DESIGNING AN AUTOMATED SYSTEM FOR PLANT LEAF RECOGNITION

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ABSTRACT

This paper proposes an automated system for recognizing plant species based on leaf images. Plant leaf images corresponding to three plant types, are analyzed using three different shape modelling techniques, the first two based on the Moments-Invariant (M-I) model and the Centroid-Radii (C-R) model and the third based on a proposed technique of Binary-Superposition (B-S). For the M-I model the first four central normalized moments have been considered. For the C-R model an edge detector has been used to identify the boundary of the leaf shape and 36 radii at 10 degree angular separation have been used to build the shape vector. The proposed approach consists of comparing binary versions of the leaf images through superposition and using the sum of non-zero pixel values of the resultant as the feature vector. The data set for experimentations consists of 180 images divided into training and testing sets and comparison between them is done using Manhattan, Euclidean and intersection norms. Accuracies obtained using the proposed technique is seen to be an improvement over the M-I and C-R based techniques, and comparable to the best figures reported in extant literature.

KEYWORDS: Plant recognition, Moment Invariants, Centroid Radii, Binary Superposition, Computer Vision

I.   INTRODUCTION

It is well known that plants play a crucial role in preserving earth's ecology and environment by maintaining a healthy atmosphere and providing sustenance and shelter to innumerable insect and animal species. Plants are also important for their medicinal properties, as alternative energy sources like bio-fuel and for meeting our various domestic requirements like timber, clothing, food and cosmetics. Building a plant database for quick and efficient classification and recognition of various flora diversities is an important step towards their conservation and preservation. This is more important as many types of plants are now at the brink of extinction. In recent times computer vision methodologies and pattern recognition techniques have been successfully applied towards automated systems of plant cataloguing. From this perspective the current paper proposes the design of a system which uses shape recognition techniques to recognize and catalogue plants based on the shape of their leaves, extracted from digital images. The organization of the paper is as follows : section 2 discusses an overview of related works, section 3 outlines the proposed approach with discussions on feature computation and classification schemes, section 4 provides details of the dataset and experimental results obtained, and section 5 brings up the overall conclusion and scopes for future research.

II.   PREVIOUS WORKS

Many methodologies have been proposed to analyze plant leaves in an automated fashion. A large percentage of such works utilize shape recognition techniques to model and represent the contour shapes of leaves, however additionally, color and texture of leaves have also been taken into consideration to improve recognition accuracies. One of the earliest works [1] employs geometrical parameters like area, perimeter, maximum length, maximum width, elongation to differentiate between four types of rice grains, with accuracies around 95%. Use of statistical discriminant analysis

along with color based clustering and neural networks have been used in [2] for classification of a flowered plant and a cactus plant. In [3] the authors use the Curvature Scale Space (CSS) technique and k-NN classifiers to classify chrysanthemum leaves. Both color and geometrical features have been used in [4] to detect weeds in crop fields employing k-NN classifiers. In [5] the authors propose a hierarchical technique of representing leaf shapes by first their polygonal approximations and then introducing more and more local details in subsequent steps. Fuzzy logic decision making has been utilized in [6] to detect weeds in an agricultural field. In [7] the authors propose a two step approach of using a shape characterization function called centroid-contour distance curve and the object eccentricity for leaf image retrieval. The centroid-contour distance (CCD) curve and eccentricity along with an angle code histogram (ACH) have been used in [8] for plant recognition. The effectiveness of using fractal dimensions in describing leaf shapes has been explored in [9]. In contrast to contour-based methods, region-based shape recognition techniques have been used in [10] for leaf image classification. Wang et al. [11] describes a method based on fuzzy integral for leaf image retrieval. In [12] the authors used an improved CSS method and applied it to leaf classification with self intersection. Elliptic Fourier harmonic functions have been used to recognize leaf shapes in [13] along with principal component analysis for selecting the best Fourier coefficients. In [14] the authors propose a leaf image retrieval scheme based on leaf venation, represented using points selected by the curvature scale scope corner detection method on the venation image and categorized by calculating the density of feature points using non parametric estimation density. In [15] the authors propose a new classification method based on hypersphere classifier based on digital morphological feature. In [16] 12 leaf features are extracted and orthogonalized into 5 principal variables which consist of the input vector to a neural network (NN), trained by 1800 leaves to classify 32 kinds of plants. NNs have also been used in [17] to classify plants based on parameters like size, radius, perimeter, solidity and eccentricity of the leaf shape. In [18] shape representation is done using a new contour descriptor based on the curvature of the leaf contour. Wavelet and fractal based features have been used in [19] to model the uneven shapes of leaves. Texture features along with shape identifiers have been used in [20] to improve recognition accuracies. Other techniques like Zernike moments and Polar Fourier Transform have been proposed in [21] for modeling leaf structures. In [22] authors propose a thresholding method and H-maxima transformation based method to extract the leaf veins for vein pattern classification. In [23] authors propose an approach for combining global shape descriptors with local curvature-based features, for classifying leaf shapes of nearly 50 tree species. Finally in [24] a combination of all image features viz. color, texture and shape, have been used for leaf image retrieval.

