Mango Crop Pathological Problem Diagnosis using DWT-PCA based Statistical Features

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Abstract: In past few decades, disease recognition (Powdery Mildew and Anthracnose) in Mango Crop has been an area of major concern due to deficiency of apparent, shape and texture features. Soft computing techniques are employed using image processing to diagnose the diseases and hence to increase the yield of Mango crop. Here, we have proposed an improved Wavelet-PCA based Statistical Feature Extraction scheme in order to minimize the issues arising in various methodologies for diagnosis of pathological problems in different crops. Using this technique, we extract twenty statistical features for different plant parts like flower and fruit in order to increase the yield of Mango crop. This research work is an add-on to the research work presented in [1] by author. The features extracted here are used with Artificial Intelligence techniques with the aim of diagnosis of both Anthracnose and Powdery Mildew disease occurring in form of black spots and Fungus respectively on respective mango plant parts. The proposed research work has been implemented using MATLAB (MATrix LABoratory) software. Researcher captured 500 images each for flower and fruit using high quality Nikon 16MP digital camera during Indian mango spring season i.e. from March to July from the mango orchids and The Agricultural University situated at Dharwad district (Karnataka) location. The results obtained using proposed researches were found to be with accuracy around 96.70% and 97.50% for flower and fruit respectively.

Keywords: Anthracnose, Powdery Mildew, Wavelets, Principal Component Analysis (PCA), Statistical Features, Edge Detection, Artificial Neural Network.

Introduction

India is the country with seventh largest economy in the world with currently one of the highest GDP growth rate. The long-run development future of the Indian economy is highly encouraging because of its youth population, equivalent low dependency ratio, rates of investments, excellent savings and escalating integration with global economy. The backbone of this great Indian economy is agriculture which largely depends on the crops grown here in different seasons throughout the year. Diversity in crops like fruits, vegetables, grams etc. is also a great factor in agriculture based Indian economy. India is ranking second worldwide in field outcomes. Agriculture and associated areas like horticulture, fishing, forestry and logging are responsible for 17% of the GDP and providing employment around 49% of the total labor force in 2014. Use of modern machineries and technologies has greatly improved the yield and quality of crops. The crop cycle and the management of recurrent fruit crops are also important for yield in farms. There is a need of great attention predominantly for monitoring of diseases which are going to affect the production severely. Increasing usage of pesticides has resulted into induced diseases which affect the crops by reducing the production. Hence, a serious challenge resides for researchers to introduce the techniques to diagnose these diseases and to control the effects with preventive measures accordingly. In large farms to detect the diseases with open eye inspection becomes more tedious and time consuming task in real world. Hence, an automatic detection of these diseases in domain of agriculture science is a current area of research.

India is among the largest producers of mango crop across the world. Dashehari and Alphonson are two main varieties of mango crop grown in India. However, we are still lagging far in global export market due to quite low yield of quality grading fruit as a result of bacterial growth in mango crop. This bacterial growth in mango crops occurs in different part of plant such as fruits, flowers, stems and leaves which is a major factor for rapid decline of nurturing growth in upcoming years for the farms. There are number of diseases which occur in mango crop but Powdery Mildew (Oidium Mangiferae) and Anthracnose/ Blossom Blight (Colletotrichum Gloeosporioides) are two major diseases which are going to affect the production of mango crop greatly. In this paper, we have discussed the techniques to diagnose the Anthracnose disease. This disease results in irregular shaped black patches which appear over the leaf surface or early grown fruits. Also, the fungus may occur under damp situations in these patches. These patches start in small shape but soon they cover the entire area of the fruit or leaf and finally result in rotten leaves or rotten fruits.

In this research, we propose an image processing based mango crop disease recognition and classification approach. This machine learning based automatic pathology scheme proves to be a milestone for flourishing cultivation and enhanced marketing for mango crop. The accuracy of the recognition system mainly depends on the features extracted from the image. Here, we aim to extract wavelet and PCA based statistical features in order to recognize both Anthracnose and Powdery Mildew diseases occurring in Mango fruits and flowers in the form of black patches and fugal manner respectively. Here total 20 features have been extracted and used during training and testing phases to diagnose the disease in different parts of mango plants. While dealing with images, generally three major types of features are extracted namely shape features, texture features and color features [2] [3]. These added features have increased the accuracy of the system at the cost of increased coding and execution time. Section II covers the literature survey in related domain. Section III explains the proposed research work with flow and detailed description. In section IV experimental results have been explained. Section V presents the conclusion and future scope of the proposed research work.

