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Automated Identification of Plant Species from Images of Leaves and Flowers used in the Diagnosis of Arthritis

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Abstract

Automatic image identification and classification is challenging task due to background complexity, variation size and location, lighting conditions and so on. Since plants are used in our daily lives such as horticulture, agriculture, farming, decoration and ayurvedic medicinal treatment. In India majority of diseases are treated by plants .Of these the present work deals with identification and classification of medicinal plants that are used in treatment of rheumatoid. Rheumatoid arthritis is chronic, progressive, disabling autoimmune disease characterized by systemic inflammation of joints, damaging cartilage and bone around the joints. In the present work, plant parts mainly leaves and flower are taken as an object for identification, since these are available for all the time and have some 2D in nature size and shape. Hence the proposed work deals with image processing techniques such as feature extraction and classification. The features namely height, width, margin and texture features are used for extracting leaf shape features. Similarly for flowers, the petal count and colors are extracted in RGB and Ycbcr color space. The obtained features are trained by neural network classifier. The classification results have shown an accuracy of 85% for leaf and 85% for flower. The proposed work found to be robust. Further, the work can be enhanced by taking 3D feature and other classifier.

Keywords: *Rheumatoid arthritis, ayurveda, plant recognition, color feature, multiscale fractal, neural network.*

1. Introduction

Rheumatoid arthritis is chronic, progressive, disabling autoimmune disease characterized by systemic inflammation of joints, damaging cartilage and bone around the joints. It is a systemic disease which means that it can affect the whole body and internal organs such as lungs, heart and eyes.

When the body is exposed to this trigger, the immune system responds inappropriately. Instead of protecting the joint, the immune system begins to produce substances that attack the joint. This is what may lead to the development of rheumatoid arthritis. The synovial membrane invades the space between joints and the whole joint is swollen and become painful on movement.

Although numbers of synthetic drugs and allopathic treatment are being used as diagnosis of rheumatoid arthritis but they have adverse effect that can compromise the therapeutic treatment. Hence ayurvedic treatment found to be more appropriate for such diseases. Unfortunately, there is still no effective known medicinal treatment that cures rheumatoid arthritis as the modern medicine can only treat the symptoms of this disease that means to relieve pain and inflammation of joints. It is possible to use the herbs and plants in various forms in order to relieve the pain and inflammation in the joints. There are so many medicinal plants that have shown anti -rheumatoid arthritis properties. So the plants and plant product with significant advantages are used for the treatment of rheumatoid arthritis. The present review is focused on the medicinal plants having anti rheumatoid arthritis activity. There are many synthetic drugs that are being used as standard treatment for rheumatoid arthritis but they have adverse effect that can compromise the therapeutic treatment so these adverse effects increase the chances for the use of herbal plants for the rheumatoid arthritis treatment.

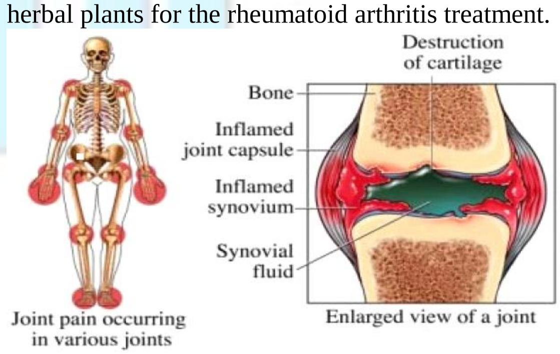


Fig. 1 Rheumatoid Arthritis joint.

Plants can be classified and identified by their leaves and flowers. There different varieties of plants grown throughout the world. Their identifications are studied using various laboratory methods. The morphological and genetically characteristics are employed to classify different leafs, flowers as well as plants. However, the presence of wide morphological varieties through evolution among the various leaf and flower cultivars made it more complex and difficult to classify them. Leaf and flower structures play a very crucial role in determining the characteristics of plant. The broad and narrow shaped leaves, leaf arrangement, leaf margin characteristics features differentiate various leaf of a plant. The number of the layers of petals, color, shapes characteristics features differentiate various flowers of a plant.

To understand and educate the peoples at research level and to give the general description about the ayurvedic treatment at home level by using the discussed flowers and leaves of the plant which have the medicine property in them.

Ayurvedic practitioners or botanist recognize these medicinal plants manually. But recognition through computers is a challenging task. The various parts of different medicinal plants are used in different disease diagnosis. The parts of the plants such as leaves, flower, bark, seed and roots are used as main component. Hence identification of medicinal plants used in the treatment of rheumatoid arthritis using only leaves and flowers with image processing technique is the objective of the work.