III.   SHAPE RECOGNITION TECHNIQUES

In this section we review two existing methods of shape recognition which have been used for plant classification, namely Moments-Invariant (M-I) and Centroid-Radii (C-R) and compare it with our proposed technique with respect to their recognition accuracies.

3.1. Moments Invariant (M-I) Approach: An Overview

M. K. Hu [25] proposes 7 moment features that can be used to describe shapes which are invariant to rotation, translation and scaling. For a digital image, the moment of a pixel $P(x, y)$ at location (x, y) is defined as the product of the pixel value with its coordinate distances i.e. $m = x.y.P(x, y)$. The moment of the entire image is the summation of the moments of all its pixels. More generally the moment of order (p, q) of an image $I(x, y)$ is given by

$$m_{pq} = \sum_x \sum_y [x^p y^q I(x, y)] \tag{1}$$

Based on the values of p and q the following are defined:

$$m_{00} = \sum_x \sum_y [x^0 y^0 . I(x,y)] = \sum_x \sum_y [I(x,y)]$$

$$m_{10} = \sum_x \sum_y [x^1 y^0 . I(x,y)] = \sum_x \sum_y [x.I(x,y)]$$

$$m_{01} = \sum_x \sum_y [x^0 y^1 . I(x,y)] = \sum_x \sum_y [y.I(x,y)]$$

$$m_{11} = \sum_x \sum_y [x^1 y^1 . I(x,y)] = \sum_x \sum_y [xy.I(x,y)]$$

$$m_{20} = \sum_x \sum_y [x^2 y^0 . I(x,y)] = \sum_x \sum_y [x^2.I(x,y)] \qquad (2)$$

$$m_{02} = \sum_x \sum_y [x^0 y^2 . I(x,y)] = \sum_x \sum_y [y^2.I(x,y)]$$

$$m_{21} = \sum_x \sum_y [x^2 y^1 . I(x,y)] = \sum_x \sum_y [x^2 y.I(x,y)]$$

$$m_{12} = \sum_x \sum_y [x^1 y^2 . I(x,y)] = \sum_x \sum_y [xy^2.I(x,y)]$$

$$m_{30} = \sum_x \sum_y [x^3 y^0 . I(x,y)] = \sum_x \sum_y [x^3.I(x,y)]$$

$$m_{03} = \sum_x \sum_y [x^0 y^3 . I(x,y)] = \sum_x \sum_y [y^3.I(x,y)]$$

The first four Hu invariant moments which are invariant to rotation are defined as follows:

$$\varphi_1 = m_{20} + m_{02}$$
$$\varphi_2 = (m_{20} - m_{02})^2 + (2m_{11})^2$$
$$\varphi_3 = (m_{30} - 3m_{12})^2 + (3m_{21} - m_{03})^2 \qquad (3)$$
$$\varphi_4 = (m_{30} + m_{12})^2 + (m_{21} + m_{03})^2$$

To make the moments invariant to translation the image is shifted such that its centroid coincides with the origin of the coordinate system. The centroid of the image in terms of the moments is given by:

$$x_c = \frac{m_{10}}{m_{00}}$$

$$y_c = \frac{m_{01}}{m_{00}} \qquad (4)$$

Then the central moments are defined as follows:

$$\mu_{pq} = \sum_x \sum_y [(x - x_c)^p (y - y_c)^q I(x,y)] \qquad (5)$$

To compute Hu moments using central moments the φ terms in equation (3) need to be replaced by μ terms. It can be verified that $\mu_{00} = m_{00}$, $\mu_{10} = 0 = \mu_{01}$.

