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Energy Based Wavelet and Multilevel Classifier for Efficient Leaf Recognition

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Abstract: ***Computer Aided Leaf Recognition (CALR) is an important field of research that provides tools for forestry, agriculture and pharmacy. Due to the deterioration of environment, rare species of plants are at the brim of extinction. Investigation of rare plants though CALR can subsidize to environmental protection. Generally, CALR system consists of four main steps, such as, enhancement, segmentation, leaf feature extraction and classification. Preprocessing step enhances the leaf image by removing noise, modifying contrast and highlighting boundaries. To separate leaf image from the background, the CALR system uses clustering combined with Energy Based Wavelet (EBW) segmentation. Optimized Principal Component Analysis (OPCA) is used to extracts 28 features falling under five categories, namely, geometry, color, texture, fractal and leaf specialization. A two-level classifier is used to improve the accuracy of recognition process. A refined training set is generated during the first level, and it is used to train the second level classifier. Standard leaf image dataset and real leaf image dataset are used to evaluate the performance of proposed algorithm. This leaf recognition model is effective in discriminating leaves and identifying plant. Hence, taxonomists can use this system to identify precious plant leaves in order to save them.***

Index Terms: ***Computer Aided Leaf Recognition (CALR), Multilevel Classifier, Optimized Principal Component Analysis, Energy Based Wavelet.***

I. INTRODUCTION

Plant Recognition is the identity determination of an unknown plant in correlation with previously collected leaf images. Plant Classification groups known plants into categories based on some relationship using features. This work concentrates on automation identification of plants through leaf recognition. Compared to other methods, leaf image based identification is highly successful and efficient [1]. The main structure of a plant is the leaf which is flexible, thus leads deformations. These structures are readily available for analysis and examination without the need of any experimentation [2]. Automatic recognition of plant species using leaf images is a beneficial goal because of the rapidly diminishing biodiversity and scarcity of qualified taxonomists. Leaf image quality is directly affected by degradation factors like blur, noise and contrast. These factors cause adverse effect on the automatic recognition process.

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A leaf undergoes various biological transitions during the life span. These variations generate multiple representations of the same leaf. A representative database is required for the implementation of a reliable plant identification system using machine learning algorithms. Due to the lack of standard leaf image database, the database use for experimentation is normally constructed by the researchers and it is time consuming and complex.

Sathyabama et al. [3] introduced divergence of Gaussians method to improve the visibility of edges details in leaf images. Chaabane et al. [4] proposed color image segmentation method based on data fusion and fuzzy correlation. In this method, the application of histogram is extended to the fuzzy domain for the proper segmentation of leaf images. Hu et.al [5] proposed a modified Chan-Vese model for segmenting plant leaves based on color lesion. RGB components are used along with K-means clustering was used to generate initial result. Segmentation results reveal higher level of accuracy for plant leaf images. Xiang [6] proposed a pulse coupled neural network (PCNN) using entropy gradient for the segmentation of plant leaf image. For determining connection matrix, the differences in intensity and distance between the center pixel and neighborhood pixels are calculated. The performance is comparatively high for images taken during night. Gao *et al* [7] achieved high accuracy in detection of outer contours of leaf using multiple markers. Marker based watershed method is easy to implement and generate accurate boundary between two regions. This algorithm overcomes complex background problem in leaf image segmenting.

Ning et al. [8] developed an interactive leaf segmentation based on region merging. It requires rough indication of location of the object through strokes (markers). In addition to this, a maximum similarity region merging technique was introduced to manage the merging process. Du et al. [9] merged morphological features such as rectangularity, aspect ratio and eccentricity along with region feature named invariant moments. A median center hyper-sphere classifier was trained using these features. Kumar et al. [10] obtained curvature features from the binary leaf images. A nearest neighborhood classifier with histogram intersection as distance parameter was used for classification. Wang et al [11] adapted the concept of bag of spectral contours and applied to the leaf classification scenario. They combined local coding and pyramid matching for shape representation in the nearest neighborhood classifier.