For the treatment of rheumatoid arthritis we use ayurvedic products for the recognition of ayurvedic products that are prepared from medicinal plants is taken as a project work. Related to these a brief literature survey is carried to study the machine vision application in these areas. The arthritis is common disease found in people due to obesity, aging etc. Hence the diagnosis of arthritis by ayurvedic is rare so some plant diagnoses are made in general but pertaining to arthritis, through flowers or leaves is not carried out.

The ayurvedic treatment as mentioned for the rheumatoid arthritis uses the ancient technology of utilizing the medical plants. The treatment uses flowers, leaves of the unique and specific medicine plants to give the cure naturally with least pain and cost. Although it is time consuming but it will assure the perfect treatment with no side effects. In the proposed work we try to identify and classify medicinal plants, leaves and flowers based on the techniques like color, shape and texture.

List of medicinal plants used in rheumatoid arthritis treatment. The plants which have the anti-rheumatoid arthritis properties are given below:

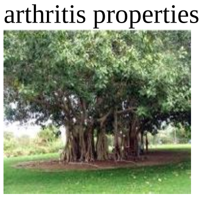


Fig. 2 Sample plants images considered in the work.

Among the above 12 plant images 5 images of plants are used in our project. Since the flower and leaf of those plants are available and its features can be extracted. Remaining 7 plants which are not used because of non availability of appropriate part and their definite structure.

The plants such as Banyan tree, Abuta are not used because of non availability of flowers in particular season, plant like Aloevera do not bloom flower in all seasons, flowers of Chhota halkusa are too small in size and its features cannot be extracted correctly.

2. Literature Review

The work related to problem are outlined as follows

N.Valliammal and Dr.S.N.Geethalakshmi (2011) have used preferential image segmentation is proposed for automatic recognition of leafs and flowers. This method encodes the prior information for preferential segmentation as a tree of shapes. The method is invariant to translation, rotation and scale transformations because both feature extraction and boundary matching are invariant to these transformations. It is observed that these features and the positive results are obtained and proved that the Preferential Image Segmentation method can be successfully exploited in leaf identification for plant recognition systems.

Stefan Fiel and Robert Sablatnig (2011) have developed a method for the automated identification of tree species from images of leaves, bark and needles is presented. This method is compared to a combination of GLCM and wavelet features. The proposed method is evaluated on a dataset provided by the "O¨ sterreichische Bundesforste AG" ("Austrian federal forests"). The dataset contains 1183 images of the most common Austrian trees. The classification rate of the bark dataset was 69.7%.

Debnath Bhattacharya, Tai-hoon Kim, and Gang-soo Lee. (2011) has demonstrated plants can be classified and identified by naturally or artificially as per botanists. Plants can be identified by their leaves. The morphological and genetical characteristics are employed to classify different leafs as well as plants. They propose the methods to identify the leaf using an image analysis based approach.

Yangcheng Shen, Changle Zhou, Kunhui Lin (2010) presented a shape descriptor of imaged leaf objects according to their boundaries for image retrieval. The experiment shows that the method has high reliability and less time consuming.

Andre R. backs and Odemir M. Bruno (2009) has presented the taxonomical classification of plants is a very complex and time-consuming task .They presented a novel approach to plant identification based on leaf texture. Yielded result shows the potential of the approach, which overcome traditional texture analysis method, such as co-occurrence matrices, gabor filters and Fourier descriptors.

Jiandu Liu, Shanwen Zhang, and Shengli deng (2009) has developed one of the most important morphological Taxonomy features; plant leaf with many strong points has significant influence on research. They proposed a novel method of plant classification from leaf image set based on wavelet transforms and support vector machines (SVMS). The experimental results about the data set with 300 leaf images show that the method has higher recognition rate and faster processing speed.

Youqian Feng and Shanwen Zhang (2009) has presented the object of traditional plant identification were too broad and the classification features of it were usually not synthetic and the recognition rate was always slightly low. One recognition approach is given based on supervised locally linear embedding (LLE) and K- nearest neighbors. Comparison with other recognition method demonstrated the proposal method is effective in advancing the recognition rate.

