Eggplant leaf disease detection and segmentation using adaptively regularized multi Kernel-Based Fuzzy$C$-Means and Optimal PNN classifier

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Abstract: Leaf diseases affect both the quantity and quality of crops in agricultural production. Early detection is preventing the plant from diseases. Therefore, in this paper, optimal probabilistic neural network (OPNN) based plant disease classification is proposed. At first, RGB transformation is performed to extract the green band of the eggplant leaf. Then, for the extracted green band; pre-processing is carried using median filter. After pre-processing, the features such as shape, color and vein are extracted. Then the extracted features are fed to the PNN classifier to classify an image as normal or abnormal. To enhance the PNN classifier, the weight values are optimally selected using Binary Crow Search Algorithm (BCSA). Finally, the affected portions are segmented using Adaptively Regularized multi Kernel-Based Fuzzy$C$-Means (ARMKFCM). This research work is compared with other existing techniques through several performance metrics to show the superiority of our proposed methodology.

Keywords: Median filter, PNN, Binary Crow Search Algorithm, ARMKFCM, leaf, egg plant

1. Introduction

One of the main problems that significantly lowers the efficiency of agricultural products is plant infections. The primary responsibilities to enhance the efficiency of crop cultivation for economic development are the identification and categorization of plant lesions [1]. It is utilized to consistently and correctly measure plant development, productivity, chlorophyll fluorescence, plant breadth and tallness, leaf area, etc. Generally, the leaves of the plant are the first source to detect most plant diseases [2]. Brinjal (eggplant), Solanum Melongena is one of the most widely grown vegetable crops all over the world for its purple or green pendulous fruit. India is one of the major producers of brinjal in the world with about 8.45% of the total area under vegetable cultivation occupied by brinjal. The farming system has increased its dependence on agro-chemicals which has led to severe ill effects that include the diseases caused by pathogens and pests. The most common parasitic diseases that affect brinjal leaves are leaf spot disease caused by Cerocospora melangina, Verticillium wilt due to Verticillium dahliae, bacterial wilt due to Psuedomonas solancearum, and mosaic which is a viral disease transmitted by aphids (Aphis gossypi and Myzuspersicae). The growing importance of brinjal cultivation in Indian agriculture and the escalating crop failures makes it necessary to develop an algorithm for early and accurate detection of diseases affecting the brinjal plants [10].

The use of a computerized approach for plant disease identification is advantageous because it lessens the amount of effort required to maintain maximum crop farms and can identify disease signs as soon as they develop on plant leaves [3]. Specialists can identify and identify plant problems with nothing more than their own naked eyes nowadays, according to the current approach for disease detection in plants. This requires a sizable team of specialists and ongoing plant monitoring, both of which are quite expensive when applied on big farms [4]. Meanwhile, in some nations, farmers lack access to sufficient resources and even know they can consult specialists. Because of this, consulting specialists is expensive and time-consuming. The suggested method works well in these circumstances for keeping an eye on extensive crop fields [5]. It is simpler and less expensive to automatically identify diseases based just on their symptoms on plant leaves. In order to enable image-based automatic process control, inspection, and robot guiding, this also supports machine vision. It can be achieved using image processing techniques which have a fine potential for early detection of diseases [6].

Image processing is a most excellent practice for agricultural applications. To improve plant growth, it is crucial to identify and classify plant diseases. Numerous methods have been developed to identify plant diseases, including threshold, regional growth, grouping, edge-based identification, and others [7]. The image should go undergo certain treatment, such as pre-processing, retrieval of features, categorization, and segmentation operations, in order to detect plant illness. Pre-processing is a method that improves image data by suppressing undesired distortion or enhancing certain visual qualities that are crucial for subsequent processing. Feature extraction is applied to extract the important features alone to enhance the system performance. An image can have a variety of qualities, including depth, motion, depth perception, colour, structure, and shape [8]. To identify normal and abnormal plant leaves, a categorization technique is employed to divide the input data into a variety of classes and groups. In order to identify diseases, it categorizes the data depending on chosen criteria. To increase the classification performance, a segmentation method is used for the classified image to determine the area of the image that is impacted [9].

The remaining sections are organized as follows. The relevant study by many researchers is described in Section 2. The problem definition of our research is highlighted in Section 3. The detection of eggplant leaf disease is processed in detail in Section 4. Section 5 provides a summary of the findings, while Section 6 provides conclusions.

2. Related work

A classification approach using survival of fittest model was presented by G.Dhingra et al [11]. To identify basil, leave disorders, a three level hierarchical structure was created. In addition, to increase contrasting and emphasize the designated target for the identification of the disease against their backdrop, a Contrast Limited Adaptive Histogram Equalization technique was used. To obtain the highly relevant components, the features are retrieved utilizing texture and color features. The Random forest method was used to identify those pertinent variables. In 2018, convolution neural network models were developed by K.P. Ferentinos [12] to basic leaf photos of normal and infected plants, deep learning approaches can be used to identify and diagnose plant diseases. Furthermore, a method for classifying and detecting leaf diseases in plants utilizing image processing was presented by V. Ramya in 2016 [13]. Three fundamental phases make up the described algorithm: Feature extraction, image pre-processing, and recognition of plant disease. Following pre-processing, the different plant leaf characteristics, including intensity, color, and size, are retrieved and submitted to an SVM classifier using a back-propagation neural network for categorization.
In 2018, J. Praveen Kumar, and S. Domnic [14] have exhibited a technique for calculating the number of leaves and extracting leaf regions from plant images. This approach was analyzed into three phases. A novel statistically oriented methodology for image improvement is used in the first step. The second phase entails the graph-based technique of extracting the leaf region from the plant image. The third stage entails using the Circular Hough Transform to count the number of leaves in the plant image (CHT). By using local binary patterns (LBPs) for feature extraction, an automated method for identifying crop diseases on multiple leaf sample photos matching various crop types was presented by X.E. Pantazi et al [15] in 2019. For every crop health problem, such as healthy, downy mildew, powdery mildew, and black rot, this employs a specific One-Class Classifier. When tested in different crops, the algorithms trained on vine leaves demonstrated extremely strong generalization behavior.

A plant leaf disease identification model based on a Deep CNN was presented by G. Geetharamani and J. ArunPandian in 2019 [16]. An accessible dataset containing 39 distinct classes of plant leaves and background photos was used to develop the Deep CNN model. Image flipping, gamma correction, noise injection, principle component analysis (PCA), color augmentation, rotation, and scaling were six different types of data augmentation techniques that were used. They discovered that applying data augmentation can improve the model's performance. Additionally, it underwent training with various training epochs, batch sizes, and dropouts. In 2018, M. Akila and P. Deepan [17] have analyzed to detect leaf diseases in many different plants using images of plant leaves. They considered three main families of detectors: Faster Region-based Convolution Neural Network (Faster R-CNN), Region-based Fully Convolutional Network (R-FCN), and Single Shot Multibox Detector (SSD), which was used in this presented technique.

