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Classification of fungal and bacterial leaf diseases using machine learning techniques

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ABSTRACT

In Farming and Gardening, leaf diseases have grown to be a challenge as it can cause considerable reduction in both quality and measure of agricultural yields. Thus, automated recognition of diseases on leaves plays a vital role in Farming and Gardening sector. This Thesis imparts a simple and computationally dexterous method used for leaf disease identification and grading using digital image processing and machine learning method. The proposed system is divided into two phases, in the first phase the plant is recognized on the basis of the features of leaf, it includes pre-processing of leaf images, and feature extraction followed by Support vector machine and decision tree based training. In the second phase the disease present in the leaf is classified, this process includes K-Means based segmentation of defected area, feature extraction of the defected portion and the Support vector machine and decision tree based classification of disease. Then the disease grading is done on the basis of the amount of disease present in the leaf.

Keywords*: Image segmentation, Leaf disease, Support vector machine, Decision tree*

1. INTRODUCTION

Fungi are the most common parasites inflicting plant disease. Most are microscopic (very small and can only be seen with the aid of a microscope) plants that feed on living green plants or on the dead organic material. When they hit living plants, it results in a sickness in plants. Fungi usually generate spores which, when carried to a plant, can begin an infection. These spores are also carried from plant to plant by air, water, insects and any equipment. So as for fungus spores to start n, ew, infections, adequate wet and also the right air temperature is needed. A plant wound is typically also required as an entry for the fungus. Fungus diseases are common throughout wet, wet seasons. Leaf spots (other names: zymosis, scab, leaf blotch, shot hole) are typically rather definite spots of varied sizes, shapes, and colors. These are nearly continuously apart the clear margin. Typically the spot, which can be caused by microorganism or fungi, is enclosed by a yellow halo. If caused by a fungus, there's nearly continuously fungus growth of some sort within the spot, significantly in damp weather. This fungus growth is also small pimple-like structures, usually black in color, or a musty growth of spores. It's usually necessary to use a hand lens or a magnifier to visualize these structures. The common names of leaf spot diseases are also general, like microorganism leaf spot; descriptive, similar to frog-eye leaf spot; or named when the fungus, similar to Septoria leaf spot. Affected leaves typically flip yellow, wither and die speedily. The matter is common on cucurbit-type vegetables and on tiny grains. Basically, leaf blights can be found on tomato and potato plants, blight is caused by the fungus Phytophthora infestans and is common throughout the U.S. faithful to its name, the unwellness arises later within the season with symptoms typically not showing till once blossom. Historically Brown spot has been largely ignored as one of the most common and most damaging rice illness. Brown spot is defined as the fungus illness that infects the coleoptile, leaves, leaf sheath, panicle branches, glumes, and spikelet. In Farming and Gardening sector plants or crop cultivation have seen fast development in both the quality and measure of food manufacture, however, the existence of pests and diseases on crops especially on leaves has hindered the quality of agricultural goods. If the existence of pests on crops and leaves is not checked properly and the timely solution is not provided then the quality and measure of food manufacture will be reduced, which results in an upsurge in poverty, food insecurity and the mortality rate [6]. This severe effect can disturb any nation's economy especially of those where 70% of the inhabitants rely on the products from the agricultural sector for their livelihood and endurance. One of the major problems for agriculturists is to lessen or eradicate the growth of pests affecting crop yields. A pest is an organism that spreads disease, causes damage or is a nuisance. The most frequent pests that affect plants are aphids, fungus, gnats, flies, thrips, slugs, snails, mites, and caterpillars. Pests lead to sporadic outbreaks of diseases, which lead to famine and food shortage [3]

2. LITERATURE SURVEY

Devi et.al in [1] for any automated image analysis process, the segmentation is an important task because all subsequent tasks in image processing heavily rely on the quality of image segmentation. It determines the eventual success or failure of the analysis. Chaudhary et.al in [2] in this research, an algorithm for disease spot segmentation using image processing method in plant leaf is implemented. This is the primary and vital time for automatic detection and classification of plant Sicknesses. Disease spots are different in color but not in intensity, in comparison with plant leaf color. So color transform of RGB image can be used for better segmentation of sickness spots. Bhattacharyya et.al in [3] multichannel information processing from a diverse range of channel information is highly time- and space-complex owing to the variety and enormity of underlying data. Most of the classical approaches rely on filtering and statistical method. Methods in this direction involve Markov random models, vector directional filters and statistical mixture models like Gaussian and Dirichlet mixtures.

