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Plant Leaf Disease Prediction Using Deep Dense Net Slice Fragmentation and Segmentation Feature Selection Using Convolution Neural Network

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Abstract: Plant disease affects the agriculture production seasonally on variety of ways. Identifying and early detection of disease is an important factor for production management to improve the economic growth. Most commonly the disease symptoms are identified by observing the disease in the plant leaf region. Existing machine learning models use images with improper and high dimensional features that lead to inaccurate classification of plant leaf disease. To tackle this issues, we introduces a deep dense net slice fragmentation and segmentation feature selection and classification through optimized convolution neural network. Initially the wavelet Filters features are applied to enhance the image through structure normalization model. The slice fragment segmentation is applied to segment the disease covered region by identifying the realistic variation based on spectral histogram feature difference. Then cascaded edges and features are extracted and trained using deep Densenet Convolution Neural Network (DnCNN) to identify the plant disease effectively. The proposed system achieves best result compared to the other existing approaches in terms of precision rate, recall, f-measure and also superior due to the fact that the diseases are identified at an earlier stage.

Keywords: *Plant leaf disease, feature selection, segmentation, classification, Dn CNN, early identification, deep learning.*

1. Introduction

Early recognition of plant diseases can open up techniques for better decision-making in agricultural sector. The country's economy pivot on agricultural results and a large portion of the population depend on agriculture. All farmers can grow different crops depending on the fertility of the soil. Also, farmers give importance in the choice of the crop and the proper pesticide. Leaves are the most sensitive parts of the plant and may be the first to show disease symptoms. This enables high-yielding crops to be monitored for disease from establishing their life cycle until they are ready for harvest. One of the most critical aspects of plant disease diagnosis is preventing loss in production and improving agricultural product quality.

Plant diseases cause significant loss of food production and eradicate species diversity. However, even though crop diseases pose a significant threat to food, the lack of the necessary infrastructure makes early detection of the disease even more difficult in many parts of the world. Manual monitoring of plant diseases is a daunting task. It requires much work, plant pathology expertise, and excessive processing time. As a result, crop damage can significantly decrease productivity, resulting in a more significant economic impact.

Figure 1 depicts deep learning (DL) based approach for a plant disease prediction flow chart. Initially, an image from the dataset is given as input to the preprocessing stage where noise is removed and the second stage involves segmentation in which the image is split based on the collection of pixel areas represented by a mask or feature image. The selection of segmented features based on histogram feature analysis and classification based on deep learning techniques results in better plant leaf disease prediction.

Furthermore, plant diseases threaten global food security and can devastate small farmers who depend on healthy crops. Determining the type of plant disease is considered a significant and critical issue. Changes in environmental

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conditions such as rainfall, temperature, and soil fertility can lead to fungal, bacterial, and viral infections in crops. The contribution of the paper is to improve the plant leaf disease prediction using deep densenet slice fragmentation and segmentation feature selection using convolution neural network.

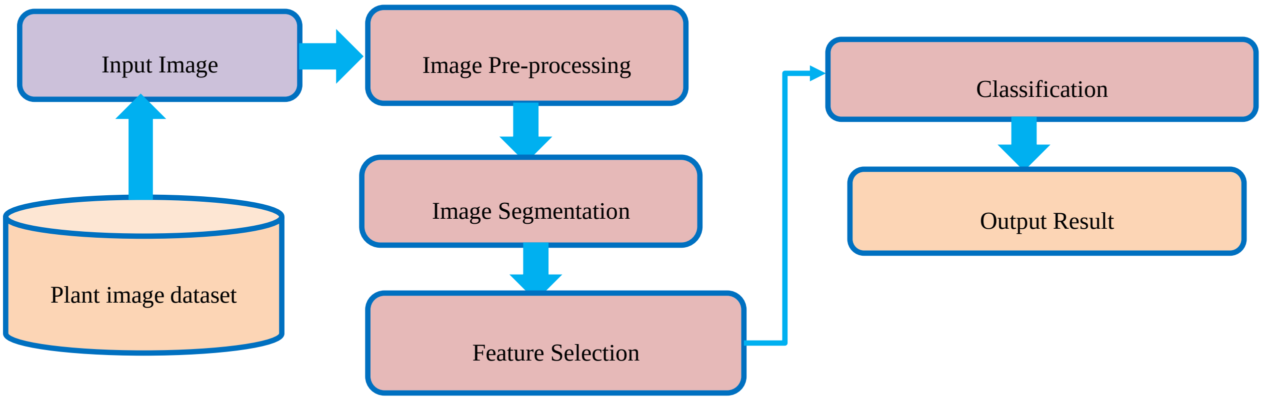

Fig. 1. Plant Leaf disease Detection basic diagram

2. Literature Survey

R. I. Hasan et al. (2020): The author proposed that agricultural productivity can be significantly improved using Machine Learning (ML) techniques in this sector. In particular, the recent emergence of Deep Learning (DL) has seen enhanced accuracy.V. K. Vishnoi et al. (2023): The author proposed to build a Convolutional Neural Network (CNN) with fewer layers, thus reducing the computational load.