3. Problem definition

Observing the leaves will allow to spot the majority of plant problems. Farmers utilized to check on the plant at regular intervals, and if they were incapable to recognize a disease's symptoms, they would administer a rough amount of fertilizer or pesticide. However, farmers are typically unable to pinpoint the precise disease deficit. This leads to the incorrect fertilizer being applied, which ultimately has an impact on both the soil and the plant. Automating the procedure of illness deficit identification is the answer to this issue. Several image processing methods can aid with this. Vegetable disease identification and recognition using machine learning can offer hints for early diagnosis and treatment. Relatively, it is difficult, ineffective, and challenging to diagnose diseases physically. Owing to these problems, the current study examines eggplant leaves using a variety of procedures to determine the disease-affected aberrant leaf type.

4. Detection of Eggplant Leaf Disease: Methodology

The main objective of the proposed methodology is to detect the disease-affected portion in the eggplant leaf disease i.e. brinjal leaf. The disease on the eggplant leaf is a critical issue that makes the sharp decrease in the production of brinjal. The dataset of eggplant leaf images is taken as an input and it is processed by image processing and artificial intelligence technique for disease detection. Initially, the leaf images gathered from the database are transformed into RGB color space. Then, the sole selection of the G band channel is done, as the G channel corresponds to the brightness/intensity information of an image. After subjecting the images to pre-processing, the noisy contents within the images are removed using median filter. Then we extract the important features from the image by means of GLCM and histogram orientation. Then, the selected features are given to the optimal Probabilistic Neural Network (OPNN) classifier to find the image as a normal or abnormal image. To improve the classification accuracy of OPNN the smoothing parameter is optimally obtained with the help of the Binary Crow Search Algorithm (BCSA). Finally, the segmentation process is carried out in the retrieved abnormal images in order to obtain the affected portion of the egg leaf plant using Adaptively Regularized multi Kernel-Based Fuzzy$C$-Means (ARMKFCM). The experimentation is done in the working platform of MATLAB by a analyzing standard agricultural database. The overall architecture of the proposed technique is given by the above Fig.1.

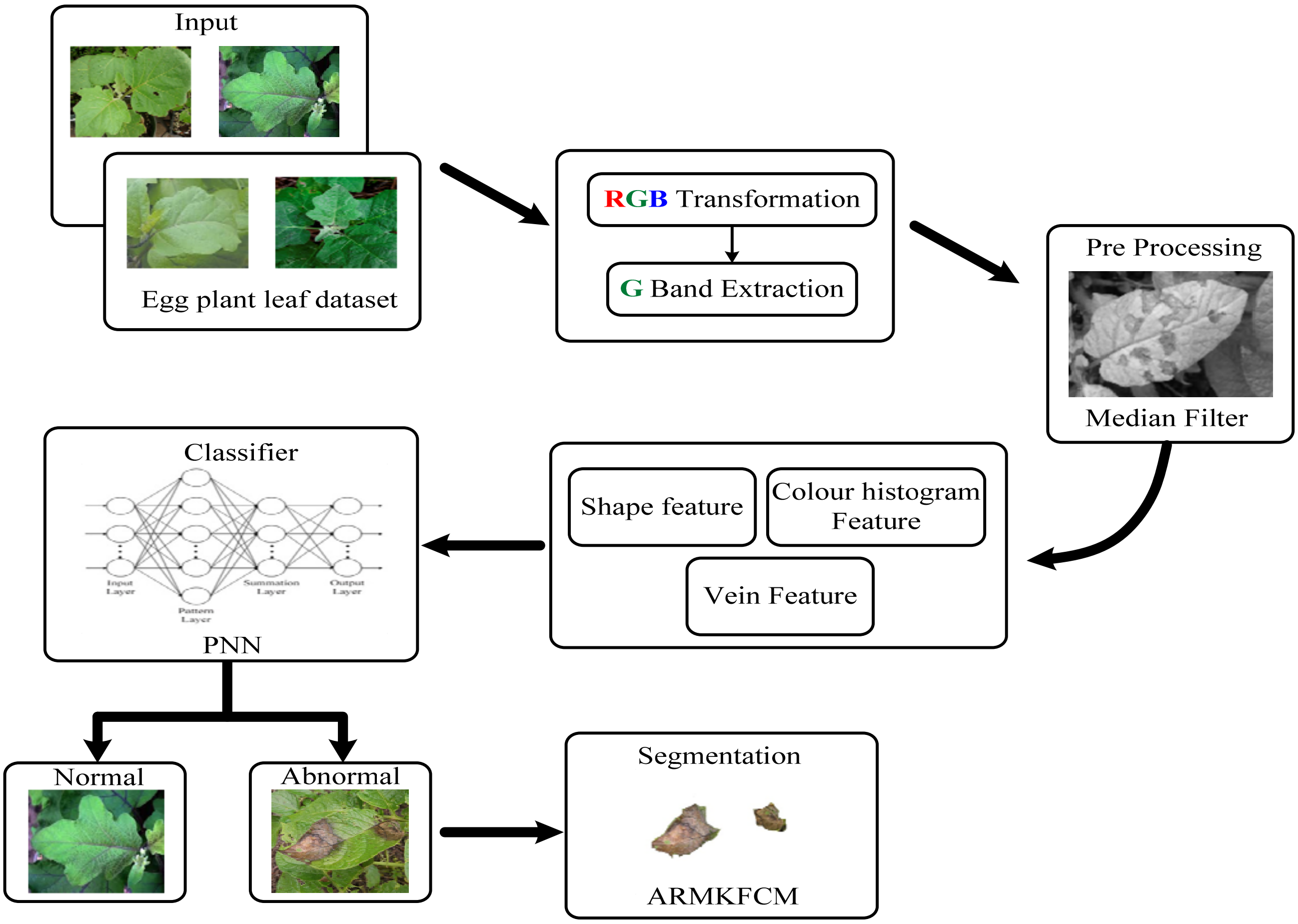


Figure 1: Structure of proposed method

Sketch of Proposed Procedure:

The steps involved in the proposed method is stated as,

- RGB transformation
- Pre-Processing by median filter
- Shape, Color and Vein feature extraction
- Normal/Abnormal Classification by OPNN
- Segmentation by means of ARMKFCM

Each stage of proposed Normal/Abnormal classification method of eggplant leaf disease is detailed in the upcoming section.

4.1. Input database images

Data collection refers to the collection of images from various sources. Usually acquiring the image is the first process in the system development. The database images used in this proposed technique is eggplant leaf which was collected from online dataset images.

4.2. RGB transformation

For more accurate segmentation of illness regions, the RGB image's color transform is utilized. Red (R), green (G), and blue (B) are combined in a variety of methods to create a wide range of colours in the RGB color space, which is a common color specification. It goes from 0 to 255 for each variable in the RGB color system. The Green band is the only one taken in our suggested piece. It is safe to operate on the green channel of the RGB color space in order to get better transformation results because it has high contrast connecting the backdrop and the bright leaf elements.

