CHAPTER 4
FEATURES AND FEATURES’ SELECTION FOR MEDICINAL PLANTS

In Chapter 3, we have discussed the feasibility of segmentation techniques to the problem domain. Once the image of medicinal plant is obtained from the background, the features selection and division become important. In this chapter, we have defined certain new features and adopted existing ones in recognition of shrubs, herbs and trees.

4.1 INTRODUCTION TO PLANT FEATURES

Human beings identify the plants by their stems, leaves, flowers and fruits. These become the features in their automatic recognition and differ from one plant to the other. Medicinal plants are not the exceptions. The classification of medicinal plants depends upon features uniqueness of the plant. The Scientists and Ayurved practitioners and plant experts have collected data on innumerable plant species by studying the plants in their natural habitats and recorded information on their characteristics in scientific literature and databases for future reference. Consequently, taxonomists have defined some nomenclature and botanical terminologies through which plant and its parts are recognized. But, a machine vision system for recognition of medicinal plants requires capture of these features through either division of new approach for feature extraction or adoption of existing methods in the literature.
The height, trunk shape and stem dimension form morphological features for medicinal plant identification. The textural feature of leafy mass, color and branches also form other features. In addition, the medicinal plants are also recognized based on subparts mainly orientation of the plants’ leaves and branching patterns. Some of the flowering plants are also identified by the shape and color of flowers and fruit bearing plants by their fruits. The seeds and their shapes also convey information about the plants. The recognition of medicinal plants is considered a challenging task due to their complex geometries and wide variations in their appearance. The features, such as color and height vary with respect to geographical location, season and soil content. Hence, an attempt is made to describe efficient features for medicinal plant identification and classification.

### 4.2 RELATED WORK ON PLANT IMAGE IDENTIFICATION

We have carried out literature survey to find out the-state-of-the-art in features and their applications in identification and classification of plants in general and medicinal plants in particular. Following is the gist of the survey.

Han-Li et. al., have developed an algorithm by combining three-dimensional computer vision techniques and image processing method for determining the height of cotton plant images. The height of cotton is represented by coordinates of two key points on the image. Based on the parameters of the camera and some constraints of the two key points, the plant height is obtained in the world coordinate
system. An approximation error of 5mm is observed during experimentation [47].

Juan Zhang and Xin-yuan Huang have proposed a survey of machine vision system for recognition of plants from leaves and flowers. The limitation of each of the methods is presented [73].

Peizhen Wang et. al., have developed a SIFT (Scale Invariant Feature Transform) algorithm for extracting features of plant images using shape features. The features are matched with the Best Bin First (BBF) algorithm. The approach is found to be efficient under different illumination conditions and directions of imaging [101].

Hans-Erik Andersen et al., have developed a method for measuring the tree height from dense forest images. The lidar data about tree images are obtained and least square adjustments are adopted for measuring the tree heights of Western North America namely, Douglas-fir and ponderosa pine. They have considered an angle of elevation approach and digital terrain model [49].

Balltsavias et. al., have provided a method for measuring tree height and tree growth estimation from an aerial images using Digital Surface Models (DSM). An analysis of the shape of a plant outline is performed giving plant shape parameters. The authors have used a commercial software package for tracing leaf edges [15].

D.S. Shrestha and B.L. Steward have developed a stereo vision system for measuring the plant height. An experimental setup is adopted with
a CCD camera and a microcontroller to capture the top view of corn plant. The edge points of two images are obtained after plant segmentation. Plant height is used as feature and estimated by triangulation using pixel disparity between two images [33].

J. Hemming and T. Rath have developed a computer vision system under controlled lighting conditions. Eight different morphological features and three color features are used for identification. Two vegetables, namely, cabbage and carrots are considered. Depending on the growth stage and weed density the plants are classified correctly [61].

Carmel et. al., have presented there is a method for computerized analysis of panchromatic aerial photographs and for a study of vegetation map images. The spectral properties of individual pixels as well as their neighborhood characteristics are used to train by standard maximum-likelihood supervised classifier and neighborhood classifier. Based on the gray level distribution of pixels and regression analysis, the vegetation map is classified into tree, non-trees, shrubs and herbaceous vegetation. The average classification accuracy of 89% is achieved [19].

J.Dijkstra and Pompe have observed that the grading of rooted and unrooted begonia cutting into three classes small, medium and large using knowledge based image processing. The parameters such as area of leaf, total height including stem and leaf, the width of leafy
area, etc., are considered and trained with three-layer feed forward neural network. The system has given a good estimate of a plant size and top weight but could not describe the plant shape well [59].

Zhang N. and C. Chaisattapagon, have used color, shape and texture features for identifying weeds in wheat fields. Various color filters are used for discrimination of different weed and plant regions. The red and green filters are effective in detecting reddish stems of some weed species. Since only color information is not sufficient, shape features are also used for the classification of broad leaves of weeds from wheat leaves [143].

J. Jia and G. W. Krutz., have presented an approach for locating the centre of maize plant using a camera from top views of plants. The local feature of the maize leaves mainly veins of the leaves are detected based on the difference of reflectance parameters between main veins and leaves blade. The height of the maize plants is located using side views of the images [60].

A. Kadir et. al., have compared four shape features for identification of plant species through leaves. The geometric features, moment invariants, Zernike moments and Polar Fourier Transform (PFT) are adopted for characterizing shape features of 52 plant species leaves. The PFT has outperformed other features with an accuracy of 64% [2].

Qingxiao Niu et al., have used chain code and Fast Fourier Transform (FFT) for describing the shape contour of leaf images. A chain code
function is constructed and normalized to give to yield a new feature called Fourier Constant Factor Descriptor (FCFD). The approach is more efficient and computationally invariant [105].

Stefan Fiel and Robert Sablatnig., have developed a machine vision system for tree species identification from leaves, bark and needles images. The Gray level co-occurrence and wavelet transform features are obtained. The leaf dataset of Ash, Beech, Hornbeam, Mountain oak and Sycamore maple plant species, 34 images of each class are considered. The bark images of eleven tree species are used for experimentation. The classification rate is about 93.6% and 69.7% for the leaf and bark data sets respectively [120].

Shitala Prasad et al., have developed automated leaf identification and classification using curvelet transform. New multi-resolution and multidirectional curvelet coefficients are generated from part of a leaf image. The mean and standard deviation of the decomposed curvelet coefficients are obtained and trained with a SVM classifier. Compared to other plant species recognition systems, the proposed approach has given 95.6% accuracy [116].

Javed Hossain and M.Ashrafur Amin., have presented leaf recognition based on morphological features. The leaf image is preprocessed and aligned horizontally by rotating through an angle of inclination. The base point and few reference points on the leaf blades are selected manually by the user. Ten-fold experimentation is conducted with
probabilistic neural network. The average recognition rate of 91.4% is obtained [65].

Krishna Singh et. al., have developed three classification techniques for the leaf classification based on geometrical and morphological features. The SVM-BDT (Binary Decision Tree), PNN and Fourier moment techniques are employed for classification. The SVM based binary decision tree architecture has superior performance than PNN and Fourier moment technique [77].

Xiaodong Tang et. al., have developed an efficient segmentation method to extract soyabean leaf from any complicated background, especially with some inferrents or overlap between adjacent leaves. The marker-controlled watershed segmentation method is applied on the gradient images. Hue, Intensity and Saturation features of images are used [135].

Peter N. Belhumeur et. al., have described an automatic system in which a user photographs an isolated leaf on a blank background and the system extracts the leaf shape and matches it to the shape of leaves of known species. The leaf is segmented from the background using K-means clustering with K=2. The Inner Distance Shape Context (IDSC) has been used for shape matching based on the distance and angle from each point to all other points. The top most leaf images are retrieved along with textual descriptions. The system is
currently used in Smithsonian Institution National Museum in US National herbarium [103].

YunFeng Li et. al., have proposed an efficient leaf vein extraction method by combining snakes technique with Cellular Neural Networks (CNN). The color information is acquired in HSI (Hue, Saturation and Intensity) color space for extracting leaf veins from the background. The leaf vein is used as the feature in the work [140].

Jose Boaventura Cunha have described a plant leaf characterization using shape features such as area, perimeter, width and length. The feature values are compared with real measurement values and found an error rate of 3% [72].

Cholhong Im. et. al., have proposed a method for recognizing plant species based on shapes of leaves. The structure and detailed shapes of leaves are approximated by set of polygons, whose vertices represent the curvature of contour of leaves lobes. The Acer plant species (Maple) is considered for the study [23].

David Warren have developed an automated system for recognition of Chrysanthemum leaves images. Initially leaf image is processed and segmented using thresholding. The number of lobes and sinuses (gaps between lobes), leaf margin is obtained using curvature. The mean values of the ten plant species leaves images are obtained and compared with manual measurements [35].
R M Haralick, et. al., have described some easily computable textural features based on gray tone spatial dependencies. They have illustrated the application in category identification tasks of different kinds of image data [108].

Most of the published research has mainly focused on identification of plants species through leaves using shape and color features in spatial and frequency domain. A very less work is cited on recognition and classification based on features of full plant image under natural illumination condition. The work on plant classification based on plant geometry is less. To the best of our knowledge, no work on recognition and classification of medicinal plants species images in the Indian context is cited in the literature. Hence, it is the motivation for the present work on features for the images of different medicinal plant species.