To make the moments invariant to scaling the moments are normalized by dividing by a power of μ_{00}. The *normalized central moments* are defined as below :

$$M_{pq} = \frac{\mu_{pq}}{(\mu_{00})^\omega}, \text{ where } \omega = 1 + \frac{p+q}{2} \qquad (6)$$

3.2. Centroid-Radii (C-R) Approach: An Overview

In [26] K. L. Tan et al. proposes the centroid-radii model for estimating shapes of objects in images. A shape is represented by an area of black on a white background. Each pixel is represented by its color (black or white) and its *x-y* co-ordinates on the canvas. The boundary of a shape consists of a series of boundary points. A *boundary point* is a black pixel with at least one white pixel as its

neighbor. Let (x_i, y_i), $i = 1,...,n$ represent the shape having n boundary points. The *centroid* is located at the position C(X_C, Y_C) which are respectively, the average of the *x* and *y* co-ordinates for all black pixels :

$$X_C = \frac{\sum_{i=1}^{n} x_i}{n}$$

$$Y_C = \frac{\sum_{i=1}^{n} y_i}{n}$$

(7)

A *radius* is a straight line joining the centroid to a boundary point. In the centroid-radii model, lengths of a shape's radii from its centroid to the boundary are captured at regular intervals as the shape's descriptor using the Euclidean distance. More formally, let θ be the measure of the angle (in degrees) between radii (Figure 1). Then, the number of angular intervals is given by $k = 360/\theta$. The length L_i of the *i*-th radius formed by joining the centroid C (X_C, Y_C) to the *i*-th sample point $s_i(x_i, y_i)$ is given by:

$$L_i = \sqrt{(X_C - x_i)^2 + (Y_C - y_i)^2}$$

(8)

All radii lengths are normalized by dividing with the longest radius length from the set of radii lengths extracted. Let the individual radii lengths be $L_1, L_2, L_3,...,L_k$ where *k* is total number of radii drawn at an angular separation of θ. If the maximum radius length is L_{max} then the normalized radii lengths are given by:

$$\ell_i = \frac{L_i}{L_{max}}, \quad i = 1,...,k$$

(9)

Furthermore, without loss of generality, suppose that the intervals are taken clockwise starting from the *x*-axis direction (0°). Then, the shape descriptor can be represented as a vector consisting of an ordered sequence of normalized radii lengths:

$$S = \{\ell_0, \ell_\theta, \ell_{2\theta},..., \ell_{(k-1)\theta}\}$$

(10)

With sufficient number of radii, dissimilar shapes can be differentiated from each other.
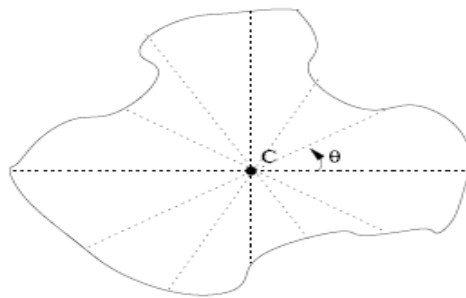

Figure 1. Centroid-radii approach

3.3. Proposed Approach: Binary Superposition (B-S)

The proposed approach is conceptually simpler than either of the above two techniques but provides comparatively better recognition accuracies. The leaf images are converted to binary images by thresholding with an appropriate value. Two binary shape images S_1 and S_2 are superimposed on each other and a resultant R is computed using logical AND operation between them.

$$R = S_1 \bigcap S_2$$

(11)

For the binary resultant image, all the non-zero pixel values are summed up. This sum is used as the feature value for discrimination. A large value of the sum would indicate high similarity between the images while a low sum value indicates low similarity. A test image is compared to all the training samples of each class and the mean resultant for each class is computed. The test image is classified to the class for which the mean resultant is maximum. Figure 2 illustrates that when two images of different classes are superimposed then the resultant image contains less non-zero pixels than for images belonging to the same class.
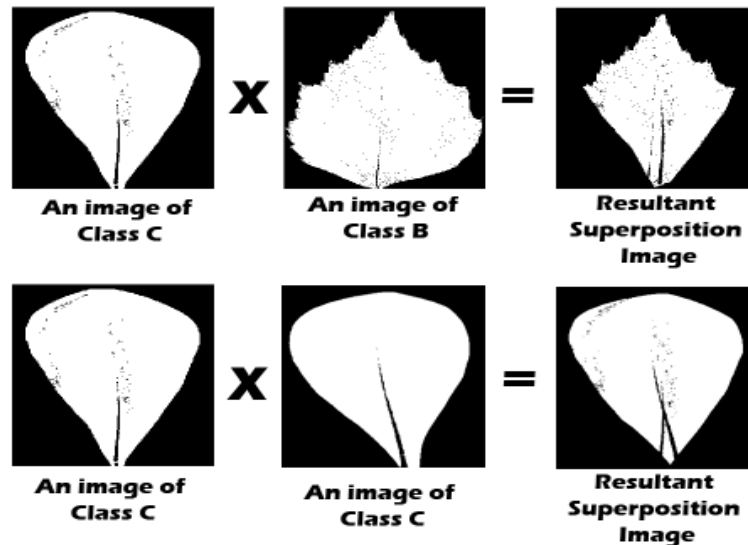
Figure 2. Resultant images after binary superposition