Vijayakumar et.al in [4] the aim of this research paper is to identify the foot rot disease infected in the betelvine plants using digital imaging method. The digital pictures of the clean betelvine leaves and the digital pictures of the infected in foot rot unhealthy betelvine leaves at different stages are collected from different betelvine plants using a high-resolution photographic camera and collected betelvine pictures are stored with JPEG format. The digital image analysis will be done using the image processing toolbox present in MATLAB. The calculated median values of all leaves are stored in the system. The median values of check betelvine leaves are computed and compared with the stored median values. As the consequence of this evaluation, it is identified whether check betelvine leaves are affected by foot rot disease or not. Finally, this research work it helps to identify the foot rot disease can be acknowledged before it spreads to complete crop.

Singh et.al in [5] in India a majority of the population in rural areas is working in the Farming and Gardening field for their livelihood. They not solely got to struggle for the higher yield against the natural disasters however also have to tackle the losses of the net output because of land fertilization specifications and unskilled labor too. In the event of inadequate utilities and resources, in the face of unpredictable crises, their gain opportunities and livelihood are proportionally and adversely affected. However, in this era of technology, the scenario may get changed as the Information and Communication and related fields of technology are providing a great for such type of crisis handling. Here in this paper, the strategy which can be accustomed to comparing the crop leaf color with the leaf color chart (LCC), has been projected for getting a detail about the requirement of the plant, before enough to get the yield affected. By using image processing technique an easy sturdy methodology for the color prediction of paddy crop plant has been discussed along with the mathematical modeling which may provide a great platform to the advisory bodies in the Farming and Gardening field for the atomization of the crop health problems and solutions.

Asfarian et.al in [6] the efforts to increase the measure and quality of rice manufacture are obstructed by the paddy disease. This research attempted to identify the four major paddy diseases in Indonesia (leaf blast, brown spot, bacterial leaf blight, and tungro) using fractal descriptors to analyze the texture of the lesions. The lesion images were extracted manually. The descriptors of `S' component of each lesion images then used in classification process using probabilistic neural networks. This method achieved at least 83.00% accuracy when identifying the diseases. This method has a potential to be used as one of the features if it combined with other features, especially when two diseases with relatively same color involved. Paprocki et.al in [7] the proposed method generates a smart partition of the initial mesh that allows identifying the main stem, branches, and leaves of the plant. Extracted regions are then processed through the next stage of the automated analysis, which retrieves accurate plant information such as stem length, leaf width, length or area. Results involved applying our top-down approach on a prototype population of 6 cotton-plant meshes studied at 3 or 4-time points. Using our partitioning pipeline, we obtained accurate meshes segmentations for 20 plants out of the initial 22. Results validate the feasibility of an automated analysis of plant data. Future work will involve extending our approach to multiple plant varieties and using an atlas-based iterative feedback scheme to improve the 3D plant reconstruction. Choong et.al in [8] segmentation on synthetic images and natural images are covered to study the performance and effect of different image complexity towards segmentation process. This study gives some research findings for effective image segmentation using graph partitioning method with computation cost reduced. Because of its cost expensive and it becomes unfavorable in performing image segmentation on high-resolution image especially in online image retrieval systems. Thus, a graph-based image segmentation method done in multistage approach is introduced here.