Jing Liu, Shanwen Zhang, and Jiandu Liu (2009) introduced a approach of plant leaf recognition. The classifier moving center hyper sphere classifier is adopted for its classification validity. The experimental results indicate that our algorithm is workable with the average correct recognition rate is up to 92 percent .Compared with other methods, this algorithm was fast in execution ,efficient in recognition and in implementation.

Jiazhi Pan and Yonh He (2008) have identified different plants by leaves digital image is one key problem in precision farming. By the combination of image processing and neutral network, Most of the image blocks of different plants could be correctly classified. In this work, the total accuracy is about 80%.These methods was simple and highly effective, So they could easily be integrated into auto machines in the field, which can largely saving labor and enhance productivity.

Takeshi Saitoh, Kimiya Aoki and Toyohisa Kaneko (2004) have described an automatic method for recognizing a blooming flower based on a photograph taken with a digital camera in an natural scene. They employ a photograph were the object is focused but the background is defocused. Experiments were conducted for 600 pictures. A successful boundary extraction rate of 97% and a flower recognition rate of 90% were obtained.

3. Proposed Architecture

The proposed work deals with implementation of an automated identification system, which helps us to identify the plant species from images of leaves, flowers for the diagnosis of arthritis. Initially digital pictures of leaves, flowers are enhanced, segmented, and a set of features were extracted from the image. The most discriminating set of features were selected and then used as inputs to a Probabilistic Neural Network (PNN).The shape features of leaf such as texture, margin, width, height are extracted. The petal counts, color features of flowers are extracted. Both the features are trained by neural network classifier. The overall classification accuracy utilizing the proposed technique for the test set is 85 %, whereas that feature extraction obtained is 90%.

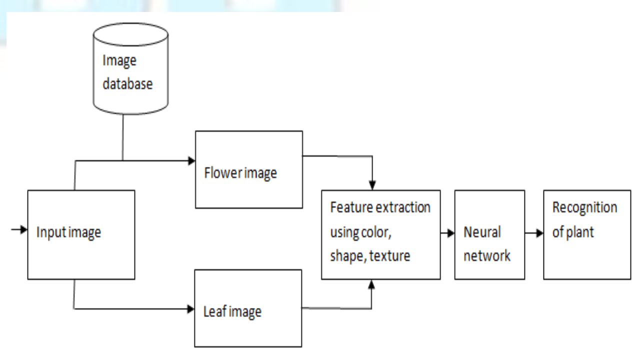


Fig. 2 Proposed Architecture

3.1 Leaf Feature Extraction

Plants can be identified by their leaves. Leaf structure such as texture, width, height, margin, plays a very crucial role in determining to which plant species leaf belong.

3.1.1 Texture
Texture is one of the most important visual attributes in images. It allows to describe the surface of a leaf in terms of the distribution of pixels over a region. Literature presents a wide number of approaches to describe texture patterns. However, the natural texture(such as, leaves texture) present a random but persistent pattern that results in a cloud like texture appearance.
Muti scale fractal dimension
Natural objects are not real fractals. They may present an infinite degree of details along the scales, although its self-similarity along these scales is not preserved since plant and leaf images are natural images and have fractal structure.
Usually, fractal dimension D is computed as angular coefficient of the logarithm curve of the volume(S(r)) in terms of dilating radius, using linear interpolation. However, the logarithm curve computed presents more details then can be expressed by a single numeric value and, eventually, the fractal dimension D is not enough to represent all the complexity of leaf such as edges, vein structure and color since the pattern is repeating everywhere. Hence multi scale fractal dimension can be used for recognition of leaves.
In order to provide a better description of objects in terms of its complexity, the Multi Scale Fractal Dimension as been proposed. This approach involves taking into the infinitesimal limit the linear interpolation by using the derivative, so achieving a function capable to express the complexity of an object in terms of the spatial-scale. This function provides more effective discrimination of the object, and it is defined as:

$$D(r) = \frac{3\log S(r)}{dr} \qquad (1)$$

Where D(r) represents the complexity of the object at scale r.

3.1.2 Margin
The margin shape constitutes however a very discriminate criterion for species identification that generally presents less variability than the global shape, with the exception of some pathological species.