Y. Zhao et al. (2022) presented a Double GAN method for plant leaf disease prediction. This method is split into two-stage to predict disease. Stage 1 is the input image of a healthy and unhealthy leaf resized, and stage 2 indicates the plant condition. M. Lv et al. (2020): The study introduced a method for detecting maize leaf blight and developed a suitable framework for optimizing maize leaf disease identification in complex situations.

T. N. Pham et al. (2020): The novel focused on the early detection of plant-leaves small lesions using the ANN method. Therefore, the dataset was segmented into all affected regions after pre-processing using a contrast enhancement technique. Z. Zhang et al. (2023): The novel used the High-Quality Image Augmentation (HQIA) technique to create clean rice images and Generative Adversarial Networks (GANs) algorithm to identify the rice leaf disease. However, smart farming has classic problems, such as the difficulty and high cost of obtaining superior disease models.

B. Liu et al. (2020) the author used a GAN technique to identify the different diseases of the grape leaf. A generator model with a regression channel can initially design and create images of grape leaf diseases. A. Ahmad et al. (2023): The author focused on plant disease identification using DL based approach called Desnet169. The study examines the five datasets: plant village, DoC, NLB, digipathos, and CD&S. This author didn't analyze the plant leaves image conditions.

S. Barburiceanu et al. (2021): et al. (2013) presented DL-based methods like AlexNet, VggNet, ResNet, and CNN for precision agriculture. The suggested CNN method extracts the features of the disease leaf. Likewise, H. Yu et al. (2021) used VGGNet, ResNet, and Kmean Clustering for corn disease diagnosis. However, theses method of disease identification is a complicated process. Q. Zeng et al. (2020) the author concentrated on citrus disease harshness identification, so they collected a Huanglongbing leaf image dataset. This study utilized the GAN algorithm to predict disease and data augmentation.

Y. Wu et al. (2022): Introduced a CNN-based Fine-grained Categorization (FGC) approach for identifying plant leaf disease. This method has a complex analysis of the perfect result of plant disease.

S. Das et al. (2023): The author suggests that traditional methods of large-scale disease surveillance are laborious, time-consuming, and imprecise. Remotely sensed parameters can help quantitatively monitor disease and crop health. M. Kumar et al. (2021) concentrated on plant disease predictions like rust, rot, blight, etc. The author used the MLP method to identify the disease and minimize financial loss.

R. Saini et al. (2022): R. Saini et al. (2022) explored the MIMONN algorithm for plant disease identification using a Multi-sensor system. The sensors gathered data like humanity and the temperature of plant diseases. S. Ahmed et al. (2022): The author proposed a lightweight based on Transfer Learning (TL) to identify diseases in tomato leaves. Effective pre-processing methods can enhance leaf images to improve the classification. C. Zhou et al. (2021): The author proposed that an adequate local spot area can be generated for spot area data augmentation to identify grape leaf spots based on the grain-GAN model. X. Liu et al. (2021): Similarly, an LSTM method for detecting plant diseases was performed using a standardized dataset in this study. The collected dataset included 271 disease species and 220,592 plant images. The author proposed a method for leaf weight analysis.

2.1 Problem of Statement

- The need for extensive training, computational complexity, overfitting, etc., is a critical issues to be addressed.
- Due to environmental changes and the difficulty of extracting disease characteristics, such as uneven light reflection from the incident light source, identifying corn leaf disease is a significant challenge.
- However, accurate and timely knowledge of plant disease severity is still essential. It prevents plant infections and minimizes financial loss, helping you make more effective decisions.
- In addition, complex networks occupy large volumes of computer memory, waste enormous amounts of computer resources, and are challenging to meet the requirements of low-cost terminals.

3. Proposed methodology

This proposed assessment of plant disease identification is based on various levels of feature observation using Densenet Convolution Neural Network. We propose a deep densenet slice fragmentation and segmentation feature selection and classification through optimized convolution neural network. Initially the wavelet features are applied to enhance the image through structure normalization model.

The slice fragment segmentation is applied to segment the disease covered region by identifying the realistic variation based on spectral histogram feature difference. Then cascaded edges and features are extracted and trained using deep densenet convolution neural network to identify the plant disease effectively. Figure 2 shows the proposed DnCNN architecture diagram. The proposed system aims to identify the disease earlier and to achieve high performance in precision rate, recall, f-measure to attain best result compared to the other existing methods.

