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Unique Shape Descriptor Algorithm for Medicinal Plant Identification (SDAMPI) With Abridged Image Database

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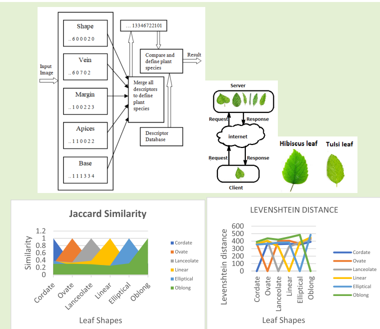
***Abstract*—In image processing, leaf shape recognition requires a huge database of similar images. Normal leaf image database construction requires more time and space. On the other hand, mobile offline applications are not able to contain huge image database with high pixel ratio. To solve this problem, mainly in medicinal plant identification, small leaf descriptors are necessary to completely provide the required plant information. Presently, the Botanists use shape reference table to recognize the following shapes of the leaf: ovate, cordate, elliptical, oblong, lanceolate and linear. As the shape numbers are invariant under scale, rotation and translation, which is highly desirable property for object recognition and chain code techniques preserve data by allowing large data reduction. Hence, in the proposed Shape Descriptor Algorithm for Medicinal Plant Identification (SDAMPI), we developed a descriptor to resolve the pixel selection issue of Freeman chain code and generate a unique leaf shape number. This leaf shape digital descriptor will act as a reference table for medicinal plant leaf shape identification. The performance of the proposed descriptor is evaluated through Jaccard similarity index graph and Levenshtein distance (LD) graph. From the results, it is confirming that, SDAMPI descriptor can detect Medicinal plant leaf shapes more accurately than existing methods.**



***Index Terms*—Chain code, image processing, plant leaves, shape features, shape number.**

I. Introduction

PLANTS plays an important role to keep up a sound breathable climate, give fuel, medicines, etc. But, accurate plant identification for different applications is a crucial task due to the great variability of plant species and the existing techniques are highly complicated, time consuming and requires huge database. The shortage of taxonomists and their lack of communication, led to non-standardized floras characteristics and poor documentation [1]. Thus, assembling a digital plant database for species recognition is a necessary step for image processing and pattern recognition.

In geometry, shapes have unique property and certain features. For example, a triangle has three sides, square and rectangle have identical angles and same count of corners. Similarly, the leaf shape describes the leaf boundary, morphological features like margin, tip (apices) and base. In this paper, a leaf shape descriptor generation algorithm has been developed to explain the leaf geometric shape properties. Some unique types of plant leaves shapes are shown in Table I.

The rest of the paper is arranged into following segments: Section II describes the existing shape based plant detection techniques and the necessity of a leaf shape descriptor. Section III describes the leaf shape descriptor generation using chain code approach. Section IV describes the neighbor selection issue of eight-chain code. Section V describes the proposed approach to resolve the neighbor selection issue of chain code generation and shape number generation. Section VI describes in detail about the proposed shape descriptor algorithm based medicinal plant identification (SDAMPI). Section VII discusses about the results. Finally, a summary of proposed method and future work are presented in Section VIII.

II. Existing Shape Based Plant Detection Techniques

In 1912, Schneider [2] used leaf shape for plant identification. Researchers of [3] had made shape and texture features using two types of neural networks which are invariant

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TABLE I
DIFFERENT PLANT LEAVES SHAPES

Leaf Shape						
Name	Cordate	Ovate	Lanceolate	Linear	Elliptical	Oblong

under scaling and orientation and also able to handle small deformation of sample images. In [4], researchers conducted shape feature-based study using Probabilistic Neural network (PNN) which provided 93.75% accuracy on Flavia dataset. In [5], researchers generated shape descriptor using Zernike moments (ZM) and Histogram of Oriented Gradient (HOG) classifier. Their studies had conducted over the 'VISLeaf' database. ZM based shape descriptor resulted in 84.66 % accuracy and HOG studies shown 92.67% accuracy. In [6], researchers designed an Android platform-based mobile application "ApLeaf" for plant identification and also studied IOS platform based plant identification mobile application "Leafsnap". "ApLeaf" and "Leafsnap" mobile applications are evaluated on Pyramid Histograms of Oriented Gradients (PHOG), Color features, Hue Saturation Value features (HSV) and Wavelet features from "ImageCLEF2012" plant identification database. In [7], shape contour curvature of leaf angle measurement is utilised for generating leaf shape characteristics. In [8], 1-D Discrete Cosine Transform is used to generate leaf shape and curve-based plant leaf recognition. In [9], silhouette measure based simulated annealing method, is used for extraction of leaf shape characteristics.

