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RESEARCH ARTICLE

An Artificial Intelligence Framework for Plant Leaf Disease Detection and Classification Using AMBF with GKFCM and GLCM

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ABSTRACT

As of 2020, the total area planted with crops in India overtook 125.78 million hectares. India is the second biggest organic product maker in the world. Thus, an Indian economy greatly depends on farming products. Nowadays, farmers suffer a drop in production due to a lot of diseases and pests. Thus, to overcome this problem, this article presents the artificial intelligence based deep learning approach for plant disease classification. Initially, the adaptive mean bilateral filter (AMBF) for noise removal and enhancement operations. Then, Gaussian kernel fuzzy C-means (GKFCM) approach is used to segment the effected disease regions. The optimal features from color, texture and shape features are extracted by using GLCM. Finally, Deep learning convolutional neural network (DLCNN) is used for the classification of five class diseases. The segmentation and classification performance of proposed method outperforms as compared with the state of art approaches.

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Introduction

According to the records of the previous year 2019 and 2020, there are approximately 145 million acres of land in India is affected by the various types of plant disease. In a country like India which has increased demand for food due to the increasing population in the country. The most disadvantaged situation is that farmers who have access to irrigation are better placed but those who are in rain-fed and drone-prone areas are most vulnerable. A single crop failure due to flood, lack of soil fertility, drought, climatic changes, lack of underground water and crop disease factors destroy the crop, and this affects the farmers. Agriculture is one of the most important sectors in the global economy. It provides food for humans and animals along with fabrics, materials for construction and paper products. Even though the farmers can identify the disease through normal eyes, but they can't recognize it in an overdue period which is a time-consuming problem.

To avoid this condition and for a speedy recovery, the images of both healthy and infected parts of a plant are taken out. This identifies the infected regions using textural features of HSI and the set of truncated feature models was created. This was used to determine the textural features in each image by using the generalized techniques [1].

The utilization of crops can be classified into four different types such as cash, food, plantation, and horticulture. Plants get affected by two major diseases such as biotic and abiotic. Fungi, bacteria, and viruses in plants are caused by biotic disease [2], whereas abiotic can cause plants in terms of weather conditions, chemicals, etc... Leaves of different plants bear different diseases that have to be identified with the support of color, texture, and shape. Based on color intensity, the histogram technique was used on paddy leaves to identify the infected regions [3]. The disease detection mechanism involves several phases such as Dataset Preparation, Preprocessing, Feature Extraction, Segmentation, and classification. It consists of two major parts such as training and testing. The Training part begins

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with the collection of images from the stem, root, leaves, etc. These images are pre-processed by evacuating blur effect, noise effect and even correcting the RGB/grey level. In the phase of segmentation, it removes the background image from the ROI and also detects the affected part during training. Feature Extraction phase is used to extract the features and produce feature vectors. These feature vectors are utilized to train the classifier. In the training part, the test image goes through all phases and recognizes either infected or healthy from the trained classifier. The effectiveness and compatibility of the model are evaluated using performance metrics. It is also called a recognition rate and success rate [4]. These rates depend upon the comparison of a model, type of classifier, techniques used and accuracy of recognition from one over another. Thus, to achieve this performance this article is contributed as follows:

- Testing and training of the network is performed using DLCNN model with five different disease classes including normal and abnormal.
- AMBF method is used to perform the noise removal and contrast enhancement, followed by GKFCM segmentation for detection of diseases. Then, texture features are extracted using GLCM.
- Finally, DLCNN method is used to classify the diseases and compared with the conventional approaches.

Rest of the paper is organized as follows; section 2 deals with the detailed analysis of related work along with their problems. Section 3 deals with the implementation details of the proposed method. Section 4 deals with the simulation analysis and comparison with existing approaches. Finally, section 5 deals with the conclusion with possible future enhancements.

