CHAPTER 5
IDENTIFICATION AND CLASSIFICATION OF MEDICINAL PLANTS IMAGES

In the previous chapter, we have presented the method for feature extraction of medicinal plants images of reasonably grown plants and their parts, leaves using geometrical shape and texture features. Using these features it is necessary to identify and classify the medicinal plants. In this chapter, we have presented classification of the medicinal plants through the developed features. Identification and comparative analysis of performance of classifiers using color, shape and texture features is presented in this chapter.

5.1 NECESSITY OF MEDICINAL PLANT CLASSIFICATION

In order to identify plants that are unfamiliar and to differentiate the medicinal plants with similar features, it is necessary to classify them with distinguishing features. The large variety in medicinal plants have a very diverse range of identifying features or properties which are used for grouping them. We used easy-to-see features, physical characteristics called morphological features for identification. The features described in Chapter 4 give possible plant morphology structural features for identification. The identification of medicinal plants is an incremental process. We have felt that hierachical identification and classification is ncessary for proper medicinal plant species identification in Ayurveda. In order to explore the application of computer vision in automating different activities of
Indian System of Medicine called Ayurveda, we have carried out the connected literature survey to know the state of the art.

5.2 RELATED WORK

Following is the gist of different works carried out connected to the work undertaken.

Herve Goeau et. al., have developed a PlantNet project to ImageCLEF 2011 for plant identification. The system is used for tree species identification based on leaf image features. The retrieval algorithms are demonstrated using leaf geometric features. Three types images, namely photographs, scans and scan like photos are considered in the work [54].

Chin Hung Teng et. al., have incorporated a set of sophisticated algorithms to implement leaves segmentation and classification. The segmented leaves are classified by comparing sketched leaf shapes. The normalized centroid-contour distance and circular-shift comparing schemes are adopted for similarity matching. It is reported that the segmentation results are promising in comparison to the methods found in the literature [27].

Ahmed Naser Hussein et. al., have compared texture feature extraction methods in retrieval of plant leaves images. They have used two texture approaches, haar Discrete Wavelet Transform (DWT) and Gray Level Co-occurrence Method (GLCM) for the recognition of leaves image samples. The DWT combined with entropy measurment
has yielded 92% retrieval accuracy, whereas GLCM has given 49.28% at the same ranking level [8].

Shitala Prasad et. al., have used relative-sub image based features for recognition of plant species identification through leaf images. The leaf image is divided into 25 subimages, each of size 5x5 pixels. The relative sub image co-efficient is used as feature for the combination of two sub-image blocks. Totally 300 features are extracted and trained with SVM classifier. The classification accuracy of 95% is obtained [114].

Maliheh Shabanzade et. al., have applied both local descriptors and global features for leaf recognition and classification. The linear discriminant analysis method is employed for classification. The work has applications in botanical gardens and horticulture science [89].

Shanwen Zhang and YouQian Feng have presented an efficient plant classification using leaves images through rough sets. Moment invariants and thirteen statistical features are extracted from 900 image samples of 30 plant species. The features are reduced by rough-set. The combination of rough set and 1-NN classifier has given an average recognition rate of 96.45% [113].

A. A. Abdulrahaman et. al., have demonstrated a computerized system called LEASYS for plant species identification through leaf shape information. The leaf is classified based on the combination of
characters received from user. The leaf morphology of Savanna tree species in Nigeria are considered for the study [1].

James S. Cope et. al., have used gabor filter for the recognition of leaf texture. The part of the leaf is convolved with Gaussian kernal and sub-sampled image is taken for vein feature analysis. The Gabor filter co-efficients are extracted and classified with distance measures [64].

Thibaut Beghin et.al., have developed a novel method for classification of leaf images based on shape and texture. The contour-signature has been used for identification of lobed and unlobed leaves. The Jeffery-divergence measure is adopted for similarity measure. The sobel direction histogram is adopted for microtexture analysis of leaf margin [122].

Jing Liu et. al., have introduced plant leaf recognition based on Locally Linear Embeding (LLE) features. The LLE is an idea of visualizing an object as an overlapping co-ordinate patches. The moving centre hypersphere classifier is adopted and has given an average recognition rate of 92% [69].

Liu J., et. al., have proposed a novel method for plant classification from leaf images based on wavelet transform and support vector machine. The method is experimented on 300 leaf images and found to be more effective and faster compared to the other methods [80].
Huang Lin and He Peng., have used shape and texture features for the classification of broad leaves tree species with combined synthetic features such as nervation type for texture analysis and fractal dimensions for vein recognition. The Probabilistic neural network is used for classification with an average classification rate of 98.3% [55].

Chuan-Min Zhai and Ji-Xiang Du have developed a machine learning algorithm called Extreme Learning Machine (ELM) for classification of plant species through plant leaf using gabor texture feature. A Comparison is carried out with neural net and found that ELM approach is more appropriate for the classification [29].

Xiao-Feng Wang et. al., have segmented plant leaves from complex background and overlapped leaves images. An automatic marker – controlled watershed segmentation method is used. The seven Hu geometric moments and sixteen Zernike moments are extracted as shape features from segmented binary images after removal of leaves stalk. The average classification rate of 92.6% is obtained with the moving center hyper sphere classifier for 20 classes of plant leaves [133].

Stephen Gang Wu et.al., have developed a fast and reliable Probabilistic Neural Network (PNN) classifier to recognize leaf images for plant classification. Twelve morphological features are trained with neural network. The classification accuracy of 90% is observed [112].
Zhi-Kai Huang and Zhi-Feng Wang have presented an algorithm for bark image classification based on Generalized Gaussian Density (GGD) model and color angles in different color spaces. The Radial Basis Probabilistic Neural Networks (RBPNN) and Support Vector Machine (SVM) are used for classification [146].

Stephen Gang Wu et.al., have developed a Probabilistic Neural Network method for automatic leaf recognition for plant classification. Twelve features are orthogonalized into five principle variables by Principle Component Analysis. An artificial neural network is trained with 1800 leaves to classify 32 kinds of plants with an accuracy of 90% [116].

Ji-Xiang Du et. al., have designed a new classifier called move median centre (MMC) hyper sphere classifier for the leaf classification based on morphological features and invariant moments. It is revealed that the proposed approach is robust than the other contour-based features such as curvature points [70].