4.3 HIERARCHICAL CLASSIFICATION OF MEDICINAL PLANTS’ IMAGES

We have used traditional shape taxonomy method for recognition and classification. The key features used for classification of plants are shown in Figure 4.1. The medicinal plants are classified in hierarchical manner into different groups based on the plant visual characteristics. The five levels of classification based on discriminating features of plants are given in Figure 4.2.
Figure 4.1: Features of a plant

![Diagram of plant with labeled parts](Image)

- Height
- Canopy
- Texture, stem pattern
- No. of Seeds
- Color
- Shape
- Sepal features
- Flower-bearing
- Non-flower bearing
- Fruit-bearing
- Non-fruit bearing
- Based on Branching pattern
- Leaf shape
- Leaf color
- Leaf margin
- Leaf arrangement

Figure 4.2: Hierarchical classification of medicinal plants

Basically, plants are classified as herbs, shrubs and trees based on height and stem/trunk dimensions. A plant image is recognized in two ways, either full plant including canopy and stem parts or by individual parts. The classification of plants also depends on how well these parameters are grouped. Among the plant features, the plant body and height features are the most important and effective visual features for classifying plants as per the plant taxonomy. The plants are recognized and classified based on height at the first level of plant
classification. The height of the plant is an identifying characteristic that defines the plants variety within a species. Many methods exist for measuring the plant height such as based on angle of elevation and the distance from the viewer. The clinometer is a device used to record the height of any object from the ground level. But, these methods do not give an accurate height value and do not suit for development of image processing applications. We have devised an approach wherein a relative height of a plant is obtained irrespective of the object distance. The features are considered based on spatial domain and frequency domain.

4.3.1 Features in Spatial Domain

The spatial domain features deal with change in pixel intensity values with respect to image space. The change in pixel positions corresponds to a change in the scene and the object. In this work, spatial domain features are extracted from the analysis of shape and texture of medicinal plants species. The aspect ratio based height feature is devised.

4.3.1.1 Medicinal Plant recognition based on height feature using Aspect ratio

The height of a plant is a changing variable. The plants are identified as herb, shrub and tree based on height. The height of a plant changes with season, soil content, weather condition and geographical location. It is observed that trees have thick stem (also called trunk) with projected crown of leaves. The trees grow more vertically than horizontally. The herbs have short green slender stems
with branches. The herbs grow horizontally and vertically but very slow compared to trees. The shrubs are short bushy plants with no distinguishable stem portion. The shrubs grow more horizontally and spread over the ground. These characteristics of varying height across the medicinal plant species are used as the discriminating features. The measurement of absolute height of a plant from the image is very difficult because of foreshortening of image size with distance. We have used the aspect ratios of canopy and stem parts. The relative height of a plant is expressed as ratio of leafy mass to its stem part.

Usually, the height ($H$) of a plant is defined as the vertical distance from the base (from ground) of the plant to the tip of the plant, as shown in Figure 4.3. The Aspect Ratios (AR) may be more or less the same for all the three types of species initially and as the days go by the aspect ratios certainly change. We study this change to classify the trees, herbs and shrubs. Hence we have considered only reasonably grown medicinal plants species, wherein the change in aspect ratios across trees, shrubs and herbs is observable.
Figure 4.3: Different ways for representing height (H) of a plant
(a) With stem and Canopy height (b) From base to tip of canopy

For the computation of height, the plant is segmented first from the background. K-means clustering is adopted for segmentation. The L*a*b* color space is used for clustering of pixels belonging to stem and canopy parts, as it is more suitable for natural images.

For determining the sizes of canopy and stem parts, these parts are segmented by representing the plant images in RGB color space. Further, the L*a*b* color space is designed to approximate human vision. It aspires to perceptual uniformity, and its L component closely matches human perception of lightness. It is thus used to make accurate color balance corrections by modifying output curves in $a$ and $b$ components, or to adjust the lightness contrast using the L component. The Figure 4.4 shows the sample medicinal plant species considered for height computation. For illustration we have considered 15 plant species, however the experimentation is carried on all 90 plant species.
Figure 4.4: Samples of medicinal plants images of Herbs, Shrubs and Trees classes

4.3.1.1 L*a*b* color space

The CIE recommended the L*a*b* features in a uniform color space, which approximates, close to, the Munshell space in term of three stimuli values X, Y and Z. The CIE L*a*b* color space is based on the three color receptors, namely, red, green and blue. The values of X, Y and Z are obtained from the RGB components as given under:

\[ X = 2.7690R + 1.7517G + 1.1301B \]
\[ Y = 1.0000R + 4.5907G + 0.0601B \]
\[ Z = 0.05656 + 5.59288 \]

The conversion formulae for obtaining the values of \( L^* \), \( a^* \), \( b^* \) are given in equation (4.1)(4.2) and (4.3) respectively.

\[ L^* = 116(x/y_0)^{1/3} - 16. \]
\[ a^* = 500[\frac{x}{y_0}]^{1/3}[\frac{y}{y_0}]^{1/3} \]  \quad \ldots \quad (4.2) \\
\[ b^* = 200[\frac{y}{y_0}]^{1/3}[\frac{z}{z_0}]^{1/3} \]  \quad \ldots \quad (4.3)

Where, the constants \( X_0, Y_0, \) and \( Z_0, \) are the three stimuli values of the standard white color. \( \text{L}^* \) gives the lightness, which corresponds to about ten times Munshell value. This space defines a uniform metric-space representation of color so that the Euclidian distance represents a perceptual color difference.

The representation of clusters in \( \text{L}^*, a^*, b^* \) color space yields pixels with close proximity. It is observed that in most of the herbs and the shrubs, both stem and leaves appear with the same color and texture. Therefore, it is quite interesting to segment them based on color or texture models. Due to this homogeneity, the exact segmentation of the parts is not possible. Hence, we have devised a method based on Scan Line Coherence Technique (SLCT) to identify the leafy part for images of herbs. A number of scan lines are drawn from the base of herb image. Looking at the images of herbs, it is observed that approximate number of green pixels at the stem part is in the range 15-20. Hence, if the number of green pixels at a particular point exceeds 15 then it is declared as leafy part. If the threshold value is increased then more leafy part gets clustered and stem area gets reduced. The tree presents distinct clusters for its leafy and stem parts. Hence, we have modeled a cluster based segmentation using K-means clustering algorithm with \( K=3. \) This has resulted into distinct two sets of clusters for the given tree image.
Once the clustering is completed, a morphological image is extracted out of the clustered images. The morphological images are eroded with [1x1] kernel to remove the single bit noises. After the application of K-means clustering technique L*, a*, b*, features are extracted from the segmented image.

The bounding boxes are drawn around the leaf and the stem portion and the corresponding areas are denoted by L1 and L2 respectively as shown in Figure 4.5. The aspect ratio of a medicinal plant is computed using equation (4.4)

$$\text{Aspect Ratio} = \frac{\text{Area of bounding box for stem portion (L2)}}{\text{Area of bounding box for leafy portion (L1)}}$$

... (4.4)

![Figure 4.5: Segmented leaf and stem areas](image)

The procedure adopted for computing the aspect ratio features is given in Algorithm 4.1.

**Algorithm 4.1: Aspect ratio feature extraction**

Input: Original 24-bit color image

Output: Aspect ratio feature values.

Start

Step 1: Separate the RGB components from the 24-bit input color image.
Step 2: Convert the given plant image from RGB to \( L^*a^*b^* \) color space.

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

Step 4: Label the segmented parts and draw the bounding boxes for leafy and stem segments. Then, estimate the areas \( L_2 \) and \( L_1 \).

Step 5: Compute the aspect ratio \((\bar{L})\) of the given plant \( \bar{L} = \frac{L_2}{L_1} \).

Step 6: Record the Aspect ratio.

Stop.

The aspect ratios of herbs, shrubs and trees for the images of medicinal plants are obtained. The graph presented in Figure 4.6 depicts the aspect ratio feature values for sample plants species given in Table 4.1. However a sub set of plants considered in the work is given in Appendix A. From the graph it is observed that aspect ratios are small for tree image samples and lie in the range 0.01 to 0.21 because of the presence of more canopy part.
Table 4.1: Scientific and common names of medicinal plant species

<table>
<thead>
<tr>
<th>Species No.</th>
<th>Scientific Name</th>
<th>Common Name</th>
<th>Plant class</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Capsicum Annuum</td>
<td>Chilli</td>
<td>Herb</td>
</tr>
<tr>
<td>2.</td>
<td>Vigna Unguiculata</td>
<td>Cow pea</td>
<td>Herb</td>
</tr>
<tr>
<td>3.</td>
<td>Costus Speciosa</td>
<td>Crape ginger</td>
<td>Herb</td>
</tr>
<tr>
<td>4.</td>
<td>Catharanthus Roseus</td>
<td>Periwinkle</td>
<td>Herb</td>
</tr>
<tr>
<td>5.</td>
<td>Withania Somnifera</td>
<td>Winter cherry</td>
<td>Herb</td>
</tr>
<tr>
<td>6.</td>
<td>Aloe Barbadensis</td>
<td>Indian Aloe</td>
<td>Shrub</td>
</tr>
<tr>
<td>7.</td>
<td>Ocimum americanum</td>
<td>Hoary basil</td>
<td>Shrub</td>
</tr>
<tr>
<td>8.</td>
<td>Cathamus Tinctoriuslin</td>
<td>Safflower</td>
<td>Shrub</td>
</tr>
<tr>
<td>9.</td>
<td>Allium Cepa</td>
<td>Onion</td>
<td>Shrub</td>
</tr>
<tr>
<td>10.</td>
<td>Calotropis Gigantea</td>
<td>Gigantic swallow wort</td>
<td>Shrub</td>
</tr>
<tr>
<td>11.</td>
<td>Cocos Nucifera</td>
<td>Coconut</td>
<td>Tree</td>
</tr>
<tr>
<td>12.</td>
<td>Tectona Grandis</td>
<td>Teak</td>
<td>Tree</td>
</tr>
<tr>
<td>13.</td>
<td>Phoenix Dactylifera</td>
<td>Date palm</td>
<td>Tree</td>
</tr>
<tr>
<td>14.</td>
<td>Carica Papaya</td>
<td>Papaya</td>
<td>Tree</td>
</tr>
<tr>
<td>15.</td>
<td>Azadirachita Indica</td>
<td>Neem</td>
<td>Tree</td>
</tr>
</tbody>
</table>