Literature Survey

The image dataset of grapefruit leaves was collected from central Florida in late spring of 2002, which has four varieties of diseases such as greasy spot, melanose, scab, and normal citrus leaf. Each variety consists of 40 leaves samples in [5]. Each of the leaf sample's edges was detected by Canny's edge detector. The discrimination of affected and healthy leaves has been done using color co-occurrence techniques to identify whether the textural based (HSI) color features related to statistical classification algorithms. In [6] authors considered the 15 plants of healthy and 15 plants of non-healthy were taken as a sample for sugar beet, which consists of various diseases like leaf spot, leaf rust, and mildew. Random forest is used as a classifier which produces low classification error. About 1434 samples of both sunflower leaves and weeds were collected. It was used to train the model in the splitting of 90 % training and 10% testing. To sort out the leaves, the author's proposed Posterior Probability Model Selection algorithm can be utilized in conjunction with the architecture of the Generalized Softmax Perceptron neural network and resulted in low classification accuracy.

Around 500 plant leaf samples of 30 diverse plant species from Tamil Nadu have been gained for the methodology of classifying plant diseases in [7], which has considered the common diseases like Late scorch, Bacterial spot, Fungal spot, Chocolate spot, Bacterial disease, Fungal disease, Sunburn, Sooty mold, Early blight, Late blight, Scorch, Ashen mold, Leaf lesion. The leaf samples were converted into HIS. Using co-occurrence matrix, features were derived, and these values have undergone the classification with minimum distance criterion. Further, the accuracy was improved by support vector machine (SVM) approach. The 200 images of infected tomato leaves were considered in [8], SVM with various kernel functions were utilized for classification to recognize the two tomato viruses in leaf. The 300 images of cucumber leaves tainted with the sicknesses of downy mildew, blight, and anthracnose were collected for crop disease recognition. From each of the infected leaves, statistical and meteorological features were extracted. The feature vector was created from these features and contributes to the multi kernel SVM to perform the classification.

In [9] authors considered the 90 images of apple leaves affected by powdery mildew, mosaic and rust were transformed from RGB to HSI, YUV and grey models using color transformation structure with thresholding-based segmentation is used. Based on the specific threshold value, the background image was evacuated, and the diseased spot can be segmented using region growing algorithms. Based on color, texture, and shape, 38 classifying features were extracted. The combination of radial basis function network (RBFN) classification and correlation-based feature selection can be utilized to choose the most significant features to improve the model efficiency. The dataset of 106 leaf samples from banana, beans, rose and lemon was taken in [10]. During training 15 samples from each species were used. After mapping the R, G, B segments of the input sample to the threshold images, the co-occurrence features were measured. Then, the infected clusters were formed by "k-means clustering". The segmented components were processed using a Genetic Algorithm and classification has been performed to produce the output image with the amount of disease infected.

In [11] authors considered the 420 samples in cucumber affected by Downy mildew, Bacterial angular, Corynesporacassiicola, Scab, Gray mold, Anthracnose, and Powdery mildew. The infected leaf samples were segmented using Fuzzy C Means (FCM) clustering. In training, the combined features of color and shape have been taken to form a dictionary and then form Sparse Representation of the Probabilistic Neutral Network (PNN) by the sparse model to attain the moderate accuracy. In [12] authors considered the vine leaves which have diseases like downy mildew, powdery mildew, and black rot were acquired. The OTSU thresholding algorithm technique can be used in segmentation to separate the foreground and background images. The pixels were labeled, and the histogram was derived using the Local Binary Pattern algorithm. Therefore, classification was performed using one-class classification and One Class Artificial Neutral Network (ANN). The conflicts were raised in one class ANN and it was resolved by the nearest support vector strategy technique to perform labeling according to proximity. In [13] authors considered an open database of 87,848 images was taken to train a model. Among all, CNN performs better with VGG architecture. The 8900-leaf curl of papaya and 570 images of papaya mosaic were collected in [14]. It was resized as 224*224 RGB using an image processing technique. Both classification and feature extraction can be performed on CNN itself. At the outcome of CNN [15], the discrimination on healthy and diseased samples can be made with considerable classification accuracy.

Proposed Method

Figure 1 presents the proposed method of plant disease detection and classification process. Initially query image applied to preprocessing stage. Here, the noises presented in test image are removed by using AMBF and image enhancement is performed by using CLAHE. Then GKFCM segmentation applied on leaves for plant disease detection and effective ROI extraction. Then, color, texture and boundary-based features are extracted by using GLCM, then different types of features are fused together to form feature matrix. Finally, DLCNN based Artificial intelligence mechanism is used for classification of multiple types of plant diseases.

