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SVM-BDT PNN and Fourier Moment Technique for Classification of Leaf Shape

[1] Krishna Singh,
Department of Electrical Engineering .IIT, Roorkee Uttrakhand India
singhkrishna5@gmail.com

[2] Indra Gupta,
Department of Electrical Engineering IIT, Roorkee Uttrakhand India
indrafee@gmail.com

[3]Sangeeta Gupta
Forest Research Institute Dehradun
Uttrakhand India
Sangeeta.fri@gmail.com

Abstract

This paper presents three techniques of plants classification based on their leaf shape the SVM-BDT, PNN and Fourier moment technique for solving multiclass problems. All the three techniques have been applied to a database of 1600 leaf shapes from 32 different classes, where most of the classes have 50 leaf samples of similar kind. In the proposed work three techniques are used for comparing the performance of classification of leaves. Probabilistic Neural Network with principal component analysis, Support Vector Machine utilizing Binary Decision Tree and Fourier Moment. The proposed SVM based Binary Decision Tree architecture takes advantage of both the efficient computation of the decision tree architecture and the high classification accuracy of SVMs. This can lead to a dramatic improvement in recognition speed when addressing problems with large number of classes. Classification results from all the three techniques were compared and it was observed that SVM-BDT performs better than Fourier and PNN technique.

Key words- Probabilistic Neural Network, Support vector machine, Binary Decisions tree

1. Introduction

Plant recognition is an important and challenging task. Leaf recognition plays an important role in plant classification and its key issue lies in whether selected features are stable and have good ability to discriminate different kinds of leaves. The recognition process is very time-consuming, as botanists mainly carry it out. Computer-aided plant recognition is still very challenging task in computer vision due to lack of proper models or representation schemes. The focus of computerized living plant recognition is to measure the leaf geometrical morphological and Fourier moment based features. This information plays an important role in identifying the different classes of plants. Ji-Xiang, Huang and Xiao-Feng [10] worked on recognizing the known plant species by salient features of the leaf such as physiological length, width, diameter, perimeter, area, smooth factor, aspect ratio and Fourier moments which could be used to discriminate with each other.

The literature reveals that the recent results in pattern recognition have shown that support vector machine (SVM) classifiers have superior recognition rates in comparison to other classification methods. Zhang and Zhao[16] proposed SVM to classify plane target on a binary remote sensing and results show that SVM is well for difficult image classification problems, where the only features are high dimensional binary values. A linear SVM finds the hyper plane leaving the largest possible fraction of points of the same class on the same side, while maximizing the distance of either class from the hyper plane. However, the SVM was originally developed for binary decision problems, and its extension to multi-class problems is not straightforward. How to effectively extend it for solving multiclass classification problem is still an on-going research issue. The popular methods for applying SVMs to multiclass classification problems usually decompose the multi-class problems into several two-class problems that can be addressed directly using several SVMs.

PNN is derived from Radial Basis Function (RBF) Network, which is an ANN using RBF. RBF is a bell shape function that scales the variable nonlinearly. PNN is adopted for it and has many advantages [4]. Its training speed is faster than other network. PNN can approach a Bayes optimal result under certain easily met conditions. Additionally, it is robust to noise. We choose it also for its simple structure and training manner. The most important advantage of PNN is that weights are not "trained" but assigned and existing weights will never be alternated but only new vectors are inserted into weight matrices while training, so it can be used in real-time. Since the training and running procedure can be implemented by matrix manipulation, the speed of PNN is very fast. The network classifies input vector into a specific class because that class has the maximum probability to be correct [1].