Figure 4.6: Aspect Ratios of sample plant species Herbs, Shrubs and Trees

4.3.1.2 Medicinal Plant recognition based on height feature using a new geometrical feature

The plant classification based on aspect ratio depends on the accuracy of segmentation of leafy mass and stem part. For the plants
which have the stem covered by the leafy mass, the feature aspect ratio is not suitable. In addition to that some of the shrub images have overlapping features with herb images due to soil background and improper results of segmentation.

Hence, we have tried the level set segmentation for improved recognition using the features aspect ratios. The level set segmentation is adopted for sample medicinal plant images as discussed in section 3.4.3. New geometrical features based on the aspect ratios, namely, $F_1$, $F_2$, $F_3$ and $F_4$ are defined, as given in equations (4.5). For segmented regions minimum bounding rectangles are drawn around the segmented leafy and stem parts. The leafy mass and stem parts dimensions are used for recognition and are depicted in Figure 4.7.

The four (also called geometrical features) aspect ratios in terms of stem and leafy parts are defined as

$$F_1 = \frac{L_{21}}{L_{22}} = \text{Leaf Length/Leaf Width}$$

$$F_2 = \frac{L_{11}}{L_{12}} = \text{Stem Length/Stem Width}$$

$$F_3 = \frac{L_{11}}{L_{21}} = \text{Stem Length/Leaf Length}$$

$$F_4 = \frac{L_{12}}{L_{22}} = \text{Stem Width/Leaf Width}$$

... (4.5)

The Table 4.2 gives the values of length and width of leafy mass and stem parts for sample images of herbs, shrubs and trees. The
values of L11 and L12 are higher for images of trees and herbs, because of distinct stem parts and these values are nearly zeros for shrub images. The ratio values of L11 to L12 are small for herb images. Figure 4.8 gives the geometrical feature values corresponding to different medicinal plant species belonging to herb, shrub and tree classes.

**Table 4.2: Values of length and width of Leafy mass and stem parts for sample plant species**

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Plant Species</th>
<th>Stem L11</th>
<th>Stem L12</th>
<th>Leaf L21</th>
<th>Leaf L22</th>
<th>Geometrical Features</th>
<th>Plant class</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Cow pea</td>
<td>12</td>
<td>6</td>
<td>48</td>
<td>85</td>
<td>0.5647</td>
<td>2.0000</td>
</tr>
<tr>
<td>2</td>
<td>Indian Aloe</td>
<td>0</td>
<td>0</td>
<td>15</td>
<td>11</td>
<td>1.3636</td>
<td>0.0000</td>
</tr>
<tr>
<td>3</td>
<td>Neem</td>
<td>36</td>
<td>05</td>
<td>57</td>
<td>85</td>
<td>0.6706</td>
<td>7.2000</td>
</tr>
</tbody>
</table>

The values of F1 are not discriminating as we have found the overlapping values in case of trees, shrubs and herbs. It is observed that the feature F2, the aspect ratio of stem length to the stem width is a discriminating feature for trees, herbs and shrubs. The value of F2 is greater than 2.0 for trees and 1.0 < F2 <= 2.0 for herbs. In case of shrubs, the stems are absent and hence, the value of F2 is zero. Further, the values of F3 and F4 are zero for shrubs. Hence, F2 is better than F1, F3 and F4 for classification of medicinal plants. The reduced feature set contains only F2 feature and used for further classification of medicinal plant images.
**Figure 4.8: Geometrical feature values of herbs, shrubs and trees Classes**

### 4.3.1.3 COLOUR FEATURE EXTRACTION METHODOLOGIES FOR CANOPY AND STEM IDENTIFICATION

One of the features that make possible the recognition of medicinal plant images by humans is color. Compared to other features, human vision system is more sensitive to color information. The medicinal plant images also exhibit unique homogeneous color invariably plants are green in color. Very few plants show different tones of green or combination of green with brown or purple or other colors. Because of the photosynthesis property and chlorophyll content, majority of the medicinal plants are green in color. Hence, the color feature is considered as a significant and most obvious feature for recognition of plant images. From the literature survey, it is also observed that researchers have considered green color band for color feature analysis. Therefore, we have extracted statistical features of the plant image in different color spaces. Figure 4.9 depicts the
sample images of a leafy mass and stems of herbs, shrubs and trees used in color and texture feature analysis.

![sample images of a leafy mass and stems of herbs, shrubs and trees](image)

**Figure 4.9: Sample images of Leafy mass and Stem images**

The color information of different parts of a medicinal plant images is represented in different color spaces. The commonly used color spaces used in machine vision system are RGB, HIS, L*, a*, b*, YCbCr and so on. The plant images we have captured are in RGB format. The RGB color space is based on the theory of three-basic colors, red, green and blue. The RGB format is the most basic color space. Other color space models are obtained through the RGB format conversion. The choice of color space depends on the image content and number of color components to be analyzed in the relevant domain. The RGB color space is not a homogeneous visual perception space. The HSI color space uses color characteristics of a direct sense of the three quantities the brightness or lightness (I), hue (H), saturation (S) to describe the color. This method is more close to what perceived by the human eye.

The values of RGB color components are in the range [0, 1]. The HSI components are extracted from these RGB components. The
equations (4.6), (4.7) and (4.8) are used to obtain the values of H, S and I components for a given image sample

\[
H = \cos^{-1} \left( \frac{\frac{1}{2}((R-G)+(R-B))}{\sqrt{(R-G)^2+(R-B)(G-B)^2}} \right) \quad \ldots \quad (4.6)
\]

\[
S = 1 - \frac{3}{R+G+B} \left[ \min (R, G, B) \right] \quad \ldots \quad (4.7)
\]

\[
I = \frac{1}{3}(R+G+B) \quad \ldots \quad (4.8)
\]

The images of canopy and stem parts are recognized by quantifying the distribution of color in the images change in the color with reference to average or mean and the difference between the highest and the lowest color values in all the color planes. This quantification is obtained by computing mean, variance and range for a given color image. Since these features represent global characteristics for a given image, we have adopted the color features, namely, mean, variance and range in this work. The equations (4.9), (4.10) and (4.11) are used to evaluate mean, variance and range of the image samples. The procedure involved in obtaining the 18 color features is given in Algorithm 4.2.

\[
\text{Mean } \mu = \sum_x \sum_y P(x, y) \quad \ldots \quad (4.9)
\]

\[
\text{Variance} = \sum_{x,y} (x - \mu)^2 P(x,y) \quad \ldots \quad (4.10)
\]

\[
\text{Range} = \max(P(x,y)) - \min(P(x,y)) \quad \ldots \quad (4.11)
\]

**Algorithm 4.2: Color Feature Extraction**

Input: Original 24-bit color image.

Output: 18 color features

Start
Step 1: Separate the RGB components from the original 24-bit input color image.

Step 2: Obtain the HSI components from RGB components using the equations (4.6) thru (4.8).

Step 3: Compute mean, variance and range for each RGB and HSI components using the equations (4.9) thru (4.11).

Stop.

**Table 4.3: Colour Features Used**

<table>
<thead>
<tr>
<th>Sl. No.</th>
<th>Color feature</th>
<th>Sl. No.</th>
<th>Color Feature</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Red mean</td>
<td>10.</td>
<td>Hue mean</td>
</tr>
<tr>
<td>2.</td>
<td>Red variance</td>
<td>11.</td>
<td>Hue variance</td>
</tr>
<tr>
<td>3.</td>
<td>Red range</td>
<td>12.</td>
<td>Hue range</td>
</tr>
<tr>
<td>4.</td>
<td>Green mean</td>
<td>13.</td>
<td>Saturation mean</td>
</tr>
<tr>
<td>5.</td>
<td>Green variance</td>
<td>14.</td>
<td>Saturation variance</td>
</tr>
<tr>
<td>6.</td>
<td>Green range</td>
<td>15.</td>
<td>Saturation range</td>
</tr>
<tr>
<td>7.</td>
<td>Blue mean</td>
<td>16.</td>
<td>Intensity mean</td>
</tr>
<tr>
<td>8.</td>
<td>Blue variance</td>
<td>17.</td>
<td>Intensity variance</td>
</tr>
<tr>
<td>9.</td>
<td>Blue range</td>
<td>18.</td>
<td>Intensity range</td>
</tr>
</tbody>
</table>

**Figure 4.10: Color Features for Herbs’ leafy mass**
The value of red mean of Taro is 0.5212 and of sesame is 0.3478. Similarly the value of green mean of Crape ginger is 0.5701 and of Sesame is 0.3934. The same is shown in the Figure 4.10. The color feature of green components is high for the herbs samples with dense leafy mass. From the color features values, it is observed that the value of blue range and saturation range are same for all the herbs samples. Hence, these features are excluded from the feature set. The value of green mean is the maximum with the value 0.5701 for Crape ginger and 0.3934 for Sesame image samples.
Figure 4.12: Color Features for Herbs stem images

It is observed that the stems of herbs are green or reddish in color. Hence, as shown in Figure 4.12, the maximum value of Red mean of 0.6366 for Crape ginger and minimum value of 0.4692 for Periwinkle are observed.