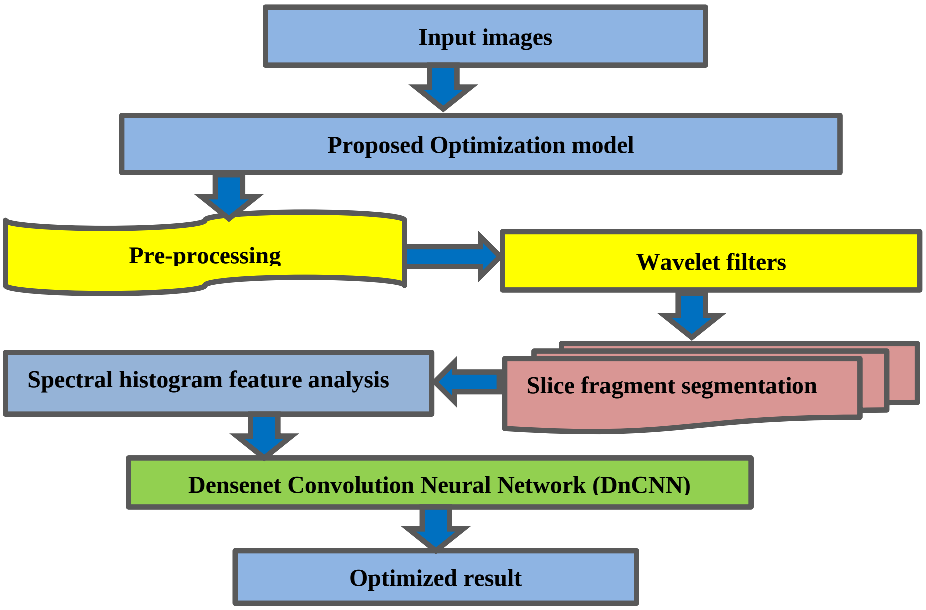

Fig. 2. Proposed: DNCNN architecture diagram

3.1 Wavelet Filters for preprocessing

In this stage, the collected diseased plant leaf images are normalized to eliminate the noise using the mean values and remove the non-sampled corrections using wavelet filters. Further resizing of the image is also done. The edges of the affected region are morphed using edge-based feature maps to improve the quality of image.

Algorithm steps

Input: Plant image dataset (Pt)

Output: Preprocessed image

Start

Step 1: Compute the mean (image size) from each training sample from each image feature.

$$a' = a - \mu \text{ (Pt)} \quad (1)$$

Step 2: Compute the training sample plant leaf image standard deviation values of each pixel.

$$a' = (a - \mu)/\Sigma. \quad (2)$$

Step 3: Compute the mean covariance matrix of the normalized data.

$$x_{ZCA} = \cup . diag\left(1/\sqrt{diag\ (Q) + \varepsilon}\right) . \cup^{R} . a^{R}. \quad (3)$$

Step 4: Evaluate the high accuracy can be confirmed from the results obtained.

Stop

Here, x –original data, a'-normalized data, μ-mean vector, Σ-standard deviation vector, ZCA- Zero Component Analysis, U denotes is the Eigen vector matrix and Q - is the Eigen value matrix of singular value, diag(a)-represents the diagonal matrix, $\cup^{R}$is the rearrange of the Eigen vector matrix, ε is the coefficient. This algorithm effectively pre-processing the image for identifying the plant disease structures.

3.2 Slice fragment Image segmentation

In this section, we apply Slice Fragment Image Segmentation (SFIS) method to identify the affected regions of the plant from pre-processed images. This effectively splits the disease region to identify the part and variation in disease using normal properties of the image.

Algorithm steps

Input: image regions for segmentation.

Output: segmented parts

Start

Step 1: Compute closed planar curves using the implicit functions

$$c = \{(a, b)u(a, b) = c\} \quad (4)$$

Step 2: Calculates the tangent direction of a position set at a given point

$$\frac{d_v}{d_s} = \frac{\partial_v}{\partial_a} \sec \alpha \frac{\partial_v}{\partial_b} \csc \alpha \quad (5)$$

Step 3: Calculate the tangent vector representation of the slope

$$v = \frac{\partial_v}{\partial_s} \Delta \text{s} \quad (6)$$

Step 4: Calculates the average unit vector representing a set of positions.

$$M = \pm \frac{|v-1|}{\sqrt{v^2+1}} \quad (7)$$

Step 5: Evaluate the curve evolution of a level-set system

$$L = \frac{{v_b}^2 + 2_{v_a v_b} + v_a {v_b}^2}{({v_a}^2 + {v_b}^2)^3} \quad (8)$$

Step 6: Provides an implicit representation of plane closed curves

Stop

Where, C-curve, (a,b)- 2d function, u(a,b)-horizontal set, α-angle, s-tangent vector, M-tangent direction of the horizontal set, v- increasing direction, a-axis, L- curve evaluation, d - directional derivative. The segmented region retains the disease-affected region to extract the disease-region features for further classification.