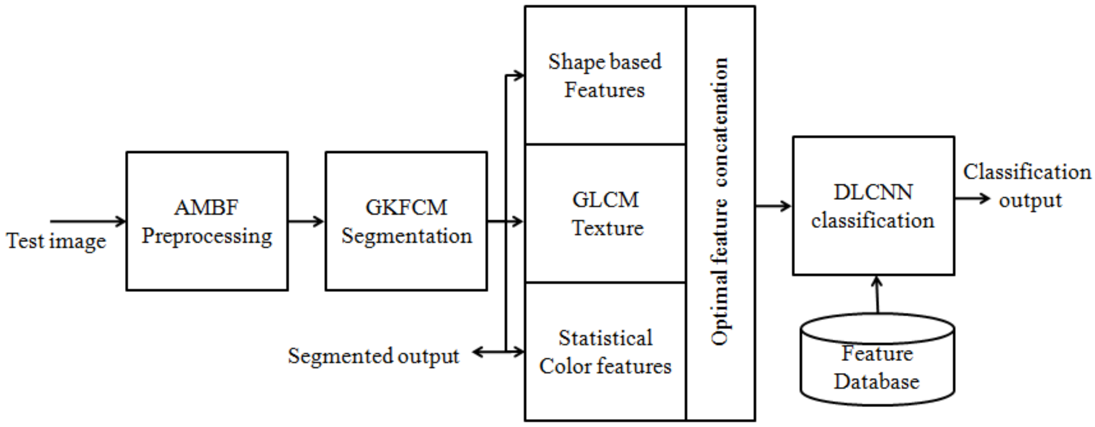

Figure 1. Proposed framework for disease detection and classification in plant leaf.

Preprocessing

Proposed framework executes preprocessing to enrich the quality of the image and classification rate of plant disease. The proposed preprocessing comprises two different processes that are noise removal and contrast enhancement. Noise removal is a significant process in disease classification to improve the classification accuracy. The proposed AMBF algorithm removes noise and sharpens the image effectually. In addition, it also maintains the fine details of the image. The proposed AMBF algorithm removes the universal noises from the given image that are salt & pepper, impulse, and Gaussian. In the AMBF algorithm noisy pixel is identified using the sorted quadrant median vector (SQMV) algorithm. The SQMV approach consisting of the three sequential blocks, they are edge detector, noise detector and switching bilinear filter (SBF). The edge detector is exploited to predict the edges of the current window accurately since it plays a vital role in disease classification. SBF approach utilizes a ranging filter that shifts the modes between impulse and Gaussian which is performed based on the noise detector result.

In most of the existing noise filtering algorithms employ constant window size such as 3*3 creates difficulties in differentiating the noisy and noise-free pixel that results in blurriness in the output image. To overwhelm above drawback, the proposed AMBF algorithm adaptively alters the window size based on the presence of noisy pixels in the input image. The way of changing the window size of the image avoids blurriness and easier the process of noisy pixel detection.

The noise detector is executed to select whether the current pixel processed into SBF Gaussian filter or SBF impulse filter. Assume that $S1$ and $S2$ are binary control signals where $S1$ is created by AMBF and $S2$ is created by noise detector. The image is filtered based on the below condition:

$$f(x) = \begin{cases} ND(in), & S1 < in \\ AMF(in), & S2 \geq in \end{cases} \quad (1)$$

By utilizing the above condition, the given image is processed into the respective filters and results in the enhanced noise free outcome.

Segmentation

The output of preprocessing block will be applied as input to the GKFCM segmentation. This algorithm efficiently overcomes the geometric allied problem in FCM algorithm; FCM is sensitive to noise due to the absence of efficient spatial information. In the proposed GKFCM algorithm, spatial information is incorporated in the form of kernel function which does not produce considerable effect on noise. Generally, the neighborhood pixels are highly correlated in spatial domain. Therefore, if the segmentation algorithm fails to incorporate the relationship between the neighborhood pixels, the performance of the algorithm would be minimized due to the effect of noise. To circumvent this shortcoming, in the proposed algorithm local neighborhood information is integrated in the similarity measure of objective function.