4.3. Pre-processing

The first step in image processing approaches is pre-processing. Pre-processing would be carried out to eliminate contaminants or noisy elements from the image in order to enhance image definition while reducing processing sophistication. Here, the processing efficiency is decreased by using a median filter.

- ***Median Filter:***

The median filter is frequently utilized to reduce image distortion. The median of the pixel set included behind the filter block is computed by a non-linear filter. Every image is identified, and it is then changed using the statistical district median. The median value maintains edge blurring and loss of image quality since it is calculated from the neighboring pixel, making it more resistant to outliners and avoiding the creation of a new realistic pixel value. Sharp high-frequency features are preserved. It works nicely to remove sprinkling noise from the image. The steps for the median filter method are as follows:

Table 1: Steps to be followed in median filter

• Place a window over pixels. • Sort the pixels value ascending or descending • Compute the median • The median value will be the new value of the center pixel of the window. • Repeat the above process for all corrupting image area.

A graphical presentation of the median filter operation is is given in Fig.2.

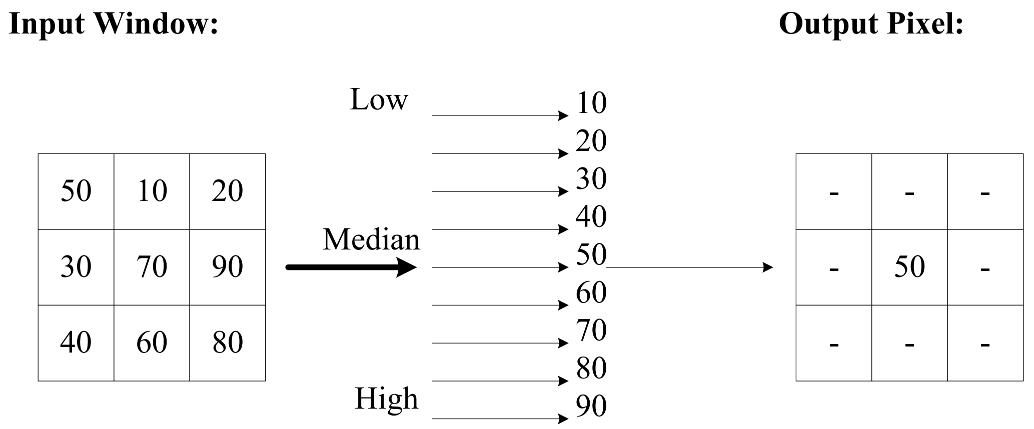


Figure 2: Graphical Representation Median filter

Every eligible pixel in an image is subjected to this filter's analysis of the pixels that surround it, as shown in the diagram above. In this instance, the outcome is calculated using a 3×3 window of pixels. The window of adjacent pixels for each pixel in the image is identified. The pixel counts in the frame are ordered in ascending proportion, as demonstrated in the instance above, and the median value is then selected; in this instance, the median value is 50. The value given by the filter order is then applied to the output image pixel that corresponds to the input image's origin pixel. 50 is substituted for the origin's value of 70.
As the window size increases, the median filter's ability to reduce distortion increases. The following is a numerical representation of the median filter:

$$\hat{Z}(i, j) = \underset{(s,t)\in S_{ij}}{median}\{g(s,t)\} \tag{1}$$

Where,

$Z(i, j)$ = median filter at a given coordinate

S_{ij} = coordinate of sub-image window of size $m \times n$

4.4. Feature Extraction

Features are the actual measurements of an image pixel that are useful for classification and/or pattern recognition. The aim of this phase is to extract features such as shape, color and vein features. Three shape features such as area, perimeter and eccentricity are extracted from the preprocessed image. Mean and standard deviation are the two color features extracted in our work. Finally, vein features were extracted for obtaining efficient outcome.

4.4.1. Shape Feature:

Shape is a powerful feature which may be recognized from their outline of an image. Efficient shape features must contain the following properties such as translation, identifiable, scale invariance, rotation, statistically independent, affine, noise resistance and occultation invariance. Structures can be described using a few basic geometrical characteristics. Simple mathematical parameters are employed as filters to weed out false hits or in conjunction with other shapes, descriptors to distinguish shapes because they can only distinguish shapes through considerable changes. The shape parameters used are area, perimeter and eccentricity.

- ❖ **Area:** Here, a specific section across the entire image is used to extract features. In an input leaf image, it is a scalar that represents the exact figure of pixels in the image that are counted in the pixels having intensity 1.

  $Area = \sum_{s,d\in S} 1$ Where s,d is the size of region S

- ❖ **Perimeter:** It is described as the space surrounding a region's border in an image of an eggplant leaf.
- ❖ **Eccentricity** The eccentricity of the ellipse contains same second moments as the region in an eggplant leaf image. It is defined as the ratio of distance between foci of an ellipse and its major axis length. It is the measure of aspect ratio. It can be computed by minimum bounding rectangle method or principal axes method.

4.4.2. Color histogram features

Color histogram is particularly suitable for the images which are difficult to describe the automatic classification and segmentation which was widely utilized for leaf image representation due to their effectiveness and simplicity. It depends on the kind of colour space and coordinate framework. It is required to estimate the colour histogram; the colour space is separated into a variety of small colour periods, and the distance in pixels among the colours of each cell is determined in order to produce the colour histogram. One of the greatest well colour characteristics for image extracting features is the colour histogram. In our proposed technique; mean and standard deviation are used to extract the color histogram features from eggplant leaf image.

- **Mean:** The brightness of an image is defined by the mean, which is the average value. Typically, a dark image has a low mean and a bright image has a high mean. Mean is formulated as given below:

$$F_j = \frac{1}{O}\sum_{i=1}^{O} Q_{ji} \tag{2}$$

Here the value of the j^{th} color channel at the i^{th} image pixel is Q_{ji}

- **Standard Deviation (SD):** It is also known as the square root of the variance. It illustrates that, low contrast image will have low variance and a high contrast image will have a high variance. It is formulated as given below:

$$\sigma_j = \sqrt{\left(\frac{1}{O}\sum_{i=1}^{O}\left(Q_{ji} - F_j\right)^2\right)} \tag{3}$$

4.4.3. <u>Vein features</u>

It is one of the most significant and intricate characteristics of the leaf that is utilized in an automated plant recognition system to classify and identify plant species automatically. These characteristics aid botanists in further precisely recognizing the major plant species from leaf photographs. Here, "leaf veins" one of the intricate features are taken into account. One of the crucial steps in locating the plant organs is the extraction of the leaf veins. The vein feature in our suggested method is expressed as follows:

$$X(l) = \frac{X * (l)}{\sqrt{X * (l)^U Dx * (l)}} \tag{4}$$

Equation (4) is the formulation of our proposed leaf venation. Where $X * (l)$ is the complex conjugate of $X(l)$ It is limited only to high quality leaf images; the methodology is fully based on color and green instances present in the leaf images.