This paper is systematically organized into four sections. Section I is the introduction, section II illustrates the proposed plant classification method, section III discusses the experimental results and finally conclusion about the paper is given in section IV.

II. METHODOLOGY

The recognition of plant species from leaf image comprise of four major steps, namely, preprocessing, segmentation, feature selection and classification. Each step plays important role in defining the accuracy and overall performance of the identifier. This work focuses on techniques that enhance each step, so that maximum accuracy in plant recognition is obtained.

A. Pre-Processing

Preprocessing use the combination of Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm and DWT coefficients to enhance the contrast of input leaf images. DWT coefficients provide an idea about edge and non-edge pixels in the image. A sigmoid function is used perform edge enhancement. CLAHE [12] is a type of high pass filter in which low frequency information is attenuated to improve the contrast and edge sharpness of an image. CLAHE is a special modification of histogram equalization method. The slope of the transformation function is directly proportional to the Cumulative Distribution Function (CDF). Before computing CDF, the histogram is clipped and the amplification is limited. Thus the slopes of CDF and transformation function are reduced. Clip limit is the value at which the histogram is clipped and it depends on the size of neighborhood region. Regions that exceed the clip limit are redistributed equally among the histogram. The redistributed adaptive histogram is illustrated in Fig. 1.

$$I_{out} = \left[I_{\max} - I_{\min}\right] \times F_k\left(I_{in}\right) + I_{\min} \tag{1}$$

where, I_{max} and I_{min} be the maximum and minimum admissible intensities respectively. I_{in} is the input intensity and I_{out} is the output intensity. F_k (I_{in}) is the Cumulative distribution Function (CDF) of input intensities.

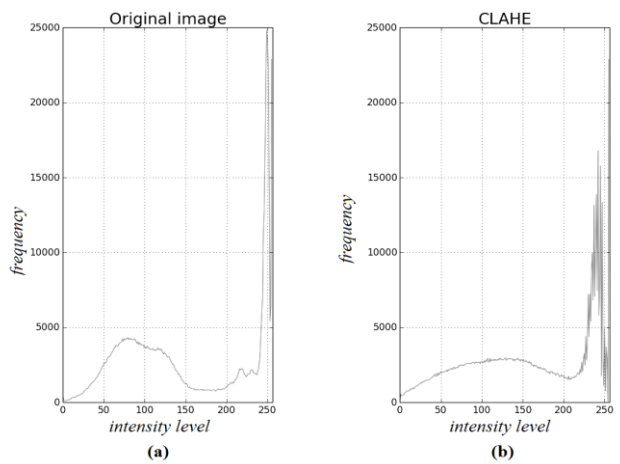

Fig. 1. Distribution of intensities (a) Original Image, (b) Image Enhanced Using CLAHE

Edge enhancement consists of two steps that are applied only on HL, LH and HH sub-bands. Initially edges are classified into strong, weak and reverberation edges. Then edge enhancement is applied on the weaker edges. Let b_1, b_2,……b_n be the set of features extracted from a particular leaf image. From this set, the maximum (max), minimum (min) mean are calculated. Quantization interval on right (q_r) and quantization interval on left (q_l) are calculated using Eqn.(2) with 6 quantization levels.

$$q_l = \frac{2(\mu - \min)}{6}; \quad q_r = \frac{2(\max - \mu)}{6} \tag{2}$$

After calculating all the above values, weaker edges are enhanced with the help of sigmoid function given in Eqn.(3)

$$y(x) = \frac{L}{1 + e^{-\left(\frac{x - m - \Delta x}{a}\right)}} + \Delta x \tag{3}$$

where, L is taken as 255, m = 128 (for 8 bit image), x is the edge pixel, $-127 \le x < +128$ and parameter 'a' is referred to as frequency of change.

This process is repeated over all the obtained coefficients. The coefficients having high intensity and high correlation coefficients are considered as strong edges. The coefficients with significant change in correlation and variance are considered as weak edges.