3.3 Deep dense net convolution neural network

Deep neural optimized with dense net convolution layer, these layers are feed-forward to initiate the feature extraction layers. The selected features are fed with a dense net layer to prove the convolution layer to produce the disease classification in training validation. The algorithms explain,

Input: Segmented plant image

Output: Predicted result

Start

Step 1: Extract the leaf image features in convolution neuron is estimated in equation 9. Let assume, l- denote the layer, a_l- meaning of output layer, a_{l-1}- output of the preceding layer, [+] - attribute to merges the previous layer, H_l- composite function.

$$a_l = a_{l-1} + H_l(a_l) \quad (9)$$

Step 2: Computes the connections of feature maps in layers.

$$a_l = [(a_0\, , a_1\, , a_2\, , \ldots , a_{l-1})] \qquad (10)$$

Where, [a_0, a_1, a_2… a_{L-1},] – single tensor formed by the concatenation of the output maps

Step 3 Computation of an improved form of the standard cross-entropy loss function using focal loss, which can significantly improve detection performance. Below equation,

$$CE(n_t) = \ -\alpha_t\ log(n_t) \qquad (11)$$

Here, CE- cross-entropy, α-normal balanced for CE, n_t- Probability tag.

Step 4: Compute α loss performance during result prediction.

$$FL(n_t) = -\alpha_t(1-n_t)^{\gamma} log(n_t) \qquad (12)$$

Where, FL –focal loss, γ-tag value of ground-truth class, α_t- weighting factor, n- probability class.

Stop

The above algorithm steps provide proficiently identify whether it is a disease-affected and non-affected plant using the DnCNN algorithm.

Figure 3 describes the images randomly assigned to leaf diseases in the first round of screening and labeling and called upon to confirm (or correct) the labeling results. A total number of images were excluded according to the following criteria: (1) poor quality; (2) image artifacts; (3) Occurrence of other diseases.