Figure 4.13: Color Features for Shrubs’ leafy mass

From the graph shown in Fig. 4.13, it is observed that 18 color features discriminate the herbs, shrubs and tree images based on values of mainly red and green and hue components. The feature
values varies mainly based on mean and range feature values than variance. The leafy mass of shrubs image have the highest feature value of 0.6308 for green component of Gigantic swort and the lowest feature value, nearly zero for variance features values.

**Figure 4.14: Color Features for Trees’ leafy mass**

![Image](image1)

**Figure 4.15: Color Features for Trees stem images**

In comparison with herbs and shrubs image samples, trees images exhibit a homogenous color component at canopy and stems parts. The value of green component depends on the coverage of branches.
with clustered leaf arrangements and background, such as sky, building or overlapping plants. For canopy with uniform leaf coverage, the green component is high. Hence, the values of green component values is higher than 0.6 (Figure 4.15) for Neem images than other images.

**4.3.1.4 TEXTURE FEATURE EXTRACTION METHODOLOGIES FOR CANOPY AND STEM IDENTIFICATION**

Most of the medicinal plants are green in color or variations of green. Since, the color value of plant changes slightly with the time of a day, season, soil content, geographical location and fluctuating lighting conditions, the recognition of plant species with only color feature will not give accurate results. Even the branching structure of plants follows a fractal nature with a repeatable texture pattern yielding tree crown. The medicinal plant species exhibit definite heterogeneous texture patterns in leafy masses and stems. Hence, texture features also become important in recognition. Therefore, we have considered two different approaches based on, namely, co-occurrence matrix and Gabor texture features for the analysis of texture of canopy and stem parts in image samples.

**4.3.1.4.1 Co-occurrence Matrix (CM)**

The co-occurrence matrix method of texture description is based on the repeated occurrences of gray levels (also called gray level configuration) in the image. The gray levels vary rapidly with distance in fine textures and slowly with distance in coarse textures. An occurrence of a gray level configuration is described by a matrix of
relative frequencies $P_{\varphi,d}(x, y)$, giving how frequently two pixels with
gray levels $x, y$ appear in the window separated by a distance $d$ in the
direction $\varphi$. The whole procedure of computing the co-occurrence
matrix is given in the form of Algorithm 4.3.

**Algorithm 4.3: Development of Co-Occurrence Matrix from the
Image $f(x,y)$.

Input: Color canopy/stem image of size $M*N$, $d=1$ and the direction $\varphi$
Output: Co-occurrence matrix $P_{\varphi,d}(x, y)$ in RGB components

Start

Step 1: Assign $P_{\varphi,d}(x, y) = 0$ for all $x, y$ belonging to $[0,L]$, where $L$ is
the maximum gray level in RGB plane.

Step 2: For all pixels $(x_1, y_1)$ in the image, determine $(x_2, y_2)$, which is
at a distance $d$ in the direction $\varphi$ and carry out

$$P_{\varphi,d}[f(x_1, y_1), f(x_2, y_2)] = P_{\varphi,d}[f(x_1, y_1), f(x_2, y_2)] + 1.$$

Step 3: Compute the $P_{\varphi,d} = (P_{00,d} + P_{45,0,d} + P_{90,0,d} + P_{135,0,d}) / 4$.

Stop.

The co-occurrence matrix is basically a reduced matrix of pixel
values in the range [0-255]. The simplest way to differentiate between
the image samples is carried by quantifying the average gray level,
change in the gray levels with respect to average gray level, minimum
and maximum gray levels within the matrix. Hence, we have used
basic co-occurrence features namely, mean, variance and range in
this work. The sample images of canopies of herbs also include small
opening, hidden/overlapped plants and soil parts in between leaf
arrangements. The branching pattern of leaves is coarsely distributed
in herbs. The shrub and tree image samples exhibit very less number of openings and background. The images of canopies of trees cover neighboring trees, sky and building. Similarly, the stem images may also be affected by shadow, camera direction and obstacles such as wall, stones and grass. These parameters have influence on the plant recognition based on texture. Hence, to characterize these features and to observe plant textures, we have considered the global texture features yielding the canopy and stem patterns separately. Initially, we have considered only nine different textural features, namely, energy, maximum probability, contrast, range, inverse difference moment, correlation, uniformity, entropy, inertia and cluster shade for the experimentation. We have found through experimentation that the features like uniformity, entropy, inertia and cluster-shade do not contribute significantly towards the identification and classification of plant images. Hence, we have reduced the feature set to include only six texture features, namely, mean, variance, range, energy, maximum probability, contrast, inverse difference moment and correlation. Among these, the mean, variance and contrast are found to be more distinguishable features. We have found that these selected textural features are adequate for discriminating effectively the images of herbs, shrubs and trees. The method used for the computation of texture features is given in Algorithm 4.4. The equations (4.12) thru (4.16) are being used in the Algorithm 4.4. The Table 4.4 gives the list of all texture features used in the work.
Energy = $\sum_{x,y} P^2(x,y)$ ... (4.12)

Maximum probability = $\max (P(x,y))$ ... (4.13)

Contrast = $\sum_{x,y} |x - y|^2 P(x,y)$ ... (4.14)

Inverse difference moment = $\sum_{x,y \neq x'} \frac{P(x,y)}{x'-x}$ ... (4.15)

Correlation $n = \sum_{x,y} \frac{[x,y] - \mu_x \mu_y}{\sigma_x \sigma_y}$ ... (4.16)

$\mu_x$, $\mu_y$ are mean values and $\sigma_x$, $\sigma_y$ are standard deviation defined by

$\sigma_x = \sum (x - \mu_x)^2 \sum P(x,y)$

$\sigma_y = \sum (y - \mu_y)^2 \sum P(x,y)$

### Table 4.4: Texture features based on Color Co-occurrence matrix

<table>
<thead>
<tr>
<th>Sl.No.</th>
<th>Features</th>
<th>Sl.No.</th>
<th>Features</th>
<th>Sl.No.</th>
<th>Features</th>
</tr>
</thead>
</table>

### Algorithm 4.4: Textural Feature Extraction

Input: RGB components of input image

Output: 24 Textural features

Start

Step 1: For all the separated RGB components, derive the Co-occurrence Matrices $P_{\varphi,d}(x,y)$ for four directions ($\varphi = 0^\circ$, $45^\circ$, $90^\circ$ and $135^\circ$) and $d = 1$. 
Step 2: Co-occurrence features, namely, mean, variance, range, are calculated using equations (4.9) to (4.11).

Step 3: Co-occurrence features like Energy, Maximum Probability, Contrast, Inverse Difference Moment and Correlation are calculated using equations (4.12) thru (4.16).

Stop.

Figure 4.16: Texture Feature values for Herbs leafy-mass image samples

Figure 4.17: Texture Feature values for Herbs-stem image samples
Figure 4.18: Texture Feature values for Shrubs-leafy-mass image samples

Figure 4.19: Texture Feature values for Trees leafy-mass image samples

Figure 4.20: Texture Feature values for Trees stem image samples
The red CM variance of periwinkle leafy mass is observed to be 1.6065 and that of its stem is 1.3091. The contrast value gives the local variation of the images and is high for leafy mass than stem images. It is clear that the distinct feature values are generated for both the image samples of leafy mass and stem parts using CM (Co-occurrence Matrix). The energy and contrast values of texture features for green component are higher for canopy than stem image samples. For the tree image samples the texture features are much distinguishable than herb samples. The Figure 4.16 thru Figure 4.20 show the plots for 24 texture features for leafy mass and stem image samples.

**4.3.1.5 Color, Edge and Edge direction histogram for representing plant edge pattern**

The visual features of medicinal plants depend on structural components of different parts, namely, trunk, branches, foliages, leaves, leaves sizes and orientation. Generally, the plant canopy develops through a repetitive production of new shoots, through stem and leaves. The developments of these parts vary from plant to plant. In order to characterize the medicinal plants, automatic feature extraction is required. These features are extracted from 2-D images of fully grown plants. In the previous section, we have given an approach for plant classification based on geometrical and texture features. The other features used for classification of plants are edges, edge histogram and color histogram. As it is observed from the sample plant species of Figure 4.4, the edge pattern of stem plays vital role in
recognition of herbs, shrubs and trees based on the edge or skeleton features of stem and leafy mass. The medicinal plants with woody color and single stem are recognized as trees. The medicinal plants with non woody color with small stem are recognized as herbs. The shrubs have certain branching patterns or sometimes the leaves shooting from base itself. Figure 4.21 gives the classification tree of plant species.