B. Segmentation

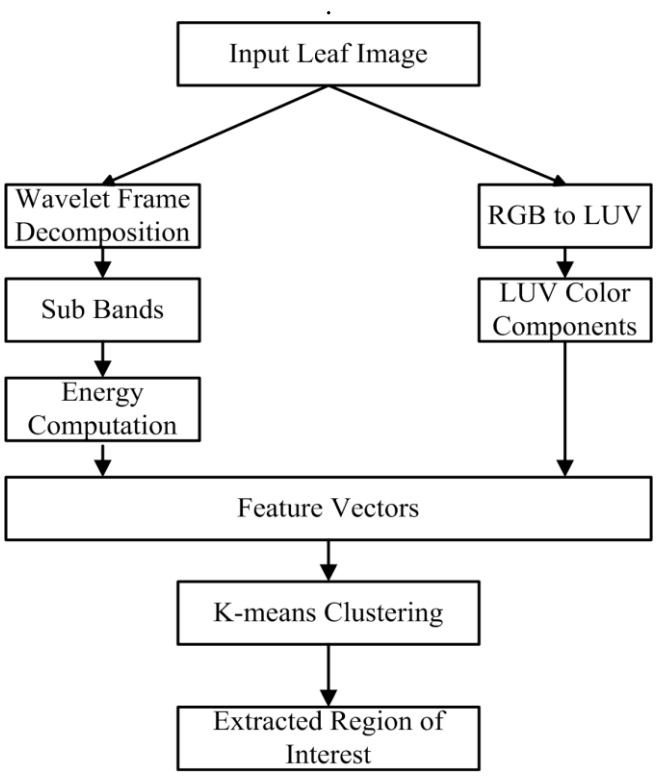

Fig. 2 Energy Based Wavelet Segmentation Method

The proposed segmentation algorithm uses texture features and color features to generate a feature vector. These feature vectors are then segmented using K-means clustering algorithm. During the extraction of texture features, Wavelet Frame decomposition (WFD) technique is used. L*u*v* model is used to extract color features. The proposed segmentation method is illustrated in Fig.2.

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Initial step uses Wavelet Frame Decomposition (WFD) for single level decomposition of the input image into four sub bands as shown in Fig.3. Here L and H represents low pass and high pass filters respectively. A texture is defined by a group of median energy values that are estimated using local window placed at the output of the filter bank. Energy can be calculated using the square of wavelet coefficients (LL, LH, HL, and HH). A pixel in the sub band region can be categorized into four different texture types based on the orientation [13]. If there is insufficient energy in any orientation it is called smooth edge. for vertical edges, dominant energy is concentrated in the vertical orientation. Horizontal edges have dominant energy in horizontal direction. Edges with zero dominant orientation are called complex edge.

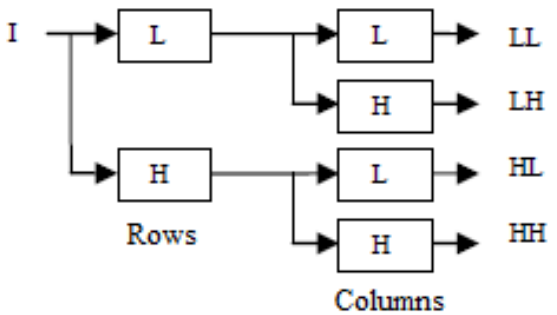

Fig.3. Wavelet Frame Decomposition

*L*u*v* color model is a reversible nonlinear color space. The information corresponding to coloring is centered at white point of the model. The non-linear equation for *L* is expected to imitate logarithmic response of human eye. The *L*, *u*, *v* components are given by,

$$L^* = \begin{cases} 116\left(\frac{Y}{Y_n}\right)^{\frac{1}{3}} - 16 & if\ \frac{Y}{Y_n} > 0.008856 \\ 903.3\left(\frac{Y}{Y_n}\right) & if\ \frac{Y}{Y_n} \le 0.008856 \end{cases} \quad (4)$$

