.

After applying the segmentation and feature extraction steps, an optimization technique was applied for the dimensionality reduction and subsequently the processed data was applied to the deep neural network for the input images classification. The unhealthy plant species suffer from European Corn Borer on the Cotton stem, Cercospora Leaf Spot on Peanut leaves (Fungal infection), Boll Weevil on Cotton buds, Bacterial Blight on Paddy (Bacterial Infection) and leaves (Insect), buds and leaves, Fall Army Worm on Peanut plant and a healthy plant species (It might be either Peanut plant, Paddy or Cotton plant) were considered here for study.

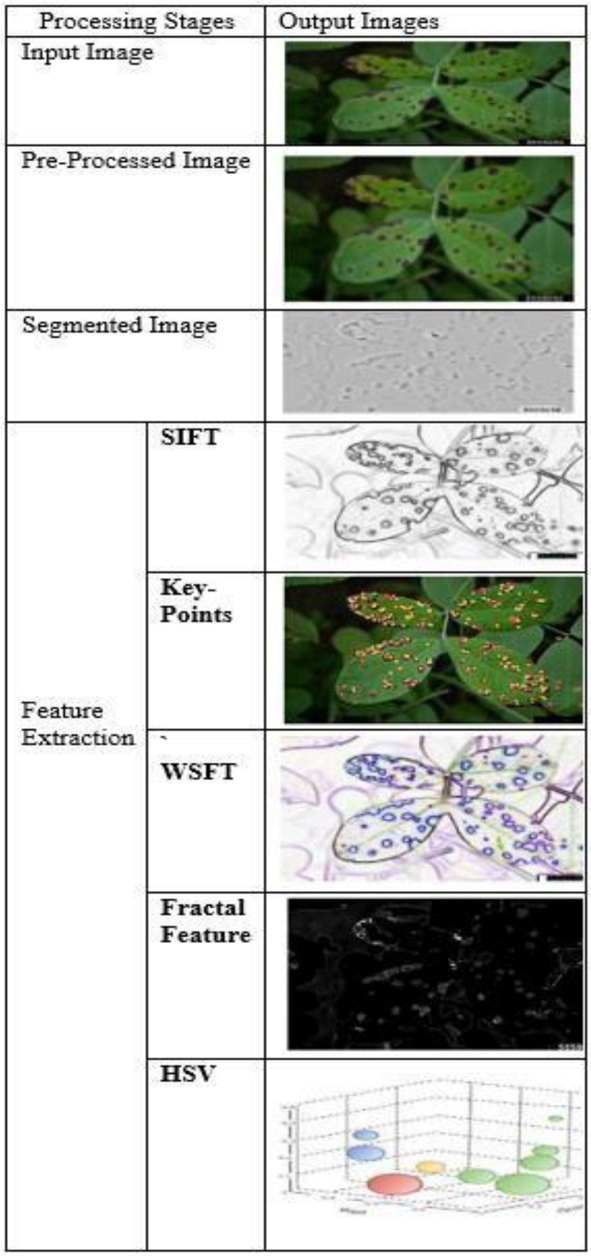


Fig. 3: Process of computing different feature sets for off DNN model

The network is structured with six input layers, 18 hidden layers, and 6 output layers and finally, a single output is generated through classification. The network is trained, validated, and then tested with a dataset of 5240 image sample images.

Architectural tuning of network includes input layer configuration, hidden layer design, output layer and final classification. The input layer has 6 nodes each representing an extract feature from leaf image for example color, texture, shape size etc ensuring that selected features are relevant by feature selection using Principal component analysis.

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Hidden layer design includes 18 layers fully connected with nonlinear activation applying batch normalization.

Output layer has 6 neurons, each neuron corresponds to class viz., healthy, leaf spot, rust, pest attack and so on using SoftMax for multiclass and validate class balance to avoid bias. Final classification has single class prediction based on highest probability matrix. To fine tune misclassified cases confusion matrix and f1-score is used.