A. Meunkaewjinda et al. [9] represented disease detection in grapes using the hybrid intelligent system in which the diseases in leaves of plants are graded by calculating the quotient of diseased area and the leaf area. Self-organizing maps back propagation neural networks were used by them for recognizing the colors of the grape leaves that were used to segment the pixels of the grape leaf within the entire image. After that disease segmentation is performed. Gabor wavelet is then used to filter the segmented image in order to analyze the color features of the leaf. After that support vector machines are applied in order to classify the different types of diseases in grape leaves. In this method, the Segmentation was good enough as it suffered from the limitation of extraction of ambiguous color pixels from the background of the image. With the usage of back propagation neural network, there is an inability to know how to precisely and accurately generate an arbitrary mapping procedure. Stephen Gang Wu [10] put into practice a leaf recognition algorithm using easily extracted features and highly efficient algorithms for recognition purpose. A Probabilistic Neural Network (PNN) was used for recognition of plant leaves. In this, various features are mined and processed by which act as an input to PNN. The drawbacks of this technique were that accuracy of recognition observed was 90% and the features extracted were not up to the mark.

Xu Pengyun et al. [11] presented a technique for monitoring plant diseases that were caused by spores. The colored images are firstly converted into the grayscale image so in order to analyze and process though histogram generation, the gray-level correction, image feature extraction, image sharpening and so on. Moreover, in order to remove the components of the image having low frequency, the edges of the grayscale image are enhancing using Median Filter and canny edge algorithm. After thresholding, morphological features like dilation, erosion, opening etc are applied to the binary image obtained. The drawbacks of this technique were that processing time appears to be high and there also exists variations in the size of spores.

3. PROBLEM IDENTIFICATION

Table 1: Problem Identification in the Previous Method

Authors	Approaches	Plant Name	Diseases / harvesting identified	Features Extracted	Classification / Algorithm	Accuracy
[12] Tasneem	Off-device image pre-processing	Potato	Early Blight and Late Blight	Color, shape	Leaf Vein Detection and Blob detection algorithm	94.1%
[13] B. Klatt et al	On-device image pre processing	Sugar beet	Cerospora beticola , Ramularia, Phomabetae	LBP	Naive Bayer Classifier	97%
[14] Shovon Paulinus Rozario		Paddy	Bacterial leaf Blight, Brown Spot, Leaf blast, Leaf Scald	Blobs, area, and color	Euclidean distance of input and extracted images	Not Given
[17] Shitala Prasad et al	On-device image segmentation	Plant	Leaf spots and leaf blotch	K-means Segmentation. GWT, GLCM – features extraction	Weighted K-Nearest Neighbour	93%
[18] Rahat Yasir et al	On-device image processing	Crop	Brown leaf spot, bacterial leaf blight, brown spot, ufra and rice blast	Color	YC_bC_r. Histogram Algorithm	85%
[19] Alham F		Palm Oil	Hawar Leaf, Anthracnose, and Pestalotiopsis, palmarum	Median of RGB, Quartile 1 of RGB, Quartile 3 of RGB, Standard Deviation of RGB, Shape	Neural Network Classification	87.75%
[10] Monika Bhatnagar et al		Tomato	Harvesting	Not Given	Clustering	Not Given

4. METHODOLOGY

Flowchart of the methodology used for detection of disease from affected leaf.

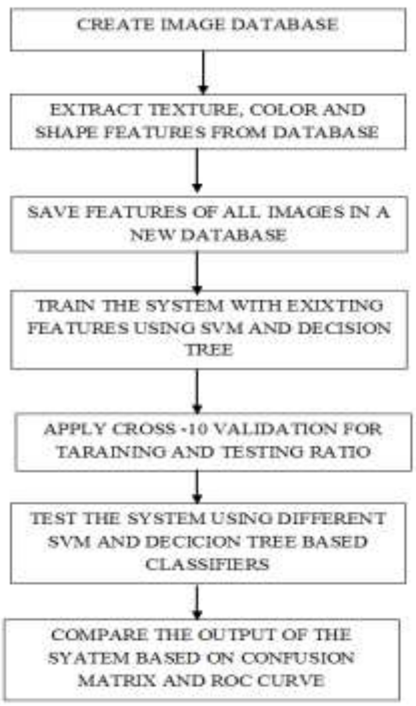

Fig. 1: Flow chart of the methodology

4.1 Step 1: Database preparation

The database contains 1000 images collected from 3 different sources:

1. Manually captured using high definition digital camera.
2. Online available datasets.
3. Images used in reference papers.