Literature Review

The security of food still looks in danger due to various issues like plant diseases [4], climate change [5] etc. Plant diseases are not only a key hazard to food security all over the world, but can also have terrible consequences for countries like India whose economy largely depends on healthy crops. Their quick recognition is still difficult due to the deficiency of the essential infrastructure. In image processing, regardless a lot of efforts [6-10] have been employed, plant identification is still a difficult and vague problem. The main reason behind this issue is that a plant in environment has very analogous shape and color version. Number of research papers has been published in the related domain with their relevant pros and cons. A number of efforts have been implemented to overcome from crop loss due to diseases. An autonomous approach for diagnosing a disease suitably when it first occurs is a critical step for proficient disease management. The traditional disease diagnosis has been assisted by agricultural extension organizations. Nowadays, such efforts have moreover been carried out along with online disease detection for providing information, in addition to the increasing internet usage worldwide. In recent times, tools based on smart phones also have been utilized.

In [11] author has presented an adaptive scheme for diagnosis of fruit diseases. Image processing techniques were employed to diagnose the disease in fruits. K-means clustering technique was employed for segmentation along with feature extraction for recognition. Extracted features were used to classify the diseased images among database with use of support vector machine. The accuracy obtained here was approximately 93%. In [12] author proposes an automatic plant identification system for image database using all three types of shape, color and texture features. The major issue occurred was transform in shape and pattern of leaf along with age of plant and leaf composition in addition to usual huddles of object recognition such as variation in pose, light and orientation. The experimental results obtained here with 60% to 80% accuracy in all types of plant species.

In [13] author has worked on convolutional neural networks (CNN) in order to learn unsupervised feature version for 44 various types of plant classes, collected at the Royal Botanic Gardens, Kew, England. To grow perception on the selected features from the CNN model, a visualization method based on the de-convolutional networks (DN) has been used. Experimental results by means of these CNN features with number of classifiers demonstrate reliability and supremacy compared to the fantasy solutions which solely depend upon hand-crafted features. For development of accurate image classifiers system for the plant disease recognition, we are in need of a large, confirmed dataset of images of diseased and healthy plants. To collect such a dataset is not an easy task, and even online datasets are not freely available. To overcome these issues, the "Plant Village" project has been initiated for collecting millions of images of diseased and healthy crop plants [13], which also have been made openly and freely accessible to each researcher. Image processing, and specially object recognition, has made marvelous enhancements in the last few years. The PASCAL VOC Challenge [14], and further freshly the Large Scale Visual Recognition Challenge (ILSVRC) [15] based on the Image Net dataset [16] have been extensively utilized as standards for various visualization-related issues in image processing domain along with object recognition and classification.

In [17] using texture features, a detection and classification system for plant leaf diseases has been designed. The work implemented here was an automated software implementation technique for diagnosis of plant leaves. Also, various researches have tried to extract a number of features based on statistical parameters [18] and junction feature parameters [19]. In [20] author implemented mathematical modeling for image processing techniques in order to do growth analysis for crops. The drawback was in case of improper edge locations of leaves where, no segmentation scheme was applicable and hence turned out to be improper technique. There were many good results which were obtained in terms of either crop pest or disease recognition too [21-24]. These all researches were either limited to specific plant parts or extracted features were not sufficient to diagnose the diseases. Hence, an effort was put ahead in order to diagnose the disease more accurately with directional features using Wavelet PCA statistical features.

Proposed Work

The flow of proposed disease recognition system is presented in Fig.1. As discussed in [25], firstly on the acquired color images of plant parts (leaves and fruits), image-preprocessing steps are performed such as color space conversion (to obtain the grayness component), illumination normalization (for recovering from non-uniform illumination). On this grayness component of image Adaptive K-means segmentation technique is applied in order to segment the image into lesion region and non-lesion region. In these segment lesion areas, sharp edges at the boundaries may be obtained by applying various types of edge detection transformation techniques and then the edges are combined with segments to achieve the segmented lesion with better accuracy.