**Figure 4.21: Medicinal plants classification tree**

These features extracted are edges and edge direction histograms. We have used HSV and YC_bC_r color spaces for obtaining the color histogram. We have used YC_bC_r color space for computing the edge component. These features are used to train a SVM classifier.

4.3.1.5.1 Color histogram

Color histogram gives the variance in color of all the pixels in a given image. The intensity of green tone helps us to recognize the plant images. When we have two similar colors with different luminance, we find large Euclidean distances in the RGB color space and hence are regarded as different. In RGB color space, the histograms are quantized into 256 bins in order to represent the coarse color content
of medicinal plants images and to reduce dimensionality during matching phase. Since R, G and B have the same distances in color space, they are quantized into same levels. In HSV and YCbCr color spaces, the numbers of bins levels are in the ratio 4:2:2. In HSV color space, the quantization of hue component resembles more of the human visual system than saturation (S) and value (V) components. Hence, it is reasonable to assign more bits to hue than to the other components. Accordingly, in YCbCr space, luminance component is given more attention. The HSV and YCbCr color space are quantized with $4 \times 2 \times 2 = 16$ histogram bins.

From the color histogram, we have estimated the average number of peaks, valleys and the maximum peak at a specific gray tone level and are used as features. The algorithm 4.5 gives the procedure for computing these features. Figure 4.22 thru Figure 4.24 shows the color histograms in RGB, HSV and YCbCr color spaces for herbs, shrubs and trees respectively. It is observed that herbs (Figure 4.20) have maximum peak value at the gray tone value 70 in RGB plane. An average green tone value is observed between values 160 to 215 of gray levels. In HSV color space, the hue plane shows the maximum peak at the hue value of 0.3 corresponding to green tone value. It is observed that the image is saturated for a hue range $[0.0 - 0.4]$ and has empty regions for the remaining values. The Value plane provides an even distribution of brightness spread in the range $[0.2 - 0.9]$. Accordingly, luminance component gives the maximum peak at
the value of 156. The color histogram features for three classes are shown in Table 4.5. An average valley count of three is observed for herbs images.

![Color Histogram of Herb image](image)

**Figure 4.22: Color Histogram of Herb image**
(a) RGB color space  
(b) HSV color space  
(c) YCbCr color space
Figure 4.23: Color Histogram of Shrub image (a) RGB color space  (b) HSV color space (c) YC_cr color space
Algorithm 4.5: Color Histogram Computation

Input: Original 24-bit color images

Output: Number of peaks, maximum peak value, gray value of maximum peak and number of valleys.

Start

Step 1: Read the RGB medicinal plant images from the database
Step 2: Separate the RGB components from the original 24-bit color image.

Step 3: Apply Quantization for each plane and set the number of bins = 256.

Step 4: Compute the histograms in the three color planes.

Step 5: Compute the number of valleys based on maximum peaks.

Step 6: Obtain the maximum pixel count, gray level of maximum pixel count, number of peaks and valleys.

Stop.

<table>
<thead>
<tr>
<th>Plant class</th>
<th># of Peaks</th>
<th>Max peak value</th>
<th>Gray level value</th>
<th>Valleys</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>R</td>
<td>G</td>
<td>B</td>
<td>R</td>
</tr>
<tr>
<td>Herbs</td>
<td>8-14</td>
<td>10-12</td>
<td>8-15</td>
<td>913-1277</td>
</tr>
<tr>
<td>Shrubs</td>
<td>9-14</td>
<td>8-14</td>
<td>9-13</td>
<td>818-935</td>
</tr>
<tr>
<td>Trees</td>
<td>6-17</td>
<td>10-14</td>
<td>7-15</td>
<td>848-4116</td>
</tr>
</tbody>
</table>

Similarly, the histograms of shrubs images as shown in Figure 4.21 have the maximum peak value at gray tone value 150 with an average valley count of three or four is observed in RGB color space. In HSV color space, the Hue plane shows high spikes at three positions. Hue plane histogram is clipped off to the right and left. This indicates that image is overexposed and does not have clear mountain peaks. The shrub image is over saturated with peaks clipped to the left and middle peak is clipped off. The Value plane shows an even distribution of brightness spread between [0.1 - 0.8]. The luminance component in YC_bC_r color space gives smooth mountain peaks with maximum peak at 150. But blue chrominance and red chrominance have not revealed any details.
From the Figure 4.22 it is observed that the tree images have depicted two peak values at gray value 30 and 170 in RGB color space. The pixel count of second valley is higher and it spreads like a bell shape than that of herbs and shrubs representing high density of green tone value. An average valley count of two is observed with more variation in spikes due to brown or woody component in tree images. Because of these reasons the first peak is much prominent and narrow. But, the second peak shows Gaussian nature with wide distribution of canopy intensity. Accordingly, Hue plane provides more variation in hue color with non-uniform distribution. The luminance component gives two peaks, representing green and brown tone values. Hence, it is inferred that HSV color space is not suitable for recognition of tree images.

However, it is observed that RGB color space gives better clustering than other spaces. Hence, we have considered only RGB color space features for the recognition and classification of medicinal plant species. Finally, as all plant images are with green or shades of green color, there are overlaps in feature values with shrubs and herbs. Hence, this motivated us to compute edge features.

4.3.1.5.2 Edge Histogram Texture Feature

The analysis of edges from the image is considered an important feature to represent the content of an image. Human eyes are sensitive to edge features during image perception. The edges of the images of medicinal plants give the branching distribution of trunk or
stem and leaves. Hence, the edges of a plant image are other features that help in recognizing images of medicinal plant species. The Edge Histogram (EH) descriptor helps to capture properties. The edges from the images of plants are categorized into vertical, horizontal, 45° diagonal, -45° diagonal and isotropic (also called non-diagonal) edges based on strengths of directional edges. In addition, edge features represent the plant boundary and is used for contour representation of medicinal plant image from background. An edge filter is applied in each direction and edges are computed in five directions (B S Anami et al., 2010). The filter coefficients used in the work are given in Figure 4.25 and are used as edge filters in the five directions. The edge histogram is obtained by computing the gradients of pixels, that is the maximum rate of change of plant image at co-ordinates (x, y), in the five directions with a threshold value of 100 as given equation (4.27).

\[
\begin{pmatrix}
1 & -1 \\
0 & -2
\end{pmatrix}
\begin{pmatrix}
1 & 0 \\
-2 & 0
\end{pmatrix}
\begin{pmatrix}
\sqrt{2} & 0 \\
0 & -\sqrt{2}
\end{pmatrix}
\begin{pmatrix}
0 & \sqrt{2} \\
-\sqrt{2} & 0
\end{pmatrix}
\begin{pmatrix}
2 & -2 \\
-2 & 2
\end{pmatrix}
\]

(a) (b) (c) (d) (e)

Figure 4.25: (a) Horizontal edge filter (b) Vertical edge filter (c) Diagonal (45°) edge filter (d) Diagonal (135°) edge filter (e) Nondiagonal (isotropic) edge filter

We have applied edge filter with different thresholds on the same image. This gives us information on the different gradations on edges of the plant image. We used five different thresholds (Figure 4.26). When a low threshold is used, the gentle edges of leafy mass are detected. As the threshold increases, only genuine edges are detected. The edges of the stem or trunk are detected when threshold values are
low. The threshold values are set by experimentation. We have combined each of these images to form a combined image. The pixels that correspond to the gentle edges have given a low gray scale values and higher values are given to images with sharper edges of leafy mass.

\[ \theta = \arctan \left( \frac{G_x}{G_y} \right), \text{where } G_x \text{ and } G_y \text{ are gradient in } x \text{ and } y \text{ direction} \]  \hfill (4.17)

![Image](image1.png)

![Image](image2.png)

**Figure 4.26: Effect of threshold on edge histogram, with threshold values = 15, 25, 35, 45 and 55**

The edge histograms for herbs, shrubs and trees are shown in Figure 4.27.
From the nature of the Edge Histogram (EH), it is observed that for herbs and shrubs images, the number of edges in $0^0$ and $45^0$ are more than tree images. The number of edges in $45^0$ and $-45^0$ for the three classes is more or less the same. It is observed that the number of edges in $90^0$ varies for all the three classes and hence used as a discriminating edge feature. In case of herb images, the isotropic edges are very sparse. It is observed that the only three directions, namely, $0^0$, $90^0$ and isotropic angles (non-diagonal) are considered as the discriminating features in this work. Hence, the reduced feature set includes only edges in these three directions for computing the edge histogram.
4.3.1.5.3 Edge Direction Histogram Texture Feature

We have used Sobel operator for determining the edges and the direction of edges. The histogram for each of the images of medicinal plants represents the frequencies of occurrences of the six classes of edges in a given image. We have used an edge mask formed with a threshold value of 100. The edge pixels are characterized by the magnitudes of gradients greater than 100. The Edge Direction Histogram (EDH) uses Sobel operator to capture the spatial distribution of edges in the considered six directions, with values of filter mask as shown in Figure 4.28. The edges of these regions are computed in $0^\circ, 45^\circ, 90^\circ, 135^\circ, 180^\circ, 270^\circ$ direction. The basic idea is to get a local distribution of five types of edges from canopy and stem parts of an image. The edge direction histogram of a sample plant images are shown in Figure 4.29. The X-axis shows the degrees of directions of edges. Algorithm 4.6 presents an approach for extracting edge features of plant images.