IV. EXPERIMENTATIONS AND RESULTS

4.1. Dataset

Experimentations are performed by using 180 leaf images from the Plantscan database [27]. The dataset is divided into 3 classes: A (Arbutus unedo), B (Betula pendula Roth), C (Pittosporum_tobira) each consisting of 60 images. Each image is 350 by 350 pixels in dimensions and in JPEG format. A total of 120 images are used as the Training set (T) and the remaining 120 images as the Testing set (S). The legends used in this work are as follows : AT, BT, CT denotes the training set while AS, BS, CS denotes the testing set, corresponding to the three classes. Sample images of each class are shown below in Figure. 3.

Figure 3. Samples of leaf images belonging to the three classes

4.2. M-I based computations

The first four moments M_1 to M_4 of each image of the training and testing sets are computed as per equation (6). Feature values are first considered individually and corresponding results are tabulated below. Comparisons between training and testing sets are done using Manhattan distances (L_1). Results are summarized below in Table 1. The last column depicts the overall percentage accuracy value.

Table 1 : Percentage accuracy using M-I approach

F	A	B	C	O
M_1	96	100	47	81
M_2	60	37	90	62
M_3	53	100	37	63
M_4	77	40	70	62

Best results of 81% are obtained using M_1. Corresponding plots depicting the variation of the M_1 feature values for the three classes over the training and testing datasets are shown below in Figure 4.
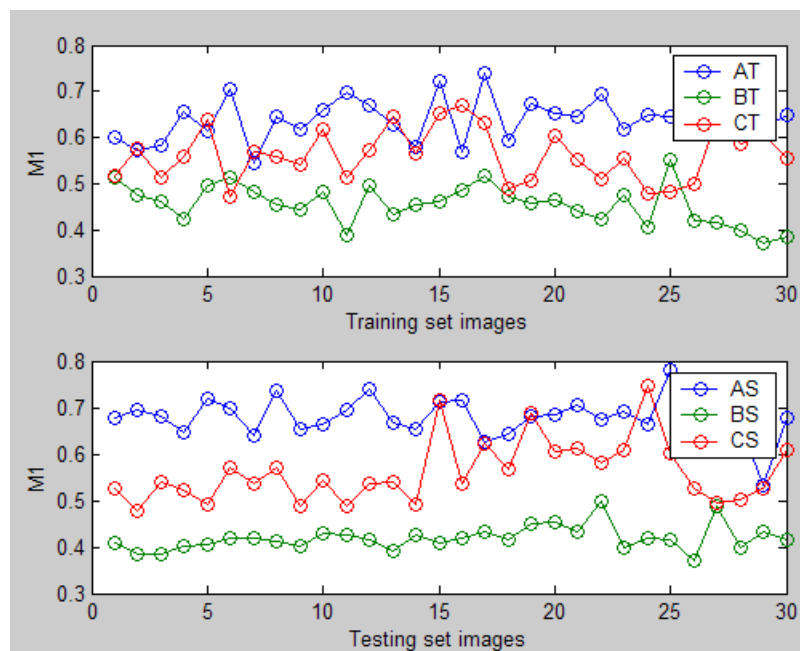