According to the theory of plant shape taxonomy, plants are basically classified according to the shapes of their leaves and flowers. Usually, leaves are approximately two-dimensional in shape and flowers are three-dimensional. According to Man and Zheng [2], it is difficult to analyze shapes and structures of flowers since they have complex 3D structures. Moreover, leaves can be easily found and collected everywhere at all seasons, while flowers can only be obtained at blooming season. Therefore, leaves are widely used for computer-aided plant classification. Nishida and Kunii [21] used a hierarchical polygon approximation representation of leaf shape to classify the *Acer* family variety. Chi and Fang [15,16] proposed combining different features based on centroid-contour distance curve and adopted fuzzy integral for leaf image retrieval. Mokhtarian and Abbasi [13] used curvature scale space image to represent leaf shapes and applied it to leaf classification with self-intersection. Fu and Chi [7] combined the thresholding method and BP neural network to extract leaf veins. Ji-Xiang and Huang [10] adopted accelerated Douglas–Peucker approximation algorithm for leaf shape approximation and used the modified dynamic programming algorithm for leaf shape matching image retrieval. Wang, Du [11], used a method of recognizing leaf images based on shape features through a hyper-sphere classifier. Wang and Feng [16], gave out a method which combines different features based on centroid-contour distance curve, and adopted fuzzy integral for leaf image retrieval. Among these methods, using leaf shape feature is the best way to recognize plant images, Neto et al [9] identified specific types of leaf shape using elliptic Fourier transform. Hu [27] introduced a set of moment invariants using a nonlinear combination based on normalized central moments. It is necessary to compute these invariants to engage all the pixels in the shape. Chen [22] proposed an improved moment invariant technique based on boundary pixels to speed up the computation. Santini and Jain [18] introduced the similarity of two patterns and measured the distance between their feature vectors. Persoon, E. and Fu,K.-S.[26] used Fourier Descriptor for classification of shapes with a closed contour, because they represent well the shapes and they have interesting invariance properties. Fourier descriptors (FD) are computed with the Fourier coefficients given by the Fourier transform of the shape signature of the contour. Conseil, Bourennane and Martin [5] used Fourier descriptors (FD) for hand posture recognition in a vision-based approach. The Fourier transform technique is used for shape description in the form of Fourier Descriptors. The Fourier Descriptor is widely used for all-purpose shape description and recognition technique [14,16,20,26]. These Fourier descriptor values produced by the Fourier transformation of a given image represent the shape of the object in the frequency domain [27]. The lower frequency descriptors store the information about the general shape and the higher frequency descriptors store the information about the smaller details of the image. Therefore, the lower frequency components of the Fourier descriptor define the rough shape of the original object. Wong, Shih and Liu [6] used fourier descriptor as a similarity measure and support vector machine for pattern classifier for a large scale database. Yadav et al [3] reports, retrieval and classification of various shapes using generic fourier descriptor.

In the proposed work machine learning based SVM-BDT techniques compared with Artificial neural network classifier i.e. Probabilistic Neural Network and Fourier moment classification techniques are employed on classification of leaf shape, and it is concluded that SVM-BDT gives very good results compared with PNN-PCNN and Fourier moment. Principal component Neural Network is used for reducing the dimension of features space, Fourier moment can be calculated using the boundary pixel of an image. This reduced the number of computation required for calculation of Fourier moment and hence the process becomes significantly faster but accuracy being less than the SVM-BDT and PNN-PCNN. The PNN-PCNN is also faster and easy in implementation but accuracy is significantly less than SVM-BDT.

1.1.1 Leaf Image Acquisition and Preprocess

The source for used leaf images are internet (Flavia source.net) RGB color images, so it is necessary to convert the colors from RGB to Gray, by which color disturbance can be avoided. These images are JPEG. All leaf images were in 800 x 600 resolutions. There is no restriction on the direction of leaves.

1.1.1. Converting RGB image to Gray scale image: Equation 1 is the formula used to convert RGB value of a pixel into its grayscale value.

Gray = 0.2989 * R + 0.5870 * G + 0.1140 * B ----1

In Eq.1, R, G, B correspond to the color of the pixel, respectively.

1.1.2. Converting Gray Scale Image into Binary: The binary image was acquired by setting the luminance histogram of grayscale image we have obtained. The luminance histogram of grayscale image is shown in Figure.1

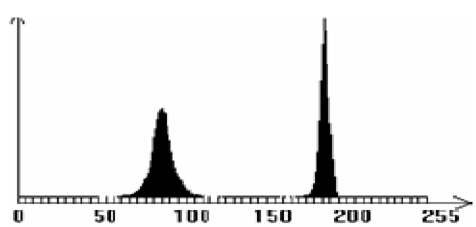


Figure 1.Luminance histogram of grayscale image

There are two peaks in every luminance histogram of grayscale image. According to the luminance of grayscale image; the left peak refers to pixels consisting the leaf image while the right peak refers to pixels consisting the background. The lowest point between two peaks is around the value 132 on an average. When luminance is smaller than this lowest point, the gray value of corresponding pixel is set '1', when greater, the gray value is set '0'. So, by setting the lowest point, the binary image can be acquired. A rectangular averaging filter of size 3 × 3 is applied to filter noises. Then pixel values are rounded to 0 or 1. A kind of rapid edge extraction algorithm is used for binary image [4] to acquire the boundary of the leaf. The extraction result showed that this edge detection algorithm can accurately and quickly extract the outline with complex details.