Algorithm 4.6: Edge and Edge Direction Histogram

Input: RGB color image
Output: Edge and Edge direction histogram of a plant image

Start:

Step 1: Read the RGB image of a medicinal plant.

Step 2: Convert the image into $Y_\text{CbCr}$ color space.

Step 3: Extract the luminance(Y) component of the image.
Step 4: Obtain the edge and edge direction histogram using filter mask coefficients.

Step 5: Compute the gradient in the respective direction of the filter mask.

Step 6: Compare the gradient value with the threshold.

Step 7: \[ \text{If (Gradient value > threshold)} \]
then
\[ \text{it is an edge pixel.} \]

Step 8: Normalize the edge histogram and edge direction histogram.

Stop.

\[
X = \begin{bmatrix}
1 & 2 & 1 \\
0 & 0 & 0 \\
-1 & -2 & -1
\end{bmatrix} \quad Y = \begin{bmatrix}
1 & 0 & -1 \\
2 & 0 & -2 \\
1 & 0 & -1
\end{bmatrix}
\]

**Figure 4.28:** Sobel operator in X and Y direction

\[ \begin{array}{c}
\text{60° edge #: 7357} \quad \text{60° edge #: 4672} \\
\text{120° edge #: 8623} \quad \text{120° edge #: 8623} \quad \text{180° edge #: 2649} \quad \text{240° edge #: 45}
\end{array} \]

\[ \begin{array}{c}
\text{30° edge #: 51065} \quad \text{30° edge #: 34217} \\
\text{90° edge #: 59284} \quad \text{90° edge #: 59284} \quad \text{270° edge #: 1947} \quad \text{270° edge #: 12320}
\end{array} \]

**Figure 4.29:** Edge Direction Histogram and normalized number of edges of herbs, shrubs and trees in six directions

(a) \quad (b) \quad (c)
It is observed from Edge Direction Histogram (EDH) that the number of edges in $0^\circ$-direction is more for shrub images than herbs and trees because herbs are bushy in appearance. The maximum number of $90^0$-edges is found in each type of images of medicinal plants. But, the number of edges with $270^0$ is more in tree images than in herbs and shrubs. Hence, the in EDH features set we have included all angles excluding $90^0$. It is evident that the EDH features are translation and scale invariant but not rotation invariant. Therefore, the number of edges varies significantly with change in the direction.

4.3.1.6 MEDICINAL PLANT RECOGNITION BY ITS PARTS-LEAVES SHAPE AND MARGIN FEATURES

The different parts of the medicinal plants such as bark powder, leaves paste, roots, fruit juice and seeds are used in drug preparation in Ayurveda. Of these, leaves are mainly used. The leaves are identified by humans based on shape, size, color, margin and sometimes the vein structure. The sizes of the leaves are more prominent features and serve in identification of many plants. Further, the shape and size of leaves can be recognized in two-dimension. Therefore, a work on automatic identification of leaves is undertaken.

We have collected leaf images of reasonably grown medicinal plants. From the detailed analysis of these medicinal leaves images, it is found that the external leaf characteristics such as shape, angle,
margin, hairs are discriminating features for identifying plant species. The structure of a leaf is as shown in Figure 4.30(a). There are basically three main parts, namely, leaf stalk or petiole, leaf blade or lamina and stipules. The stalk or petiole is the thin section joining the base to the lamina and is generally cylindrical or semicircular in nature forming secondary stem or tendril. In some of the plants, the stalk is absent. Such types of leaves are called sessile. The connecting point from stem to leaf blade gives leaf arrangement pattern and is called base point.

Every leaf has centre-vein, which starts from leaf base and extends up to the length or tip of leaf. The widest part of is called lamina or leaf blade. The stipules are grown in few plants are tiny structures located on either sides of the base of the petiole. Not every species produces leaves with all of these structural components. A petiole may be absent or the blade may not be laminar (flattened). There exist large varieties of leaves structures. Hence, we have considered only the features of the leaf blade for recognition and classification.

Figure 4.30: (a) Basic parts of a leaf and dimensions
The botanists have defined rich terminology for describing leaf characteristics. The identification of medicinal plants based on their leaves is helpful in the field of Ayurveda. We find in the literature the terminology for different leaves patterns, shapes, arrangements and margins. The different leaves shapes based on base angle, base shape, tip angle, tip shape and margin are shown in Figure 4.30(b).

The medicinal plant species with different leaves apex shapes are termed as acuminate, convex, emarginate, mucronate, obcordate, rounded and truncated. Acuminate means the leaf is tapering to a long point and has an acute angle. Convex means the leaf curving away from the center of the lamina or tooth having angle between 70°-90°. Rounded means circular with circularity factor 1. Mucronate means apex terminating in a sharp point communicating the mid-vein. Truncated means apex is 180°. Obcordate means leaf has wider tip with an angle in the range 90°-180°. Emarginate means apex is slightly concave at tip with two sides of leaf blade projected.

The leaf base includes the shapes such as complex, concave, convex, cordate, cuneate, decurrent, hastate, lobate, rounded, sagittate and sessile. But, in this work, we have considered the octave, cordate, lobate, obovate, elliptic, and oblong shapes, because the leaves of medicinal plants are of these shapes. The ovate means leaf curving away from the center of the lamina or tooth and has broader base than apex. Cordate means heart–shape, stem attaches to cleft with wide obtuse base angle. Lobate means leaf blade having lobes
and base obtuse or wide obtuse angle. Obovate means leaves with broader at tip with obtuse angle and acute angle at base point. Elliptic means leaves with acute angle at both base and apex and having the widest part at the center. Oblong means leaves with base and apex obtuse but has equidistant parallel edges at the center part of the leaf.

![Figure 4.30: (b)(i) Shapes of different medicinal leaves
(ii) Shapes of apex and base (iii) Margin shapes](image)

The leaf margin includes the shapes, namely, ciliate, crenate, dentate, entire, serrate, sinuate and undulate. The margins considered in the work are entire, crenate and serrate, as the leaves of certain medicinal plants exhibit these margins. Entire means margin is smooth without teeth. Crenate means teeth smoothly rounded without a pointed apex. Serrate means teeth pointed with their axes inclined to the trend of the leaf margin.

### Table 4.8: Apex/Base angle ranges and classification

<table>
<thead>
<tr>
<th>Class(Apex/Base)</th>
<th>Range of Angles</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acute</td>
<td>$0^0 - 90^0$</td>
</tr>
<tr>
<td>Obtuse</td>
<td>$90^0 - 180^0$</td>
</tr>
<tr>
<td>Wide Obtuse</td>
<td>$180^0 - 300^0$</td>
</tr>
</tbody>
</table>
In this work, mainly three angles, namely acute, obtuse and wide obtuse have been considered. Table 4.8 gives the ranges for base or apex angles for the given three classes of images.

**4.3.1.6.1 Basic shapes of leaves Based on Widest part**

In this section, we have extracted the morphological features of leaves images of medicinal plants. The shape features are estimated based on geometrical interpretation and specific visual characteristics. In this work, three shapes features and eight frequency strings of numbers corresponding to margins shapes are extracted.

![Figure 4.31: Basic leaf shapes](image)

(a) Elliptic (b) Obovate (c) Ovate (d) Oblong (e) Lobed

The simplest way to describe the overall shape of the lamina is to locate the major axis and minor axis. The major axis is the line joining the beginning of stalk to the apex of the leaf. This is also called mid vein of the leaf. The minor axis are the lines drawn perpendicular to the major axis. The largest width of minor axis is used to specify the leaf size. The Figure 4.31 shows the different leaves shapes that are defined based on the position of the widest minor axis.

The shapes are defined as elliptic, obovate, ovate, oblong, lobed and special. The elliptic leaves have the widest part in the middle of...
the lengths of the leaves. The obovate leaves have the widest part at 3/4 of the lengths of the leaves. The ovate leaves have the widest parts of the leaves at 1/4 of the length of the leaves. The oblong leaves have the widest parts in between 1/4 to 3/4 of the lengths of the leaves. The lobed leaves have the blade shape. The special leaves are not described by any of the stated shapes. The example of such leaves include needle or awl. The procedure for finding the widest part of a given leaf and its location is given in Algorithm 4.7.

**Algorithm 4.7: Finding the location of the widest part**

**Input:** Image of leaf  
**Output:** Widest part location

Start

Step 1. Perform preprocessing and segmentation on input.

Step 2. Correct skew and make the leaf position vertical and base pointing downwards.

Step 3. Obtain the gray level image, region of interest and leaf contour

Step 4. Scan the input leaf image from top to bottom and obtain the number of intersections.

Step 5. Compute the leaf length $l_m$ Divide the length into four equal parts.

Step 6. Calculate the largest width and its location ($loc$)

Step 7. If (number of intersection $>$ 2)  
then Leaf Type = ‘lobed’

Step 8. If (number of intersection $=2$) and ($loc = l_m /2$)  
then Leaf Type = ‘Elliptic’;
If (number of intersection =2) and (loc = \( l_m / 4 \))

then Leaf Type = ‘Ovate’;

If (number of intersection =2) and (loc =3 \( l_m / 4 \))

then Leaf Type = ‘Obovate’;

If (number of intersection =2) and ( \( l_m / 4 < \text{loc} < 3 l_m / 4 \))

then Leaf Type = ‘Oblong’;

Stop.