3.1.3 Height
The distance between the two terminals of the main veins of the leaf. It is denoted as L.

3.1.4 Width
The maximum length of a line, which is orthogonal to the main vein. It is denoted as W.

3.2 Flower Feature Extraction

Flowers are the reproductive structures of a flowering plant. Flowers are the primary structures used in grouping plant families. By extracting the flower features such as shape detection, petal count and color, we can identify to which plant species the flower belongs to. The flower with one layer of petals with definite shape is called simple flower and the flower barring multiple layers of petals is called compound flower. The compound flower is complex and varies in color and shape randomly. Hence we cannot identify the petal count exactly whereas in case of simple flower we can get exact petal count. Therefore the present work deals with the development of petal count for simple flowers which are used in rheumatoid treatment. The color and shape features of the flower images are extracted. To detect the boundary of flower region, edge detection is obtained using first order gradient.

3.2.1 Shape features
To detect the shape of flower, edge detection has to be applied.
Edge detection is the name for a set of mathematical methods which aim at identifying points in a digital at which the image brightness changes sharply or, more formally, has discontinuities. The points at which image brightness changes sharply are typically organized into a set of curved line segments termed *edges*. The same problem of finding discontinuities in 1D signal is known as step detection and the problem of finding signal discontinuities over time is known as change detection. Edge detection is a fundamental tool in image processing, machine vision and computer vision, particularly in the areas of feature detection and feature extraction.
The purpose of detecting sharp changes in image brightness is to capture important events and changes in properties of the world.
Applying an edge detector to an image may lead to a set of connected curves that indicate the boundaries of objects, the boundaries of surface markings as well as curves that correspond to discontinuities in surface orientation. From the detailed analysis of flower, it is found that first order gradient can be applied to obtain the boundary.

Edge detection using the gradient
The gradient is a vector which has certain magnitude and direction:

$$\nabla f = \begin{pmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{pmatrix} \qquad (2)$$

$$magn(\nabla f) = \sqrt{(\frac{\partial f}{\partial x})^2 + (\frac{\partial f}{\partial y})^2} = \sqrt{M_x{}^2 + M_y{}^2} \qquad (3)$$

$$dir(\nabla f) = \tan^{-1}(M_y/M_x)$$

To save computations, the magnitude of gradient is usually approximated by:

magn (∇f) ≈ |Mx | + |My| (4)

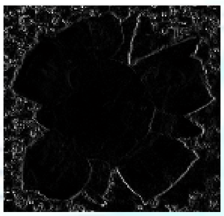


Fig. 4 shape detection of mango flower

The above figure shows the shape detection using threshold of 150. By using the gradient edge detection technique the boundary of the mango flower is extracted.

3.2.2 Petal Count

Petals are modified leaves that surround the reproductive parts of flowers. They are often brightly colored or unusually shaped to attract pollinators. Together, all of the petals of flowers are called a corolla. Petals are usually accompanied by another set of special leaves called sepals that collectively form the calyx and lie just beneath the corolla. When the petals and sepals of a flower look similar they are called tepals. Petals of different species of plants vary greatly in color or color pattern, both in visible light and in ultraviolet.

Petals can differ dramatically in different species.
The number of petals in flower may hold clues to a plant's classification. For example, flowers on eudicots (the largest group of dicots) most frequently have four or five petals while flowers on monocots have three or six petals, although there are many exceptions to this rule.
The petal count of these flower images is obtained by converting the image in polar co-ordinates with a radius r and angle θ. The symmetrical nature is obtained based on the value of n and θ. The angle is obtained in between 0 and π.

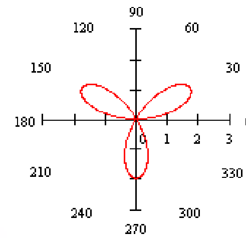
r= a sinnθ

r= a cosnθ

where a and n are NOT equal to 0

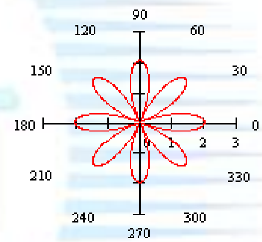
When n is odd, the entire curve is generated as θ increases from 0 to π. The curve has n petals.
When n is even, the entire curve is generated as θ increases from 0 to 2π. The curve has 2n petals.

a. r = 2 sin3t (equation of a flower Curve with 3 petals)



Note that n = 3 is odd, therefore the rose curve has 3 petals.

b. r = 2 cos4t (equation of a flower Curve with 8 petals)



Note that n = 4 is even, therefore the flower curve has 2(4) = 8 petals.

3.2.3 Color

The color features are obtained in RGB and Ycbcr color space. The color moments represents efficient features to extract color of natural images. The color moments namely mean, standard deviation and skewness are obtained.