4.5. Proposed Probabilistic Neural Network (PNN)

The leaf image's retrieved features are used as the input for our suggested classification algorithm. To distinguish between the normal and abnormal types of leaf picture, an unique PNN classifier is used. It is a sophisticated feed-forward neural network of some sort. The PNN construction is a straight neural network execution of the Bayes classification algorithm with the Parzen Non-parametric Probability Density Function (PDF) estimate. An input layer, pattern layer, summation layer, and output layer make up its structure. Due to this trait, PNNs can be trained more quickly than feed-forward, backward-propagation (FFBP) neural networks. The optimization of the weight function, which is a fundamental component and frequently data-dependent, is a persistent problem with PNNs. By employing BCSA, a meta-heuristic optimization technique that optimizes the network weight, this sort of quantitative issue has been solved utilizing a straightforward and reliable optimization methodology in the current research. The PNN structure is shown in Fig.3.

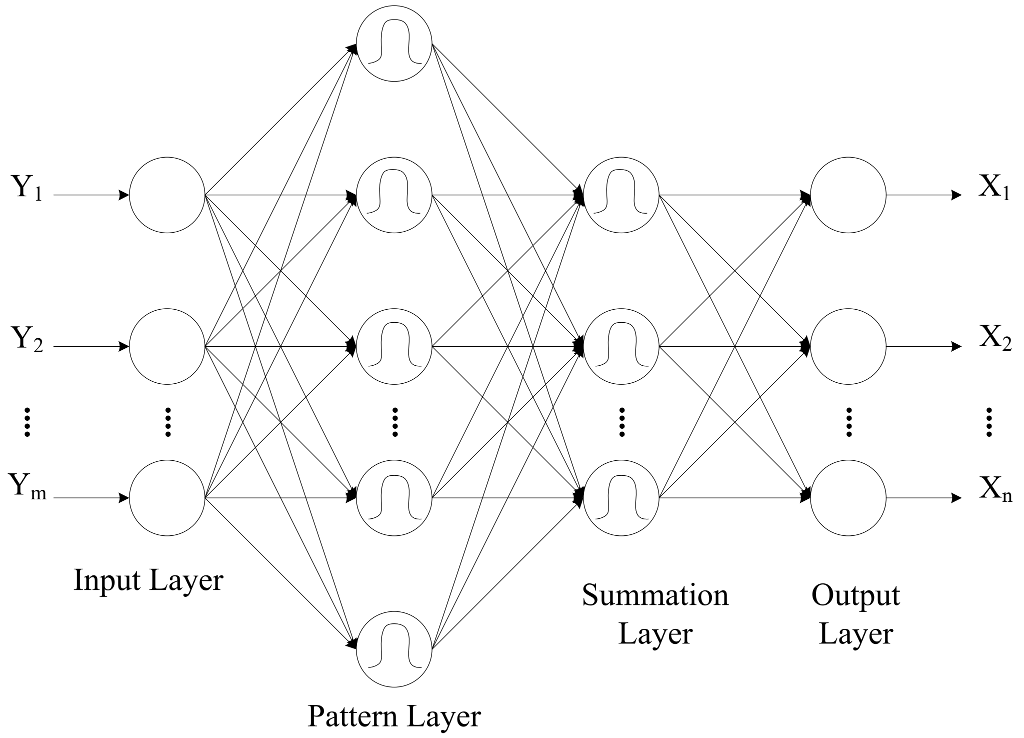


Figure 3: Architecture of PNN

Step 1: The outcome of the training examples is sent to the input layer. The sample vector's dimension is equal to the number of neurons. As indicated the training sample is given below,

$$Y = (y_1, y_2, \ldots y_m)^T \tag{5}$$

Step 2: After performing a radial basis nonlinear mapping, the pattern layer determines the distance between the training samples and the weight vector, and then produces an output vector. The radial basis function of choice is typically the Gaussian function. The chance that the input training sample belongs to any class is represented by the output vector. The following defines its computation formula:

$$N_{ji}(Y) = \frac{1}{(2\pi\sigma^2)m/2} \exp\left(\frac{\|Y - W_{ji}\|}{2\sigma^2}\right) \tag{6}$$

Where σ is smoothening parameter, and its value represents the bell-shaped curve's breadth, whose center serves as the sampling point.

Step 3: Summation layer determines the weighted sum R of output vector N :

$$R_j(Y) = \sum_{j=1}^{M} w_{ji} N_{ji}(Y),\ j \in \{1,2,\ldots,m\} \tag{7}$$

Where w_{ji} denotes mixed weights and it subjects to $\sum_{j=1}^{M} w_{ji} = 1,\ j \in \{1,2\ldots,m\}$

Here $w_{ji} \in [0,1]$

(8)

Where m denotes total pattern quantity, M_j denotes neuron number of the j^{th} pattern layer.

Step 4: Output layer obtains the output of network on the basis of R

$$O(Y) = \arg\max_{1 \le j \le m}(R_j) \tag{9}$$

The output of neuron which owns the largest probability density function is 1; the output of other neuron is O.

4.6. Weight optimization using BCSA

The main difficulty affecting efficiency of the scheme is the weight optimization difficulty in the classification method. As a result, BCSA is thought to be more effective than CSA at handling the weight optimal solution.

The crow is regarded as one of the cleverest birds. Crow birds' cunning method of food-finding serves as an inspiration for CSA. Crows are well known for stealing the food from other birds and concealing where they keep their own food supplies. They attempt to lead other crows astray in order to prevent them from stealing their concealed food. If the crow flock size and dimension is considered to be CFS and MD respectively, the variables of the crow flock is represented as CF and their memorized hidden positions (HP) can be given as follows:

$$CF = \begin{bmatrix} c_1^1 & c_2^1 & \dots & c_{MD}^1 \\ c_1^2 & c_2^2 & \dots & c_{MD}^2 \\ \dots & \dots & \dots & \dots \\ c_1^{CFS} & c_2^{CFS} & \dots & c_{MD}^{CFS} \end{bmatrix}; \quad HP = \begin{bmatrix} h_1^1 & h_2^1 & \dots & h_{MD}^1 \\ h_1^2 & h_2^2 & \dots & h_{MD}^2 \\ \dots & \dots & \dots & \dots \\ h_1^{CFS} & h_2^{CFS} & \dots & h_{MD}^{CFS} \end{bmatrix} \tag{10}$$

Each crow can be represented as crow $= \lfloor c_1, c_2, \dots c_j \dots c_{MD} \rfloor$ and it is obvious that the dimension of CF and HP must be equal to $MD \times CFS$. Initialization makes the assumption that the crows have never before been hidden, consequently, their current locations are taken into account as their invisible locations.
The consciousness level of a crow ultimately determines the likelihood that another crow would steal its food throughout an iteration. Analytically, if one is aware that is following it, it will drive to another route, but if it doesn't, it will steal the food and have to move to a new, random area. The following equation can be used to illustrate the aforementioned phenomenon:

$$crow_j^{(l+1)} = \begin{cases} crow_j^l + \{S_j \bullet E_{Bj} \bullet (hm_i^l - crow_j^l)\}; if\ S_i \geq A_{p_i^l} \\ a\ random\ position \end{cases} \tag{11}$$