Zhi-Kai Huang has proposed bark image recognition method using color and texture features. The multiresolution wavelet features are extracted. The features are trained with Radial Basis Probabilistic Network (RBPNN) and Support Vector Machine (SVM). The combined color and texture features are found more effective than histogram and co-occurrence based approaches [145].

James Clarke et. al., have investigated pattern recognition methods to detect venation patterns of leaves. The scale-space analysis technique
is used on Ivy, Nettle, Ochna and Ribes and Monstera sample images. The scale-space technique with smoothing and edge detection is used and found effective veins on each sample. The performance of both the techniques are compared [63].

Camargo Neto et. al., have used Elliptic Fourier (EF) and discriminant analyses to identify plants based on leaf shape. The Chain encoded, Elliptic Fourier harmonic functions are generated based on leaf boundary. Principle component analysis and Canonical discriminant analysis are used to select Fourier coefficients. The leaves images grown for the duration of three weeks are considered. The average classification rate of 88.4% is achieved [17].

Wang Dai-lin et. al., have devised an edge detection approach to identify the individual tokens of leaf boundary. The small right-angled triangle is used for representing a token and a part of leaf edge. The sine and cosine of angles of the triangle are used as features. A back-propagation neuronal network is trained with these features. The maximum and minimum accuracies of 98% and 45% are reported respectively [130].

Jixiang Du et. al., have given leaf shape recognition method based on radial basis probabilistic neural network. The features are extracted using fourier transform. Forty images of twenty plant species are used for training. The recognition rate of 94% is obtained [71].
Meyer et. al., have used a canopy structure and leaf shape as key features for plant species identification. Machine vision system was employed for isolating, plant canopy crowns. For identifying green plants from soil and residue, the unsupervised fuzzy color index and clustering methods are developed. Fuzzy excess Red (ExR), excess Green (ExG) indices, fuzzy c-means (FCM) clustering algorithms and Gustafson–Kessel (GK) are studied for unsupervised classification of plant images. The Corn, Wheat straw and soil are considered for the study. The classification accuracy of 96%, 95% and 99% are observed for bare soil, corn residue and wheat straw respectively [92].

Takeshi Saitoh and Toyohisa Kaneko., have proposed an automatic recognition system for plant species using flower and leaves images. K-means clustering is used for segmentation of flower and leaf images. The shape features of flower and leaf images are extracted. Ten features of flower and eleven features of leaf are discriminated using piecewise linear discriminant function. The combined features have yielded recognition rate of 96%. After feature reduction, the accuracy is improved to 96.8% [121].

Chia-Ling Lee and Shu-Yuan Chen., have compared the region based features with contour based for the classification of leaf images. The region based features aspect ratio, compactness, centroid and horizontal/vertical projections are extracted from 60 plant species leaf images (each 100 images). The feature weights and 1-NN rule is used for classification. The classification accuracy of 82.33% is obtained
with a recall rate of 48.27%. The classification rate is less with contour approach, 37.67% and 21.7% respectively [26].

Zhiyong Wang et. al., have developed an application of fuzzy integral for combining different shape features for leaf image retrieval. The shape features namely, centroid contour distance, eccentricity and angle code histogram features are given as input to weighted summation matching. The retrieval performance is better than Curvature Scale Space (CSS) and modified fourier descriptor [148].

Basavaraj Anami., et. al., have described a method for the recognition of images of plant leaves using a neural network. The leaves are scanned and segmented from background. The invariant moment features are extracted and used as input to the developed neural network model [14].

Dong Kwon Park ., have used an edge histogram descriptor for MPEG-7 for image matching by global and semi-local edge histograms from the local histogram bins. Efforts have also been made for recognition of MPEG-7 using color and edge features. Perceptually uniform HSV (Hue, Saturation and Value) color space has been used for color histograms and YCrCb (luminance/red chrominance/blue chrominance) color space for edge histograms with different distance measures for retrieval. The work describes 4-bin edge histogram to represent the strength of edge in four directions namely 0°, 45°, 90°, 135° [37].
Timmermans A.J. and Hulzebosch., have proposed grading system for pot plants. The experiment is conducted on flowering plant and Cactus plant. The statistical discriminant analysis and neural network classifier were adopted for classification. Two approaches Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA), were tested and found better classification results [123].

Carol L. Novak and Steven A. Safar., have demonstrated that color histograms have identifiable features that relate to a precise mathematical way to describe scene properties. It is reported that object color and illumination features are the most obvious properties for better recognition [20].

From the literature survey, it is observed that image processing techniques are used for weed classification and crop growth analysis. The plant classification and identification are carried by parts, namely bark and leaves. The work on plant species classification using geometry is scarce. It is observed that most of the researchers have used mainly leaf image for plant recognition and classification. To the best of our knowledge, no noticeable work is observed in the literature on height based recognition and classification of fully grown medicinal plants such as herbs, shrubs and trees. Hence, it is the motivation for taking up the work on recognition and classification of medicinal plants of fairly grown plant and leaves images.
5.3 KNOWLEDGE BASED CLASSIFICATION USING ASPECT RATIO

The aspect ratio features of fifteen plant species shown in Table 4.1 are obtained using algorithm 4.1. We have developed knowledge based classifier for recognition of medicinal plants image samples shown in Figure 4.4. The knowledge of mean and standard deviation of aspect ratio values are used as features in the classification of medicinal plants image samples. The major components of any knowledge based classifier are identified as a fact base and an inference engine. The fact base and the rule base combine to form a knowledge base and form the kernel of any knowledge based classifier.

The knowledge based classifier uses three rules constituting an inference engine and used for the classification. In this work, we have considered a total of 750 image samples of fifteen medicinal plants species, comprising of five plants species of each class, herbs, shrubs and trees. In the training phase, we have considered features of 375 samples, considering 25 samples of each plant spices amounting to 125 images. For testing, the remaining 375 samples are used. In the testing phase, 125 test images of each class are used.

Mean and standard deviation of aspect ratios of fifteen plant species are obtained separately. Further, the minimum and maximum mean values of each class are used as knowledge base. The Table 5.1 shows the classification range, based on minimum ($\bar{l}_{\text{min}}$) and maximum ($\bar{l}_{\text{max}}$) values of aspect ratios ($\bar{l}$) of herbs, shrubs and trees. The general rule for the classification is given as:
If \( (\tilde{l}_{\text{min}} \leq \tilde{l} \leq \tilde{l}_{\text{max}}) \), then plant is of the type \( C_i \), where \( i = 1,2,3 \) corresponds to herb, shrub and tree.