An example of image pre-processing techniques is illustrated in Figure. 2. To make boundary as a black curve on white background, the "0" and "1" value of pixels is swapped.

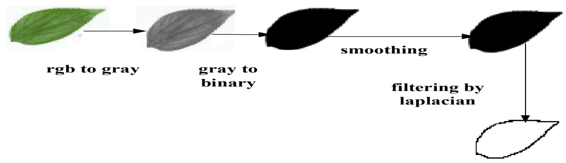


Figure 2. Leaf Images Preprocessing

2. Feature Extractions

Twelve commonly used digital morphological features (DMFs), derived from five basic features, are extracted so that a computer can obtain feature values quickly and automatically.

2.1. Basic Geometric Features

Firstly, we obtained 5 basic geometric features.

2.1.1. Diameter: The diameter is defined as the longest distance between any two points on the margin of the leaf. It is denoted as D.

2.1.2. Physiological Length: The distance between the two terminals of the main veins of the leaf is defined as the physiological length. It is denoted as Lp.

2.1.3. Physiological Width: The maximum length of a line, which is orthogonal to the main vein, is defined as the physiological width. It is denoted as Wp. Since the coordinates of pixels are discrete, we consider two lines are orthogonal if their degree is $90^{\circ} \pm 0.5^{\circ}$. The relationship between Physiological Length and Physiological Width is shown in Figure 3.

2.1.4. Leaf Area: The value of leaf area is easy to evaluate, just counting the number of pixels of binary value 1 on smoothed leaf image. It is denoted as A.

2.1.5. Leaf Perimeter: Denoted as P, leaf perimeter is calculated by counting the number of pixels consisting leaf margin.

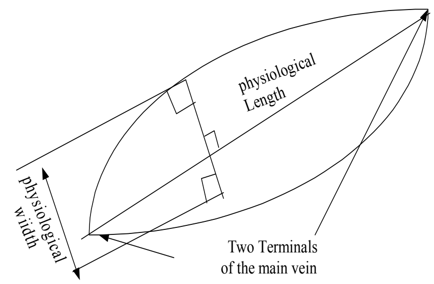


Figure 3. Relationship between Physiological Length and Physiological Width.

2.2. Digital Morphological Features

Based on 5 basic features introduced previously, we can define following 12 digital morphological features used for leaf recognition.

2.2.1. Smooth factor: smooth factor is defined as the ratio between area of leaf image smoothed by 5 × 5 rectangular averaging filter and the one smoothed by 2 × 2 rectangular averaging filter.

2.2.2. Aspect ratio: The aspect ratio is defined as the ratio of physiological length Lp to physiological width Wp, thus Lp/Wp

2.2.3. Form factor: This feature is used to describe the difference between a leaf and a circle. It is defined as $4\pi A/P^2$, where A is the leaf area and P is the perimeter of the leaf margin.

2.2.4. Rectangularity: Rectangularity describes the similarity between a leaf and a rectangle. It is defined as LpWp/A, where Lp is the physiological length, Wp is the physiological width and A is the leaf area.

2.2.5. Narrow factor: Narrow factor is defined as the ratio of the diameter D and physiological length Lp, thus D/Lp.

2.2.6. Perimeter ratio of diameter: Ratio of perimeter to diameter, representing the ratio of leaf perimeter P and leaf diameter D, is calculated by P/D.

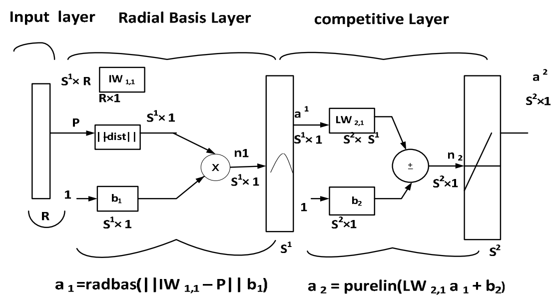
2.2.7. Perimeter ratio of physiological length and physiological width: This feature is defined as the ratio of leaf perimeter P and the sum of physiological length Lp and physiological width Wp, thus P/(Lp +Wp).