Image Acquisition and Pre-Processing

For experimental analysis of research work we have captured about 500 images individually for leaf and fruit with healthy parts and diseased parts using high quality Nikon 16MP digital camera during Indian mango spring season i.e. from March to July from the mango orchids and The Agricultural University situated at Dharwad district (Karnataka) location. Each of the captured images is having high resolution of 4320x3240. The captured images are the colored image. However, there may be possibility of unevenly illuminated regions occurring due to imaging equipment or external environmental issues. To recover the image parts from such situations a wavelet based technique is used where the image is decomposed into two parts as approximate coefficients (cA) and detail coefficients (cD). Furthermore, for contrast enhancement histogram equalization is employed on the approximation coefficients. Along with this for edge enhancement, Gamma correction methodology (with $\gamma>1$) is used on detail coefficients. Finally, a uniformly illuminated image is reconstructed from these altered coefficients using inverse wavelet transform technique. Here, any signal can be expressed in terms of wavelet and scaling basis functions as following –

$$f(x) = \sum_i \propto_{0,i} \Phi_{0,i}(x) + \sum_j \sum_i \beta_{j,i}\psi_{j,i}(x) \qquad (1)$$

Where, $\propto_{j,i}$ are the scaling coefficients, $\Phi_{j,i}$is scaling function for scale j,$\psi_{j,i}$ is wavelet function for scale of j and$\beta_{j,i}$ are the wavelet coefficients. Next, in order to normalize the brightness of captured image and to make it beneficial for human visual perspective, the color space conversion from RGB to YIQ is performed. Here, Y (Grayness) is used for illumination level along with value I (Hue) and Q (Saturation) both for chrominance information. The Grayness level (Y) varies from 0 to 255 and the chrominance (I & Q) varies from -127 to 127.

Segmentation of Lesion Region

Adaptive K-Means Clustering based segmentation technique is used to segment the lesion area from the plant part. This is the modified version of conventional K-Means segmentation method. In this technique, an iterative scheme is used by optimal minimization of objective function, which generates optimal solutions for initial k- centroids. The objective function used here is–

$$E_d = \sum_{k=1}^{c} \sum_{n=1}^{P} \partial(I_{min}, I_{max}) \qquad (2)$$

Where, E_d is the Euclidean distance obtained between the local minimum pixel value I_{min} and local maximum pixel valueI_{max}; P represents the total number of pixels present in image and c is the total number of cluster for image. Also, for determining the edges or boundaries of these lesion areas, we apply various types of edge detection transforms based on pixel discontinuity scheme using calculation of first order and second order derivatives and other transforms such as Sobel, Prewitt, and Roberts etc. Next, these extracted edges are superimposed on the segmented image. The Absolute Gradient or magnitude and Direction of Gradient or phase for these different types of transforms is commonly expressed as –

$$Magnitude\ of\ Gradient(Gr) = \sqrt{{w_1}^2 + {w_2}^2} \qquad (3)$$

$$Phase\ of\ Gradient(\varphi) = \arctan\left(\frac{w_1}{w_2}\right) \qquad (4)$$

Where, w_1 and w_2 are transformed values which are generated using first and second window of the particular transform respectively.

Wavelet - PCA based Statistical Feature Extraction

In order to enhance the recognition accuracy of our work we have also extracted wavelet-based PCA statistical features. In recent years, wavelet transform is being used enormously in image processing domain for image decomposition due to its various salient features as decomposing image in sub bands with various frequency bands, applications in both frequency and spatial domain. The wavelet transform is generally expressed as decomposition of any signal $f(x) \in K^2(G)$into a functions' family. These functions are generally dilations and translations of their mother wavelet function $\varphi(x)$. After 2D wavelet