The objective function of the proposed algorithm is defined as

$$J_{GKFCM} = \sum_{i=1}^{C} \left(\sum_{k=1}^{n} \mathrm{U}_{\mathrm{ik}}^{\mathrm{m}} \left|\left| \varphi_L(x_k) - \varphi_L(v_i) \right|\right|^2 \right) \quad (2)$$

The membership function U_{ik} is updated as

$$U_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{D_{ik}{}^2}{D_{jk}{}^2} \right)^{1/(m-1)}} \quad (3)$$

Where m is the fuzzy coefficient, and D_{ik} is the similarity measure which is given as

$$D_{ik} = ||\varphi_L(x_k) - \varphi_L(v_i)||^2 \quad (4)$$

Generally, c numbers of membership values are to be computed for the pixel under consideration while segmentation an image into c clusters. Segmentation is achieved by assigning the pixel to any cluster i for which it possesses high membership value. From this, one can deduce that the segmentation results rely on the similarity measure which is utilized to calculate the membership value. Therefore, in the proposed algorithm novel spatial neighborhood information is incorporated in its similarity measure to overcome the effect of noise. Incorporating spatial neighborhood information in the similarity measure results in

$$D_{ik} = ||\varphi_L(x_k) - \varphi_L(v_i)||^2 \; g_{ik} \quad (5)$$

In above equation the term g_{ik} indicates the spatial information and is defined as

$$g_{ik} = (1 - \beta H_{ik}) \quad (6)$$

Here, H_{ik}indicates spatial function for region of interest (ROI), and $\beta\epsilon[0,1]$ is neighborhood attraction parameter that controls the significance of neighboring pixels on center pixel x_k. The value of β between 0 and 1 indicates the influence of neighboring pixels on center pixel. If β value is 0, then the similarity measure tends to be that of GKFCM algorithm without the above-specified spatial information.

The noise resistance capability of GKFCM algorithm relies on the spatial function for any noisy center pixel x_k having large gray level difference with its neighboring pixel x_a, the spatial information H_{ik} computed will be large, and thus the spatial function in above Equation becomes small for all values β of other than zero. After the first iteration, the noisy pixel x_k will be attracted to the cluster i to which its closest neighbor x_a belongs. If the value of H_{ik} remains to be high till the last iteration, despite being its dissimilarity, the center pixel x_k will be forced to cluster it is clear that after each iteration, the similarity measure of noisy pixels as well as other pixels in a window tend to a similar value, ignoring the noisy pixels. In this case, the gray level value of noisy pixel is large when compared to other pixels within the window, but the spatial functiong_{ik} incorporated balances their similarity measure. The spatial function thus eliminates the effect of noise in the segmentation process.

Table 1. GKFCM algorithm

Input: Noise removed image (I) **output:** Disease detected image (U)
Step 1: Randomly initialize membership matrix U_{ik} on input image I
Step 2: Compute the spatial neighborhood information using Equation (6)
Step 3: Compute the probability similarity measure using Equation (4)
Step 4: Compute the updated membership value using Equation (3)
Step 5: Update objective function objective function J_{GKFCM}
Step 6: return U if the membership degrees of each pixel of the image to different clusters

Feature Extraction

The feature extraction stage plays especially important role in successful detection and classification of plant diseases. Feature extraction deals with the process of extracting attributes, which produce some quantitative information of interest, to differentiate one class of objects from another. When the input data used for manipulation is complex, then it is converted into the group of characteristics called feature vector. It is process of collecting image information such as color, shape, and texture. Features comprise the appropriate information of an image and it is used in the image processing task (e.g., searching, retrieval, storing). The proposed framework extracts texture, shape and Color features as shown in Table 2.