**Table 5.1: Knowledge base of mean and standard deviation values of Aspect ratio**

<table>
<thead>
<tr>
<th>Class (( C_i ))</th>
<th>( \tilde{l}_{\text{min}} )</th>
<th>( \tilde{l}_{\text{max}} )</th>
<th>Mean(( \mu_i ))</th>
<th>Standard Deviation (( \sigma_i ))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Herbs ( (C1) )</td>
<td>0.31</td>
<td>0.97</td>
<td>0.595</td>
<td>0.3355</td>
</tr>
<tr>
<td>Shrubs ( (C2) )</td>
<td>0.22</td>
<td>0.29</td>
<td>0.2448</td>
<td>0.0195</td>
</tr>
<tr>
<td>Trees ( (C3) )</td>
<td>0.01</td>
<td>0.21</td>
<td>0.1275</td>
<td>0.0924</td>
</tr>
</tbody>
</table>

**Algorithm 5.1: Knowledge based classification**

Input: RGB medicinal plant images.

Output: Classification of images into Herbs, Shrubs and Trees.

Description: L2 and L1 are areas of bounding boxes of stem and leafy parts, and \( \tilde{l} \) is the aspect ratio, \( \tilde{l}_{\text{min}} \) and \( \tilde{l}_{\text{max}} \) are minimum and maximum value of \( \tilde{l} \), where \( i=1,2,3 \) corresponds to herbs, shrubs and trees classes, respectively.

Start:

Step 1: Convert the given plant image from RGB to L*a*b* color space.

Step 2: Apply K-means clustering (\( K = 3 \)) and scan line method to segment leafy and stem parts.

Step 3: Label the segmented parts and draw the bounding boxes for leafy and stem segments and estimate L1 and L2.

Step 4: Compute the aspect ratio \( \tilde{l} \) of the given image of plant

\[
\tilde{l} = \frac{L2}{L1}.
\]
Step 5: Repeat steps 1-4 for all the 25 images of a given plant species. Compute mean ($\mu$) and standard deviation ($\sigma$) of the aspect ratio $\widetilde{L}$.

Step 6: Repeat steps 1-5 for each of the 15 different plant species.

Step 7: (Classification rule) If the aspect ratio $\widetilde{L}$ of a plant is in the range $R_i = [\widetilde{L}_{\min}, \widetilde{L}_{\max}]$, then the plant is classified as of type $C_i$.

Stop.

During classification phase, the aspect ratio value of test sample plant image is computed. The classification rule is applied using the knowledge base built and the test plant is classified as herb, shrub or tree. From the results, we have observed that the classification accuracy is good for trees. The values of aspect ratios overlap for herbs and shrubs and hence the classification based on aspect ratios is not adequate.

### 5.3.1 Percentage accuracy of recognition and classification

\[
\text{Classification Rate}\left(\%\right) = \frac{\text{Number of correctly classified samples}}{\text{Total number of samples}} \times 100 \quad \ldots \quad (5.1)
\]

We have defined the percentage accuracy of recognition and classification as the ratio of correctly classified image samples to the total number of image samples and is given in equation (5.1).

From experimentation, it is found that the classification accuracy is good for tree images. But the method is vulnerable to herbs and shrubs, as the features overlap. It is possible to overcome this
anomaly by taking images from a fixed distance and angle. It is also
observed that the classification is not appropriate for non-fully grown
plants of herbs and shrubs.

**Table 5.2: Confusion Matrix for three classes of Medicinal Plants**

<table>
<thead>
<tr>
<th>PlantClass</th>
<th>Herbs</th>
<th>Shrubs</th>
<th>Trees</th>
<th>Percentage Of Classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Herbs</td>
<td>82</td>
<td>20</td>
<td>23</td>
<td>65%</td>
</tr>
<tr>
<td>Shrubs</td>
<td>40</td>
<td>65</td>
<td>20</td>
<td>52%</td>
</tr>
<tr>
<td>Trees</td>
<td>20</td>
<td>15</td>
<td>90</td>
<td>72%</td>
</tr>
</tbody>
</table>

We have developed a confusion matrix and is given in Table 5.2
which gives details of classification obtained by the proposed method.
The classification errors are classified into True Positive ($T_P$), True
Negative ($T_N$), False Positive ($F_P$) and False Negative ($F_N$). The error is
said to be $F_P$ when herbs are classified as trees or shrubs. The error is
said to be $F_N$ when medicinal plants other than herbs are recognized
as herbs. If an efficient segmentation method is used and proper
decision rules are designed, then these errors get minimized. The $F_P$
and $F_N$ errors are interpreted as specificity (true negative rate) and
sensitivity (true positive rate), respectively. These measures indicate
how likely a test catches whatever is being tested. The herbs are
classified as herbs which gives $T_P$ results. Hence, specificity and
sensitivity are obtained with the formulae (5.2) and (5.3) respectively.

\[
\text{Specificity (true negative rate)} = \frac{T_N}{T_N + F_P} \quad \cdots \quad (5.2)
\]

\[
\text{Sensitivity (true positive rate)} = \frac{T_P}{T_P + F_N} \quad \cdots \quad (5.3)
\]
We have computed sensitivity and specificity values for trees, herbs and shrubs. A Receiver Operating Characteristic (ROC) curve is drawn for these classes. The curve represents the trade off between the sensitivity and specificity for every class of medicinal plants. In this graphical technique sensitivity is plotted against specificity. The ROC curve is shown in Figure 5.1. Equal Error Rate (ERR) is the value for which specificity is equal to sensitivity, that is the point where the line $y$ equals to $x$ intersects the ROC curve. Figure 5.2 shows the plot in which trees are better classified than herbs and shrubs. In order to improve the classification performance we have used level set segmentation and further with robust geometrical features.

**Figure 5.1: Receiver operating characteristic curve**

**Figure 5.2: Classification rate of medicinal plants using aspect ratio**
5.4 RECOGNITION AND CLASSIFICATION OF MEDICINAL PLANTS BASED ON NEW GEOMETRICAL FEATURES

The geometrical features are extracted as discussed in Section 4.3.1.2. The geometrical ratios for the sample plant images are obtained using equation (4.5) and used to train different classifiers namely, minimum distance classifier, artificial neural network and support vector machine classifier.