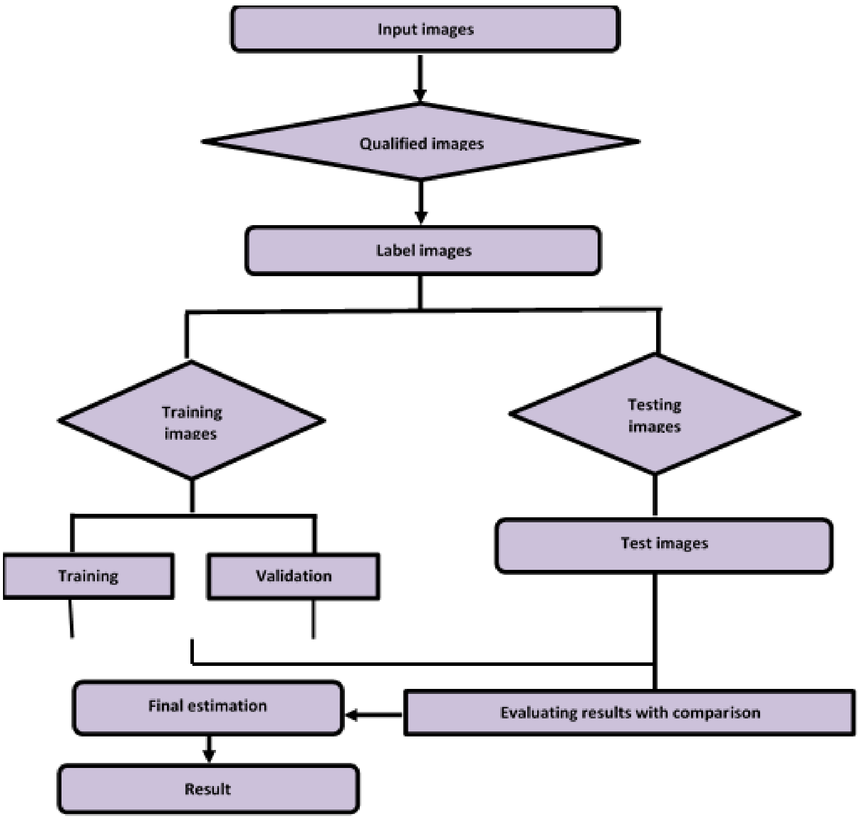

Fig. 3. Plant disease prediction flowchart

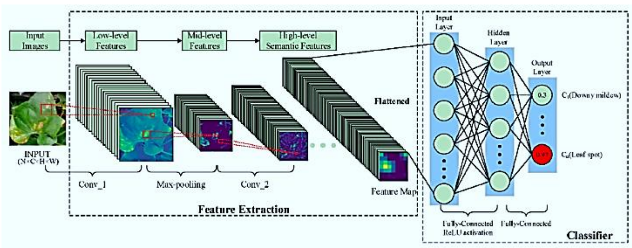

Fig. 4: DnCNN Architecture

Features are extracted using DnCNN-based architecture shown in figure 4. It includes convolutional, Max-Pooling (MP), and Fully Connected (FC) neurons. A convolutional layer is mainly used to extract leaf image features. The convolutional layer is used to extract disease structure information, the pooling layer is used to extract some complex structure and semantic information, and the deep layer is employed to extract high-level attributes. Use maximum pooling and convolutional layers to save important information in the image. At the architecture's end is a classifier consisting of fully connected layers.

4. Result and discussion

The inputs are from the new plant disease dataset gathered from the Kaggle repository to assess the model's performance. The simulation is developed using Mat Lab software, with 1:3 used for training and 40% for validation. Compared to traditional techniques, the proposed DnCNN model has good accuracy (i.e., 97.73%) for detecting disease plant leaf images. Table 1 describes the proposed Adaptive DnCNN system's simulation configuration parameters. The proposed implementation simulation tool is Matlab 2017a, based on Windows 10 operating system with 16GB RAM.

Table 1. Simulation configuration details

Parameter	Value
Data Set	Plant disease dataset
No of Images	5000
Training Images	3852
Testing images	1,148
Tool Used	Matlab 2017 a

The existing algorithms for plant leaf disease detection are Decomposed Neural Network (DNN), Radial Bias Neural Network (RBNN), and Long Short Term Memory (LSTM). Table 1 illustrates the simulation configuration details.

4.1 Collection of Leaf Images

This dataset includes 20 classes of roughly 80k RGB images of healthy and diseased leaves. A 70/30 training images/validation images are taken from the image dataset. For prediction, a new directory containing 20 test images will be created.

Table 2: Collection of plant leaf images and count

Plant _ Leaf Image	Count
Tomato___Late_blight	1851
Tomato___healthy	1926
Grape___healthy	1692
Orange___Haunglongbing_(Citrus_greening)	2010
Soybean___healthy	2022
Squash___Powdery_mildew	1736
Potato___healthy	1824
Corn_(maize)___Northern_Leaf_Blight	1908
Tomato___Early_blight	1920
Tomato___Septoria_leaf_spot	1745
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot	1642
Strawberry___Leaf_scorch	1774
Peach___healthy	1728

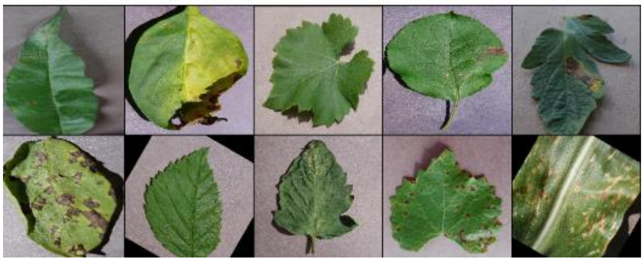

Fig. 5. Collection plant leaf images

Figure 5 illustrates the sample plant images of healthy and non-healthy collected from the Kaggle repository. Table 2 describes the various plant leaf disease and non-disease counts. All the leaf images transform to 256 x 256 pixels, and further model optimization and prediction are performed on these images.

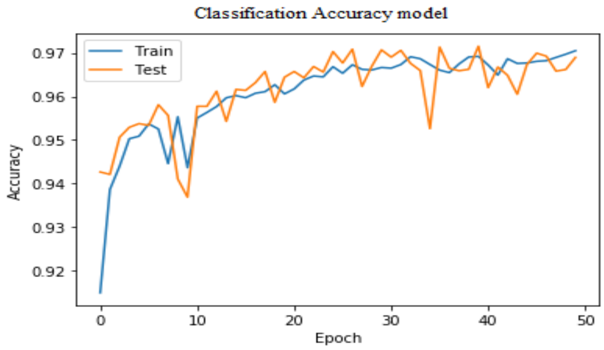

Fig. 6. Classification accuracy model

Figure 6 denotes training and testing plant disease prediction accuracy performance. The proposed training accuracy performance is 97%, and the testing accuracy is 96%. Therefore proposed DnCNN algorithm efficiently predicts plant disease in the early stage.