4.3.1.6.2 Base angle

In order to find the base angle and apex angle, the leaf projections and their geometrical distances are defined as shown in Figure 4.30. The different leaf shapes are characterized based on their geometrical distances, namely, mid vein length (\( l_m \)), apical extension length (\( l_a \)), Basal extension length (\( l_b \)) and leaf length (\( L \)). \( l_m \) is the midvein length that is distance from proximal most to the distal most point of the mid vein (Figures 4.32(a)-4.32(d)). Apical extension length, \( l_a \) is the perpendicular distance from the distal most point of the mid vein to the distal most extension of leaf tissue (Figures 4.32(c), Figure and 4.32(d)). These are equal to zero (Figure 4.32(a) and Figure 4.32(b)). Basal extension length, \( l_b \) is distance on a perpendicular from the proximal most point of the mid vein to the proximal most extension of leaf tissue (Figure 4.32(b) and Figure 4.32(d)). These are equal to zero (Figure 4.32(a) and Figure 4.32(c)). The leaf length is expressed as arithmetic sum of these values. Leaf Length, \( L = l_m + l_a + l_b \).
Figure 4.32: Leaf shapes defined based on geometrical projection value

The vertex of the base angle lies at the centre of the petiole at the point, where the basal most laminar tissue touches the petiole. Base angle is the angle from the vertex to the pair of points, where a line perpendicular to the mid vein at 0.25 $l_m$ from the base intersects the margin. In leaves with a basal extension ($l_b > 0$), the base angle is measured from the same vertex point to the basal most points of the leaf on each side as shown in Figure 4.33(c). The procedure for computing the base angle is same as apex angle.

Figure 4.33: Leaf base angle computation for three classes
The details of angle computation are shown in Figure 4.34. The basepoint1 (BP1) and basepoint2 (BP2) are obtained using minimum and maximum values of pixels’ locations at distance of 25% of the \( l_m \) from the base point. The midpoint of these two points correspond to basepoint12 (BP12). The mean value of the base points having value greater than zero and opposite to basepoint12 gives basepoint (BP). The distance between basepoint (BP) and basepoint12 (BP12) are obtained and this represents height of the triangle. Similarly, the distance between basepoint12 (BP12) and basepoint2 (BP2) corresponds to opposite side of triangle. The base angle of leaf is computed using geometry as \( \theta_1 + \theta_2 \). For the wide obtuse leaves, the base angle is computed based on the triangles formed by the projections \( l_b \) and the angle addition of 180° as shown in Figure 4.34 (b). Hence, the base angle is 180° + \( \theta_1 + \theta_2 \).

### 4.3.1.6.3 Apex angle

An apex angle is the angle formed by the apical termination of the midvein to the pair of points, where a line perpendicular to the mid vein and 0.75\( l_m \) from the base intersects the margin as shown in
Figure 4.35. For the leaves with an odd number of lobes, the apex angle is measured as with unlobed leaves, wherein the line perpendicular to mid vein intersects the lobes and forms the point as shown in Figure 4.35(d) and Figure 4.35(e).

![Figure 4.35: Apex angle](image)

(a) (b) (c) (d) (e)

**Figure 4.35: Apex angle** (a) acute (b) obtuse (c) wide obtuse (d) odd-lobed acute apex (e) odd-lobed obtuse apex

In case of leaves with an apical extension \((la>0)\), as shown in Figure 4.35(c), the apex angle is measured using the termination of the mid-vein as the vertex and the apices of the lobes on the either sides. The apical angle is always measured on the basal side of the rays, even in leaves where the angle is greater than 180°.

![Figure 4.36: Leaf Apex angle computation](image)

(a) (b) (c) (d)

**Figure 4.36: Leaf Apex angle computation** (a) Acute apex angle (b) Obtuse apex angle (c) Wide obtuse apex angle (d) Acute angle apex with lobes

### 4.3.1.6.4 Margin coarseness

The structure of the leaf margin also plays a role in leaf identification. Usually, the leaf edge pattern repeats all over the boundary. But few leaf images have combination of edge patterns, one
at the base and another at the tip, as shown in Figure 4.37. The center part of the leaf has unique leaf edge, through which leaves are easily identified. Therefore, to recognize leaf margin, we have measured slope of convex points, computing the bending moment and curvature scale space.

**Figure 4.37:** (a) Coarseness calculation of leaf margin (b) Binary pixel and shape pattern. (b) Differential chain code sequence starting from base point (eight connected grids)

The medicinal leaves are recognized based on marginal projections with sinuses indented, called tooth. The leaves with significant sharp teeth are called corrugated leaves and with smooth edges are called non-corrugated leaves. These teeth are round or curved elliptically, sharp triangular segments for different plant species. Based on teeth patterns leaf margins are called serrate, dentate, crenate and entire. These features are recognized using the technique of chain code directional approximation. The chain code is a contour based shape descriptor used to describe the boundary of an object. In this work, we have used the eight-direction chain code as described in [105]. The chain code values [0-7] represent eight directions as depicted in Figure 4.37(b). The leaf contour is traversed in counter clockwise direction. The codes for the contours in all directions are obtained and a code frequency is estimated. The count of each direction code is normalized
and a code frequency in the eight directions is used for the representation of leaf margin. The different margin types based on margin coarseness and convexity are shown in Figure 4.38.

Figure 4.38: (a) Crenate  (b) Dentate (c) Serrate (d) Entire

The crenate leaves have the margin with teeth smoothly rounded without a pointed apex. The dentate leaves have the margin with teeth pointed with their axis perpendicular to the trend of the leaf margin. The serrate leaves have the margin pointed with their axes inclined to the trend of the margin. The entire leaves have smooth margin without teeth. The margin coarseness of different margin patterns for sample medicinal plants images of the Figure 1.3 are presented in Figure 4.39.

Figure 4.39: Leaf margin pattern for sample leaf images
4.3.2 Frequency domain features

The image is transformed from spatial domain to frequency domain. The rate of change of frequency signal corresponds to the pixel values that change rapidly. The heterogeneous objects have high frequency components, whereas homogeneous objects have low frequency components and give uniform textures. The frequency domain features are invariant to translation, rotation and scale change. Hence, we have considered the frequency domain features to corroborate the effectiveness of work.

❖ Shape Features

• Fourier Descriptor

Fourier transformation on shape signatures is used for shape analysis for medicinal plants. The Fourier transformed coefficients form the Fourier descriptors of the shape. These descriptors represent the shapes of the medicinal plants in a frequency domain. The lower frequency descriptors contain information about the general features of a plant shape, and the higher frequency descriptors contain information about finer details of the plant such as leaflets and branch patterns. The algorithm 4.8 gives extraction of Fourier descriptors.

Algorithm 4.8: Feature extraction using Fourier descriptor

Input: Plants RGB color image.
Output: Shape signature, complex coordinates, centroid distance, boundary points and angle.
Start:

Step 1. Accept input medicinal plant image and preprocess and resize it to 64x64.

Step 2. Compute x(t) and y(t) coordinates of the boundary

Step 3. Compute centroid of the plant image using equation (4.18)

\[ x_0 = \frac{1}{L} \sum_{t=0}^{L-1} x(t), \quad y_0 = \frac{1}{L} \sum_{t=0}^{L-1} y(t) \]  \hspace{1cm} (4.18)

Step 4. For N=512 sample points, the shape signature s(t), where t = 0, 1, ..., L, calculate the discrete Fourier transform of s(t) using equation (4.19)

\[ U_n = \frac{1}{N} \sum_{t=0}^{N-1} s(t) \exp \left( \frac{-2\pi i nt}{N} \right), \quad n = 0, 1, ..., N-1 \] \hspace{1cm} (4.19)

The coefficients \( u_n \), \( n = 0, 1, ..., N-1 \), are called Fourier descriptors (FD) of the shape, denoted as \( \text{FD}_n \), \( n = 0, 1, ..., N-1 \).

Step 5. Compute complex coordinates from the set of boundary coordinates using equation (4.20)

\[ z(t) = x(t) + iy(t) \] \hspace{1cm} (4.20)

Use shift coordinates to eliminate the effect of bias using function (4.21)

\[ z(t) = [x(t) - x_0] + iy(t) - y_0 \] \hspace{1cm} (4.21)

Where \((x_0, y_0)\) is the centroid of the medicinal plant, which is the average of the plant boundary coordinates.
Step 6. Obtain centroid distance $r(t)$ from $(x_{n}, y_{n})$ of plant image using equation (4.22)

\[ r(t) = \left( (x(t) - x_{n})^2 + (y(t) - y_{n})^2 \right)^{1/2} \]  \hspace{1cm} (4.22)

Step 7. For the set of boundary points $[x(t), y(t)], t = 0...L$, calculate curvature signature.

Step 8. Obtain boundary angle $\theta(t)$ and the curvature angle between successive plant boundary points using the equation (4.23)

\[ K(t) = \theta(t) - \theta(t-1) \quad \text{where} \quad \theta(t) = \arctan \frac{y(t) - y(t-1)}{x(t) - x(t-1)} \]  \hspace{1cm} (4.23)

Step 9. Obtain net amount of angular bend between the starting position $z(0)$ and position $z(t)$ on the medicinal plant boundary using equation (4.24).

\[ \varphi(t) = \left[ \theta(t) - \theta(0) \right] \mod(2\pi) \]  \hspace{1cm} (4.24)

Stop.