Where h_j^l represents the hidden location; S_j and S_i are two uniformly generated random numbers, E_B and A_p are defined as the flying distance and awareness probability, respectively. They both have great influence in finding the global optima. Higher values of E_B and A_p can lead to exploration while exploitation can be obtained by setting a smaller value. It is to be noted from the above equation that the j^{th} crow is forced to find a new hidden location when A_p of i^{th} crow becomes less than S_j of i^{th} crow.
After the crow flock is updated the memorized hidden position of the j^{th} crow is also updated using the following equation

$$hm_j^{(l+1)} \begin{cases} = crow_j^{(l+1)}; if\ (hm_j^{(l+1)}) is\ better\ than\ f(crow_j^l) \\ = hm_j^{(l)} \end{cases} \tag{12}$$

The best fitness function is evaluated from HP . The process is continued till termination condition satisfies.
In BCSA, the decision variables are defined in the binary trajectories and to implement it, the following modifications over CSA are needed.
The decision variables consider only binary value either 1 or 0.
A sigmoid transformation $'sig\,t'$ is introduced to transform the position of the crows into binary form. The formulation of $'sig\,t'$ is given in the below equation:

$$sig\,t(c_j^{l+1}) = \frac{1}{1 + \exp(-c_j^l)} \tag{13}$$

The position of c_j^{l+1} is then updated into binary form using the below formula:

$$c_j^{l+1} = \begin{cases} 1, \, if \; S_{sig\,t} < sig\,t\left(c_j^{l+1}\right) \\ 0, \, otherwise \end{cases} \tag{14}$$

Where $S_{sig\,t}$ is a random number generated between [0, 1].

The two important tuning parameters in standard CSA such as E_B and A_p were taken as constant and remained unchanged throughout the iterations. Both E_B and A_p are taken into consideration in the present work to get rid of local optima and to search for the new and unexplored outcomes in the search space. The parameter values of each individual crow are changed within a certain limit at each iteration. The maximum and minimum allowable limit of $E_B\left\lfloor E_B^{\min}, E_B^{\max}\right\rfloor$ and $A_P\left\lfloor A_P^{\min}, A_P^{\max}\right\rfloor$ are empirically determined which are formulated by the following equation:

$$A_{p_j} = \frac{f\left(crow_j^l\right) \bullet S_{ap}}{f\left(crow_{avg}^l\right)} \tag{15}$$

$$E_{B_j}{}^l = E_B{}^{\max} - \frac{f\left(crow_{best}^l\right)}{f\left(crow_j^l\right)} \tag{16}$$

Where $f\left(crow_j^l\right)$ is the fitness function of the j^{th} crow S_{ap} is any random number selected between $A_p{}^{\min}$ and $A_p{}^{\max}$, $f\left(crow\right)_{avg}^l = \frac{f\left(crow_{best}^l\right) + f\left(crow_{worst}^l\right)}{2}$; $f\left(crow_{best}^l\right)$ and $f\left(crow_{worst}^l\right)$ are the best and worst fitness values at l^{th} iteration. These parameters were greatly dependent on the fitness values. However, A_p depends on both fitness value of both best and worst crow while E_B only depends on the futness value of the best crow at l^{th} iteration.

4.7. Segmentation-Adaptively Regularized multi Kernel-Based Fuzzy*C*-Means (ARMKFCM)

The affected portion of the egg leaf plant is segmented using Adaptively Regularized multi Kernel-Based Fuzzy$C$-Means (ARMKFCM). First, we calculate the adaptive regularization parameter θ_j associated with every pixel. The objective function is defined as,

$$F_{ARKFCM} = 2\left[\sum_{i=1}^{D}\sum_{j=1}^{c} z_{ij}^q\left(1 - N\left(a_i, w_j\right)\right) + \sum_{i=1}^{D}\sum_{j=1}^{c}\theta_i z_{ij}^q\left(1 - N\left(\bar{a}_i, w_j\right)\right)\right] \tag{17}$$

The minimization of J_{ARKFCM} (u, V) can be calculated through an alternate optimization procedure using

$$z_{ij} = \frac{\left(\left(1 - N\left(a_i, w_j\right)\right) + \theta_i\left(1 - N\left(\bar{a}_i, w_j\right)\right)\right)^{-1/(q-1)}}{\sum_{n=1}^{c}\left(1 - N\left(a_i, w_n\right) + \theta\left(1 - N\left(\bar{a}_i, w_n\right)\right)\right)^{-1/(q-1)}} \tag{18}$$

$$w_j = \frac{\sum_{i=1}^{D} z_{ij}^q\left(N\left(a_i, w_j\right)a_i + \theta_i N\left(\bar{a}_i, w_j\right)\bar{a}_i\right)}{\sum_{i=1}^{D} z_{ij}^q\left(N\left(a_i, w_j\right) + \theta_i N\left(\bar{a}_i, w_j\right)\right)} \tag{19}$$

The algorithm is referred to as ARKFCM when it is changed to the strength of the average/median filter of the original image. This segmentation method processes the RGB color space's R band through the input image. Four groups with intensity values of 0 and 1 make up the segmented output. Other portions of the image have a value of 0, while the segmented portion has a value of 1. The input image's color space intensity was then used to replace the four categories.

5. Result and Discussion

The outcome and analysis of the classification and extraction of eggplant leave using Adaptively Regularized Multi Kernel-Based Fuzzy C-Means and an Optimal PNN classifier are shown in this part. We utilized the

MATLAB version to execute the achieved success (7.12). This proposed methodology is used on a Windows computer with a 1.6 GHz Intel Core i5 processor and 4 GB of RAM. On freely accessible online data sets of eggplant leaves, the proposed approach has been evaluated.

5.1. Evaluation *metrics*

Sensitivity, Specificity, Accuracy, PPV, NPV, FPR, FNR, and FDR are examples of evaluation methods that are used to evaluate the system efficiency.