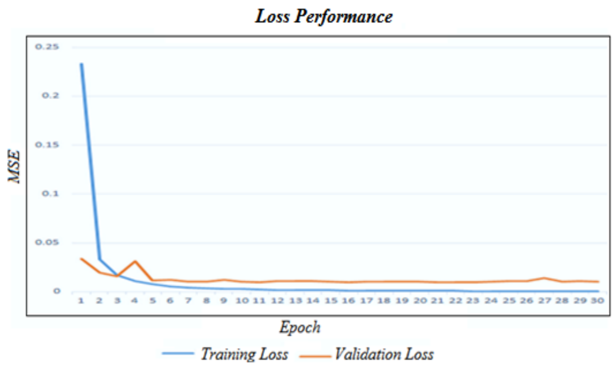

Fig. 7, Simulation Result of DN-CNN for loss Evaluation

Figure 7 presents the proposed DnCNN experimental results of training and testing loss performance for disease identification. By using ASN-CNN, the MSE value is 0.009.

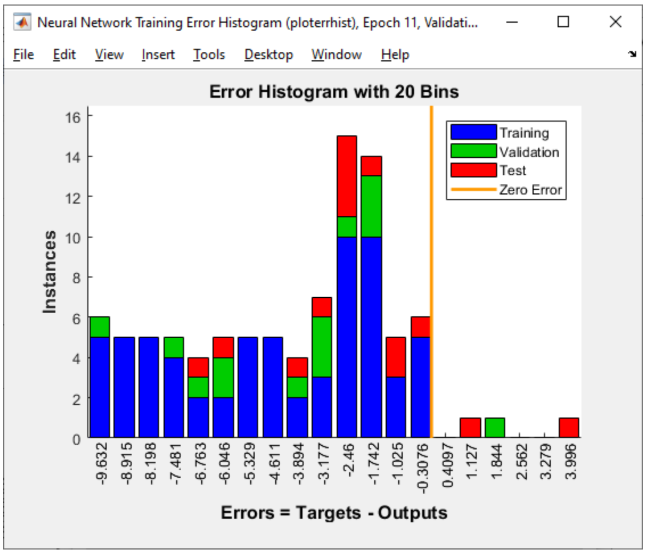

Fig. 8 Histogram evaluation

Histogram values represent the object entity mean values. It finds the object's differences based on the absolute error rate. During training, testing and validation, the represented histogram was used to find the color intensity ranges efficiently. Identifying the features takes 20 bins of color evaluation with low error dependencies. Figure 8 shows the Histogram evaluation. The performance accuracy in class labels predicted class from the normalized confusion matrix. The detection rate from disease and non-disease class color variation is shown in the figure 8 in the actual training class. The proposed system also predicts the valid positive rate in precision accuracy in the best-level predicted class.

4.1 Performance Analysis of pre-processing

The following parameters are used to validate the pre-processing Mean Squared Error (MSE) response: MSE measures the quality difference among the pre-processed image and the real image.

$$MSE = \frac{1}{X*Y}\sum_{g=0,k=0}^{X-1,Y-1}[w(g,k) - h(g,k)]^2$$
(13)

Wherein X denotes width of improved images$\left(w(g,k)\right)$, H is the input image $\left(h(g,k)\right)$ and their row and column pixels in the images.

Peak Signal to Noise Ratio (PSNR): The PSNR is the proportion of the most significant potential power to distort noise in image representation. BSNR is a standard measure to evaluate the reconstruction of image quality. A higher PSNR score indicates better picture quality. The MSE and associated bias metrics illustrate that.

$$PSNR = 10log_{10}[\frac{MAX_i^2}{MSE}]$$
(14)

Here Max_i denotes Maximum possible number of pixels in the image.

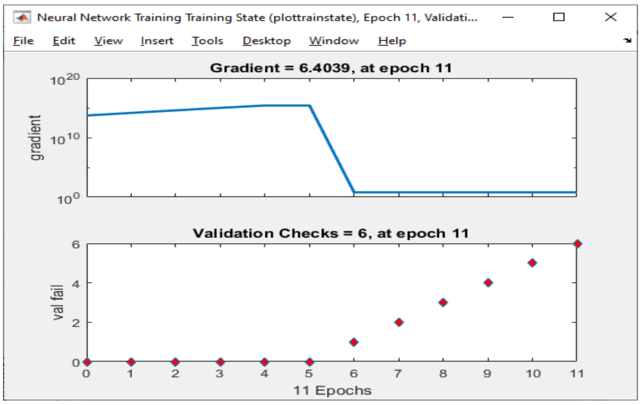

Fig. 9. Neural network validation summary

Mean Absolute Error: The difference in intensity between the input image and the denoised image is measured using MAE. Figure 9 shows the neural network validation summary

$$MAE = |E(x) - E(y)|$$
(15)