For tuning action Levenberg–Marquardt (LM) for fast convergence on small to mid-sized datasets is used, to optimize weights GA-PSO is alternatively used for better generalization.

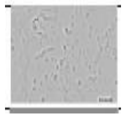
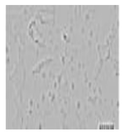
The severity estimated with the proposed OFF_DNN model is presented in Table 3.

The measured accuracy and loss value for the proposed OFF_DNN model is presented in Figure 4. The optimization is performed on the assigned weights captured by the LM method, while backpropagating the errors are identified and corrected based on the optimization. GA-PSO is an optimization algorithm that is used to regularize the generated weights.

Figure 5 presented the Confusion- matrix measured for the consideration of different classes with the calculation of performance metrices.

Table 4 provides the classification performance for the 6 classes in the dataset for the disease's prediction and classification for the different features in the proposed OFF_DNN.

Table 3: Output of Severity Calculation

Image	Spotted Lesion region	Total Area of the object	Infected Area	% of Infection
		772142	293413	37.9%
		136028	55772	41%
		764643	114696	14.9%
		781587	375161	47.9%
		784708	71623	9.12%
		678452	35678	8.73%

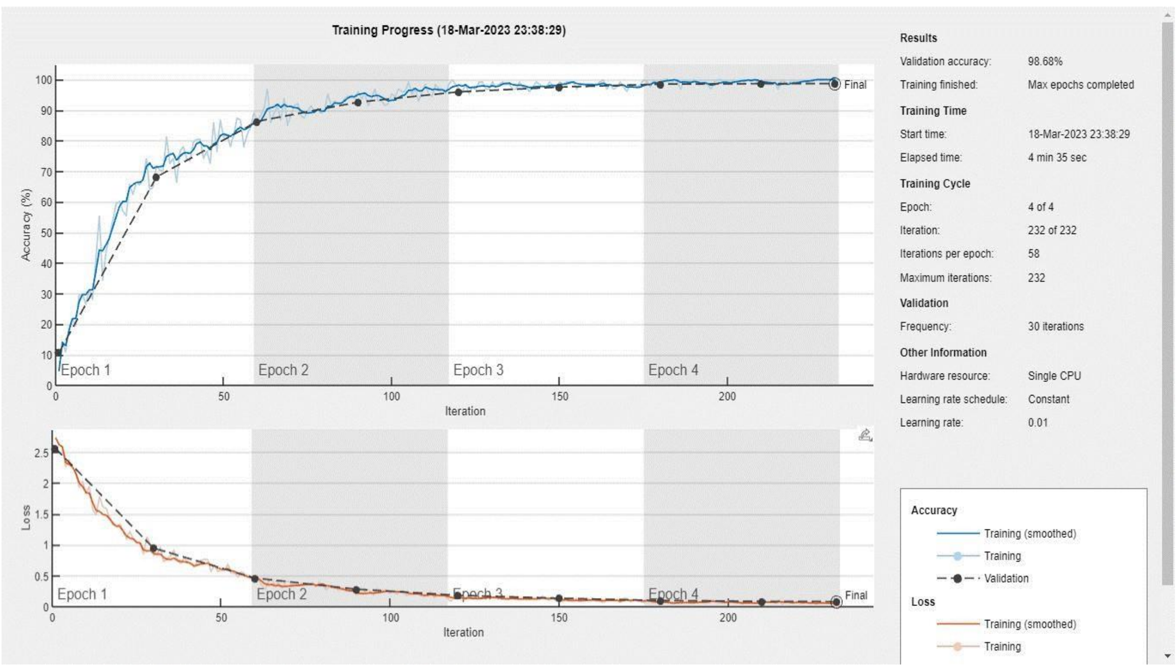


Fig. 4: Accuracy and Loss for the OFF_DNN

Table 4: Comparison of OFF_DNN with different features

Performance Measures	OFF_D NN SIFT	OFF_D NN GLCM	OFF_D NN WSFT	OFF_D NN HSV	OFF_D NN
Accuracy	0.9056	0.8356	0.9035	0.9214	0.9864
F1 score	0.9167	0.8414	0.8746	0.90752	0.9885
Recall/Sensitivity	0.9145	0.8461	0.85781	0.9046	0.9861
Precision	0.8913	0.8356	0.8735	0.9236	0.9879
Negative Prediction Value	0.2781	0.2134	0.2659	0.2852	0.4583
False Positive Rate	0.8673	0.7756	0.7925	0.85709	0.9241
False Discovery Rate	0.00168	0.00158	0.00246	0.0253	0.0175
False Negative Rate	0.0014	0.0014	0.025	0.0018	0.0017

Table 5: Comparison of Performance with different Classes