$$u^* = 13(L^*)(u' - u'_n) \quad (5)$$

$$v^* = 13(L^*)(v' - v'_n) \quad (6)$$

Next step is to create a Feature Space vector. In this step generates the feature all pixels will be represented by a p-dimensional feature vector, which consist of spatial (x, y), color (L*u*v) and texture (vertical, smooth, , horizontal and complex) information. The converted low dimensional group of pixels from feature vectors is used as input to the K-means algorithm. K Means algorithm generates a distinct number of unrelated clusters. The number of clusters (K) remains constant during the process and the generated clusters do not overlap. A particular element in a cluster is closer to its cluster center in terms of Euclidean distance.

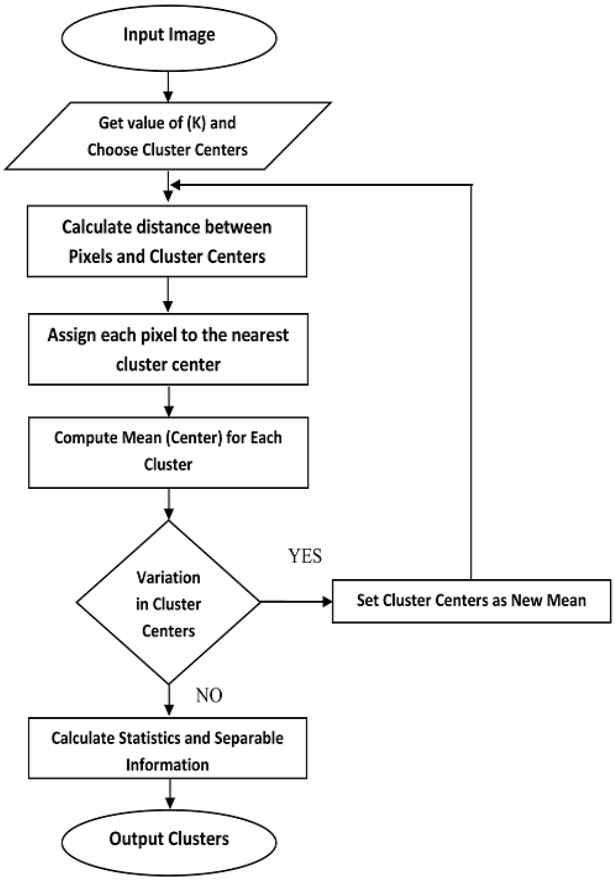

Fig. 4 Flow chart of K-means Clustering method

Cluster centers (means) are updated before (n+ 1)th iteration. The Euclidean distance between cluster intensities and cluster center are calculated. Sum of square of these distances are calculated for the cluster $C_j(n)$ and it is minimized. New mean intensity for cluster $C_j(n)$ is given by,

$$\mu_j(n+1) = \frac{1}{N_j} \sum_{I \in C_j(n)} I \quad (7)$$

N_j = number of intensities present in the cluster of pre-processed MR image. This algorithm converges when Eqn.(8) is satisfied and cluster mean updating process will be terminated.

$$\mu_j(n+1) = \mu_j(n) \qquad \forall j = 1, 2, 3, ...K \quad (8)$$

After the convergence of cluster mean recalculation, image intensities are reorganized among the clusters so that the output contains pixel class labels from 1 to K.

C. Feature Extraction

Feature Extraction transforms image pixels into representations that allow comparisons between leaf images by obtaining leaf properties. Feature Selection finds appropriate features suitable for classification from the extracted features. The main purpose of feature selection is the improvement of prediction process. It also increase the sped of classification process by providing a better understanding about the background process.Gray Level Co-occurrence Matrix (GLCM) is used to calculate the spatial dependency of different gray levels in an MR image [14].