In [10], text classification-based algorithm is used to extract shape contours of plant leaf. These shapes are tested using nearest neighbor classifier over Swedish leaf data set. In [11], researchers explained various attributes for classifying leaf using surface and shape using hue features. Leaf classification based on shape, improved the categorization process of both simple and compound leaf. In [12], leaf morphological features and different parameters for leaf identification are explained. Detailed study of leaf segmentation techniques is explained in [13] and [14]. In [15], large-scale plant species identification was performed by constructing a digital visual tree and training inter-relation of plant species using this digital tree. The method presented in [15] emphasizes the need of digital virtual tree in the huge database of images.

In [16], authors introduced PlantCLEF 2015 benchmarked algorithm for species classification with the help of hybrid generic-organ convolutional neural network (HGO-CNN) and recurrent neural network framework. Authors of [17] introduced tree classifier performing high image identification accuracy on huge image database. This performance is achieved by layer-wise mixture model (LMM) with deep network which highly supports for visual hierarchy adaption.

In [18], a shape geometry descriptor called multiscale distance matrix is based on contour used for real-time shape recognition is discussed and results are experimented over two leaf datasets. A string cuts (HSCs) method [19] is discussed to extract features for shape retrieval techniques. Optimization algorithms are replaced by introducing a fast metric matching algorithm for image shape partition in the feature extraction level.

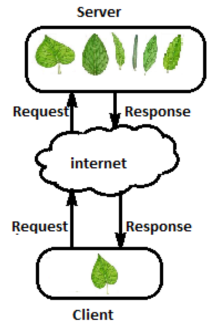


Fig. 1. Server response based image recognition system.

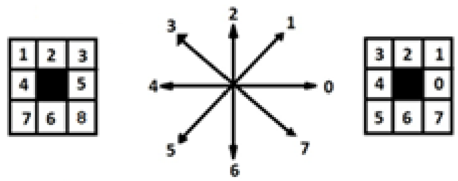
In the aforesaid techniques, researchers have used shape features for leaf identification, but, failed in explaining to find out the leaf shape category. Therefore, developing a leaf descriptor will help to details elementary information in order to search and classify them. Comparing to the existing methods, our proposed method can provide a compact definition for the leaf shape. The proposed leaf shape descriptors are translation invariant representation and also it preserves all the morphological information of leaf shape which brings out another benefit in terms of speed and effectiveness for the analysis and classification of leaves.

From the above literatures reviews [2]–[18], it may be concluded that the leaf shape and shape descriptor are playing important role in leaf identification. But, at the same time, this identification criterion requires a huge image database for processing. Most of the above literatures compared newly received leaf with processed or unprocessed image data base for the identification. In the case of mobile applications, Application Process Interface (API) are utilised to send image and receive result data. A server response based image recognition system is shown in Fig.1.

Sometimes, it is necessary to integrate image database and recognition process along with the offline mode applications. Offline image processing applications are not able to connect to the server but, they create fast output response by processing their own integrated image database. Handling huge image database in offline and real-time applications attracts several overheads. For avoiding the dependency on APIs, avoiding the server result waiting time and holding huge image database, we proposed to generate image descriptors for different leaf shapes. Because, the shape numbers are invariant under rotation and scaling that will reduce database size and comparison overheads in future plant identification scenario.

III. CHAIN CODE APPROACH

If an object is defined by pixel cells with the connected boundary lines, then the specified length and directions are used to represent chain code of that object. Chain code features are used to compute area and perimeter of objects. Basically, Freeman chain code is defined for creating descriptors for line and open shapes. The first chain code approach for representing digital curves is defined by Freeman [20] in 1961. In [20], Freeman explained that a chain code must faithfully preserve the information of interest, ensure compact



(a) (b) (c)

Fig. 2. (a) Neighbor pixel, (b) Eight chain code and (c) Eight chain code for each neighbor pixel.