5.4.1 Minimum Distance Classifier

The feature vector $F^k = (F^k_1, F^k_2, F^k_3, F^k_4)$ comprises of the four aspect ratios (S S Nandyal et al., 2012) F1 to F4. The index k = 1, 2, 3 correspond to herb, shrub and tree respectively. During classification, the Euclidean distance is used as the similarity measure between the mean values of trained and test feature vectors. The procedure adopted for the classification of unknown plant species is given in Algorithms 5.2 and 5.3.

Algorithm 5.2: Training algorithm

Input: Input RGB color images of medicinal plants.

Output: The four geometrical feature values.

Start:

Step 1: Read RGB color components of a plant image.

Step 2: Apply level set method for segmentation of plant image into canopy and stem parts.

Step 3: Draw the bounding box around the stem and canopy segments.
Step 4: Compute the feature vector $F_k^k = (F_1^k, F_2^k, F_3^k, F_4^k)$ for the segmented image, where $k = 1, 2, 3$ corresponds to herb, shrub and tree, respectively.

Step 5: Repeat step 1 to 4 for all the training samples of different class $k$.

Step 6: Compute the mean feature values $(\bar{F}_1^k, \bar{F}_2^k, \bar{F}_3^k, \bar{F}_4^k)$ for a plant class $k$.

Step 7: Repeat the steps 1 to 6 for all plant classes $k=1, 2, 3$.

Step 8: Store the $\bar{F}_k^k$ in the feature library, for each $k$.

Stop.

**Algorithm 5.3: Testing algorithm**

Input: RGB color image of test medicinal plant.

Output: Plants classified as Herbs, Shrubs and Trees.

Start:

Step 1: Read RGB color component of test plant image.

Step 2: Apply level set method to segment background into canopy and stem parts.

Step 3: Draw the bounding box around the stem and canopy segments.

Step 4: Compute the feature vector $F_{\text{test}} = (F_{\text{test}}^1, F_{\text{test}}^2, F_{\text{test}}^3, F_{\text{test}}^4)$ for test image.
Step 5: (Classification) Compute the Euclidean distance $D$ between feature vector $F^{test}$ and feature vector $F^k$ which is $D(F^{test}, F^m)$, $k=1, 2, 3$.

Step 6: The plant is classified as herb, shrub or tree, if the $D$ value is minimum for $k=1, 2$ or $3$ respectively.

Stop.

To corroborate the results of classification using knowledge based classifier, we have used two more classifiers namely, Artificial Neural Network (ANN) and Support Vector Machine (SVM).

5.4.2 Artificial Neural Network Classifier

An Artificial Neural Network (ANN) is an information processing paradigm that simulates the way biological nervous systems, such as the brain, process the information. An artificial neuron is processor with many inputs and one output as shown in Figure 5.3.

![Figure 5.3: A Sample Neuron](image)

Artificial Neural Network (ANN) is composed of a large number of highly interconnected processing elements (neurons). The ANN has two phases of operations, namely, the training phase and the testing
phase. In the training phase, the ANN is trained with particular input patterns. During testing phase when a taught input pattern is detected at the input, an output is obtained.

Figure 5.4: Architecture of Artificial Neural Network

Figure 5.4 shows architecture of typical Feed Forward Back Propagation Neural Network (FF-BPNN). The nodes F1, F2...Fn represent the corresponding input features and the nodes O1, O2...Om represent the output corresponding to the plant class.

A FF-BPNN uses a gradient descent learning algorithm, in which the network weights are moved along the negative of the gradient of the performance function. The term backpropagation refers to the manner in which the gradient is computed for non-linear multilayer networks. We have used 3-hidden layer with sigmoid activation function. Sigmoid functions are characterized by the fact that their slopes must approach zero as the input gets large.

The number of input nodes corresponds to the elements in the feature vector, three output nodes correspond to the three classes, herbs, shrubs and trees. Descent gradient algorithm is adopted in the work.
The output target values are set to \( P(1\ 0\ 0) \), \( P(0\ 1\ 0) \) and \( P(0\ 0\ 1) \) for herbs, shrubs and trees, respectively. The number of epochs is set to 1000. The error function is ‘mean square error (mse)’ which is set to 0.15. We have considered seven nodes in the hidden layer. The Figure 5.5 shows the performance of the optimal classification achieved for three classes with epochs 803 and learning rate 0.9. The comparative analysis of accuracies of three plants classes using different segmentation approaches and different classifiers is presented in Table 5.3 and also pictorial representation in Figure 5.6.

![Figure 5.5: Training performance of the neural network using geometrical feature](image)

**5.4.3 Support Vector Machine classifier**

In order to have a third classifier for comparison we have chosen Support Vector Machine (SVM) classifier. Three class SVM-classifier is designed for classification of plants into herbs, shrubs and trees. It comprises three pair-wise two-class SVM-classifier. We have used radial basis function (RBF) with gamma and cost penalty of one as parameters during experimentation. The input training samples and labels of training samples are passed as parameters to two-class
SVM classifier. The SVM classifier is trained with four geometrical features, aspect ratios of canopy and stem parts for the considered three classes. The SVM classifier uses a decision function to group the input training samples into three class labels. The labels are generated with respect to number of support vectors.

5.4.4 Percentage accuracy of recognition and classification

The classification accuracy improved with K-means segmentation using SVM and Neural Network classifier, but yet less accurate than the level set based method (Basavaraj S. Anami et al., 2010). The classification accuracies obtained using minimum distance classifier is 92%, 90% and 95% for herbs, shrubs and trees respectively as shown in Figure 5.6. The level set method with SVM classifier has yielded better classification results, namely, 94% for herbs, 92% for shrubs and 98% for trees. The classification accuracy for sample medicinal plant species using level set segmentation and SVM classifier is presented in Figure 5.7. Furthermore, it is found that the level set method with SVM approach helps in better classification of shrubs as it is considered a challenging task owing to the absence of stem part. This is attributed to exact segmentation by the level set method and chosen feature set for the images of medicinal plants. The confusion matrix using level set and K-means segmentation with different classifiers is presented in Table 5.3(a) to Table 5.3(d).
Figure 5.6: Comparative analysis of Classification rate (%) with level set and K-means segmentation with other classifiers

![Comparative Performance Graph](image)

Figure 5.7: Classification accuracy of different medicinal plant species

Table 5.3: The confusion matrices for Medicinal plant image classification

(a) Level set segmentation and SVM classifier

<table>
<thead>
<tr>
<th>Plant Class</th>
<th>Herbs</th>
<th>Shrubs</th>
<th>Trees</th>
</tr>
</thead>
<tbody>
<tr>
<td>Herbs</td>
<td>121</td>
<td>02</td>
<td>02</td>
</tr>
<tr>
<td>Shrubs</td>
<td>03</td>
<td>119</td>
<td>03</td>
</tr>
<tr>
<td>Trees</td>
<td>01</td>
<td>01</td>
<td>123</td>
</tr>
</tbody>
</table>