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In GLCM the total number of columns and rows are exactly same as that of the number of gray levels in the segmented image. GLCM is created in 4 spatial directions (0°, 45°, 90° and 135°). Another matrix is developed using the mean of preceding matrices. Let the Co-occurrence matrix be $P_{i,j}$ and the size of the matrix is N x N. The elements of GLCM (i,j) denotes the frequency by which pixels having gray level i are spatially related to pixels with gray level j.

Construction of GLCM from a gray scale image is illustrated in Fig.5. GLCM represents the relation between reference pixel (i) and neighbour pixel (j) in various orientation. Here the relation between pixels is calculated horizontally towards the right (0°). Initially, the value of each elements in GLCM (i,j) are zero. The value of each element is updated as per the occurrence of pixels together. Haralick Texture features calculated using GLCM are Contrast, Energy, Entropy, Variance and Mean.

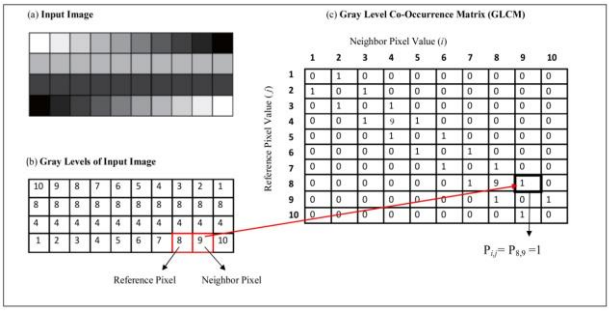

Fig.5 Construction of GLCM from a gray scale image.

Contrast can be described as the variation in intensities that helps an object in an image to be distinguishable. Human eye is sensitive to contrast so that the objects are identified. Maximum range of contrast in an image is called dynamic range.

$$CON = \sum_{i,j=0}^{N-1} P_{i,j} \left(i-j\right)^2 \tag{9}$$

Energy or Angular Second Moment (ASM) is the measure of uniformity. The value of energy will be high, if the image is homogeneous. It measures the number of times a particular pixel repeats and the value will be equal to 1, if the image is constant.

$$E = \sum_{i,j=0}^{N-1} P_{i,j}^2 \tag{10}$$

Entropy is defined as the randomness of intensity levels in an image. The value of entropy becomes high when all the elements of the matrix are equal.

$$H = \sum_{i,j=0}^{N-1} P_{i,j} \left(-\ln P_{i,j}\right) \tag{11}$$

GLCM Mean can be described as the average value of all the elements in GLCM. It is used to measure the center of the pixel intensities.

$$\mu = \sum_{i,j=0}^{N-1} i\left(P_{i,j}\right) \tag{12}$$

Variance is the statistical measure of diverseness and it is highly related to the standard deviation of the image. Variance raises when the value gray level differs from GLCM mean.

$$V = \sum_{i,j=0}^{N-1} P_{i,j} \left(i-\mu\right)^2 \tag{13}$$

D. Classification

A classifier involving combination of two machine learning techniques is designed for efficient recognition of leaves. First level classifier aims to boost the performance of second level classifier. First classifier is used to train the network, and the second classifier uses the preprocessed data to perform recognition task. First classifier identifies failed classification results and refines the feature set. The advantages of this algorithm are accuracy, reduced error rate and reduced time complexity. Here, Back Propagation Neural Network (BPNN) is used as the first classifier and Support Vector Machine (SVM) is used as second classifier.

BPNN is a generalization of the Least Mean Square (LMS) algorithm. It uses mean square error as the performance index. When an input is applied to the network, the output (a) is compared with the target value (t). The algorithm then adjusts the weights (w) so that, the mean square error is minimized. Error in the network is defined as,

$$e = [t-a] \tag{14}$$

The expectation of mean square error is defined as,

$$f(x) = E[e^T e] = E[(t-a)^T (t-a)] \tag{15}$$

The expectation of the squared error at iteration k is given by,

$$f(x) = E[(t(k)-a(k))^T (t(k)-a(k))] \tag{16}$$

BPNN adjusts weights and biases as follows,

$$w_{i,j}^M(\mathrm{k}+1) = w_{i,j}^M(\mathrm{k}) - \alpha \frac{\partial f}{\partial w_{i,j}^M} \tag{17}$$

$$b_i^M(k+1) = b_i^M(k) - \alpha \frac{\partial f}{\partial b_i^M} \tag{18}$$

where, α is the learning rate.