Finally, the database is divided into 5 classes:

1. Fungal Infection
2. Bacterial Blight
3. Brown Spot
4. Leaf Spot
5. Healthy Leaf

4.2 Step 2: Feature extraction

We have extracted 12 features from all input images, features are mainly based on:

1. The shape of Leaf.
2. Texture of Leaf
3. Color of Leaf
4. Intensity variation in Leaf

The brief description of extracted features are as follows:

Angular Second Moment (ASM)

ASM may be a measure of homogeneity of a picture. A homogenous scene can contain solely a couple of grey levels, giving a GLCM with solely a couple of however comparatively high values of P(i, j). Thus, the total of squares is high.

$$ASM = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\{P(i,j)\}^2 \quad (1)$$

Contrast:

$$CONTRAST = \sum_{n=0}^{G-1} n^2 \{\sum_{i=1}^{G}\sum_{j=1}^{G} P(i,j)\}, \quad |i-j| = n \qquad (2)$$

This measure of contrast or native intensity variation can favour contributions from P(i, j) far away from the diagonal, i.e. i != j.

Inverse Difference Moment (IDM):

$$IDM = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{1}{1+(i-j)^2} P(i,j) \qquad (3)$$

IDM is additionally influenced by the homogeneity of the image. Due to the weight issue (1+(i−j)2)−1 IDM can get little contributions from heterogeneous areas (i != j). The result's a coffee IDM value for heterogeneous pictures, and a comparatively higher value for homogenized pictures.

Entropy:

Heterogeneous images have low first order entropy, while a homogeneous scene has high entropy.

$$ENTROPY = -\sum_{i=0}^{G-1}\sum_{j=0}^{G-1} P(i,j) \times log(P(i,j)) \qquad (4)$$

Correlation:

$$CORRELATION = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \frac{\{i \times j\} \times P(i,j) - \{\mu_x \times \mu_y\}}{\sigma_x \times \sigma_y} \qquad (5)$$

Correlation is defined as the measure of grey level linear dependence between the pixels at the desired positions relative to every alternative.

Variance:

$$VARIANCE = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} (i-\mu)^2 P(i,j) \qquad (6)$$

This feature puts relatively high weights on the elements that differ from the average value of P(i, j).

Mean:

$$AVER = \sum_{i=0}^{2G-2} i P_{x+y}(i) \qquad (7)$$

It calculates the average of all pixels

Sum Entropy:

$$SENT = -\sum_{i=0}^{2G-2} P_{x+y}(i) log(P_{x+y}(i)) \qquad (8)$$

Difference Entropy:

$$DENT = -\sum_{i=0}^{G-1} P_{x+y}(i) log(P_{x+y}(i)) \qquad (9)$$

Inertia:

$$INERTIA = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \{i-j\}^2 \times P(i,j) \qquad (10)$$

Homogeneity:

Returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

Range = [0 1]

Homogeneity is 1 for a diagonal GLCM for other matrix element it can be calculated by using following formula:

Homogeneity = ∑ [P (I, j) / (1+ | i – j |)] (11)

Cluster Prominence:

$$PROM = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1} \{i+j-\mu_x-\mu_y\}^4 \times P(i,j) \qquad (12)$$

4.3 Step 3: Perform training and testing

Support Vector Machine:

Given the training dataset of n point

Where, the y_1 are either 1 or −1, each indicating the class to which the point $\vec{x}_i$ is a p-dimensional real vector. We have to find the "maximum-margin hyper plane" that divides the group of points for which y_i=1from the group of points $\vec{x}_i$ for which y_i= -1, which is defined so that the distance from the hyper plane to the nearest point $\vec{x}_i$ from either group is maximized.