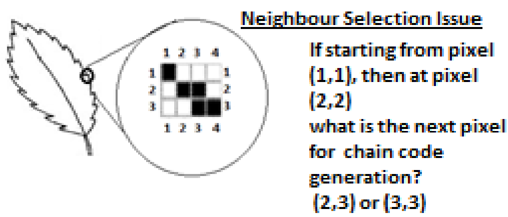


Fig. 3. Neighbor selection issue of Freeman chain code with Multi boundary pixels of a leaf.

storage, should be convenient for display and help any required processing. In 1974 [21], Freeman introduced a sequence of methods for processing chains codes. Chain codes allow considerable data reduction by preserving the information of objects. In [22], chain code properties have been explored.

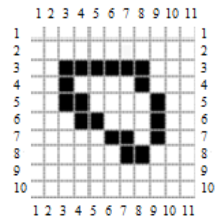
Selection of the next neighbor pixel will mark the selection of next angle route movement in eight chain code i.e. while moving from 0 to 2 or selecting second neighbor pixel in image will mark 90^0 changes in route. In Freeman chain code, selection of different code (one step movement to select neighborhood) will mark a new angle in route, otherwise, traversal will continue in same direction. This will provide high compression in the resulting chain code.

In Fig. 2 (a), a number scheme is used to traverse through each chain sections in clockwise manner. Fig. 2 (b) shows the selection of neighbor pixel according to the eight-chain code. In this paper, we will compute the chain code of common leaf shape model images using Freeman eight chain code method. The images considered here are all converted to binary images with extracted boundary outline. Here, Freeman chain code is used in selection of neighbor in closed traversal from start point to reaching the same staring point based on the eight chain code.

IV. The Neighbor Selection Issue of Eight-Chain Code

In the existing chain code approach, linear boundary is considered for shape number extraction. In case of leaf images boundary images, sometimes, it shows multi boundary lines to describe their edges. Leaf image with multi boundary pixels is shown in Fig.3.