This shows that, weight at any particular iteration is equal to the weight at previous iteration adjusted by some fraction, α, of the sensitivity of the error to that weight. In other words, the weights at iteration are adjusted in a way that it reduces the error at the previous iteration. BPNN network consists of mainly three processes. First, the input is propagated forward through the network to compute the sensitivity. Beginning from the final layer, these sensitivities are propagated in the backward direction through the network. Finally, using these sensitivities, weights and biases are updated. The model of BPPN is illustrated in Fig.6.

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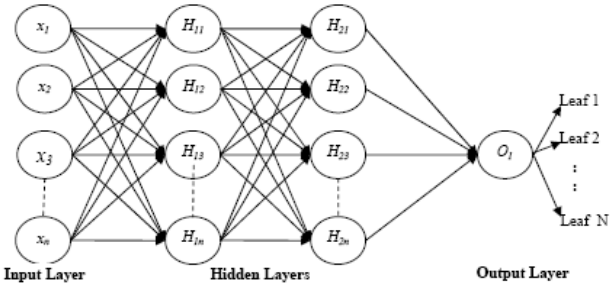

Fig.6. BPNN Architecture

A Support Vector Machine (SVM) is a supervised learning method that involves analysis of data and identifies patterns that are used for classification. Consider a binary classification case in which $((x_1, y_1) \ldots (x_n, y_n))$ is the training dataset where xi are the feature vectors and $y_i \in (-1, +1)$ be two labels that can be assigned to each observation. SVM builds an optimum hyper plane that effectively separates two classes with maximum margin by minimizing the objective function. A linearly separable set of 2D-points belonging to two classes is shown in Fig, 7. Here multiple straight lines exist to separate the data points into two groups. Deciding the optimal divider is an intuitive criterion.

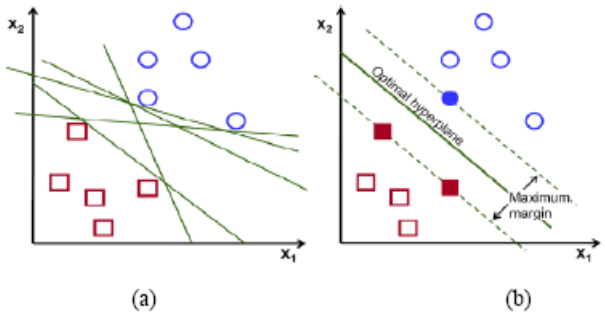

Fig.7. SVM Hyper-planes (a) Set of all Hyper-planes separating two classes, (b) Optimal Hyper-plane

The hyper plane is defined as,

$$f(x) = \beta_0 + \beta^T x \tag{19}$$

where, β is the weight and β_0 is the bias. Optimal hyper plane is represented in different ways by scaling of β and β_0.The representations of all possible hyper planes, can be defined using Eqn. (20),

$$\beta_0 + \beta^T x = 1 \tag{20}$$

where, x represents the training samples which are closer to the hyper plane. These closer samples are called support vectors and this type of representation is called canonical hyper plane. The distance between given point x and hyper plane $\{\beta, \beta_0\}$ is calculated using Eqn. (21).

$$d = \frac{\beta_0 + \beta^T x}{\|\beta\|} \tag{21}$$

For a canonical hyper plane, numerator is 1 and the distance to support vectors is given by Eqn. (22).

$$d_{sv} = \frac{\|\beta_0 + \beta^T x\|}{\|\beta\|} = \frac{1}{\|\beta\|} \tag{22}$$