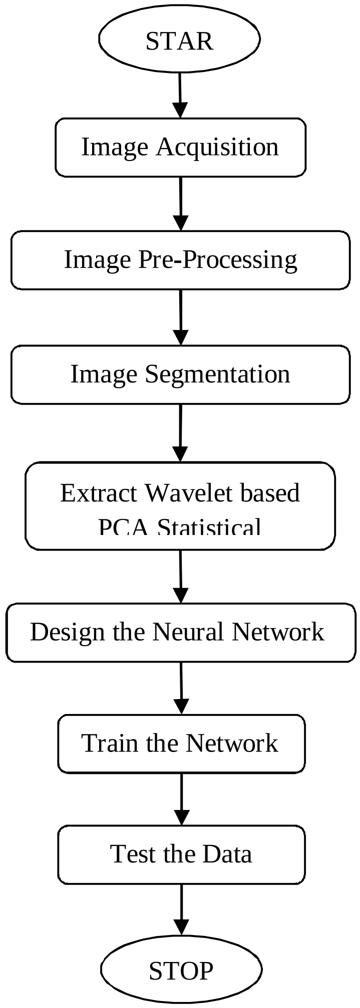

Figure 1. Flow Diagram of Proposed Work

transformation, the image is decomposed in four sub bands. These bands are obtained on subsequent filtering (Low pass (L) or High Pass (H)). The Wavelet transform is commonly implemented performing convolution and down-sampling along the both rows and columns each at a time. The obtained four sub-bands are LL, LH, HL, and HH. These sub-bands represent different information such as Average (A), Horizontal (H), Vertical (V), and Diagonal (D). We can also obtain more sub-bands after performing multi-level decomposition iteratively.

Along with Wavelet, Principal Component Analysis (PCA) is used to reduce the dimensions of data to a suited size which is more feasible for computations. It is also used to extract the most representative feature data out of the complete input data besides the reduced size of data in order to retain the significant features to represent the original data. It uses Eigen value decomposition methodology on the covariance matrix and evaluates the data on Eigen basis which are generally defined by the corresponding Eigen vectors. In obtained Eigen values only few of the Eigen values have larger values while rest of the Eigen values are significantly very small and hence they are not the part of major data variations. Consequently these directions of significantly higher variances are only utilized by calculating the inner product of data with the Eigen vectors for relevant Eigen values. The general steps of PCA methodology are given below –

Step-1: Calculate the covariance matrix of given input data as

$$\sum V = \frac{1}{Num}\left\{\left(diag(m) - \overline{diag}(m)\right)\left(diag(n) - \overline{diag}(n)\right)^{T}\right\} \quad (5)$$

Where, $1 \leq m, n \leq Num$

Step-2: Calculate the Eigen vectors matrix (V) and diagonal matrix (D) of obtained Eigen values as

$$V^{-1} \sum V = D \quad (6)$$

Step-3: Arrange the obtained Eigen vectors in the descending order of corresponding magnitude of Eigen values and obtain the principal component parameter.

Step-4: Finally, in the direction of principal components data is projected by calculating the inner product of data with the Eigen vectors for relevant Eigen values.

In our research, we have input segmented images obtained with resolution of 256x256. We have applied a three level 'Haar' wavelet transform in order to obtain sub bands of resolution of 32x32. Using these sub-band images further PCA is applied and PCA parameter values are obtained. This PCA matrix is further used to calculate twenty statistical features which are formulated below. Let's first divide all captured images in two groups Fruit (Fr) and Flower (Fl). Now, take a set of fruit images for analysis of research, which is represented as –

$$I_{MP} = \{Fr_1, Fr_2, Fr_3, \dots Fr_m\} \quad (7)$$

Where, Fr represents an image from Fruit group and m representing the number of images of fruit used for analysis. The key objective of this wavelet based PCA component feature extraction implemented here is to enhance the accuracy for recognition of pathological problems in mango crop. Let the set of images used for classification here is represented as –

$$SFr = \{sfr_1, sfr_2, sfr_3, \dots sfr_n\} \quad (8)$$

Where, n represents the number of class sets and particular class is represented by *sfr* for respective image. Here, we are going to extract 20 wavelet based features which have been used for an efficient classification scheme in order to diagnose the disease in mango crop. Let, the obtained feature values set be represented as –

$$FV = \{fv_1, fv_2, fv_3, \dots fv_{20}\} \quad (9)$$

a). Contrast:

$$fv_1 = \sum_i \sum_j (i-j)^2 \,.\, sfr(i,j) \quad (10)$$

b). Correlation:

$$fv_2 = \frac{\sum_i \sum_j (ij).sfr(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (11)$$