Consider chain code generation for the given pixel portion of leaf image given in Fig. 3. Boundary traversal is beginning from pixel (1, 1). Pixel (1, 1) has only one neighbor pixel, so pixel (2, 2) is selected as next pixel. From location (2, 2), there are two pixels (2, 3) and (3, 3). Therefore, the existing descriptor generators fail to explain the selection of the next pixel.




```
[1,1,1,1,1,1,1,1,1,1,1;
 1,1,1,1,1,1,1,1,1,1,1;
 1,1,0,0,0,0,0,0,1,1,1;
 1,1,0,1,1,1,1,0,1,1,1;
 1,1,0,0,1,1,1,1,0,1,1;
 1,1,1,0,0,1,1,1,0,1,1;
 1,1,1,1,1,0,0,1,0,1,1;
 1,1,1,1,1,1,0,0,1,1,1;
 1,1,1,1,1,1,1,1,1,1,1;
 1,1,1,1,1,1,1,1,1,1,1]
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Fig. 4. (a) Boundary Image (b) Extracted binary code.

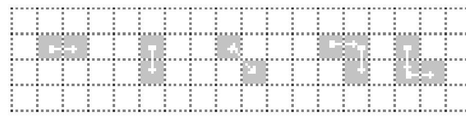

Fig. 5. Selection of neighbor pixel in priority based.

V. Proposed Approach

In leaf shape, tip and base shape are constant in scaling. But number of margins or edge of leaf shape varies according to the size of the image. In our method, we are considering leaf shape as explained in [23]. Here, leaf shape is closed boundary, so chain code extraction selection initiate and conclude at same point.

A. Binary Conversion of Image

In the first step, image is converted into binary format. Leaf boundaries are extracted using Moore neighbor tracing procedure improved by Jacob's stopping conditions:

i.e. Let P is boundary image with M x N size and the P (i, j) denote the pixel of image as P = {P (i, j); i = 1, 2…M and j = 1,2 …N}. For each P (i, j) having value P (i, j) = 0 or 1, zero denotes P (i, j) as contour pixel, and one otherwise [24].

B. Neighbor Code Selection and Chain Code Generation

Next, a closed traversal is conducting through extracted image boundary. In each movement, neighbor angle is extracted from boundary according to eight chain code. A chain code generation method is discussed through Fig. 4 where, boundary image is shown in Fig. 4(a) and extracted binary code given in Fig. 4(b). The boundary traversal is beginning from location (4, 8) of the matrix as shown in Fig.4 (b). In existing boundary descriptors, linear boundary is considering for shape number extraction. In the Fig. 4(a), after reaching the pixel location (5, 3), a confusion will arise for the selection of next neighbor pixel. At the location (5, 3), there are two neighbor pixels (5,4) and (6,4).

C. Resolving the Neighbor Selection Problem

In the proposed method, neighbor selection is based on priority. The detailed selection of neighbor is shown in Fig.5.

In Fig. 5, the first three cases there is only a single neighbor pixel in the boundary. So that pixel will get selected as neighbor pixel. But, in the case of fourth and fifth neighbor selection, there are two neighbors, if selecting the diagonal pixel; we will miss the other one in the traversal. To resolve the neighbor pixel selection problem of the multi neighbor

TABLE II
CHAIN CODE GENERATED FOR IMAGE CONTOUR

Boundary Location	4 8	3 8	3 7	3 6	3 5	3 4	3 3	4 3	5 3	5 4	6 4	6 5	7 6	7 7	8 7	8 8	7 9	6 9	5 9
Neighbour Code	1	2	4	4	4	4	4	7	7	5	7	5	8	5	7	5	3	2	2
Chain Code	3	2	4	4	4	4	4	6	6	0	6	0	7	0	6	0	1	2	2

pixels, we are proposing the following method: i.e. "select the neighbor which is not in boundary location table and, first priority to choose neighbor in same row, second priority for neighbor of same column and finally for neighbor who sharing diagonal."

The proposed neighbor selection algorithm:

Step 1: Repeat all the steps, until adding all the shape pixels into boundary list.

Step 2: If P (i, j) has only one neighbor pixel P (m, n) then add P (m, n), into boundary list.

Step 3: Otherwise

a. If P (i, j) has neighbor pixel P(m, n) in the same row and P(m, n) is not found in the boundary list then add P (m, n) into the boundary list.

b. If P (i, j) has neighbor pixel P(m, n) in the same column and P(m, n) is not found in the boundary list then add P (m, n) into the boundary list.