(b) Level set segmentation and NN classifier

<table>
<thead>
<tr>
<th>Plant Class</th>
<th>Herbs</th>
<th>Shrubs</th>
<th>Trees</th>
</tr>
</thead>
<tbody>
<tr>
<td>Herbs</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shrubs</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trees</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### (c) Level set segmentation and minimum distance classifier

<table>
<thead>
<tr>
<th>Plant Class</th>
<th>Herbs</th>
<th>Shrubs</th>
<th>Trees</th>
</tr>
</thead>
<tbody>
<tr>
<td>Herbs</td>
<td>116</td>
<td>05</td>
<td>04</td>
</tr>
<tr>
<td>Shrubs</td>
<td>08</td>
<td>113</td>
<td>04</td>
</tr>
<tr>
<td>Trees</td>
<td>02</td>
<td>04</td>
<td>119</td>
</tr>
</tbody>
</table>

### (d) K-means segmentation and minimum distance classifier

<table>
<thead>
<tr>
<th>Plant Class</th>
<th>Herbs</th>
<th>Shrubs</th>
<th>Trees</th>
</tr>
</thead>
<tbody>
<tr>
<td>Herbs</td>
<td>82</td>
<td>22</td>
<td>21</td>
</tr>
<tr>
<td>Shrubs</td>
<td>36</td>
<td>65</td>
<td>24</td>
</tr>
<tr>
<td>Trees</td>
<td>14</td>
<td>21</td>
<td>90</td>
</tr>
</tbody>
</table>
5.5 RECOGNITION AND CLASSIFICATION OF MEDICINAL PLANTS BASED ON COLOR, EDGE AND EDGE DIRECTION HISTOGRAM

The histogram based features are also trained with SVM classifier. In case of SVM three classes are used. A multi-class problem is reduced to three 2-class and pair wise multiclass scheme. We have used three, 2-class Support Vector Machine (SVM) for classification of medicinal plants. Radial basis function (RBF) with scaling factor 1 is applied. The input training samples and labels of training samples are passed as parameters with 2-class SVM classifier.

The performance of the work is compared with Radial Basis Exact fit (RBENN) classifier. The network architecture consists of two layers. In case of color histogram, the input layer consists of 256 neurons, corresponding to number of input features. The output layer consists of three neurons, representing the number of output classes. Radial basis network with exact fit function is constructed with 0.15 error. The trained feature vectors are validated and tested with images of plants of different classes. A radial basis neuron with a weight vector close to the input feature vector produces a value nearer to unity. If a neuron has an output of 1, the output weights in the second layer pass their values to the linear neurons in the second layer. The output of linear layer is 1 for one input feature vector only based on the distance between input and weight matrix and for all other vectors the outputs are 0's. The output target values are set to
T(1 0 0), T(0 1 0) and T(0 0 1) for herbs, shrubs and trees respectively. The image samples are divided into training and testing data sets.

5.5.1 Based on Color histogram Feature

Two-class SVM classifier is trained with color distribution values for each color space, RGB, HSV and YCbCr. Hence, a SVM classifier is constructed with 256 features and 3 output classes. It is observed few overlapping values in herbs and shrubs images for color histogram values. The RGB color space provides better results for color histogram. Therefore, SVM classifier is trained with only RGB space color histogram features. The SVM classifier uses a decision function to group the input training samples into three class labels. The labels are generated with respect to number of support vectors.

From the experimentation, it is clear that trees are fairly classified since trees have well defined color distribution values. The maximum classification accuracy of 74% is obtained for tree image samples with SVM classifier and minimum accuracy of 60% is reported for the shrub image samples with neural network classifier as shown in Figure 5.8. Other than color, the edge features of medicinal plants are also helpful in distinguishing the herbs, shrubs and trees. Hence, we have attempted recognition with edge histogram and edge direction histogram as texture features.
Figure 5.8: Color histogram based classification accuracy in RGB

5.5.2 Edge based texture features

The devised classifier is trained with three edge histogram features and four edge direction histogram features. The edge texture feature performed well in extracting trunk parts from images of different medicinal plants images. The edge information gives the most discriminating feature for herb, shrub and tree recognition and classification. Hence, the edge direction histogram feature yielded higher classification rate for both the classifier. Figure 5.9 shows, the percentage accuracies of recognition for herbs, shrubs and trees images (84.33%,80.67%), (70.7%,66.58%) and (88.23%,84.59%) respectively with SVM classifier and neural network classifier using edge histogram features. It is revealed that the classification accuracy for trees is good. But the methodology is vulnerable to herbs and shrubs, as these plants do not have a distinguishable stem part. The recognition and classification accuracy is improved, when we have used edge direction information for the same set of plant image
species. This is because each plant is identified mainly based on the edges and branching patterns of stem or trunk or leafy mass. Hence, edge texture becomes the more discriminating feature for classification. The average accuracies have increased from 74% (Color histogram) to 88% for tree image samples using edge histogram information with SVM classifier.

![Edge Histogram](image)

**Figure 5.9: Edge histogram texture features classification accuracy**

### 5.5.3 Edge Direction histogram feature

The SVM and neural network is trained with edge direction information in four direction. From the classification results, the edge direction histogram is found to be quite effective for representing texture and branching patterns. From the Figure 5.10, it is observed that the classification accuracies are 88%, 70% and 90% with herb, shrub and tree images respectively. The tree image samples with clear stem length have given encouraging results than herbs and shrubs.
samples.