Sensitivity
The ratio of a number of true positives to the sum of true positive and false negative is called as sensitivity.

$$Sensitivity = \frac{No.of\ (TP)}{No.of\ (TP)\ + No.of\ (FN)} \times 100 \tag{20}$$

Specificity
Specificity is the ratio of a number of true negative to the sum of true negative and false positive.

$$Specificity = \frac{No.of\ (TN)}{No.of\ (TN)\ +\ No.of\ (FP)} \times 100 \tag{22}$$

Accuracy
Accuracy is calculated by the measures of sensitivity and specificity. It is denoted as follows,

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{23}$$

Positive Predictive Value (PPV)
The fraction of positive experiment consequences which are considered as the Positive Predictive Value:

$$PPV = \frac{TP}{TP + FP} \tag{24}$$

Negative Predictive Value (NPV)
The fraction of negative experiment consequences which are considered as the Negative Predictive Value:

$$NPV = \frac{TN}{TN + FN} \tag{25}$$

False Positive Rate (FPR)
FPR is calculated as the number of incorrect positive predictions divided by the total number of negatives. It can also be calculated as 1 – specificity.

$$FPR = \frac{FP}{FP + TN} \tag{26}$$

False Negative Rate (FNR)
FNR is calculated as the number of incorrect negative predictions divided by the total number of negatives.

$$FNR = \frac{FN}{FN + TP} \tag{27}$$

5.2. Experimental setup

The fundamental concept behind our suggested approach is the use of various stages to identify disease in eggplant leaves. Different assessment indicators are used to assess the performance. Here, we've divided the performance metric into two categories: normal leaf type and aberrant leaf type. Segmenting the impacted area in the aberrant leaf is the central focus of our research. We also contrasted the OPNN methodology we've presented with other, more established approaches like PNN and FBNN. Eggplant leaf data obtained from the internet were used for the investigation, and their performance metrics were assessed. Below is some sample eggplant leaf database input images that were selected for examination:

Figure 4: Set of sample eggplant leaf images

The example leaf images from above are used as input. To extract the Green band alone, the RGB transformation is first applied to the captured input images. By the use of a median filter, the recovered green transformation of leaf images is sent into the preprocessing stage. The crucial traits were then extracted. A unique OPNN classifier is then used to distinguish between normal and aberrant leaf images. Finally, from the acquired aberrant leaf image, the damaged area is segmented using ARMKFCM.
The proposed and current classifiers, which are shown in the table below, test the input sample images.

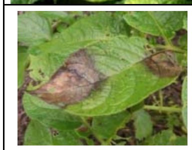
Table 2: Classification result comparison of proposed and existing techniques

Method	Sensitivity	Specificity	Accuracy	PPV	NPV	FPR	FNR	FDR
OPNN	**0.909091**	**1**	**0.947368**	**1**	**0.888889**	**0**	**0.090909**	**0**
PNN	0.727273	0.875	0.789474	0.888889	0.7	0.125	0.272727	0.111111
FBNN	0.545455	0.875	0.684211	0.857143	0.583333	0.125	0.454545	0.142857

The categorization results for suggested OPNN and existing PNN and FBNN approaches are shown in the above table. When compared to other previous methodologies, our suggested methodology produced metrics for sensitivity, specificity, compared accuracy, PPV, and NPV with the greatest values, such as 0.909091, 1, 0.947368, 1, and 0.888889. Furthermore, compared to other approaches, FPR, FNR, and FDR measurements yield the smallest effective value for the suggested work.

Table 3: Segmentation result for proposed ARMKFCM and existing k-means algorithm

Input Image	***Segmented Image***	***Sensitivity***		***Specificity***		***Accuracy***	
		ARMKFCM	***k-means***	***ARMKFCM***	***k-means***	***ARMKFCM***	***k-means***
		0.944	0.652	0.994	0.978	0.992	0.961
		0.932	0.560	0.996	0.984	0.995	0.971

		0.891	0.277	0.992	0.939	0.990	0.892
		0.896	0.256	0.994	0.945	0.992	0.901
		0.881	0.459	0.994	0.978	0.992	0.962
		0.928	0.209	0.994	0.898	0.992	0.822
		0.875	0.538	0.994	0.984	0.992	0.973
		0.983	0.539	0.996	0.932	0.995	0.883

The segmentation results utilizing the conventional k-means technique and our suggested ARMKFCM are compared in Table 3. To acquire the afflicted area of the aberrant leaf images, this segmented step is carried out. Here, the segmented eggplant leaf image that corresponds to the abnormally categorized input is provided. To assess the effectiveness of the network of both the proposed and the existing method, its sensitivity, specificity, and accuracy numbers are also calculated. For instance, the sensitivity for leaf image 1 is 0.944 for ARMKFCM and 0.652 for k-means, respectively. It demonstrates that the suggested strategy outperforms the current approach in every way. Similar to that, specificity and accuracy are also assessed to assess how well suggested and existing procedures operate.

Table 4: Segmentation result for ARMKFCM and k-means using different metrics

PPV		***NPV***		***FPR***		***FNR***	
ARMKFCM	***k-means***	***ARMKFCM***	***k-means***	***ARMKFCM***	***k-means***	***ARMKFCM***	***k-means***
0.848	0.605	0.998	0.982	0.006	0.022	0.056	0.348
0.821	0.518	0.999	0.986	0.004	0.016	0.068	0.440
0.731	0.259	0.997	0.944	0.008	0.061	0.109	0.723
0.742	0.241	0.998	0.949	0.006	0.055	0.104	0.744
0.712	0.409	0.998	0.982	0.006	0.022	0.119	0.541
0.811	0.203	0.998	0.901	0.006	0.102	0.072	0.791

0.700	0.466	0.998	0.988	0.006	0.016	0.125	0.462
0.950	0.529	0.999	0.934	0.004	0.068	0.017	0.461

Table 4 describes the segmentation outcomes of PPV, NPV, FPR and FNR for both proposed and existing techniques. While PPV and NPV achieves maximum esteem and other two metrics like FPR and FNR acquires minimum false rate. Thus we clearly understand our proposed approach ARMKFCM is superior to previous k-means algorithm.

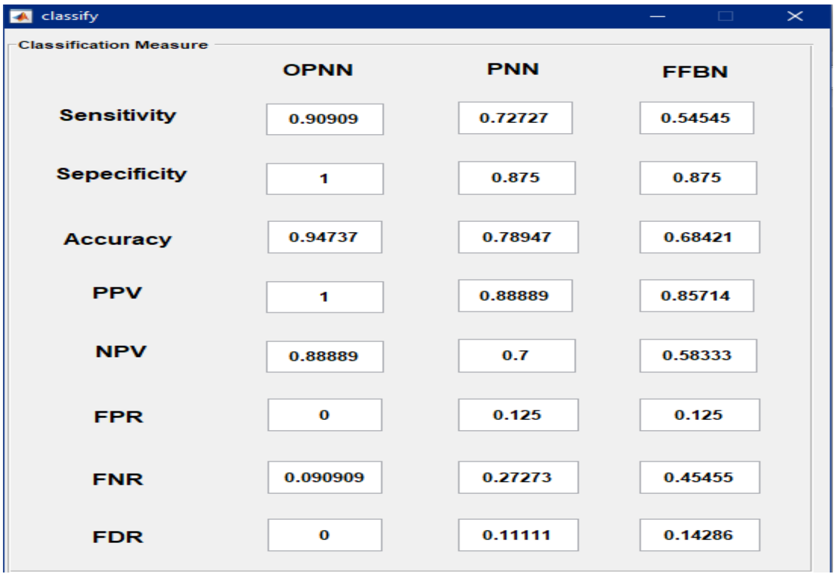


Figure 5: GUI representation for classification measure

Figure 5 shows the classification measure in GUI representation for different metrics using the proposed OPNN and existing techniques. The sensitivity of OPNN is 0.90909, PNN is 0.72727 and FBNN is 0.54545. Likewise; sensitivity, accuracy, PPV, NPV, FPR, FNR and FDR values are also evaluated while running the input dataset images. Next the overall sample output in GUI is represented below:

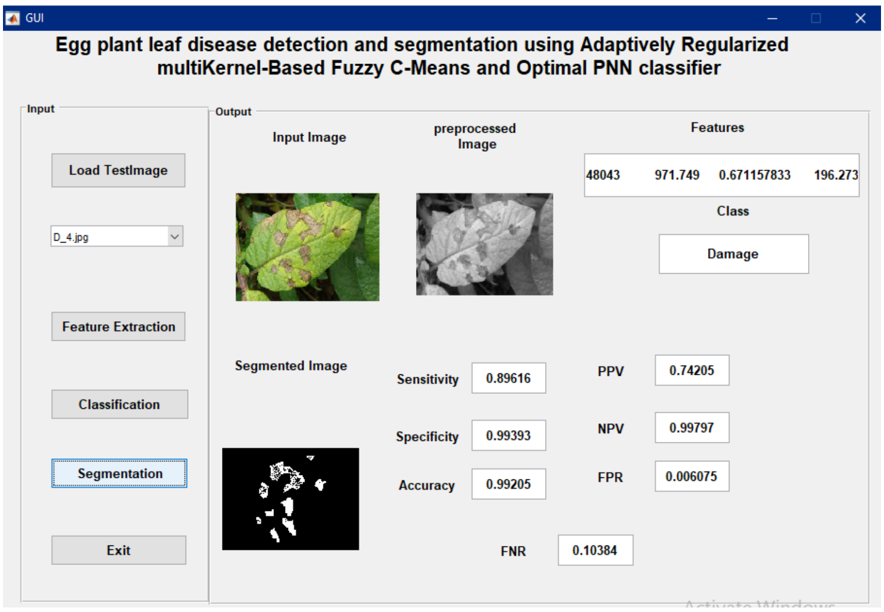


Figure 6: sample GUI representation for leaf disease detection

Fig.6 displays an example output for the input image acquired using a Graphical User Interface (GUI). The classification and segmentation results are displayed when the input test image has been processed. By changing

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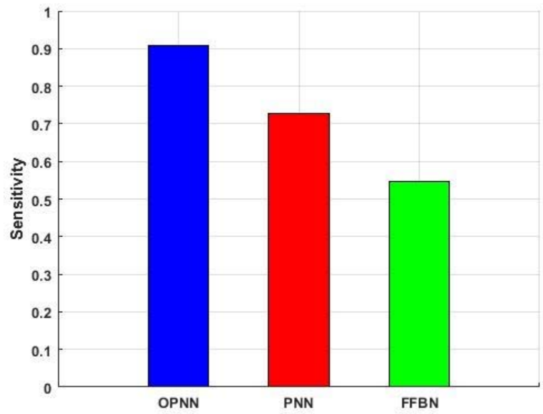
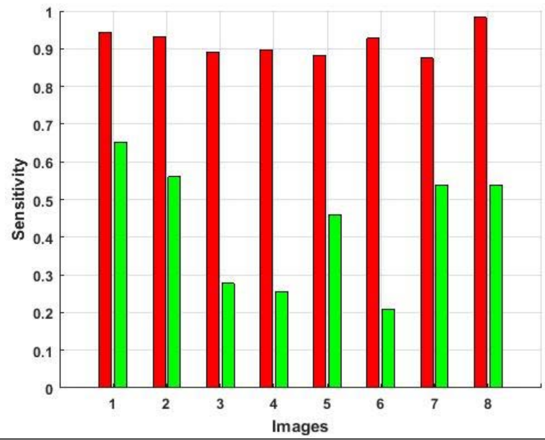
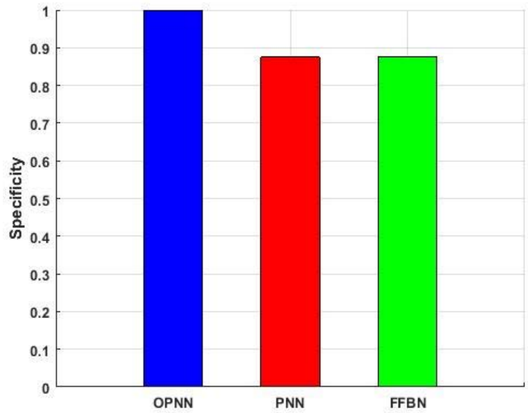
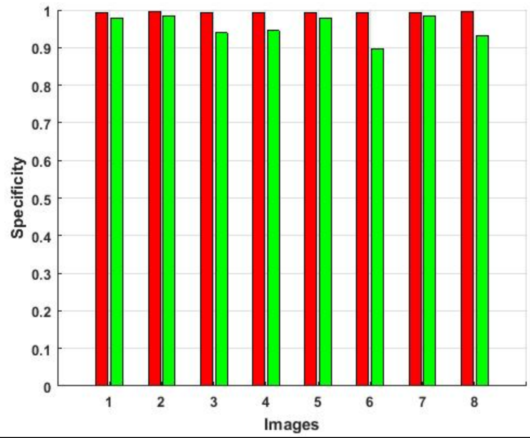
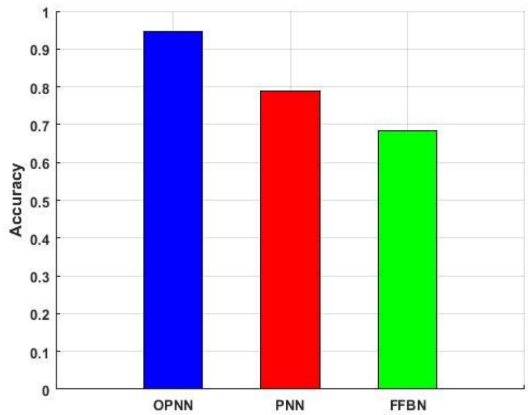
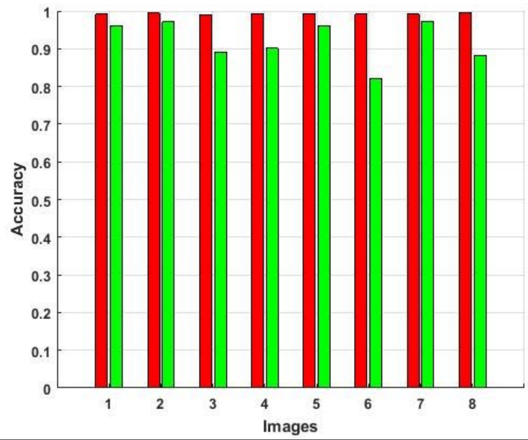
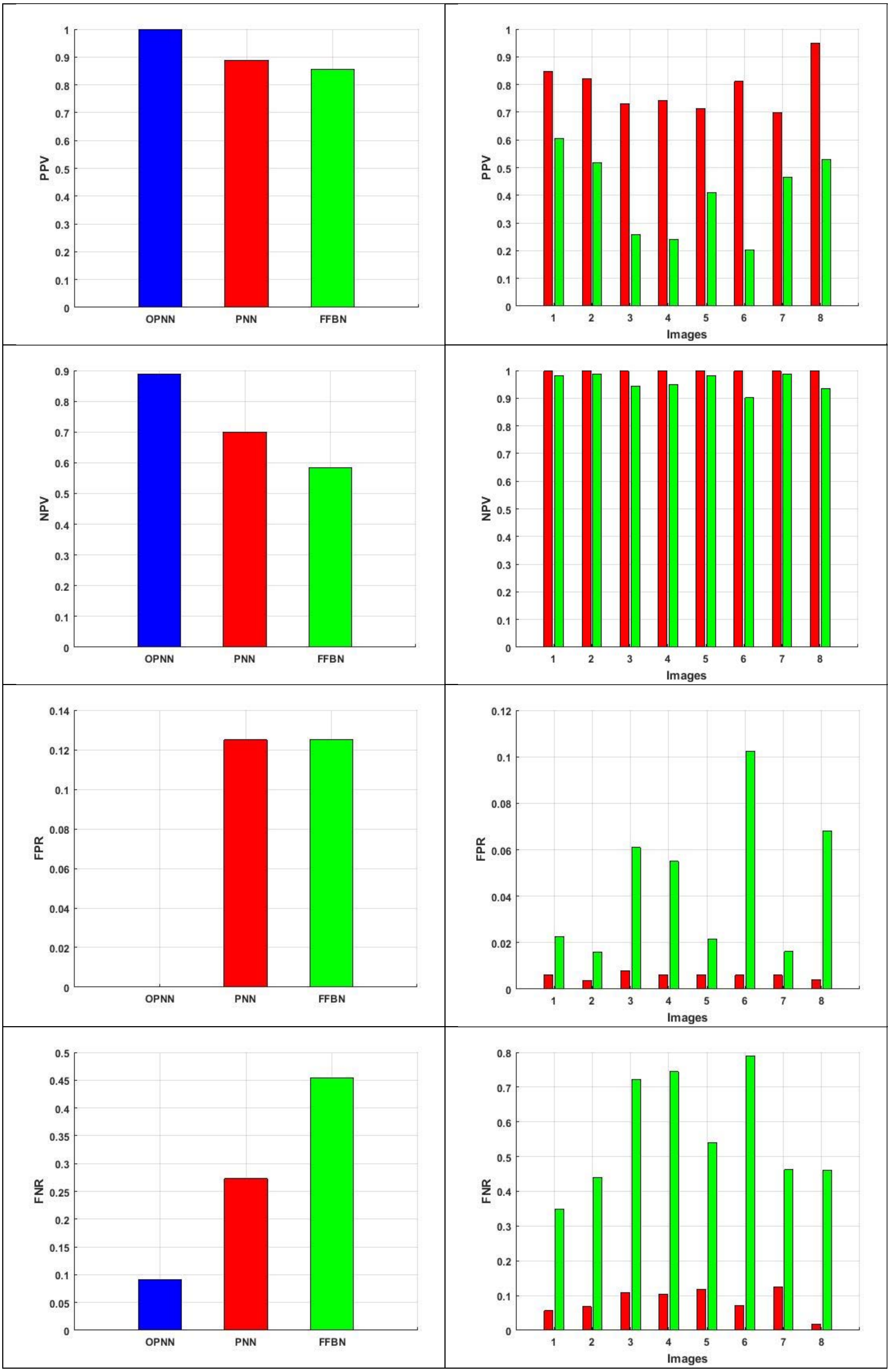
the input image of the eggplant leaf, their associated outputs are evaluated in this GUI-based technique The attained outputs are Sensitivity, Specificity, Accuracy, PPV, NPV, FPR and FNR for existing PNN, FBNN and the proposed OPNN technique under different testing database images. We have used the efficient classier and segmentation technique to overcome the drawback of existing systems. Hence the proposed methodology helps to improve the system performance in efficient manner.