Table 2. Feature description

Features	Description	Types of Feature
Texture	Texture feature represents the surface characteristics of the image	Contrast, Dissimilarity, Entropy, Homogeneity, Correlation and Angular Second Moment
Shape	Shape features represents the disease region identification of given image	Boundary, Edges and Region based
Statistical Color	Color features represent the individual uniqueness (color) of the given image.	Color, Saturation, Hue

The proposed algorithm extracts texture features by implementing the GLCM descriptor. The reason for selecting GLCM for texture feature extraction is that it provides better performance in extracting features from each image using different layers. The proposed method extracts six texture features from the given image are Contrast, Dissimilarity, Entropy, Homogeneity, Correlation and Angular Second Moment. In GLCM, the relevance of radius and angle are the most crucial input parameters. Several First Order Statistics (FOS) texture features like mean, variance, energy skewness and entropy and Second Order Statistics (SOS) comprises of GLCM, contains features such as contrast, correlation, cluster prominence, cluster shade, dissimilarity, homogeneity, sum average, sum of squares, difference entropy and sum entropy are to be extricated from the segmented nodule. GLCM uses second order image statistics; it has an advantage that it considers the spatial properties. But, it has limitation that it does not consider the primitive shapes. Hence, the performance of GLCM is amazingly effective in the classification of plant diseases compared to the other conventional features.

Texture measures based on FOS (or histogram based) are measured from the image pixel information and not considering the relationship between neighboring pixels.

Intensity levels of the entire image are used in the texture analysis of histogram-based approaches. Several FOS based features includes mean, variance, average energy, skewness, and entropy. Computation of histogram based gray level entails only single pixels. Histogram based method are easy to compute the gray level images. Using histogram-based features, the characteristics of the lung nodule can be found. Spatial distribution of gray level images estimates the property of the image correlated to SOS which consider the correlation between pixels. The SO image histograms are defined by GLCM, which presents higher data concerning to periodicity; spatial dependency and inter pixel bond of gray level image. The GLCM is considered as the well-known, commonly used statistical technique for extracting texture features. It computes not only the single pixel but also the neighborhood properties for extraction of features. Based on joint probability distributions of pixel pair, this method can be employed. GLCM depicts how frequently the pixels are positioned in the geometric location in relation with another pixel.

GLCM of image $P(i,j)$ can be expressed as

$$P(i,j) = count\left((P_{x,y,z}, v)(\ P_{x,y,z}, \alpha)\right) \quad (7)$$
$$= j, \alpha \ \text{€} \ \{1,2,3, \dots \dots \dots \dots \dots 26\}$$

where v is the function which takes one voxel from 26 neighboring voxels according to the index α, $P_{x,y,z}$ is the value of the voxel with xyz coordinates α is the ith entry of the marginal probability matrix is achieved by the summation of the row of $P(i,j)$.

GLCM can be calculated from texture images using different values of θ and d and these probability values create the co-occurrence matrix $P\ (I, j, d|\,, \theta\ )$ as shown in figure 2.

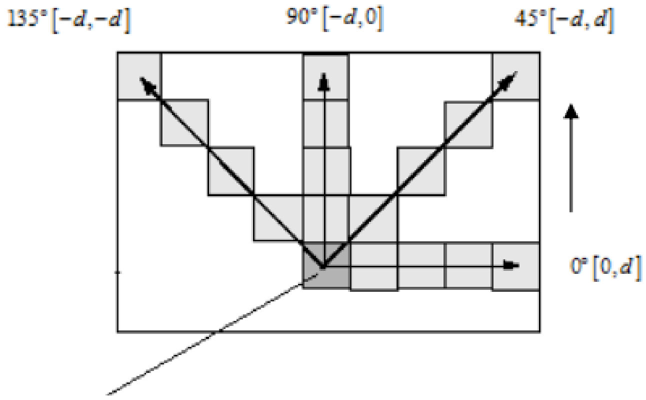

Figure 2. Distances and orientations to compute GLCM.

GLCM are considered for the orientations of 0°, 45°, 90°, and 135°; distance d =1,2,3 and 4 are calculated.

DLCNN Classification

Different layers are involved in the structure of DLCNN such as output layer, fully connected layer, input layer, pooling layer, and convolution layer. Using convolutional layer and sampling layer alternately that is one volume that build-up number of hidden layers connect to a pooling layer, and then a convolution connects after the pooling layer, and so on. The process is similar to the convolution process inputs are connected locally to each output feature of convolutional layer. To get the input value of neuron, local inputs are summed and weighted together with the offset value through the corresponding right value of connection. Figure 3 presents the detailed procedure of proposed DLCNN classification and operation of each layer is as follows:

Convolutional layer: Convolutional layer comprises multiple feature surfaces or Feature Map in which multiple neuron groups contain in each feature surface and each neuron connects through the upper layer of local area feature surface and the convolution kernel. The kernel of convolution is referred to a weight matrix (1*1*12 and 3*3*64 matrix in two dimensions). Based on the operation of convolution, the input with different features extracts by the convolution layer of DLCNN.