![Edge Direction Histogram](image)

**Figure 5.10: Edge direction histogram texture features classification accuracy**

5.5.4 Combined Color and Texture features

Experiments are performed on combined color, edge histogram (EH) and edge direction histogram (EDH) texture features using SVM and ANN classifiers. The number of input features is 263. The output classes are 3. Figure 5.11 gives the classification accuracies observed for the medicinal plant images of the three classes. The maximum and minimum classification accuracies observed are 94% and 70% with SVM classifier for tree and shrub image samples respectively. The accuracy is about 90% and 65% with ANN classifier for tree and shrub image samples respectively. The classification accuracy is maximum for trees and minimum for shrubs, with both the types of classifiers. The images of shrubs species do not have stem information and hence the accuracy suffers. The experimental results have shown that the combination of colour and edge histogram texture features has improved the average classification accuracy from 74% to 90%.
5.6 RECOGNITION AND CLASSIFICATION OF CANOPY AND STEM IMAGES BASED ON COLOUR MOMENTS AND TEXTURE FEATURES

The leafy mass (also called canopy) and stem parts of plants represents an unique color and texture patterns. The spatial distribution of pixels provides the branching pattern and intensity variation in the canopy and stem. Hence, the leafy mass and stem images of sample medicinal plant images considered as appropriate for recognition and classification.

In order to corroborate the accuracy of classification of medicinal plant species obtained from geometrical and histogram based classifications, we have considered feed forward backpropagation neural network using canopy and stem texture. We have used 42 input nodes and three output nodes corresponding to input features and three output classes respectively. The number of hidden layers are set to two with hidden nodes four and three respectively in each hidden layer. The neural network is configured...
with learning rate of 0.7 and goal of 0.22. The performance of the network is obtained at 262 iterations. The output patterns for ANN are represented in binary form as \((1 \ 0 \ 0)\), \((0 \ 1 \ 0)\) and \((0 \ 0 \ 1)\) corresponding to herbs, shrubs and trees respectively. The Figure 5.12 shows the performance achieved in classification of three plant classes.

![Training performance of the neural network](image)

**Figure 5.12: Training performance of the neural network**

We have considered the leafy mass and stem images of the corresponding plant species for training and testing. Totally, five plant species of each class are considered, amounting to 15 plant species. The training dataset includes 750 image samples of leafy mass, 50 samples of each plant species. Similarily, 500 image samples, 250 image samples of herbs stem and 250 image samples of tree stem are considered. The neural network is trained with 1250 image samples. Another set of testing dataset equal to 50% of training are used for testing. Twenty five images of each plant species excluding shrub stem, 250 image samples are used for testing. The developed network is trained with 18 color features, 24 texture features as discussed in Chapter 4. The graphs shown in Figure 5.13(a) and Figure 5.13(b) give the classification accuracies of three classes using color and texture
features for canopy and stem respectively. From the graph, it is observed that the canopy has provided an average classification accuracy of 80%, 84% and 90% for herb, shrub and tree images respectively using color features. Since, the branching pattern of foliage, overlapping pattern of leave, small openings, bushiness or spreadness of leaves with twigs and rachis gives rise to an unique texture pattern of herbs, shrubs and tree images. The classification accuracy of plant species is high with texture features. The recognition accuracy with stem images is less compared to leafy mass because of insignificant development of stem in herbs sample images and varying color characteristics. From the Figure 5.13(b), it is observed that, the stem information is absent in shrubs, hence it is not considered for experimentation. The classification accuracy of herbs and tree samples is (78%, 84%) and (86%, 98%) respectively with color and texture features.

Figure 5.13(a): Classification accuracies of canopy images using color and texture
Further neural network is also constructed for individual plant species recognition using color and texture features. The feed forward network is constructed with the same configuration but with five output nodes corresponding to five plant species. The average classification of medicinal plants are depicted in Figure 5.14. It is observed that maximum and minimum classification accuracies of 96% and 80% are obtained for Indian Oleander and Taro plant species respectively with color features. Texture based classification has provided a better average classification accuracy of 98% and 90% for Neem and Gigantic swallow wort. The present work gives better classification accuracy than the Meyer et al.,[92] who have used fuzzy color index, Excess green for the classification of corn plants canopy structure. Similarly, the stem based recognition and classification accuracy is presented in Figure 5.15 only for herbs and trees sample images. The classification accuracy based on stem/bark are found to
be more effective than multiresolution and color features found in [145].

**Figure 5.14:** Classification accuracy of medicinal plant species based on leafy mass

**Figure 5.15:** Classification accuracy of medicinal plant species based on stem
5.7 LEAF SHAPE BASED CLASSIFICATION OF MEDICINAL PLANTS IMAGES

From the interaction with experts it found that leaves are most helpful in providing an unique and easily observable features. The literature survey provides recognition and classification of leaves based on basic shape features, vein detection and multiresolution analysis. But the leaf recognition based on angle and margin is cited very less. Hence, this section provides leaf image classification from the features developed in Section 3.1.6.

5.7.1 Leaf Classification by Neural network classifier

In this work, the number of neurons in the output layer is set to 18 representing considered leaf images of sample plant species. The input nodes is 4 for shape features, 8 for margin coarseness features and 12 number of nodes when used in combination. In all the cases, the output layer has 18 nodes. A total of 450 images, 25 samples of each type of plant species are used for training the network. Another set of 450 leaf images, 25 of each plant species are used for testing. In this, we have considered a neural architecture with one input layer, three hidden layer, and one output layer.

The number of hidden neurons used in three layers are [7 6 7] amounting to total of 20 neurons. The FFBP neural network is constructed 4-20-18 (4 inputs, 20 neurons in the hidden layer, and 1 output) and minimum error of below 3% is adopted with 10,000 iterations. The network recognizes a pattern vector P as belonging to
class $O_i$ if the $i^{th}$ output of the network is “high” while all other outputs are “low”.

### 5.7.2 Classification based on the Basic shapes of Leaves images

The summarized results of shape based recognition and classification of medicinal leaf image samples are shown in Figure 5.16. The graph reveals that the classification accuracy of elliptic leaf images is around 96%. It is observed that few images of ovate leaves are misclassified as elliptic. We have observed that the widest part of the leaf for some of the oblong leaf images such as Periwinkle plant species, occur at only one location, namely, center of the midvein. This is due to weather conditions or water content of plant species affecting the slight variation in leaf size. Hence, the classification accuracy of oblong leaf image samples is around 90%. The accuracy of lobed leaf image is less compared to other leaves due to whirled and folded nature of lobed leaves images and improper alignment of stem parts. There are leaves which are irregularly arranged with small conical projections such as papaya leaf images. Thus, it is inferred that, to recognize and classify the image samples based on lobes is difficult.
The classification accuracy of leaf images of the medicinal plant species based on widest part of a leaf feature is shown in Figure 5.17. The accuracy of Ashoka and Almond plant species is 96% and is the largest. Similarly, for Hibiscus, Rose and Parijath leaf images the classification accuracy is 94%, 95% and 94% respectively which is more effective and faster compared to [112]. The features of Periwinkle leaf images overlap with Taro leaf images. This attributed to less projection of Taro images at the base of leaf and has equal distance at two locations for some of the leaf images. The average accuracy of
Anjeer and Cotton plant leaves images is less about 90%-92% which is more than [8][133].