Where, $\mu_x = \sum_i \sum_j i \,.\, sfr(i,j)$

$$\mu_y = \sum_i \sum_j j \,.\, sfr(i,j)$$

$$\sigma_x = \sum_i \sum_j (i - \mu_x)^2 \,.\, sfr(i,j)$$

$$\sigma_y = \sum_i \sum_j (j - \mu_y)^2 \,.\, sfr(i,j) \quad (12)$$

c). Energy (Uniformity):

$$fv_3 = \sum_i \sum_j sfr(i,j)^2 \quad (13)$$

d). Homogeneity:

$$fv_4 = \sum_i \sum_j \frac{1}{1+(i-j)^2} \,.\, sfr(i,j) \quad (14)$$

e). Mean:

$$fv_5 = \frac{\sum_i \sum_j sfr(i,j)}{m*n} \quad (15)$$

f). Standard Deviation:

$$fv_6 = \sqrt{\frac{\sum_i \sum_j (sfr(i,j) - fv_5)^2}{(N-1)}} \quad (16)$$

g). Entropy (Randomness):

$$fv_7 = -\sum_i \sum_j sfr(i,j).\log(sfr(i,j)) \quad (17)$$

h). Root Mean Square (RMS):

$$fv_8 = \sqrt{\frac{\sum_i \sum_j sfr(i,j)^2}{m*n}} \quad (18)$$

i). Skewness:

$$fv_9 = \frac{\sum_i \sum_j (sfr(i,j) - fv_5)^3}{N} * {fv_6}^3 \quad (19)$$

j). Kurtosis:

$$fv_{10} = \frac{\sum_i \sum_j (sfr(i,j) - fv_5)^4}{N} * {fv_6}^4 \quad (20)$$

k). Variance:

$$fv_{11} = \frac{\sum_i \sum_j (sfr(i,j) - fv_5)^2}{N} \quad (21)$$

l). Smoothness:

$$fv_{12} = 1 - \frac{1}{(1+\sum_i \sum_j sfr(i,j))} \tag{22}$$

m). Inverse Difference Moment (IDM):

$$fv_{13} = \sum_i \sum_j \frac{1}{1+(i-j)^2} . sfr(i,j) \tag{23}$$

n). Max Value:

$$fv_{14} = \max(sfr(i,j)) \tag{24}$$

o). Min Value:

$$fv_{15} = \min(sfr(i,j)) \tag{25}$$

p). Range Value:

$$fv_{16} = fv_{14} - fv_{15} \tag{26}$$

q). Median:

$$fv_{17} = \begin{cases} \frac{sfr_p + sfr_{p+1}}{2} \; ; \; p \in Whole\ Number \\ sfr_p \; ; \; p \in Fraction \end{cases} \tag{27}$$

Where, all $sfr_i's$ are arranged in the ascending order and $p = 50 * N/100$

r). First Quartile:

$$fv_{18} = \begin{cases} \frac{sfr_p + sfr_{p+1}}{2} \; ; \; p \in Whole\ Number \\ sfr_p \; ; \; p \in Fraction \end{cases} \tag{28}$$

Where, all $sfr_i's$ are arranged in the ascending order and $p = 25 * N/100$

s). Third Quartile:

$$fv_{19} = \begin{cases} \frac{sfr_p + sfr_{p+1}}{2} \; ; \; p \in Whole\ Number \\ sfr_p \; ; \; p \in Fraction \end{cases} \tag{29}$$

Where, all $sfr_i's$ are arranged in the ascending order and $p = 75 * N/100$

t). Inter Quartile Range (IQR):

$$fv_{20} = fv_{19} - fv_{18} \tag{30}$$

Classification using Artificial Neural Network

Artificial neural network is also known as sixth generation of soft computing. This system has three different types of layers named as, input layer, hidden layers and the output layer. The number of layers and the neurons or nodes present in a particular layer are assigned depending on the problem definition of the system. In this research work, the feed forward neural network has been used with input layer having 20 nodes, specified by total 20 valued feature set consisting of extracted Wavelet-PCA based statistical features as explained above. However, four hidden layers with each having four nodes have been used. We have used different types of training functions for training of network such as trainlm, trainrp, traingdx, trainoss, traincgp etc. with Multi category Continuous Perceptron Training Algorithm (MCPTA).