Table 5: Comparison graph obtained by proposed and existing method for classification and segmentation

Classification outcome	**Segmentation outcome**
	
	
	


PPV
OPNN
PNN
FFBN
PPV
1
2
3
4
5
6
7
8
Images
NPV
OPNN
PNN
FFBN
NPV
Images
FPR
OPNN
PNN
FFBN
FPR
Images
FNR
OPNN
PNN
FFBN
FNR
Images

The comparative graphs of suggested and existing classification and prediction techniques is shown in Table 5. Three colour combinations—blue (proposed OPNN), red (PNN), and green (PNR) are used in the bar chart to show sensitivity, specificity, accuracy, PPV, NPV, FPR, and FNR (FFBN). Except for FPR and FNR, all metrics obtained are within the maximum distance. Due to the hybrid segmentation method rather than the current complexity of the k-means algorithm, the total proposed system achieves a minimum error rate. Also, it is clear that the proposed methodology OPNN obtains the efficient value compared with the existing methods PNN and FBNN.

6. Conclusion

The main aim of this work is to identify the affected portion of leaf image. For that, the input eggplant leaf image is transformed by using RGB transformation to capture green band channel. Preprocessing is then carried out using a median filter, after which the specific attributes are obtained using the shape, color histogram, and vein properties. PNN is used to categorize normal and abnormal leaf images using the retrieved features as input during the classification stage. PNN uses BCSA to select the best network weight. The impacted disease area is then segmented using the ARMKFCM approach for the aberrant leaf image. The MATLAB working platform is used to implement the entire project. To distinguish between the proposed and existing methodologies, various evaluation indicators are studied. Overall examination shows that our suggested method produces more effective results than other works already in use.

Future Scope

Three classifiers will be chosen in the future, evaluated using our dataset, and the outcomes will be documented. We will only utilize the most accurate classifier. To assess the effectiveness of the classifiers, we might need to take into account images with lots of leaves, though.

Conflicts of interest: There is no conflict of interest

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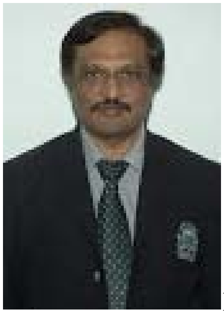Dr. Dandinashivara Revanna Shashikumar received BE degree from Mysore University and ME degree from Bangalore University, Bangalore and Ph.D in Information and Communication Technology of Fakir Mohan University, Balasore, Orissa. He is currently working as Professor and HoD, Dept. of Computer Science, Cambridge Institute of Technology, Visvesvaraya Technological University (VTU). His research interests include Microprocessors, Pattern Recognition, and Biometrics, Computer Networks, Data mining and Data Warehouse He has published 20 research publications in referred National and International Journals. He is the reviewer for some of the International journals.

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