5.7.3 Classification based on Base angle

The botanists, taxonomists, Ayurveda practitioners, identify leaves based on shapes. Amongst many shape features found in the literature it is observed that there is more overlapping results and misclassifications. Hence it is very difficult to recognize a plant only by visual shape features. Therefore, an angle based classification is adopted. From the database of leaf images, base angles are computed as described in the Section 4.3.1.6.2.

The classification accuracy of three different base angles are given in Figure 5.18(a). We have considered 100, 600 and 200 images of acute, obtuse and wide obtuse leaf images. From Table 5.5, it is observed that acute and obtuse angled leaf images are recognized better than wide obtuse angle. The stems of wide obtuse leaf images are attached at the back or twisted. For some wide obtuse angled leaf images, the stalk is attached at the backside of the leaf and at the center. Hence, the segmentation of wide obtuse leaf images the perfect base point is not obtained. The classification accuracy of wide obtuse leaf images is less and is around 86%. This is due to imprecise identification of base point and stem attachment during angle computation. The classification accuracy of sample images is presented in 5.18(b).
Table 5.5: Mean shape feature values of sample medicinal plants species leaf images

<table>
<thead>
<tr>
<th>Sl No</th>
<th>Plantspecies name</th>
<th>Basic Shape</th>
<th>LW</th>
<th>Loe (From Apex)</th>
<th>Apex angle</th>
<th>Base angle</th>
<th>Margin Coarseness</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Ashoka</td>
<td>Obtuse</td>
<td>71</td>
<td>179</td>
<td>36</td>
<td>41</td>
<td>1.85</td>
</tr>
<tr>
<td>2.</td>
<td>Norman</td>
<td>Elliptic</td>
<td>90</td>
<td>173</td>
<td>13</td>
<td>38</td>
<td>3.05</td>
</tr>
<tr>
<td>3.</td>
<td>Almond</td>
<td>Obtuse</td>
<td>210</td>
<td>122</td>
<td>98</td>
<td>79</td>
<td>1.55</td>
</tr>
<tr>
<td>4.</td>
<td>Golden Shower</td>
<td>Obtuse</td>
<td>219</td>
<td>123</td>
<td>103</td>
<td>44</td>
<td>2.49</td>
</tr>
<tr>
<td>5.</td>
<td>Hibiscus</td>
<td>Elliptic</td>
<td>264</td>
<td>188</td>
<td>96</td>
<td>113</td>
<td>2.18</td>
</tr>
<tr>
<td>6.</td>
<td>Paper plant</td>
<td>Elliptic</td>
<td>197</td>
<td>145</td>
<td>64</td>
<td>85</td>
<td>1.80</td>
</tr>
<tr>
<td>7.</td>
<td>Rose</td>
<td>Elliptic</td>
<td>253</td>
<td>154</td>
<td>96</td>
<td>114</td>
<td>1.86</td>
</tr>
<tr>
<td>8.</td>
<td>Sunhemp</td>
<td>Obtuse</td>
<td>173</td>
<td>145</td>
<td>107</td>
<td>171</td>
<td>2.00</td>
</tr>
<tr>
<td>9.</td>
<td>Punja</td>
<td>Obtuse</td>
<td>265</td>
<td>188</td>
<td>82</td>
<td>177</td>
<td>1.66</td>
</tr>
<tr>
<td>10.</td>
<td>Brital</td>
<td>Elliptic</td>
<td>288</td>
<td>170</td>
<td>92</td>
<td>195</td>
<td>1.92</td>
</tr>
<tr>
<td>11.</td>
<td>Periwinkle</td>
<td>Obovate</td>
<td>148</td>
<td>144</td>
<td>72</td>
<td>61</td>
<td>2.51</td>
</tr>
<tr>
<td>12.</td>
<td>Guava</td>
<td>Obovate</td>
<td>139</td>
<td>163</td>
<td>76</td>
<td>51</td>
<td>2.33</td>
</tr>
<tr>
<td>13.</td>
<td>Tarn</td>
<td>Elliptic</td>
<td>216</td>
<td>171</td>
<td>72</td>
<td>233</td>
<td>2.10</td>
</tr>
<tr>
<td>14.</td>
<td>Auriculae</td>
<td>Obovate</td>
<td>298</td>
<td>137</td>
<td>106</td>
<td>226</td>
<td>2.64</td>
</tr>
<tr>
<td>15.</td>
<td>Asper</td>
<td>Lobed</td>
<td>256</td>
<td>146</td>
<td>83</td>
<td>216</td>
<td>2.16</td>
</tr>
<tr>
<td>16.</td>
<td>Cotton</td>
<td>Lobed</td>
<td>288</td>
<td>143</td>
<td>49</td>
<td>210</td>
<td>1.43</td>
</tr>
<tr>
<td>17.</td>
<td>Helenium</td>
<td>Obovate</td>
<td>255</td>
<td>165</td>
<td>195</td>
<td>182</td>
<td>1.36</td>
</tr>
<tr>
<td>18.</td>
<td>Kankar</td>
<td>Obovate</td>
<td>258</td>
<td>137</td>
<td>198</td>
<td>196</td>
<td>1.67</td>
</tr>
</tbody>
</table>
Figure 5.18(b): Classification accuracy of sample plant species based on base angle

5.7.4 Classification accuracy based on apex angle

Since two leaf images have the same base angle but varying apex angles. We have tried to recognize leaf images based on apex angles. The elliptic and obovate leaf images have acute base angles but vary in apex angles. Obtuse acuminate leaves images have base obtuse and apex acute angles. For lobed leaves, the apex angle is obtained for central lobe only. Hence, apex angle is an important feature for discriminating leaf images with various shapes.