RGB

The RGB color model relates very closely to the way we perceive color with the r, g and b receptors in our retinas. RGB uses additive color mixing and is the basic color model used in television or any other medium that projects color with light. It is the basic color model used in computers and for web graphics, but it cannot be used for print production.
The secondary colors of RGB – cyan, magenta, and yellow – are formed by mixing two of the primary colors (red, green or blue) and excluding the third color. Red and green combine to make yellow, green and blue to make cyan, and blue and red form magenta. The combination of red, green, and blue in full intensity makes white.
In Photoshop using the "screen" mode for the different layers in an image will make the intensities mix together according to the additive color mixing model. This is

analogous to stacking slide images on top of each other and shining light through them.

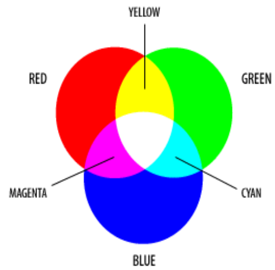


Figure. 5 The additive model of RGB.

Red, green, and blue are the primary stimuli for human color perception and are the primary additive colors

Ycbcr

This color space represents each color with 3 numbers, similarly as the RGB space. The Y component represents the intensity of the light. The Cb and Cr components indicate the intensities of the blue and red components relative to the green component. This color space exploits the properties of the human eye. The eye is more sensitive to light intensity changes and less sensitive to hue changes. When the amount of information is to be minimized, the intensity component can be stored with higher accuracy than the Cb and Cr components. The JPEG file format makes use of this color space to throw away unimportant information.

Color moments are measures that can be used to differentiate images based on their features of color. Once calculated, these moments provide a measurement for color similarity between images. These values of similarity can then be compared to the values of images indexed in a database for tasks like image retrieval. The basis of color moments lays in the assumption that the distribution of color in an image can be interpreted as a probability distribution. Probability distributions are characterized by a number of unique moments (e.g. Normal distributions are differentiated by their mean and variance). It therefore follows that if the color in an image follows a certain probability distribution, the moments of that distribution can then be used as features to identify that image based on color.

The basis of color moments lays in the assumption that the distribution of color in an image can be interpreted as a probability distribution. Probability distributions are characterized by a number of unique moments. It therefore follows that if the color in an image follows a certain probability distribution, the moments of that distribution can then be used as features to identify that image based on color. The three central moments of an image that represents the color distribution are Mean, Standard deviation and Skewness are given Eq. (1) and (3).

The work is restricted to YCbCr color space representing color by three values, Y is the Luminance component and CB and CR are the blue-difference and red-difference chroma components. Moments are calculated for each of these channels in an image. We will define the i^{th} color channel at the j^{th} image pixel as p^{ij}. The three color moments can then be defined as:

Mean

$$E_i = \sum_{N}^{j=1} \frac{1}{N} P_{ij} \quad (5)$$

Mean can be understood as the average color value in the image.

Standard Deviation

$$\sigma_i = \sqrt{(1/N) \sum^{j=1}{}_{N} (P_{ij} - E_i)^2} \quad (6)$$

The standard deviation is the square root of the variance of the distribution.

Skewness

Skewness can be understood as a measure of the degree of asymmetry in the distribution. A function of the dissimilarity between color distributions of two consecutive frames from video can be defined as the sum of weighted differences between the moments of the two distributions. Formally this is:

$$d_{mom}(H, I) = \sigma (E1i - E2i) + (\sigma 1i - \sigma 2i) + (s1i - s2i) \quad (7)$$

Where
(H, I): are the two image distributions being compared.
i: is the current channel index (e.g. 1 = Y, 2 = Cr, 3= Cb)
E1 i E2 i*: are* the first moments (mean) of the two image distributions.
σ1 i σ2 i*: are* the second moments (std) of the two image distributions.
s1 i s2 i*: are* the third moments (skewness) of the two image distributions.

In the proposed work this dissimilarity value is measure of discontinuity against frame index. If the dissimilarity measure is higher than a predefined threshold indicates the presence of a Shot boundary.

3.3 Classification

In this paper, neural network classifier is used for plant recognition.

Neural network is formed in three layers, called the input layer, hidden layer, and output layer. Each layer consists of one or more nodes, represented in this diagram by the small circles. The lines between the nodes indicate the flow of information from one node to the next. In this particular type of neural network, the information flows only from the input to the output (that is, from left-to-right).