Any hyper plane written as the set of points $\vec{x}$ fulfills the :

$$\vec{w}.\vec{x} - b = 0, \qquad (13)$$

Where $\vec{w}$ is the normal vector to the hyperplane. This can be like hence normal form, except that $\vec{w}$ is not necessarily a unit vector. The parameter $\frac{b}{\|\vec{w}\|}$ determines the offset of the hyper plane from the origin on the normal vector $\vec{w}$.

Setting SVM Parameters:

The type of SVM we tend to use is multiclass SVM. The objective of this machine is to assign labels into instances by using support vector machines, where the labels are drawn from a definite set of many elements.

For doing so we have to reduce the single multiclass problem into multiple binary classification problems. We are applying "one of the labels and the rest (one-versus-all)" for our classification.

The Classification of new instances for the 1 vs. all case is done by a winner-takes-all strategy, in which the classifier with the highest output function assigns the class.

Now, as we can see that it is converted into the linear kernel, the equation for prediction for a new input using the dot product between the input (x) and each support vector (xi) is calculated as follows:

f(x) = B(0) + sum(ai * (x,xi)) (14)

This is an equation that involves calculating the inner products of a new input vector (x) with all support vectors in training data. The coefficients B0 and ai (for each input) is estimated from the training data by the learning algorithm.

Here is the example (x_i, y_i) we can define the functional margin of (w, b) with respect to the training example

$$(x_1, y_1), \ldots.., (\vec{x}_n, y_n)$$

gamma_i = y_i((w^T)x_i + b) (15)

If y_i > 0 then for the functional margin to be large (i.e., for our prediction to be confident and correct), so, we need (w^T)x + b to be a large positive number. Conversely, if the value of y_i < 0, then for the functional margin to be large, we need (w^T)x + b to be a large negative number. Moreover, if,

$$y_i((w^T)x_i + b) > 0 \tag{16}$$

The functional margin = W T X + b which is the equation of the hyper plane used for linear separation. The geometrical margin is equal to1/||W| |. And the constant in this case is equal to 1. To separate the data non-linearly, a dual optimization form and the Kernel trick is used.

Decision Tree

A decision tree may be a tree within which every branch node represents an alternative between a variety of alternatives and every leaf node represents a choice.

It is a sort of supervised learning classifier that is largely utilized in classification issues and works for each categorical and continuous input and output variables. It's one in all the foremost wide used and sensible ways for inductive illation.

Entropy:

Entropy is defined as the measure of the uncertainty a couple of supply of messages. It provides the degree of disorganization in our information.

$$H(S) = -\sum p(x)\log p(x) \tag{17}$$

Information Gain:

Information Gain measures the relative changes in entropy with reference to the independent variables.

$$IG(S,A) = H(S) - H(S,A) \tag{18}$$

Where, $IG(S,A)$ is the information gain by applying feature A,

H(S) is the Entropy,

$H(S,A)$ The second term calculates the Entropy after applying the feature A,

P(x) is the probability of event x.

4.4 Step 4: Cross-10 validation for Training and Testing

Finally, We performed 10-fold stratified cross-validation to evaluate each classifier. Here, the dataset was split into 100 nearly equal parts, each part containing the same proportion of instances. In the first experiment, 90 folds were used for training and 10 fold was used for testing. This process was repeated number of times with a different fold as a test set.

4.5 Step 5: Output Comparison

(I) Obtaining Confusion Matrix, ROC

Applying different classifiers confusion matrix and ROC is obtained. The confusion matrix is used to generate True Positive (TP), False Negative (FN), False Positive (FP) and True Negative (TN)

(II)Calculation of Accuracy

The Calculation of Accuracy is obtained for SVM, Logistic Regression, and Decision Tree.