Here,

E(x) = Original image of intensity

E(y) = Improved image of intensity

Table 3. Analysis of filtering performance

Various Parameters	**Various Filters**	Response (dB)
	Gaussian Filter (GF)	19.52
MSE (dB)	Wavelet Filters (WF)	15.13
	Median Filter (MeF)	9.35
	GF	0.0698
	WF	0.0524
MAE (dB)	MeF	0.00430
	DNCNN	0.00380
	GF	33.10
PSNR(dB)	WF	36.61
	MeF	41.01
	DNCNN	42.51

Table 3 illustrates the analysis of the filtering performance. This table depicts that the proposed Wavelet Filters gives better results than the Gaussian Filter and median filters. The proposed averaging filter's MSE, MAE, and PSNR are 9.35dB, 0.00380dB, and 42.51dB, respectively. The following metrics are used to verify segmentation performance.

Global Consistency Error (GCE): The GCE is a metric that determines how close one partition is to being a refinement of another. The equation represents the mathematical description of global consistency errors.

$$GCE = \frac{1}{n} min \{\sum_i E(b1, b2, pi), \sum_i E(b2, b1, pi),\}$$
(16)

The GCE metric accepts b1 and b2 as inputs and produces a real-valued output in the range [0:1]; zero forms are not treated as errors. Pi denotes the segments b1 and b2, including a specific pixel for a given pixel.

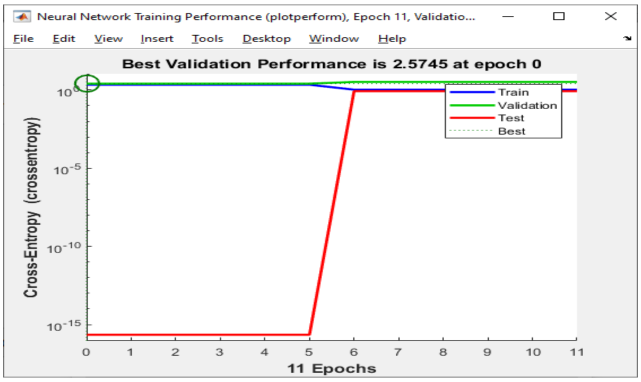

Fig. 10. Validation performance evaluation

DICE coefficient parameters: The DICE metric mainly validates the number of segments in plant disease images. Figure 10 shows the Validation performance evaluation DICE is commonly used for reproducibility (repeatability) assessments and direct comparisons between automated and ground truth segmentations. The formula mathematically expresses the dice coefficients:

$$DICE = \frac{2|A \cap B|}{|A|+|B|}$$
(17)

Here, A denotes predicted class, and B denoted ground truth values in the image.

The following are the parameters used to evaluate the performance of classification.

Accuracy: The number of appropriately ordered trials is related to the number of attempts assigned.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$
(18)

Sensitivity: This statistic may be used to determine the correct identification rate. The actual positive rate is the term for this. It is often represented as a percentage.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP+FN}}$$
(19)

Specificity: The actual negative rate is a statistical metric that assesses the proportion of negatively classified parameters. It is often represented as a percentage.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN+FP}}$$
(20)

Here, FP refers to False Positive plant disease values, FN refers to false negative disease values, TN denotes True Negative disease values, and TP represents True Positive disease-affected values.

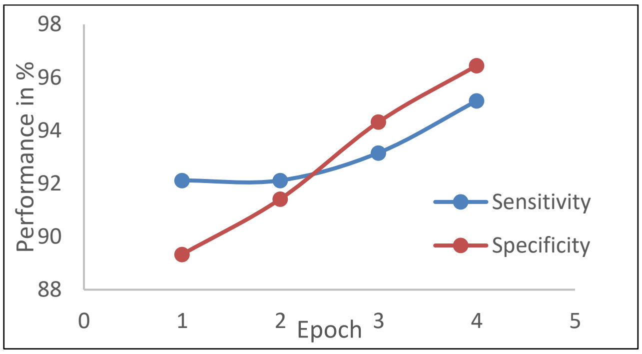

Fig. 11. Impact of sensitivity and specificity performance

Figure 11 defines the sensitivity and specificity performance with various epochs 1, 2, 3, 4, and 5 for plant disease detection using the proposed DnCNN algorithm. The proposed method produces a result sensitivity is 95.12% and a specificity of 96.45%.

Table 3: Impact of performance accuracy and F1-score analysis

Accuracy and F1-score performance in %		
Different methods	Accuracy (%)	F1-score (%)
PCA	82.16	14.33
NN	93.15	92.46
ACNN	93.88	92.83
ADNRNN	96.89	96.83
DNCNN	97.91	98.12

The comparison of performance accuracy and F1-score analysis values are described in Table 3. This comparison shows that the proposed methods produce better results against all working conditions.