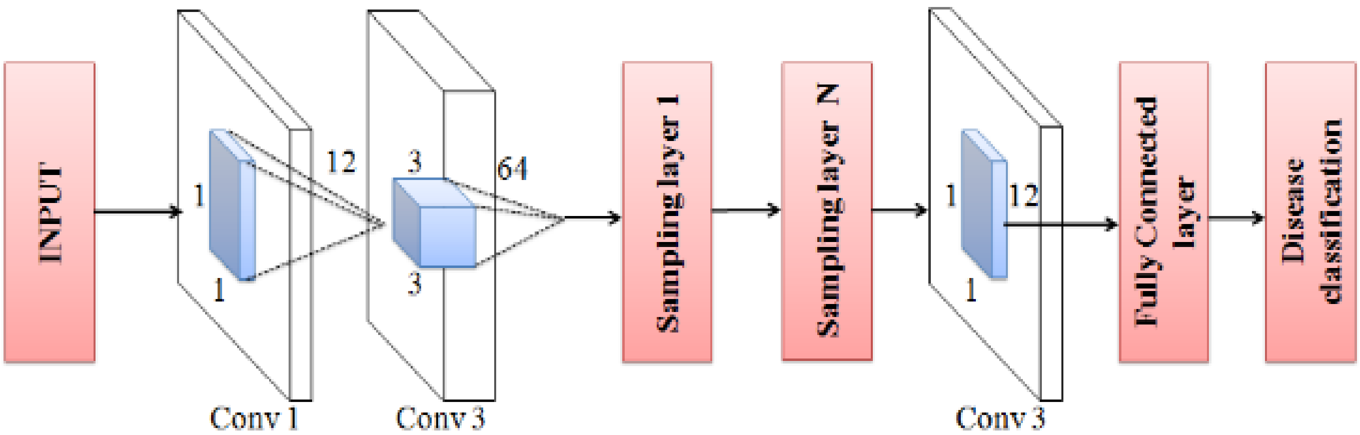

Figure 3. Plant leaf disease classification using DLCNN

The low-level features like corners, lines, and edges retrieve using the first layer of convolution and more advanced features can extract by higher-level volumes layers. A structure of DLCNN is obtained with a smaller convolution kernel. Some of the conclusions are described as follows:

- The accuracy rate can improve by improving the network depth.
- By increasing the number of feature diseases, the accuracy can also improve.
- A higher rate of accuracy is obtained by adding a fully connected layer to the convolutional layer.

Sampling layer: After the convolutional layer, the sampling layer or pooling layer follows immediately that includes multiple feature diseases, each of which has the characteristic surface that corresponds to the upper layer's characteristic surface and will not modify the number of feature diseases. The sampling layer input is the convolutional layer. A feature surface of the sampling layer and convolutional layer are corresponding uniquely each other and the sampling layer neurons are connected to the input layer locally. The role of secondary feature extraction is played by the sampling layer which has neurons each of which processes the pooling operations on the local receptive field. The most widely used pooling methods is the max-pooling which involves the point with the largest value in the receptive field. In the domain of local acceptance, the random pooling and averaging of all values is done.

ReLU activation layer: The structure in the fully connected layer of MLP and DLCNN is similar in general. The algorithm of BP uses the DLCNN training algorithm. The retaining of test data is performed poorly if a training of large feed forward neural network is done on a small data in the collection owing to the high capacity. Although the hidden layer neuron's output value is 0.5, some hidden nodes fail, and the probability reaches to 0 through the technology, the regularization utilizes in the method of fully connected layer i.e. dropout technology to restrict the training of over-fitting. In the procedures of forward propagation and post propagation of DLCNN, these nodes are not participated for each input of sample into the network. The corresponding structure of a network is not similar, but all structures share weights owing to the dropout technology randomness. The complexity of adoption between Meta-learning neurons reduces by this technology as neurons cannot exist on other neurons and it obtains more robust features. The technologies of ReLU + dropout uses by most research of DLCNN and good results have obtained in classification performance.