Figure 4. Variation of M_1 for Training and Testing set images

4.3. C-R based computations

Each image is converted to binary form and the Canny edge detector is used to identify its contour. Its centroid is computed from the average of its edge pixels. Corresponding to each edge pixel the angle it subtends at the centroid is calculated and stored in an array along with its *x*- and *y*- coordinate values. From the array 36 coordinate values of edge pixels which join the centroid at 10 degree intervals from 0 to 359 degrees are identified. The radii length of joining these 36 points with the centroid is calculated using the Euclidean distance and the radii lengths are normalized to the range [0, 1]. For each leaf image 36 such normalized lengths are stored in an ordered sequence as per equation (10). Figure 5 shows a visual representation of a leaf image, the edge detected version, the location of the centroid and edge pixels, and the normalized radii vector.
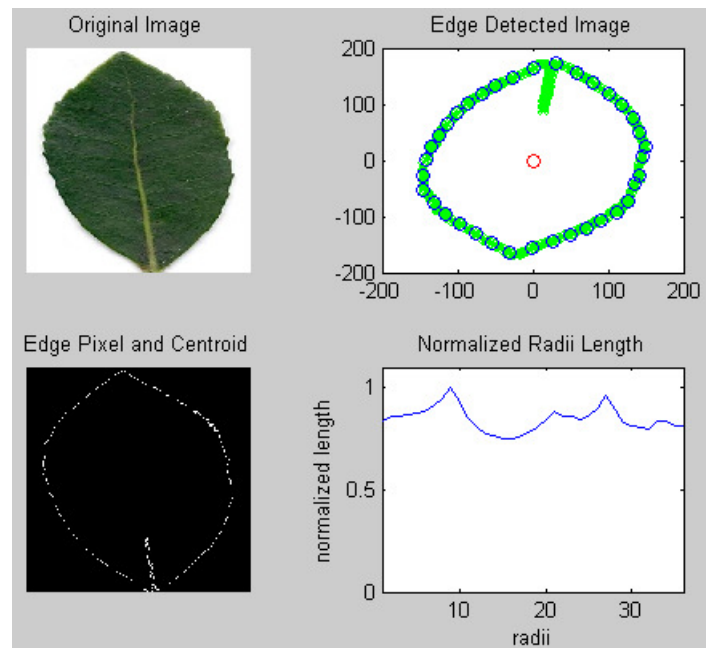
Figure 5. Interface for Centroid-Radii computation

The average of the 36 radii lengths for each image of each class both for the training and testing sets, is plotted in Figure 6, to depict the overall feature range and variation for each class.
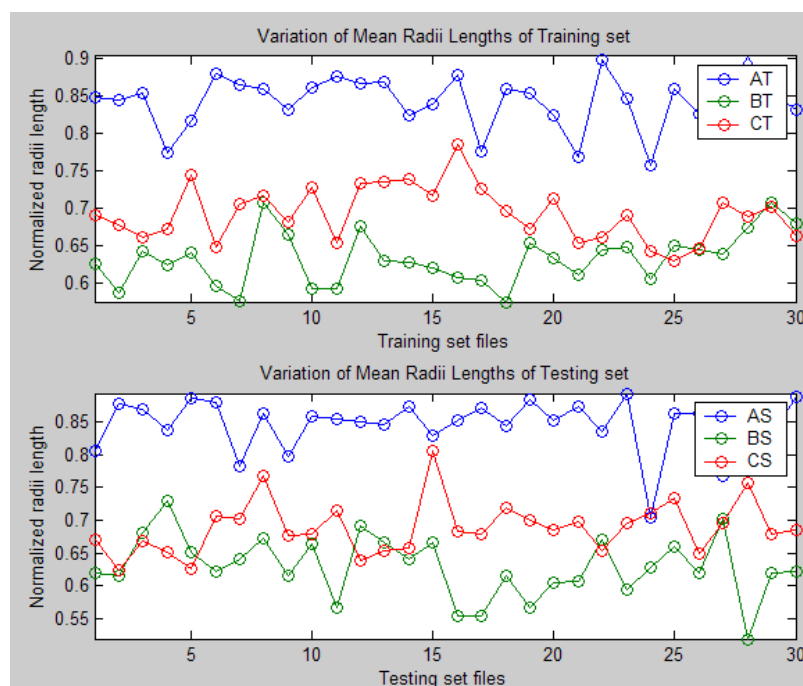

Figure 6. Variation of mean radii length for Training and Testing set images

Classes are discriminated using Euclidean distance (L_2) metric between the 36-element C-R vectors of training and testing samples. Results are summarized below in Table 2.