Classes	Accuracy	Precision	Sensitivity	F1-Score
Healthy	0.988	0.9936	0.9824	0.9825
Mildew	0.9857	0.9821	0.9934	0.9924
Bacterial Spot	0.9845	0.9936	0.9825	0.9869
Early Blight	0.9901	0.9814	0.9836	0.9928
Late Blight	0.9872	0.9936	0.9914	0.9836
Others	0.9825	0.9836	0.9834	0.9928
Average	0.9864	0.98798	0.98611	0.9885

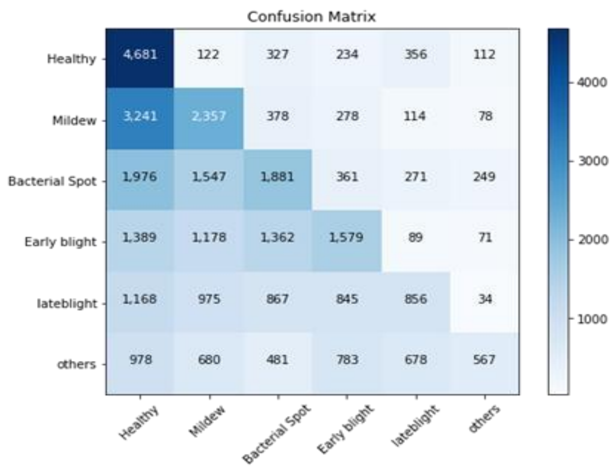


Fig. 5: Confusion matrix

The comparative analysis of the OFF_DNN performance with distinctive features expressed that OFF_DNN model exhibits higher performance measures for the distinctive features. In this study, we used 4192 sample images in the training phase i.e., 80% of the total sample images from the dataset (5240). Out of which 3431 images have classified as TP and the remaining group of sample images 678, 42, 41 were classified as TN, FP, and FN respectively with the accuracy of 99.10%. Similar to validation phase, 10% sample images were taken for testing phase. Table 5 provides the estimation of the parameters measured for the consideration of the different classes in the plant diseases.

From the analysis, it is observed that the validation phase resulted in a classification accuracy of 98.85% and the testing phase resulted in a classification accuracy of 98.21%. So, the system produced an overall classification accuracy of 98.72%. Figure 6 illustrates the performance of different classes and illustrated the measurement of different of different metrices precision, accuracy, precision and sensitivity measured for the different classes.

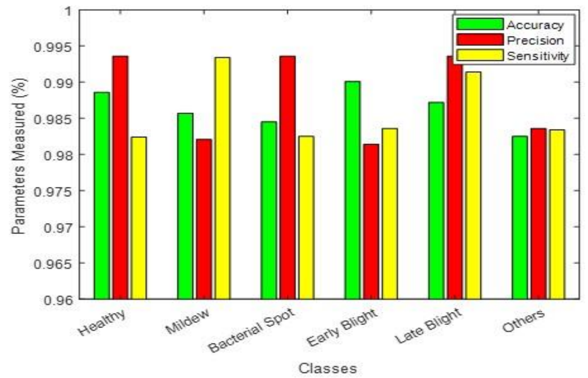


Fig. 6: Comparison of Performance in terms of precision, accuracy, precision and sensitivity for different Classes

The measurement of the parameters with the different classes stated that OFF_DNN model achieves the average accuracy of 0.98. The examination stated that light blight achieves the higher performance measure of accuracy, precision, and sensitivity.