Accuracy is calculated as:

Accuracy = Sum of All Diagonal Elements in Confusion Matrix

$$\text{Accuracy} = ((TP+TN) / (TP+TN+FP+FN)) * 100 \tag{19}$$

5. RESULT ANALYSIS

5.1 Database

The database contains 1000 images collected from 3 different sources i.e. manually captured using high definition digital camera, Online available datasets, and Images used in reference papers. Finally, the database is divided into 5 classes i.e. Fungal Infection, Bacterial Blight, Brown Spot, Leaf Spot and Healthy Leaf.

5.2 Feature Extraction

Contrast	Correlation	Energy	Homogeneity	Mean	S.D.	Entropy	RMS	Variance	Smoothness	ASM	IDM	Class
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0
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[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0
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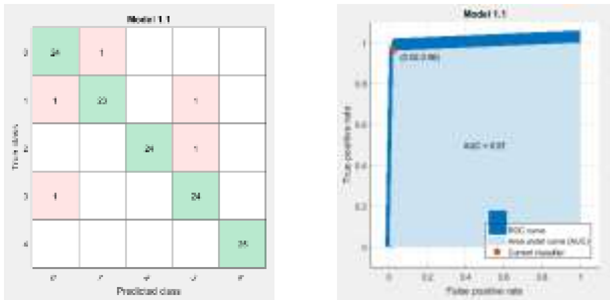
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	255	0

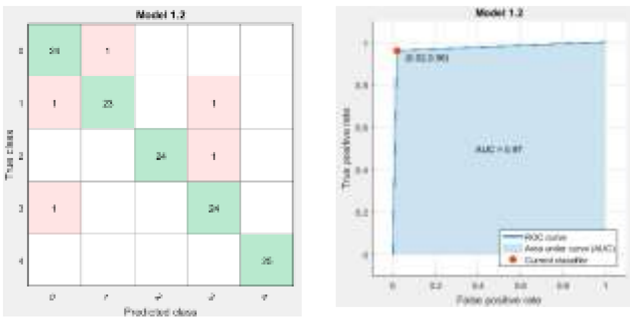
Fig. 3: Feature dataset

Above figure 3 shows the features extracted from different leaves, the feature mainly contains texture, shape and color features of the leaf.

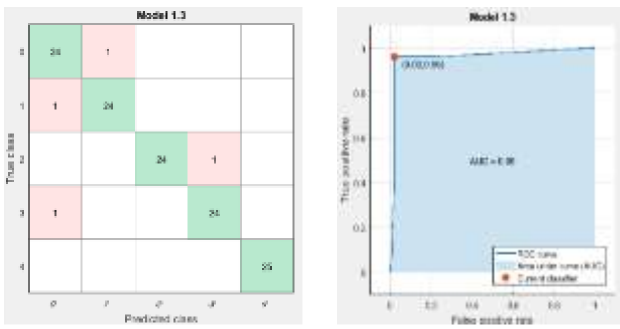
5.3 Confusion matrix and ROC



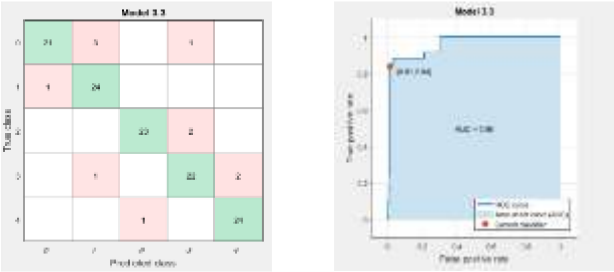
(A)



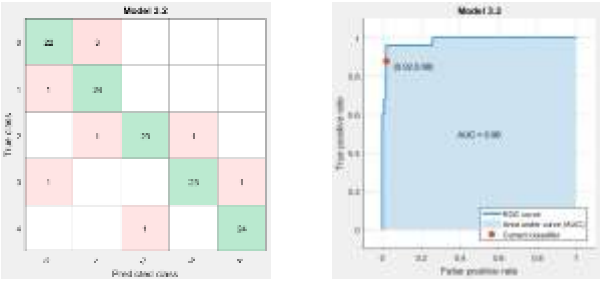
(B)