c. If P (i, j) has neighbour pixel P(m, n) in the diagonal pixels and P(m, n) is not found in the boundary list then add P (m, n) into the boundary list.

Step 4: Set P(i, j) = P(m, n).

For example, in Fig. 4(a), a closed traversal starting from location (4, 8), after reaching the location (5, 3) the proposed algorithm will choose (5, 4) according to the priority criteria. And, from the location (5, 4), this algorithm selects location (6, 4) as nearest neighbor. Similarly, from the location (7, 6), the algorithm will move to location (7, 7) and location (8, 7) will selected as next neighbor location. Hence, the neighbor code and chain code extracted from image in Fig. 4 (a) is as follows:

Neighbor code: *1244444775758575322*

Chain code: *3244444660607060122*

Location of boundary pixel, neighbor code and chain code generated for each pixel is given in Table II. Here, eight code method is used to create chain code of the boundary image.

D. Chain Code Normalization

In this step, three types of normalization are performed over chain code. In the Initial step, a differential chain code is generated for the rotation normalization, and then by choosing minimum magnitude from the differential chain code, the starting point normalization is achieved. Image grid is altering for the size normalization.

By counting the number of direction changes in counter clockwise direction, chain code for rotation is normalized. Counter clockwise changes for each chain code pair as shown in Table III. This result is called first difference of chain code. First difference chain code for boundary image shown in Fig. 4 (a) is *2000020262716211017*.

Finally, for standardizing the initial point, lexicographically minimum value is chosen from all cyclic rotations of first difference code e.g. *0000202627162110172* is the shape number for Fig.4 (a).

TABLE III
DIFFERENTIAL CHAIN CODE

Chain Code	24	44	44	44	44	46	66	60	06	60	07	70	06	60	01	12	22	23	32
First Difference	2	0	0	0	0	2	0	2	6	2	7	1	6	2	1	1	0	1	7

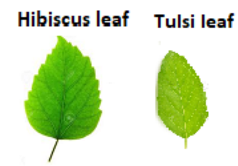

Fig. 6. Sample Medicinal leaves.

VI. SHAPE DESCRIPTOR ALGORITHM BASED MEDICINAL PLANT IDENTIFICATION (SDAMPI)

In [12], authors have emphasized on the importance of using multi feature set for medicinal plant identification. In normal scenario, color, texture, shape or vein is utilized in the image processing based plant identification. But, for medicinal plant recognition methods, accuracy is the main concern. Two medicinal leaves are shown in Fig. 6. From the Fig. 6, it is clear that leaf shapes are very similar to each other. Hence, to get high accurate recognition in medicinal plant identification, it is important to use multi feature set.

For more accurate result, common five Shape features: vein, shape, base, apices and margin are generating using the proposed SDAMPI method. The flowchart of SDAMPI for shape number generation is shown in Fig. 7. In Fig. 8, image detection phase of a unique SDAMPI is shown.

In medicinal plant identification process, first phase is species description database generation. The five main shape descriptors vein, shape, base, apices and margin are extracted from collected leaf images and using a text merging algorithm, SDAMPI merges those five descriptors to form a plant species description and saved in description database. When a new leaf image arrives for decision making, the input image is passed through five main shape descriptor generators and using merger a single description is formed. New description is compared in to descriptor database to define the plant species.

VII. RESULTS AND DISCUSSION

The proposed SDAMPI shape number extraction method has tested on the "Leaf" image dataset given by [25] which contain a collection of digital images of 40 different plant species. Increasing number of features in the detection phase will increase the accuracy of result [12]. So extending this shape recognition algorithm using SDAMPI descriptors to multi pixel selection can generate shape descriptors for vein, margin, apices, based and other shape related morphological features of plant leaf.