Table 6: Comparative Analysis of proposed approach existing state-of-art technique

Parameters	TGAN	CNN – GAN	RAHC - GAN	OFF_DNN
Accuracy	97	97	93.28	98.64
F1 score	97	87	97	98.85
Recall / Sensitivity	48.1	85	98	98.6117
Precision	51.7	90	96	98.7983
Negative Prediction Value	0.5	0.5	0.5	0.4583
False Positive Rate	0.667	0.75	0.9	0.9241
False Discovery Rate	0.013	0.02	0.05	0.0175
False Negative Rate	0.0069	0.0069	0.0069	0.0017

Table 6 provides the comparative analysis of the proposed OFF_DNN model with the existing state-of-art technique for the plant diseases detection in terms of specificity, precision, recall and other performance metrics

Figure 7 presents the comparative analysis of the proposed OFF_DNN model with the existing techniques such as T-GAN (Zhang *et al*., 2022), CNN-GAN (Padmanabhuni and Gera, 2022) and RAHC-GAN (Padmanabhuni *et al*., 2022) techniques. The proposed OFF_DNN model achieves the higher accuracy of 98.64% while T-GAN, CNN-GAN and RAHC-GAN model achieves the accuracy of 97, 97 and 93.28% respectively.

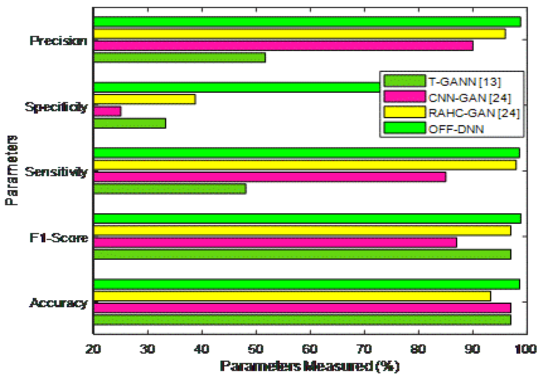


Fig. 7: Comparative Analysis of proposed approach existing state-of-art techniques

The F1-Score achieved with the OFF_DNN model is 98.85% while the T-GAN, CNN-GAN and RAHC-GAN model exhibit the value of 97, 87 and 97% respectively. The sensitivity value of the OFF_DNN model is achieved as 98%

Conclusion

Pest attack and Plant Disease are a big threat to the farmers and the farming industries. It may impact the economy majorly by plant destruction due to plant disease or pest attack and production quality. An automatic plant disease detection system might play a crucial role in the growth and benefit of farm production. This study focused on developing a feature engineering-based novice computer aided diagnosis system (that is abbreviated as OFF_DNN in this study) for plant disease detection and classification. The proposed OFF_DNN applied GAN technique to generate synthetic images to increase the volume of data to get better classification performance. Subsequently, we used ALMS algorithm with directional clustering approach to perform the segmentation operation, followed by the extraction of SIFT, WSFT, GLCM and HSV features. The extracted features were finally normalized and optimized to yield the desired set of features to train the proposed DNN model. The proposed OFF_DNN model obtained the overall classification accuracy of 98.64% with precision, recall and F1 score of 98.79, 98.6, and 98.85%, respectively. This implies that proposed OFF_DNN is effective for plant diseases classification and prediction.

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Author’s Contributions

Deepkiran: Wrote the first draft of the manuscript, collected the dataset and conducted experimental work.

Mrinal Pandey: Performed a partial scientific literature review and proofread the manuscript.

Laxman Singh: Full coordination of research and data analysis. Drafted, reviewed, and edited the manuscript.

Ethics

The manuscript is an original work. The authors declare that no ethical concerns are associated with the submission of this work.

Conflicts of interest

The authors have no conflicts of interest to declare

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