Experimental Results

The proposed research work has been implemented using MATLAB (MATrix LABoratory) software. Researcher captured 500 images each for leaf and fruit using high quality Nikon 16MP digital camera during Indian mango spring season i.e. from March to July from the mango orchids and The Agricultural University situated at Dharwad district (Karnataka) location. Fig.2 (a)-(b) show the original captured images for flower with healthy part and with affected by Powdery Mildew disease respectively. Fig.3 (a)-(b) show the comparative analysis of some Wavelet-PCA based statistical features of images shown in Fig.2 (a) & (b). Similarly, Fig.4 (a)-(b) show the original captured images for fruit with healthy part and with affected by Anthracnose disease respectively. Fig.5 (a)-(b) show the comparative analysis of some Wavelet-PCA based statistical features of images shown in Fig.4 (a) & (b).

Figure 2.Original images for (a). Healthy Flower (b) Powdery Mildew Flower

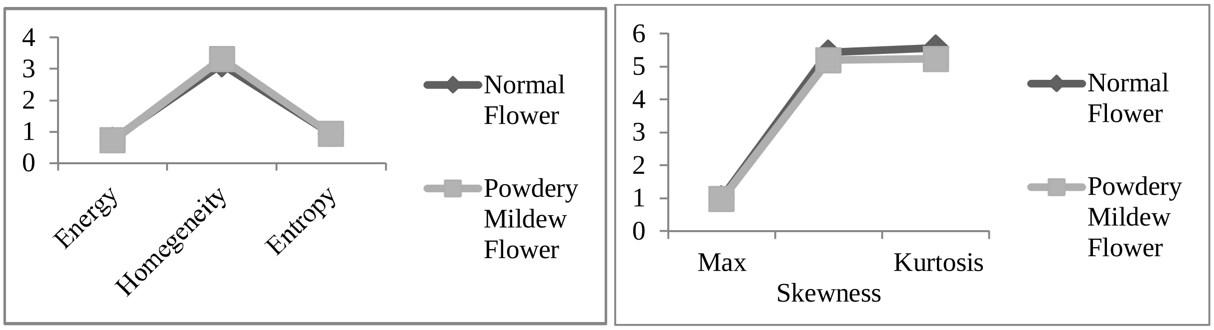

Figure 3. (a)-(b) Comparative Analysis of Wavelet-PCA based Features for Normal and Powdery Mildew Flower

Figure 4.Original images for (a). Healthy Fruit (b) Anthracnose Fruit

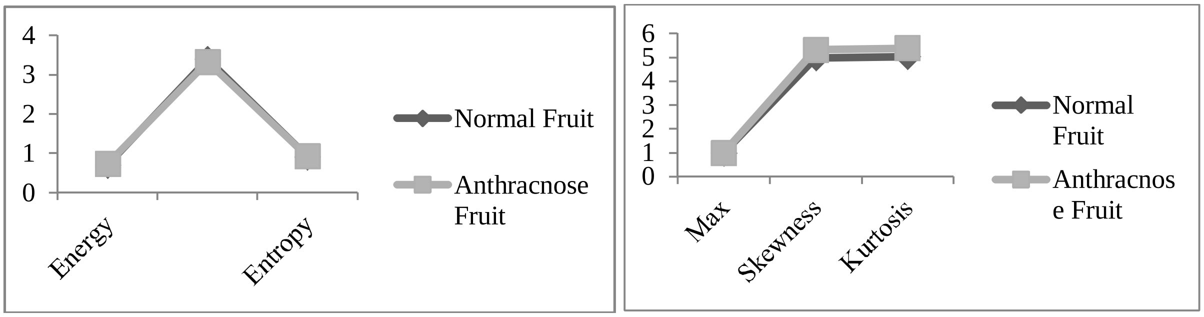

Figure 5. (a)-(b) Comparative Analysis of Wavelet-PCA based Features for Normal and Anthracnose Fruit