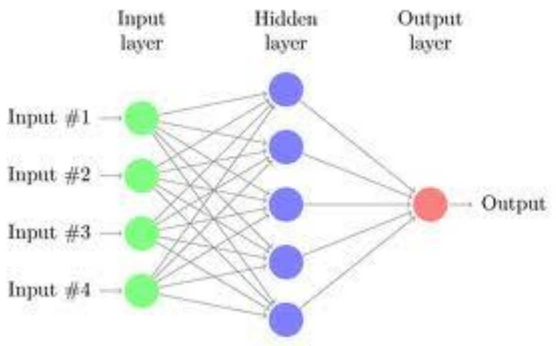
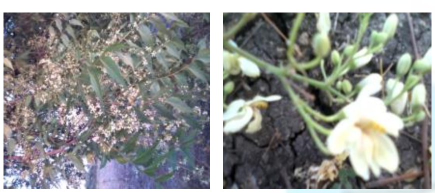


Fig. 7 Neural network Architecture

In the feed forward neural network input layer consists of 20 features and at the hidden layer there are five classes of plant images. The five classes of plants are:

Night jasmine Arka Mango



Neem Shigru

Fig. 6 Five classes of plant images.

Among these five classes of plants, one of the class is matched which is given as an output. Network is trained using sigmoid and pure linear function with a learning rate of 0.04 and 1000 iterations. The goal is to set with an error rate of 0.001.

The neural network architecture is the most common structure for neural networks: three layers with full interconnection. The input layer nodes are passive; the nodes of the hidden and output layers are active. The action of this neural network is determined by the weights applied in the hidden and output nodes. An epoch is just iteration. An epoch is a measure of number of times all of the training vectors are used once to update the weights.

4. Results and Discussions

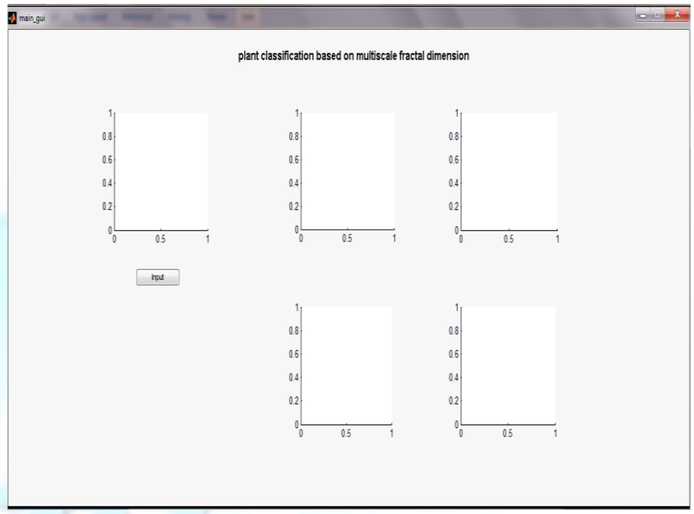


Fig. 8 GUI of proposed system.

In this module we first select the input image by clicking on input button. After clicking on input button we get the database of flower and leaf images. Among those images select one flower or leaf image.

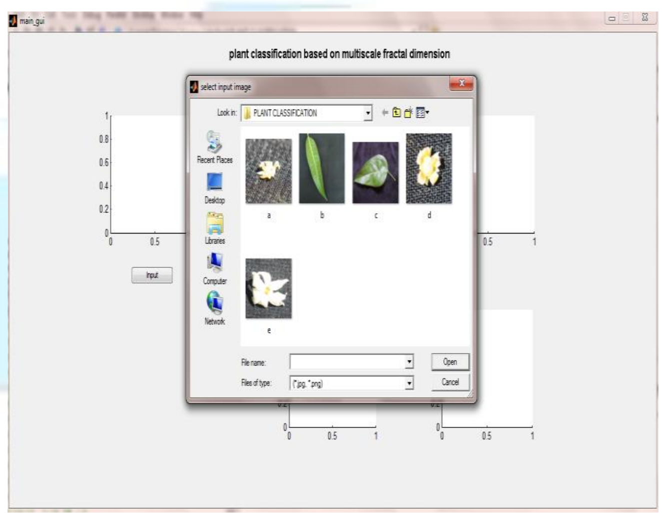


Fig. 9 GUI for browsing input plant selection.

Figure shows the database of leaf and flower images is displayed. Among these images first we select one of flower image. We select the flower of mango plant.