III. RESULTS AND DISCUSSION

The software used to implement the proposed plant recognition system is MATLAB 2017b. We used image processing toolbox and machine learning toolbox for the experimental purpose. The first stage in this plant identification, using leaf recognition is leaf database creation. The leaf images are obtained by using scanners and digital cameras. Since classification is a complex procedure, which requires high memory usage, a lossy compression (JPEG) is used. Sample leaf images obtained through scanner is shown in Fig.8

Fig. 8. Sample Leaf Images

The proposed has the fastest enhancement module to improve the quality of the leaf image by wavelet. This algorithm uses CLAHE and sigmoid function for the enhancement task. Visual comparison between the original image and the enhance image is given in Fig.9. It is then confirmed that this enhancement procedure is successful and have effect in improving the quality of the image.

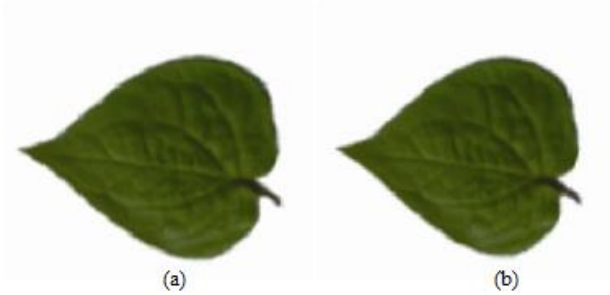

Fig.9. Enhancement Results (a) Original Image (b) Enhanced Image

Energy based wavelets and K-means clustering is introduced to improve the performance of the proposed plant recognition system. Speed of the proposed algorithm is increased while comparing with existing wavelet based segmentation algorithms. Average time required for existing segmentation algorithm is 10.38 seconds to segment the leaf image. Proposed algorithm took only 9.57 seconds to segment the leaf from its background. This shows that the enhanced segmentation algorithm is highly efficient in the segmentation scenario. The segmentation results are shown in Fig.10.

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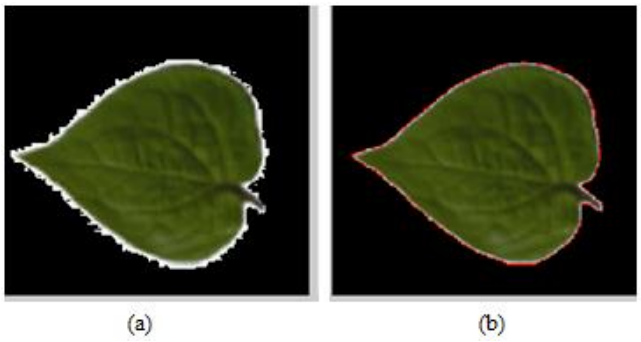

Fig.10. Segmentation Results (a) Wavelet Output (b) Segmented Leaf Image

Haralick features are calculated from the GLCM to create feature vector for ANN classifier. 10 leaf images are randomly selected from the dataset for extracting texture features. The value of Haralick features computed is shown in Table 1.

Table 1. Extracted GLCM Features

Input	Contrast	Energy	Entropy	Mean	Variance
Image1	87.85	0.9657	0.0683	3.7180	718.68
Image2	78.17	0.9832	0.2822	1.7571	225.61
Image3	175.14	0.9657	0.7754	3.8171	74.76
Image4	54.47	0.9821	0.0476	2.1478	251.82
Image5	95.72	0.9751	0.0477	2.6064	413.76
Image6	242.37	0.9469	0.2681	8.8525	1865.15
Image7	252.84	0.9429	0.1629	7.8214	1618.57
Image8	236.44	0.9837	0.0742	4.0788	781.45
Image9	339.22	0.9858	0.3278	13.817	2773.58
Image10	188.78	0.9568	0.3574	7.7547	1574.75

200 images from the leaf dataset are used for performing classification experiment. 100 leaf images are employed for training ANN. Then, another 100 leaf images are applied for testing the multilevel classifier. The classification performance of our system is evaluated using the parameter, recognition rate (R). The Equation for recognition rate (R) is given in the equation (23).