Table 2 : Percentage accuracy using C-R approach

F	A	B	C	O
C-R	97	100	97	98

4.4. B-S based computations

Each image is converted to binary form by using a 50% thresholding. A binarized test image is multiplied with each of the binarized training samples for each class as per equation (11) and the sum of the '1s' in the resultant image is used as the feature vector for discrimination. Figure 7 shows the variation of feature values for the three classes. The upper plot is obtained by binary superposition of Class-A testing images with all training samples, the middle plot is obtained by binary superposition of Class-B testing images with all training samples and the lower plot is obtained by binary superposition of Class-C testing images with all training samples.
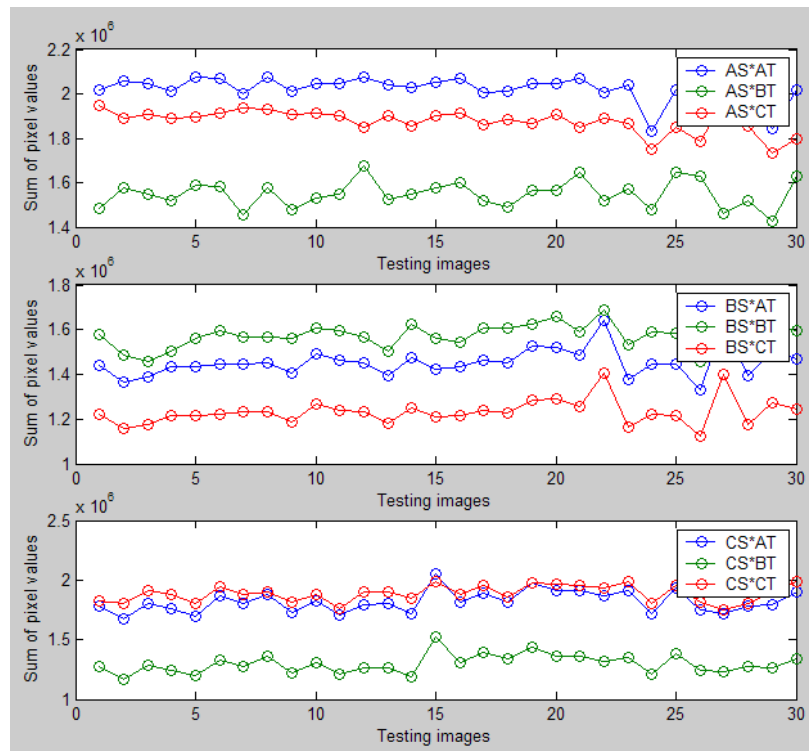

Figure 7. Variation of feature value for Testing set images using B-S approach

Classes are discriminated by determining the maximum values of the resultant B-S matrices computed by superimposing the training and testing samples. Results are summarized below in Table 3.

Table 3 : Percentage accuracy using B-S approach

F	A	B	C	O
B-S	100	100	97	99

V.   ANALYSIS

Automated discrimination between three leaf shapes was done using a variety of approaches to find the optimum results. The study reveals that for M-I approach provide best results for the M1 feature. Accuracies based on C-R method using a 36-element radii vector provide results better than individual M-I features. The proposed approach of binary superposition improved upon the results provided by the M-I approach. Best results obtained using different methods are summarized below in Table 4.

Table 4 : Summary of accuracy results

F	A	B	C	O
M-I	96	100	47	81
C-R	97	100	97	98
B-S	100	100	97	99

To put the above results in perspective with the state of the art, the best results reported in [8] is a recall rate of 60% for discrimination of chrysanthemum leaves from a database of 1400 color images. Accuracy for classification for 10 leaf categories over 600 images is reported to be 82.33% in [10]. Overall classification accuracy reported in [11] for 4 categories of leaf images obtained during three weeks of germination, is around 90%. Accuracy reported in [13] for classification of 32 leaf types from a collection of 1800 images is around 90%. An overall classification of 80% is reported in [14] for identifying two types of leaf shapes from images taken using different frequency bands of the spectrum. Best accuracies reported in [17] are around 93% using Polar Fourier Transforms. Results reported in [20] are in the region of 80% for classifying 50 species. Accuracies of around 97% have been reported in [21] for a database of 500 images. It therefore can be said that the accuracies reported in the current paper are comparable to the best results reported in extant literature. It may however be noted that in many of the above cases color and geometrical parameters have also been combined with shape based features to improve results, while the current work is based solely on shape characteristics.

VI.   CONCLUSIONS AND FUTURE SCOPES

This paper proposes an automated system for plant identification using shape features of their leaves. Two shape modelling approaches are discussed: one technique based on M-I model and the other on C-R model, and these are compared with a proposed approach based on binary superposition. The feature plots and recognition accuracies for each of the approaches are studied and reported. Such automated classification systems can prove extremely useful for quick and efficient classification of plant species. The accuracy of the current proposed approach is comparable to those reported in contemporary works. A salient feature of the proposed approach is the low-complexity data modelling scheme used whereby the computations only involve binary values.

Future work would involve research along two directions: (1) combining other shape based techniques like Hough transform and Fourier descriptors, and (2) combining color and texture features along with shape features for improving recognition accuracies.

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