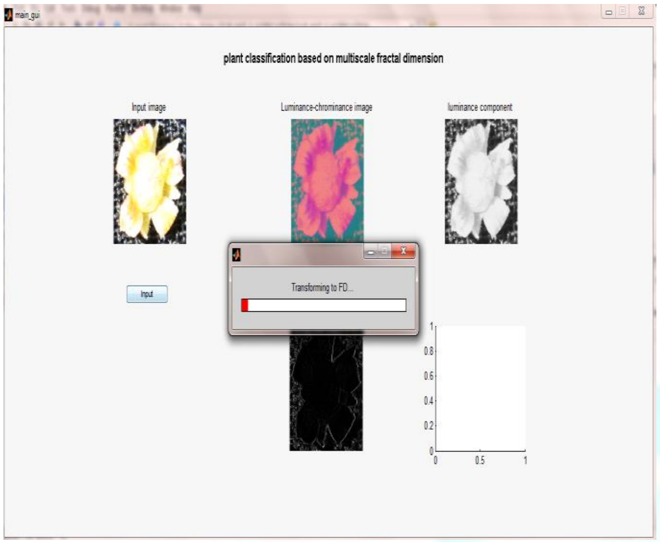


Fig. 10 RGB to Ycbcr converted image.

Figure shows that the mango flower is taken as an input image and its converted Luminance chrominance image, luminance component image, shape is detected by method Edge detection using the gradient. The gradient is a vector which has certain magnitude and direction. Along with that it shows wait bar which can be seen during transformation of fractal dimension.

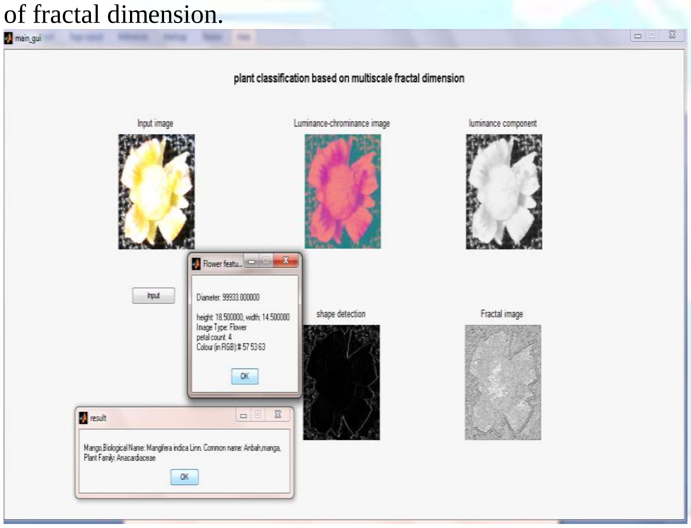


Fig. 11 Classification result.

Figure shows the fractal image of the mango flower and message box shows the flower features and displays the result as to which plant species the flower belongs to.

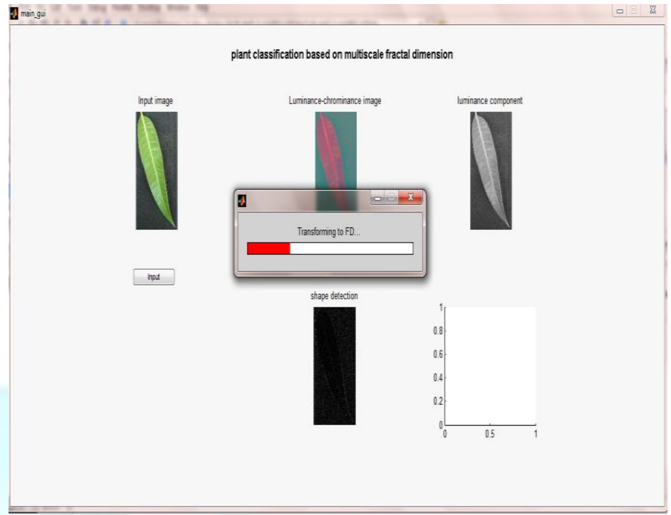


Fig.12 RGB to Ycbcr converted image.

Figure shows that leaf is taken as an input image and its converted Luminance chrominance image, luminance component image, shape extractions are displayed.