Fully connected layer: One or more fully connected layers connect in the structure of CNN after sampling layers and multiple convolutional layers. The convolutional layer is integrated with fully connected layer or the sampling of local information in the layer is differentiated based on the disease type. The ReLU function is used by each neuron's activation function for improving the performance of CNN network. The last fully connected layer's output value is passed to an output layer and it is termed as SoftMax layer that can utilize the SoftMax logistic regression (SoftMax regression) for the purpose of classification. Through this layer multi class classification operation can be effectively performed.

Results and Discussion

This section gives the detailed analysis of simulation results with the both subjective and objective evaluation, implemented using MATLAB R2020a. Total 1000 images are considered from the Plant Pathology 2020 - FGVC7 dataset with five types of diseases including both normal and abnormal. They are Alternaria Alternata, Anthracnose disease, Bacterial Blight, Cercospora Leaf Spot and Healthy Leaf, respectively. Here, 800 images are considered training, 100 images are considered for validation and 100 images are considered for testing.

Subjective Evaluation

From figure 4, it is observed that the input image contrast is perfectly enhanced, and all the noises are accurately removed by using the AMBF approach. And it is also observed that the effected region of disease is perfectly segmented by using the GKFCM method. First represents the input images, second row presents the preprocessed outcomes and last row represents the segmented outcomes. The proposed method gives the outstanding performance for all the five classes, respectively.

Objective Evaluation

The performance metrics used to evaluate the proposed methods are accuracy (AC), sensitivity (SC), and specificity (SP). Let TP, TN, FP, and FN be the count of true positive, true negative, false positive, and false negative, respectively. Then the equations are shown in following equations:

Accuracy: It is defined as the number of data points predicted correctly to the total sum of all data points.