From the comparative results obtained in Fig.3 and 5, it is obvious that no particular statistical analysis and no single feature value extracted is enough to exactly classify the lesion area of the mango crop image data set into healthy and diseased classes. A complete feature set of twenty Wavelet-PCA based feature vector is used in order to classify the data set more accurately. Furthermore, for classification we have used neural networks with different training functions. For analysis, we have prepared a database with 20 dimensional feature vectors for all 500 images for each part of mango crop i.e. flower and fruit. Out of this database, 70% of database is used for training of the network and remaining 30% is used for testing purpose. Subsequently, we have calculated the Confusion Matrix for the performance analysis, which is a 2x2 matrix with its elements as True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) respectively. Where, TP & TN are the values for the number of samples with proper classification and FP & FN are the values for the number of samples with improper classification. Using these four values we can further calculate some more statistical parameters such as Accuracy, Miss Rate, Specificity and Sensitivity. These all statistical parameters are given by set of Equations (31-35). For the proposed research work, the accuracy and sensitivity for both flowers and fruits with different training function is listed in Table-I-II. Also, Fig.6-7 show the comparison analysis of accuracy and sensitivity for different training functions. Fig.8 shows performance plots in terms of Mean Square Error (MSE) of best network.

$$\text{Sensitivity (TPR)} = TP/P \quad \text{where, } P=TP+FN \tag{31}$$

$$\text{Specificity (TNR)} = TN/N \quad \text{where, } N=TN+FP \tag{32}$$

$$\text{Fall Out (FPR)} = FP/N \tag{33}$$

$$\text{Miss Rate (FNR)} = FN/P \tag{34}$$

$$\text{Accuracy} = (TP+TN/P+N)*100\% \tag{35}$$

Table 1. Accuracy and Sensitivity for different training functions for flower

Training Algorithm	Accuracy (%)	Sensitivity (%)
Traincgp	92.40	93.10
Traincgf	93.20	94.25
Traingdm	94.95	96.35
Traingdx	96.70	97.15
Trainlm	94.60	95.70
Trainrp	95.15	95.80
Trainoss	92.10	92.85
Trainscg	93.15	94.20

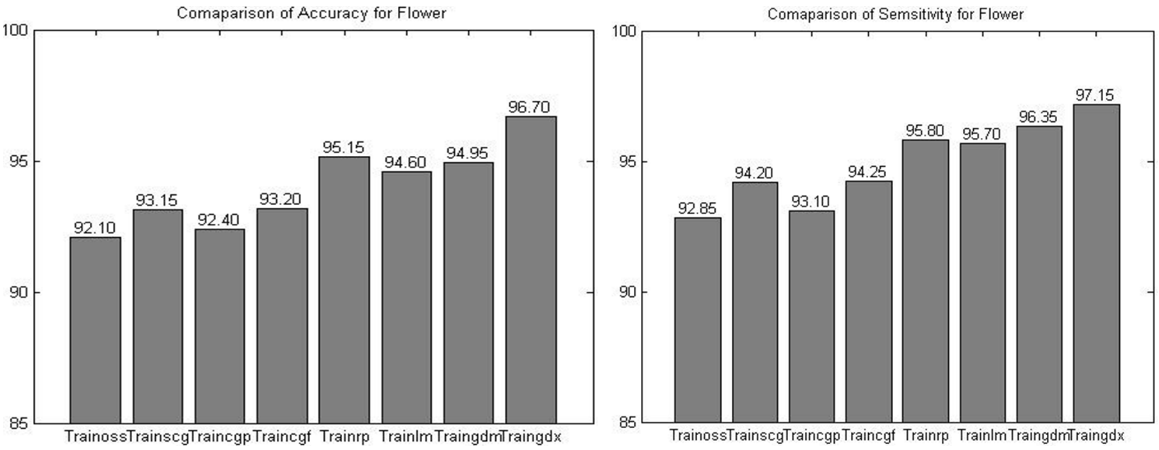

Figure 6. (a). Accuracy and (b). Sensitivity comparison for different training functions for flowers