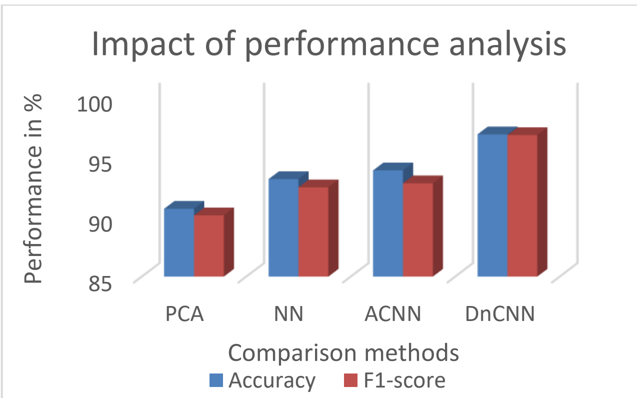

Fig. 12. Comparison of Accuracy and F1-score

Figure 12 depicts the comparison of accuracy and F1-score performance for plant disease prediction. The proposed method produces an accuracy of ~~is~~ 96.89%, and the F1-Score of ~~is~~ 96.83%; similarly, the result of another method is PCA technique whose accuracy is 90.67%, and F1-score is 90.12%, NN technique accuracy is 93.15%, and F1-score is 92.46%, and ACNN technique accuracy performance is 83.88%, DNCNN F1-score is 98.12%.

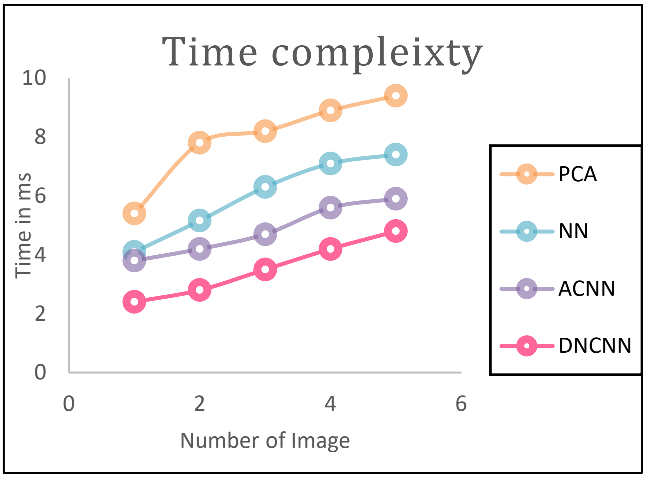

Fig. 13. Comparison of plant disease prediction time complexity

Figure 13 shows the chart representing the time complexity performance comparison result. Given a plant leaf image as input, it takes 2.4ms to detect whether it contains disease region or not. It provides results in significantly less time as compared to other methods.

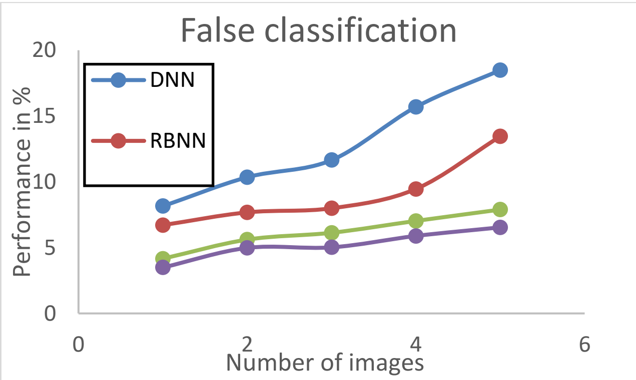

Fig. 14: Analysis of false classification performance

Figure 14 describes the impact of false classification performance with the different numbers of plant images (1, 2, 3, 4, and 5). The proposed DnCNN method produces fewer false rates compared to another method.

5. Conclusion

To conclude, the proposed ~~a~~ deep dense net slice fragmentation and segmentation feature selection performs effectively to detect the plant leaf disease. The classification using convolution neural network produce high performance. The wavelet features are ~~is~~ applied to enhance the image through structure normalization model to attain best result. The performance improvement is carried out by slice fragment segmentation which is applied to segment the disease covered region by identifying the realistic variation based on spectral histogram feature difference. Then cascaded edges and features are extracted and used to train the deep densenet convolution neural network to identify~~ing~~ the plant disease effectively. In the proposed method, DnCNN performance analysis shows an accuracy of 89%, precision of 85%, recall of 83% and the reduced false rate is 47.2%. Future work includes improving plant disease accuracy and disease spot detection using deep learning techniques. Therefore future will efficiently identify the disease spot in the leaf.

Conflict of Interest

The author declares that they have no conflict of interest.

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