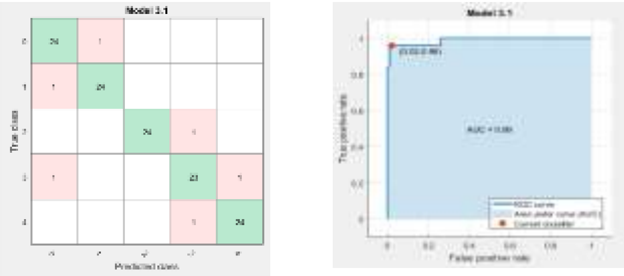
(C)



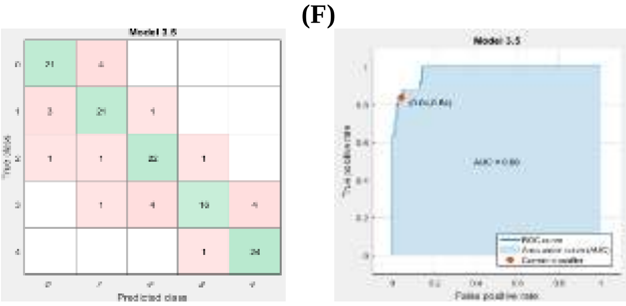
(D)



(E)



(F)



(G)

Fig. 4: (a), (b), (c), (d), (e), (f) and (g) Output showing confusion matrix and ROC of different classifiers

On applying different classification algorithm following confusion matrix and ROC has been obtained which is shown in figure 5.4. Here confusion matrix is used to generate True Positive (TP), False Negative (FN), False Positive (FP) and True Negative (TN) classification results and Receiver Operating Characteristic curve (or ROC curve is a plot of the true positive rate against the false positive rate for the different possible cutpoints of a diagnostic test

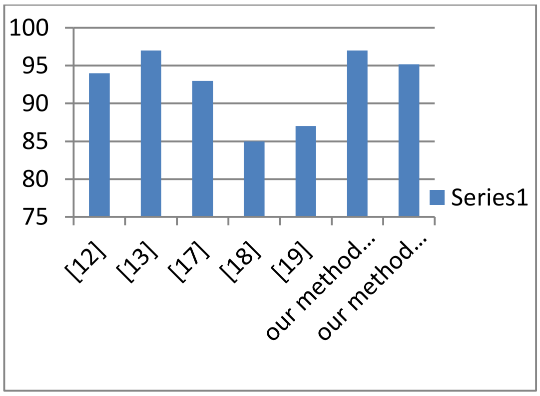


Fig. 5: Accuracy Comparison between the proposed method and previous method

Table 2: Results after applying proposed method with the previous method

Classifier	Accuracy
Complex Tree	96%
Medium Tree	96%
Simple Tree	96.8%
Linear SVM	95.2%
Quadratic SVM	92.8%
Cubic SVM	91.2%
Medium Gaussian SVM	83.2%
[12] Tasneem	94.1%
[13] B. Klatt et al	97%
[14] Shovon Paulinus Rozario	Not Available
[17] Shitala Prasad et al	93%
[18] Rahat Yasir et al	85%
[19] Alham F	87.75%

From figure 5 and table 2 we can easily observe the accuracy of our method, here we obtain the best result on applying simple tree classification where accuracy is 97% approximately. While applying different SVM classifiers the best result obtains for linear SVM classifier where accuracy is 95.2%. The process is repeated several times and the average result is recorded in table 2.

Figure 5 shows the accurate comparison of our method with some existing methods.

6. CONCLUSION

From figure 5 and table 2 we can conclude that-

1. Highest Accuracy we can get using Simple Decision Tree Method i.e. 97%
2. After applying all SVM classifiers we can see that highest accuracy is 95.2% for Linear SVM.
3. In previous methods range of accuracy was 82% to 97% which is less than our method here a range of accuracy for different classifiers is 83.2% to 97% which is better than the previous method.

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