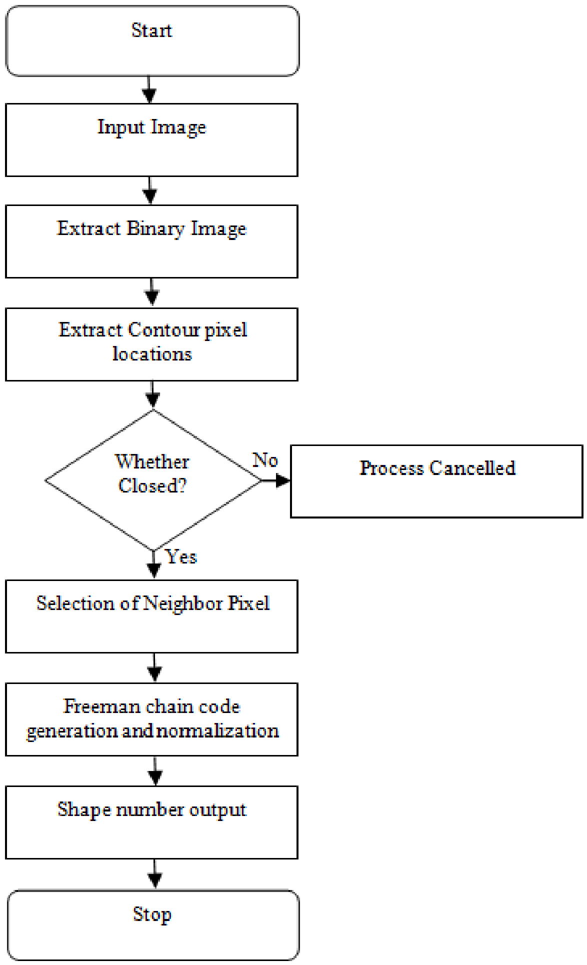

Fig. 7. Flow chart of shape descriptor algorithm based medicinal plant identification (SDAMPI).

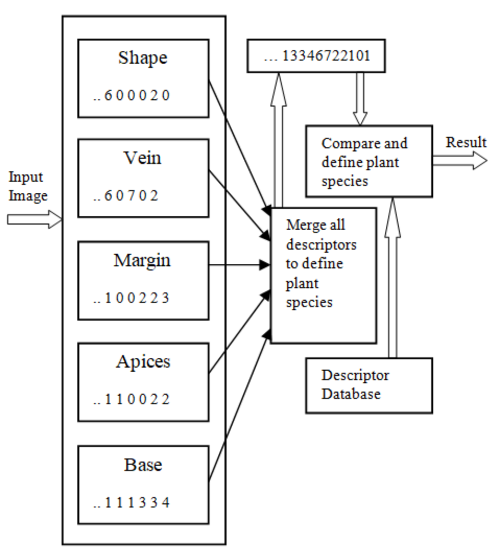

Fig. 8. Image detection phase of Shape descriptor algorithm based medicinal plant identification (SDAMPI).

By extending this descriptor generation for vein, margin, apices, based and other shape related morphological features of plant leaf will again speed up the plant identification process and accuracy of plant leaf recognition.

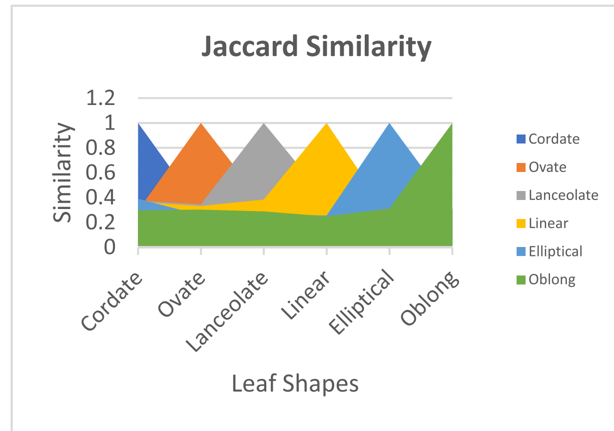

Fig. 9. Jaccard similarity calculated on tokens of shape number extracted from leaf data set.

The knowledge of medicinal plant recognition was the main asset of *Indian Ayurveda* culture. Generation of plant descriptor glossary for plant identification leads to awake more researches and studies in the image descriptor based image identification area. Leaf descriptors can reduce the medicinal plant leaf collection overhead.

In SDAMPI, we used five leaf shape feature descriptors, but, upon increasing the feature sets, it may leads to more accurate plant identification. At the same time, upon increasing the feature sets may leads to more complex descriptor design. Hence, we need to optimize the feature set and descriptor complexity with accuracy. On improving simple descriptor merger with fast merging algorithms and more improved and fast comparison for searching in description database increases the accuracy of medicinal plant identification algorithm.

The proposed SDAMPI is first stepping stone to generate shape number for plant leaf shapes namely ovate, cordate, elliptical, oblong, lanceolate and linear. Instead of huge image data base, In SDAMPI, shape descriptor data base is being used for leaf species classification. To generate the shape number for basic leaf shapes, 40 different plant species of "leaf" database are used. These leaf descriptors reduce the required size of huge database in image recognition process. The Jaccard similarity [26] is calculated for shape number extraction and graph is generated from the leaf data set as shown in Fig.9.

During extraction time, small sized images are used for easy of handling. While increasing the size of the leaf image, length of shape number is also increasing due to repeating string patters in different parts of a shape number. This repetition is depends upon variation in the number of blades/margins. Sometimes, increasing the length of apex and base is also leads to increase in the repeated patterns in shape number.

Extending the proposed method by adding more leaf morphological features one can make more clarity in leaf identification results. Comparing the shape number instead of different images of leaf morphological data can save the time, space and energy too.

Levenshtein distance (LD) [26] calculated for shape number extracted and graph is generated from leaf data set as shown

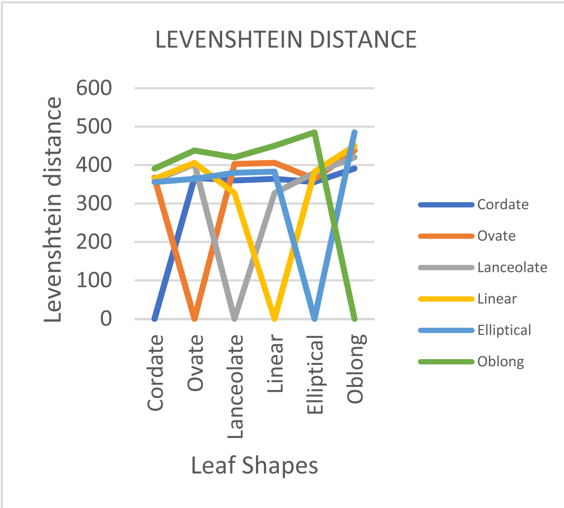

Fig. 10. Levenshtein distance calculated on tokens of shape number extracted from leaf data set.

in Fig.10. LD gives the minimum difference between two sequences.

The pattern of Jaccard similarity index graph and Levenshtein distance graph indicates that the proposed SDAMPI has correctly generated the descriptor data and accurately identified and classified the medicinal plant for the available plant species data. The proposed SDAMPI will definitely help a lot to the botanist, horticulturist, Ayurveda doctors and researchers.

In image recognition or classification methods, identification of images is performed by comparing extracted image object or image features along with image database. But in SDAMPI, shape numbers are compared for image recognition which reduces the space and time complexity. Because, the image comparison is based on iteration of multi-dimensional arrays, whereas, the string comparison is based on single dimensional array i.e. the time and space required for single dimensional string array is very much lesser than the multi-dimensional image array [27].