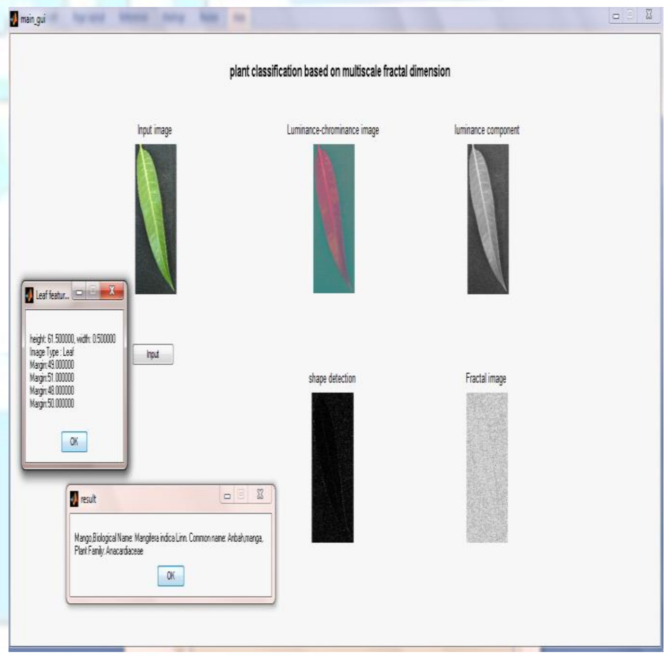


Fig. 13 Classification result.

Figure shows the fractal image of the leaf and message box shows the leaf features and displays the result as to which plant species the leaf belongs to.

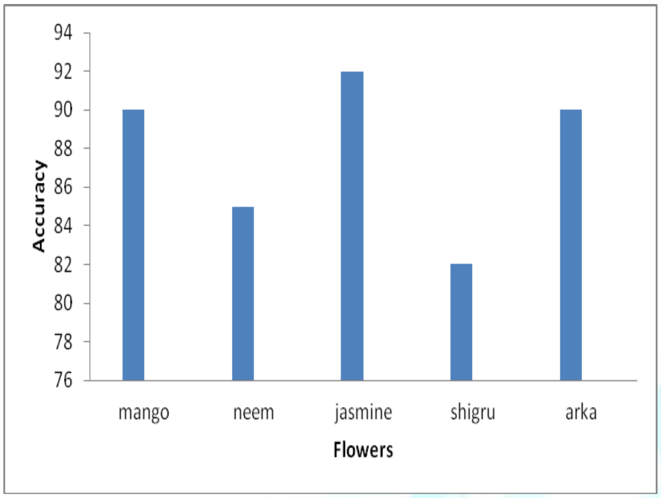


Fig. 14 Graph of Flowers.

From the above graph it is observed that based on analysis of shape and color features of flower, the maximum accuracy of 92% is obtained for jasmine plant and the minimum accuracy of 82% is obtained for Shigru plant.

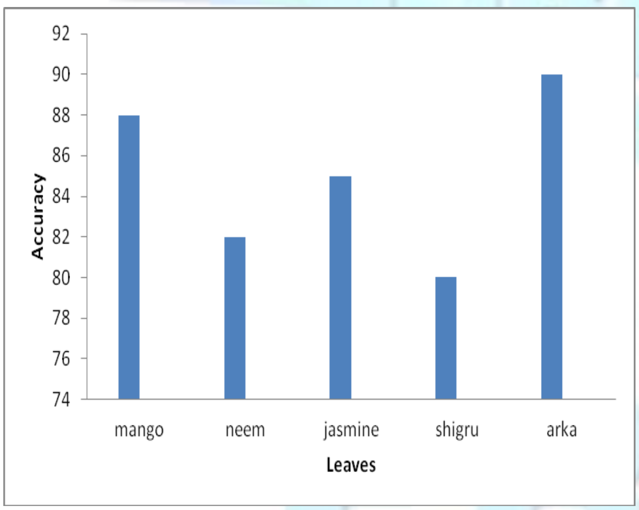


Fig. 15 Graph of leaves.

From the above graph it is observed that based on analysis of shape and texture features of leaf, the maximum accuracy of 90% is obtained for Arka plant and the minimum accuracy of 80% is obtained for Shigru plant.

5. Conclusion

The present work deals with development of a system where a user in the field can take a picture of an unknown plants, leaf and flower and feed it to the system carried on a portable computer, and have the system to classify the species. In the proposed work, shape and texture features of sample plant images of five classes are used in the rheumatoid are extracted. The features are trained with neural network. The maximum accuracy of 89% is found for mango plant and minimum of 81% is observed for neem plant. An average accuracy of 85% is observed for all plant images. Further the accuracy can be increased by taking an efficient shape features in frequency domain. The work can be extended by taking more features and other classifier.

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