$$AC = \frac{TP+TN}{TP+FP+TN+FN} \tag{9}$$

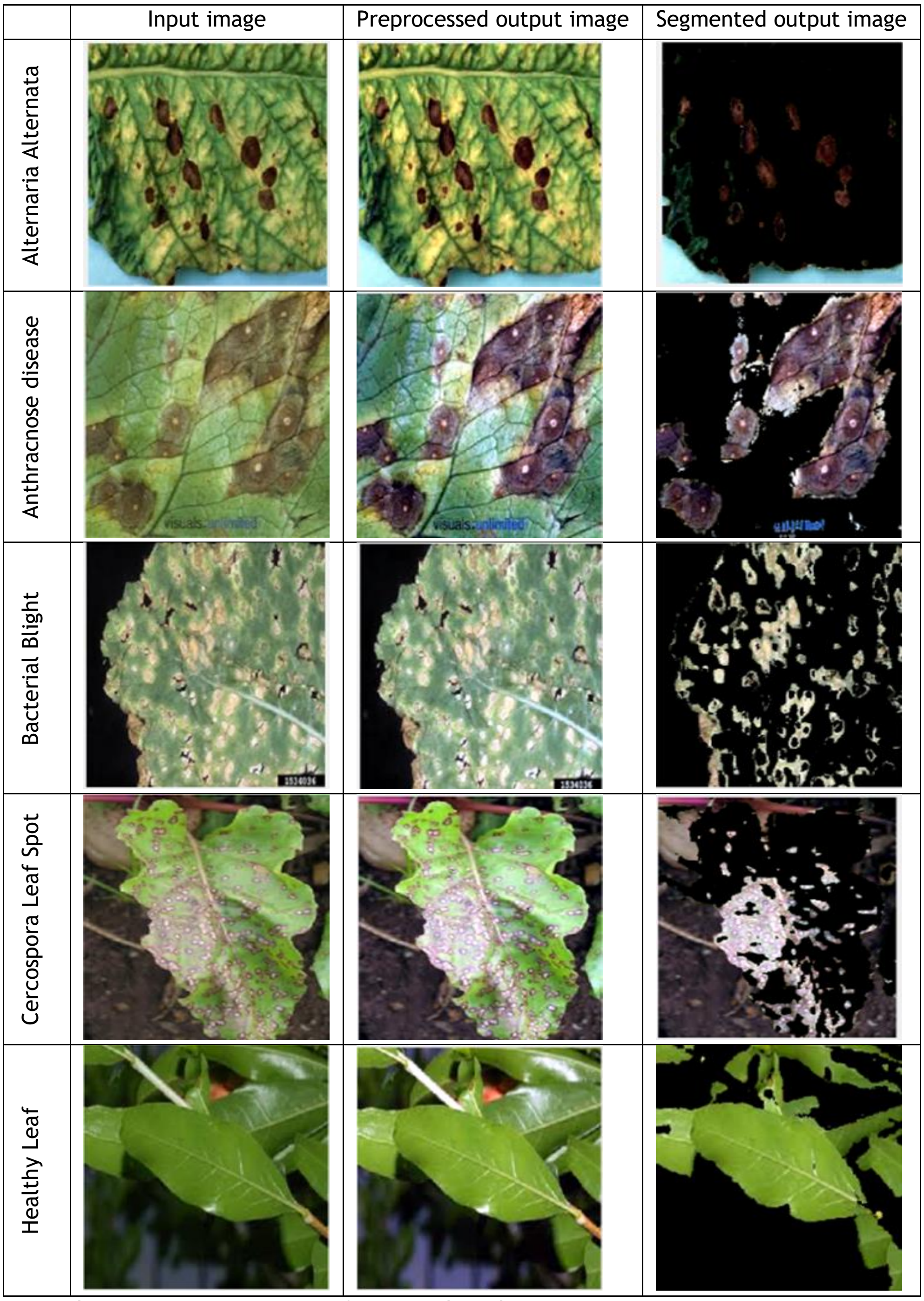

Figure 4. Preprocessing and segmentation outcomes of various plant diseases

Sensitivity: It tells the proportion of plants having disease and leaves detected tested positive.

$$SC = \frac{TP}{TP+FN} \quad (10)$$

Specificity: It tells the proportion of plants having disease and leaves detected tested negative.

$$SP = \frac{TN}{FP+TN} \quad (11)$$

Precision: It tells the proportion of plants having disease and leaves detected tested positive, had disease.

$$PR = \frac{TP}{TP+FP} \quad (12)$$

Table 3. Performance comparison of segmentation approaches.

Model	Sensitivity	Precision	Accuracy
Thresholding [9]	76%	36%	48.52
K-Means [10]	69%	67%	50.0
FCM [11]	76%	79%	81.46
OTSU [12]	77%	74%	70%
Proposed GKFCM	**97.34%**	**96.43%**	**98.3%**

From Table 3, it is observed that the proposed method gives the best segmented area of disease as compared to the conventional approaches Thresholding [9], K-Means [10], FCM [11] and OTSU [12]. This is achieved because the proposed method utilizes the AMBF initially on the test image, so various types of noises are removed and perfectly enhanced. Then, the proposed GKFCM method gives the better performance of segmentation.

From table 4, it is observed that the proposed method outperforms as compared to the conventional approaches SVM [7], RBFN [9], PNN [11], ANN [12] and CNN [13]. This is achieved because the proposed method utilizes the optimal features selection approach, so optimal features are selected and trained, whereas the conventional approaches trained with the fundamental features.

Table 4. Performance comparison of classification approaches

Method	Specificity	Sensitivity	Accuracy	Precision
SVM [7]	82	92	87	83
RBFN [9]	90	93	91	89.5
PNN [11]	41.8	57.3	89.5	83.4
ANN [12]	93.6	94.3	97.49	95.6
CNN [13]	98.61	98.93	98.33	97.73
Proposed DLCNN	**99.12**	**99.04**	**99.13**	**98.60**

Conclusion

This article presents the detailed analysis of segmentation and classification analysis of plant diseases by using leaves. Initially, test leaf image was applied to the AMBF pre-processing stage; it removed the noises along with enhancement. Then, GKFCM algorithm was applied to segment the disease affected region of the pre-processed leaf image. Then, multi-level feature extraction procedure was applied on the segmented outcome. Then, optimality approach was used to select the best features from the GLCM, colour and texture features, respectively. Finally, DLCNN method was applied for both training and testing purpose and gives the optimal performance of classification as compared to the state of art approaches. This work can be extended to implement the multi-class plant disease classification by using GoogLeNet, ResNet and Alexa Net based transfer learning models.

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