To evaluate the performance of SDAMPI method, Needleman-Wunsch Similarity method [28] was used. SDAMPI shape number extraction and leaf shape identification has also evaluated over the "Flavia" leaf data set [4] and the "Swedish" leaf data set [29]. The performance of our algorithm has calculated using the test results and quantitative evaluation. Statistical measures are employed to evaluate performance of the SDAMPI algorithm. Sensitivity (recall) value of SDAMPI algorithm is the ratio between how many leaf shapes of given data set were correctly identified as positive to how many leaf shapes were actually positive in the given data base. Specificity value of SDAMPI algorithm is the ratio between how many leaf shapes of given data set were correctly classified as negative to how many leaf shapes was actually negative in the given data base. Classification accuracy of SDAMPI algorithm is the ratio of number of correct predictions to the total number of input samples. F1 score of SDAMPI algorithm is also calculated to evaluate the performance of classification ability of SDAMPI algorithm.

TABLE IV
ACCURACY OF THE SDAMPI ALGORITHM ON "LEAF" "FLAVIA" AND "SWEDISH" LEAF DATASETS

Dataset	shape	Sensitivity	Specificity	Accuracy	F1 Score
Leaf	cordate	0.86	0.96	0.93	0.89
	ovate	0.87	0.92	0.90	0.87
	lanceolate	0.91	0.93	0.93	0.87
	elliptical	0.82	0.91	0.88	0.85
	linear	0.88	0.96	0.93	0.91
	oblong	0.93	0.92	0.93	0.94
Flavia	cordate	0.95	0.92	0.94	0.95
	ovate	0.88	0.78	0.85	0.89
	lanceolate	0.90	0.85	0.88	0.90
	elliptical	0.89	0.60	0.85	0.91
	linear	0.94	0.93	0.94	0.94
	oblong	0.85	0.95	0.91	0.88
Swedish	cordate	0.92	0.67	0.87	0.92
	ovate	0.82	0.50	0.73	0.82
	lanceolate	0.91	0.50	0.80	0.87
	elliptical	0.91	0.50	0.80	0.87
	linear	0.92	0.50	0.87	0.92
	oblong	0.83	0.67	0.80	0.87

The shape detection accuracy of the SDAMPI algorithm on "Leaf" "Flavia" and "Swedish" leaf datasets are given in Table IV.

A. Advantages of SDAMPI Algorithm

Identifiability is the main advantage of SDAMPI algorithm. Shape numbers can explain all the perceptual features of leaf shapes. Rotational invariance is another feature of SDAMPI algorithm, where the rotation of leaf image not affecting the shape descriptor. SDAMPI algorithm is statistically independent. This independency represents the compactness of the shape number to clearly define the leaf shape. Shape number generated using SDAMPI algorithm always remain the same. This feature is representing the reliability of our shape descriptor.

B. Limitations of SDAMPI Algorithm

Limitation of SDAMPI algorithm is that increasing the size of image leads to increase in the length of shape number.

VIII. CONCLUSION AND FUTURE STUDIES

In this paper, we introduced Shape Descriptor Algorithm for Medicinal Plant Identification (SDAMPI). The proposed SDAMPI has resolved the pixel selection issue of multi pixel boundary images and generated shape number for plant leaf. Common six leaf shapes namely ovate, cordate, elliptical, oblong, lanceolate and linear are selected for their shape numbers generation. Using shape numbers, the database requirement in plant leaf identification reduces and the accuracy of identification increases. Performance of the proposed SDAMPI have been evaluated through Jaccard similarity index graph and Levenshtein distance (LD) graph and found that the descriptors have correctly generated the shape number for the identification of given medicinal plant data.

These plant leaf descriptors explaining the common shape category of a plant leaf. Extended study on this area for extracting shape number for other plant leaf features like, leaf apex, margin, base, venation and texture will lead to more efficient plant identification and image pattern recognition.

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