Table 2. Accuracy and Sensitivity for different training functions for fruit

Training Algorithm	Accuracy (%)	Sensitivity (%)
Traincgp	93.20	93.90
Traincgf	93.50	94.55
Traingdm	95.10	96.50
Traingdx	97.50	97.95
Trainlm	94.20	95.30
Trainrp	95.55	96.20
Trainoss	92.70	93.50
Trainscg	93.50	94.55

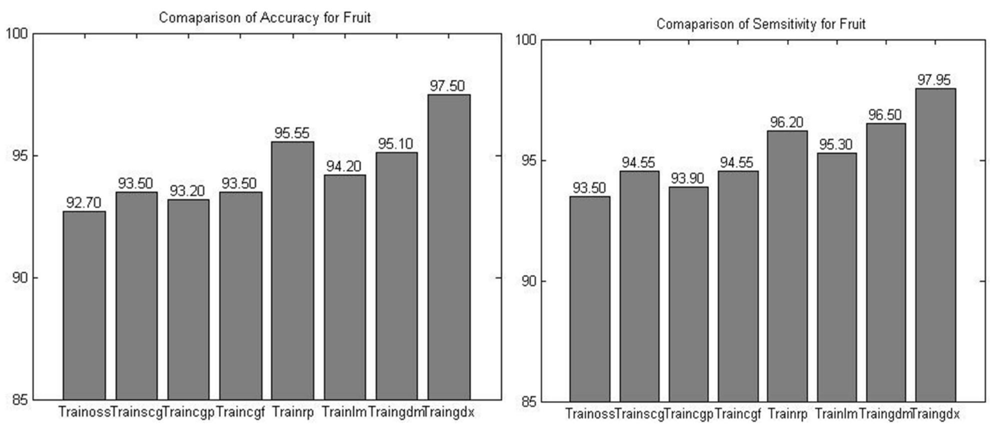

Figure 7. (a). Accuracy and (b). Sensitivity comparison for different training functions for fruits

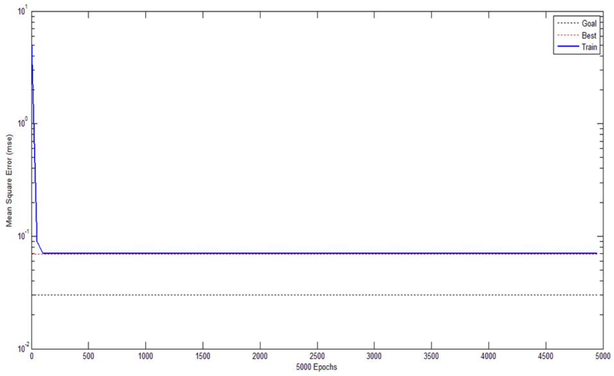

Figure 8. Performance plot for the Traingdx function

Conclusion

In our country where agriculture is backbone of the economy, diseases in crops and plants are the major barrier in growth of Indian economy. Hence, protection of crops against diseases becomes the most significant task. These diseases are greatly responsible for the decline in production hence to boost the yield of crop; recognition of these diseases has become the key job. In this research, efforts have been put to recognize the Powdery Mildew and Anthracnose disease occurring in Mango plant parts such as flower and fruit in form of fungal pattern and black spots respectively for segmented images obtained in [1]. For recognition twenty Wavelet-PCA based statistical features have been extracted. These features are further used as input to artificial neural network in order to classify a plant part image either healthy or diseased one. Comparative analysis has also been shown in order to indicate the significance of various statistical features. The obtained accuracy was found to be 96.70% and 97.50%, for flower, and fruit respectively. The proposed research work can further be extended to diagnose pathological problems occurring in Leaves and Stem parts of mango plants in order to increase the yield to a huge amount by taking appropriate preventive measures.

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