- **Generic-Fourier Descriptor (GFD)**

Generic Fourier Descriptor is used (Dengsheng Zhang and Guojun Lu., 2002) to extract features from spectral domain by applying 2-D Fourier transform (FT) on polar raster medicinal plant image. However, it is not desirable to acquire shape features using FT directly, because the acquired features are not rotation invariant. Therefore, a Modified Polar Fourier Transform (MPFT) is proposed by treating the polar image in polar space as a normal two-dimensional
rectangular image in Cartesian space. Consequently, for a given medicinal plant image \( f(x, y) \), the MPFT is defined as in equation (4.25)

\[
PF(r, \varphi) = \sum_{l} \sum_{i} \exp \left[ j \left( \frac{2\pi}{R} r + \frac{2\pi}{T} \varphi \right) \right] f(r, \theta) \exp \left[ j \left( \frac{2\pi}{R} r + \frac{2\pi}{T} \varphi \right) \right]
\]

where \( 0 \leq r \leq R \), \( 0 \leq \varphi \leq T \).

\((x_c, y_c)\) is the centre of mass of the shape. \( 0 \leq r \leq R \), \( 0 \leq \varphi \leq T \).

The parameter \( R \) is the radius of a plant image in polar space, \( T \) is angular resolution varying between \( 0^0 \) to \( 360^0 \), \( \rho^\text{th} \) radial frequency and the \( \varphi^\text{th} \) angular frequency. The determination of the number of \( \rho \) and \( \varphi \) for shape description is physically achievable, because shape features are normally captured by the few lower frequencies. For medicinal plant image, we have used \((0 < \rho \leq 3)\) and \((0 < \varphi \leq 9)\). The algorithm 4.9 gives extraction of generic Fourier descriptors.

**Algorithm 4.9: Feature extraction using GFD**

Input: RGB color plant image

Output: 36 GFD feature vectors.

Start:

Step 1: Obtain the input image \( I(x, y) \), pre-process and resize it to \( 64 \times 64 \).

Step 2: Compute the Fourier transform of grayscale image call it as \( f(x, y) \).

Step 3: Convert the Fourier transform \( f(x, y) \) image to polar coordinate space using the equation

\[ x \cdot \cos \theta + y \cdot \sin \theta, \text{ where as } 0 < \theta < 2\pi. \text{ Call it as } f(r, \theta) \]
Step 4: Calculate the generic fourier descriptor feature vector

Stop.

The acquired polar Fourier coefficients are translation and rotation invariant. For efficient shape description, only a small number of GFD features are selected for shape representation. In our work, we have implemented 36 GFD features reflecting 4 radial frequencies and 9 angular frequencies to index the shape of a medicinal plant. The selected GFD features form a feature vector which is used for indexing the shape.

- **Zernike moments**

Zernike moments (ZM) are the most popular shape descriptors and have many desirable properties, such as rotation invariance, robustness to noise and expression efficiency. Hence, in this work, we have used Zernike moments for extracting the plant shape with moment order (n) of four and repetition (m) of 4. The complex ZM are derived from Zernike polynomials, which is a set of complex and orthogonal polynomials defined over the interior of a unit circle \((x^2 + y^2 = 1)\).

\[
V_{nm}(x,y) = V_{nm}(\theta) = R_{nm}(\rho) \exp(jm)
\]

where \(\rho = \sqrt{x^2 + y^2}\), \(\theta = \arctan\left(\frac{y}{x}\right)\)

\[
A_{nm} = \frac{\pi \rho}{\pi} \sum_{x} \sum_{y} f(x,y) V_{nm}(x,y), x^2 + y^2 \leq 1
\]

\[
R_{nm}(\rho) = \sum_{s=0}^{n-|m|} (-1)^s \frac{(n-s)!}{s!(n-s-m)!} \frac{(n-s)!}{(n-s+m)!} \rho^{n-2s}
\]
It is shown that the ZM on a rotated image have the same magnitudes Therefore $|A_{nm}|$ is used as a rotation invariant feature of the image function. ZM feature vector with moment order of four and repetition of one is given by

$$f = [|A_{00}|, |A_{01}|, ..., |A_{14}|] \quad \ldots \quad (4.29)$$

This feature vector is normalized $[0,1]$ by z-score normalization

$$f_{\text{Zernike}} = \frac{f - \mu}{\sigma}, \text{where } \mu \text{ is the mean and } \sigma \text{ is the standard deviation.} \quad \ldots \quad (4.30)$$

The extraction of Zernike moments is given in algorithm 4.10.

**Algorithm 4.10: Feature extraction using Zernike Moments**

**Input:** RGB color image of plants

**Output:** Zernike shape feature values.

**Start:**

**Step 1:** Read input image and apply preprocessing.

**Step 2:** Calculate the Zernike polynomials $\rho$, $\theta$ and $V_{nm}$.

**Step 3:** Eleven Zernike feature values are calculated for $n=4$ and $m=4$

$$f = [A_{00}, A_{01}, A_{10}, A_{12}, A_{21}, A_{31}, A_{13}, A_{23}, A_{32}, A_{41}, A_{14}].$$

**Step 4:** Calculate the mean and standard deviation values of ‘f’.

**Step 5:** Obtain the normalized Zernike feature values.

**Stop.**

**Texture features**

The texture gives the global shape feature, which is used to associate with related shapes. Here, we have used the Gabor filters to extract texture features.
• **Gabor filters (GF)**

The Gabor filter is also one of a signal processing based approach for texture extraction. Basically, Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and specific direction. It acts as a local band pass filter with certain optimal joint localization properties in both the spatial domain and the frequency domain. We have computed texture features of medicinal plants canopy and stem images with mean and variation of the Gabor filtered image.

\[
G_{mn}(x,y) = \sum_{s} \sum_{t} I(x-s,y-t)\psi_{mn}^*(s,t)
\]  

... (4.31)

where \(s\) and \(t\) are filter mask size variables and \(\psi_{mn}^*\) is the complex conjugate of \(\psi_{mn}\), which is a class of self-similar functions generated from dilation and rotation of the following mother wavelet,

\[
\psi(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} \exp\left[\frac{1}{2} \left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right]\exp(j2\pi Wx)
\]  

... (4.32)

where \(W\) is the modulation frequency. The self similar Gabor wavelets are obtained through the generating function,

\[
\psi_{mn}(x,y) = a^{-m}\psi(x,y)
\]  

... (4.33)

Where \(m\) and \(n\) specify scale and orientation of the wavelet respectively with \(m = 0, 1...(M-1)\) and \(n = 0, 1...(N-1)\) and

\[
\tilde{x} = a^{-m}(x\cos\theta + y\sin\theta)
\]

\[
\tilde{y} = a^{-m}(-x\sin\theta + y\cos\theta)
\]  

... (4.34)

Where \(a>1\) and \(\theta = m\pi/N\)
The variables in the above equation are defined as follows:

\[
\alpha = \left( \frac{U_h}{U_l} \right)^{1/2}, \quad W_{mn} = a^m U_l
\]

\[
\sigma_{xmn} = \frac{(x+i)^2 h_m}{2 \pi a^m (a-1) U_s}
\]

... (4.35)

\[
\sigma_{ymn} = \frac{1}{2 \pi \tan \left( \frac{\pi}{2} \right)} \left[ u^2 \frac{ \sigma_{xmn}^2 - \left( \frac{s}{\sigma_{xmn}} \right)^2}{2} \right]
\]

... (4.36)

In our implementation, we have used the following constants \( U_l = 0.05, U_h = 0.4 \), \( s \) and \( t \) range from 0 to 60. After applying Gabor filters on the image with different orientations and at different scales, we have obtained an array of magnitudes,

\[
E(m,n) = \sum_x \sum_y |G_{mn}(x,y)|
\]

... (4.37)

These magnitudes represent the energy content at different scales and orientations of an image. The texture features are found by calculating the mean \( \mu_{mn} \) and standard deviation \( \sigma_{mn} \) of the energy magnitude. The extraction of Gabor texture features is given in algorithm 4.11.

\[
\mu_{mn} = \frac{E(m,n)}{P \times Q}
\]

... (4.38)

\[
\sigma_{mn} = \sqrt{\frac{\sum_x \sum_y \left| E_{mn}(x,y) - \mu_{mn} \right|^2}{P \times Q}}
\]

... (4.40)

**Algorithm 4.11: Feature extraction using Gabor texture feature**

Input: RGB color images of medicinal plants.

Output: Gabor texture features

Start:
Step 1: Obtain input images, convert it to grayscale, preprocess and obtain the size of an image (P,Q).

Step 2: Calculate the Gabor texture values for \( m = 0 \ldots 2 \) scales and for \( n = 0 \ldots 1 \) orientations. Obtain transformed values.

Step 3: Obtain Gabor wavelet transform convolving input image with shifted complex conjugate Gabor texture values.

Step 4: Obtain energy values and standard deviation co-efficients 

\[
[\sigma_{00}, \sigma_{01}, \sigma_{10}, \sigma_{20}, \sigma_{21}].
\]

Stop.

**Summary**

We have discussed structural and spectral features for the recognition of medicinal plants and its parts. From the visual features of plants, it is observed that recognition of height from an image is a challenging. The geometrical features of leafy mass and stem are found robust. The edge patterns of leafy mass and stem are also found suitable. The histogram based features have helped in plant recognition. A leaf feature based approach is developed. Other features like, angle and margin based features have helped in recognition. The work on frequency domain shape and texture features has given invariant characteristics of medicinal plant obtained from different directions.