$$R = \frac{No : of\ Leaves\ Identified\ Correctly}{Total\ No : of\ Leaves} \times 100$$

(23)

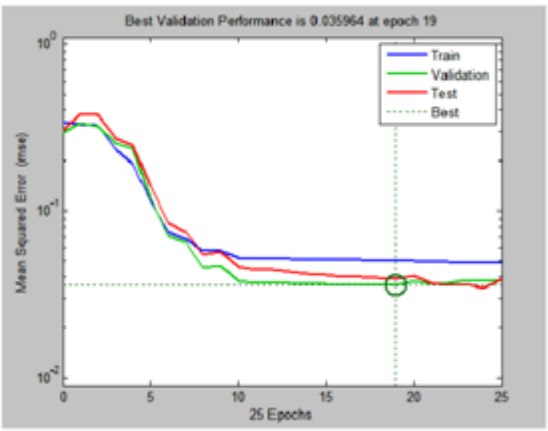

Fig.11. Performance Plot

The classifier performance depends on the MSE values during training. The dataset with 100 images provided minimum value for MSE (0.035964) at 19th epoch. As shown in the performance plot, the training curve, validation curve and testing curve converges at a point. The time required for convergence is 2 seconds. The performance plot is given in Fig. (12)

Table 2 reveals the recognition rate attained by various classification algorithms for different datasets of leaf images. From the results, it is conspicuous that the proposed BPNN-SVM model provided improved results while comparing with traditional BPNN models.

Table 2 Recognition Rate for Various Classifiers

Method	Recognition Rate (%)			
	Dataset 1	Dataset 2	Dataset 3	Dataset 4
BPNN	87.85	83.45	88.09	90.34
BPNN-BPNN	93.23	91.02	91.73	89.75
WNN-BPNN	95.64	90.13	92.89	94.83
BPNN-SVM (Proposed)	97.34	96.43	94.56	98.14

Comparison between different models reveals that BPNN in level 1 produced the best recognition rate when compared to other methods. Proposed classifier provided maximum recognition rate for dataset 4 (98.14 %) and minimum recognition rate for dataset 3 (94.56 %). The average recognition rate of the plant recognition system is 96.61 %. Fig.12 provides a comparison between the performances of various machine learning algorithms using different leaf datasets.

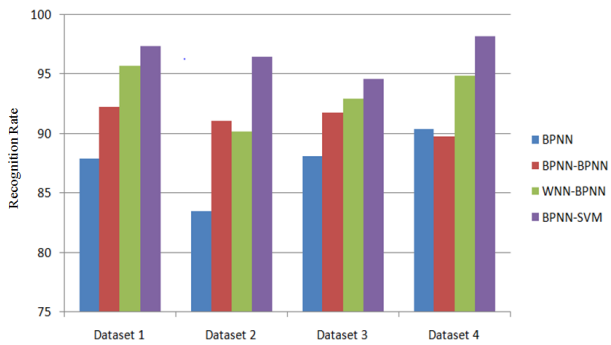

Fig.12.Classifier Performance Comparison

IV. CONCLUSION

Use either Leaf recognition for the identification of plant has a demand for efficient and fast classification algorithms. This led to the development of various techniques which have reformed the field of automatic plant classification. Availability of huge number of classifiers has given dilemma in deciding the optimum classifier for a precise application. An enhancement system based on CLAHE and sigmoid function is proposed to enhance the quality of leaf image. The texture features were extracted using GLCM and these features were used to train the classifier. The classifier consists of two levels in which one level is used for training and the other is used for testing.

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First level classifier is designed using BPNN and the second level classifier is designed using SVM. Recognition rate and time taken for the recognition of plant is also analyzed to measure the performance of the proposed system. Based on the experimental results, it can be concluded that the proposed system is capable of providing best recognition rate in a shorter period of time. The peak recognition rate obtained is 98.14 %. Future works aims to identify leaves that are dry, occulted and wrinkled. We plan to incorporate parallel processing to improve the speed of the recognition process.

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