In this work, we have considered 500, 300 and 100 leaves samples of acute, obtuse and wide obtuse angled leaves respectively. The classification accuracy of leaves samples based on three types of apex angles is shown in Figure 5.19(a). The maximum and minimum classification accuracy of 96% and 88% are obtained for acute and wide obtuse leaf images respectively. Few leaves images of obtuse angled leaves images are classified as acute angled leaves images. The classification accuracy of sample plant species is presented in Figure 5.19(b). From the graph, it is observed that only angle based retrieval is not sufficient feature for medicinal plant information retrieval. Further, we tried with other shape features such as margin.
Figure 5.19(a): Classification Accuracy based on Apex angle

Figure 5.19(b): Classification Accuracy of sample plant species based on Apex angle

5.7.5 Classification based on leaf margin

There are leaves with same base and apex angles. To distinguish such types of leaves images, an effective feature is required. The two leaf images with the same base and apex angles have varying margins. Hence, margin is considered as one of the important feature for classification. In total 500 images of entire, 150 images of serrate, 100 images of crenate and 150 images of dentate leaf samples are considered in this part of the work. The recognition and classification accuracy for different margin types with corrugated teeth is less and it is high for leaves with smooth margin as given in
Figure 5.20(a). The average accuracy of sample medicinal plant species is presented in Figure 5.20(b).

![Classification accuracy based on margin types](image1)

**Figure 5.20(a): Classification accuracy based on margin types**

![Classification accuracy of sample plant species leaf based on margin](image2)

**Figure 5.20(b): Classification accuracy of sample plant species leaf based on margin**

### 5.7.6 Classification accuracy based on combined angle and margin features

In order to investigate the plant features, we have combined margin and angle features and is applied on three types (Acute, Obtuse and wide obtuse) leaves images. The recognition accuracies are increased for each type of leaves shapes and are presented in Figure 5.21. The comparative analysis of leaf image classification reveals that the combined features gives better classification accuracy than individual features. The classification accuracies of Ashoka, Neem, Almond, Hibiscus and Parijath plant species leaves are good
compared to other plants species. The classification accuracies are in the range 90%-99%. The proposed method presented robust features which helped in better recognition for leaves with varying tip and base shapes than other works menatined in [26][70][130].

![Classification Accuracy](image)

**Figure 5.21:** Classification accuracy of plant species based on combined features

## 5.8 Classification Based on Spectral Features

The shape and texture features obtained from Chapter 4 are used for the classification of medicinal plants images as herbs, shrubs and trees using Neural Network classifier.

### 5.8.1 Classification based on Shape descriptor

- **Fourier Descriptors**

  The four important Fourier Descriptors (FDs) that are formed using four shape signature functions namely, complex coordinates, centroid distance, curvature signature and cumulative angular function are used to train the feed-forward neural network for identification and classification of medicinal plants. The back propagation algorithm is used for training. The shape features are
used as inputs. The error function is set to 0.15. The learning rate of 0.9 is adopted. The input layer has four number of neurons equal to the number of FDs, and output layer has three output nodes corresponding to plant class. For each of the signature a separate feed forward network is configured. The recognition and classification accuracies of medicinal plants samples is depicted in Figure 5.22. The results show that the classification using FDs derived from centroid distance and cumulative angular function signature are significantly better than that using FDs derived from the other two signatures. The centroid distance and cumulative angular function are very sensitive to minor changes on the contours. These features are very discriminant and hence the classification of herbs, shrubs and trees is effected. Since, the spectral pattern of herbs and tree plant species varies significantly, the classification accuracy of trees is better than herbs and shrubs.

![Figure 5.22: Classification accuracy based on Fourier Descriptors](image)

- **Generic Fourier Descriptors and Zernike moments**
The Generic Fourier Descriptor (GFD) represents the modified polar fourier transform. Since, the GFD features are rotation and translation invariant, the classification accuracy is better than Fourier Descriptor. Zernike moments are the one more feature used for classification. The comparison of FD, GFD and Zernike moments shape features are shown in Figure 5.23. Since, the Zernike moments are a class of orthogonal moments and are very much effective in terms of image representation. The zernike moments are represented by set of orthogonal complex polynomials, thus reducing the redundancy. Hence, with Zernike moments, the plant image samples which has been captured from different direction yielded approximately similar features. The zernike moments are rotation invariance, robust to noise, effective and provides the invariant features much expressively than any other moments. The low order zernike moments polynomials approximate the global shape feature of plant and higher order polynomials capture the local shape. An average accuracy of combined features yielded classification rate of 88%, 72% and 92% for herbs, shrubs and tree image samples respectively.
5.8.2 Classification based on texture descriptor

- **Gabor descriptor**

The energy content at different scale and orientations are obtained as discussed in Chapter 4. Each plant image is filtered with three orientations and frequencies and the resulting values are used as feature vector. The classification accuracy of tree images using gabor features is better than shape descriptors. An improved rate of classification of 84% is observed in the case of shrub image samples. From, the graph shown in Figure 5.24, reveals that gabor texture features are suitable for the texture analysis of plant image species.
5.8.2 Classification based on combined shape and texture descriptor

The results are also compared with the classification achieved using shape descriptors, texture descriptors and combined features. An improved rate of classification is observed in the case of combined features. An increase in the average classification accuracy of 4% is observed compared to individual features.

![Figure 5.25: Comparative analysis of classification accuracy using combined features](image)

**Summary**

This Chapter reports automatic classification of medicinal plant species through full plant, leafy mass, stem and leaves images. The work has adopted a robust approach for the classification of medicinal plant images using different classifiers. It is revealed that geometrical feature based classification has yielded better classification results based on height. The comparison of performances of classifiers and segmentation methods has reported that level set segmentation with Support Vector Machine has given good recognition accuracy. Due to growing characteristic of plants and soil characteristics, the medicinal plants may exhibit varying height in different locations. Hence, the
histogram based features are experimented mainly for the analysis of stem information among herbs, shrubs and trees. Further, for the detailed analysis of the study, the parts of the plants, namely leafy mass, stem and leaves are recognized and classified. The color and texture features are found to be suitable for the task of identification and classification of leafy mass and stem. From the experimental results it is observed reduction in accuracy for stem image samples. The same is true with human vision system too.

Finally, the medicinal plants are also recognized based on leaf characteristics. The base angle, apex angle and margin information are found to be more appropriate for classification. The outcome of study show that the recognition and classification of medicinal plants from shape and margin features of leaves are significantly better than any other parts. Also, the rate of classification using leaf images of individual medicinal plant species is much better than the classification made with full plant image. The work provides the classification of leaves using the same terminolgy as used by botonist and ayurvedic practioners. Further, the classification accuracies using frequency domain features are also reported. It is inferred that combined shape and texture descriptors are more suitable for the analysis of tree image samples and less for herbs and shrubs images. Therefore, the proposed approach is very similar to how human beings recognize the plants and leaves in the real world.