2.2.8. Vein features: We perform morphological opening [25] on grayscale image with falt, disk-shaped structuring element of radius 1,2,3,4 and subtract remained image by the margin. The results look like the vein. That is why following 5 features are called vein features. Areas of left pixels are denoted as Av1, Av2, Av3 and Av4 respectively. Then we obtained the last 5 features viz. Av1/A, Av2/A, Av3/A, Av4/A, Av4/Av1

3. Classification Methodology

3.1. Probabilistic Neural Networks

PNN is derived from Radial Basis Function (RBF) Network. Probabilistic neural networks can be used for classification problems. When an input is presented, the first layer computes distances from the input vector to the training input vectors and produces a vector whose elements indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, a complete transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 for that class and a 0 for the other classes. The architecture for this system is shown in figure 4. [31].



$R=5, S^1=1280$, $s^2=32$

Figure 4. PNN Structure

The PNN has three layers: the Input layer, Radial Basis Layer and the Competitive Layer. Radial Basis Layer evaluates vector distances between input vector and row weight vectors in weight matrix. These distances are scaled by Radial Basis Function nonlinearly. Then the Competitive Layer finds the shortest distance among them, and thus finds closest to the input pattern based on their distance [6]. PNN is adopted for it has many advantages. Its training speed is many times faster than a BP network. PNN can approach a Bayes optimal result under certain easily met conditions. Additionally, it is robust to noise and has simple structure and training manner.

3.1.1. Principal component Analysis: Principal component analysis is a quantitatively rigorous method for reducing the dimension of input vector of neural network. The method generates a new set of variables, called principal components. Each principal component is a linear combination of the original variables. All the principal components are orthogonal to each other, so there is no redundant information. The principal components as a whole form an orthogonal basis for the space of the data. Mathematically, PCA transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate, the second greatest variance on the second coordinate, and so on. Each coordinate is called a principal component. Here 5 principal components and mapping f: R12 → R5 is used to obtain the values of components in the new coordinate system.

3.2. Support vector machine

SVMs are a relatively new machine-learning tool and have emerged as a powerful technique for learning from data and in particular, for solving binary classification problems. SVMs originate from Vapnik's statistical learning theory [29], and they formulated the learning problem as a quadratic optimization problem whose error surface is free of local minima and has global optimum, the aim is to find an optimal separating hyper plane (OSH) between the two data sets.

SVM finds the OSH by maximizing the margin between the classes. The main concepts of SVM are to first transform input data into a higher dimensional space by means of a kernel function and then construct an OSH between the two classes in the transformed space. Those data vectors nearest to the constructed line in the transformed space are called the support vectors [30]. The SVM estimates a function for classifying data into two classes [29]. Using a nonlinear transformation that depends on a regularization parameter [30], the input vectors are placed into a high-dimensional feature space, where a linear separation is employed. Figure 5 shows the linear separating hyper plane where support vector are encircled.

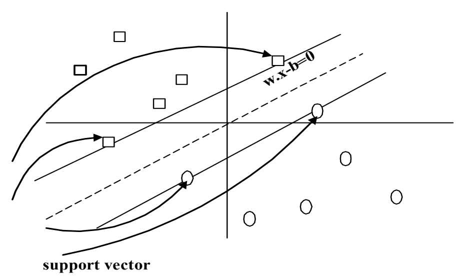


Figure 5. Linear separating hyper planes, the support vectors are circled.

To construct a nonlinear support vector classifier, the inner product (x, y) is replaced by a kernel function K (x ,y)

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{l} \alpha_i y_i K(x_i x) + b \right) \text{..........(2)}$$

Where f (x) determines the membership of x. In this study, the normal subjects were labeled as -1 and other subjects as +1. The SVM has two layers. During the learning process, the first layer selects the basis K($\mathbf{x_i}$,$\mathbf{x}$), i=1,2,….N from the given set of kernels, while the second layer constructs a linear function in the space. This is equivalent to finding the optimal hyper plane in the corresponding feature space. The SVM algorithm can construct a variety of learning machines using different kernel functions.

3.2.2 Binary tree of SVM (BTS): This method uses multiple SVMs arranged in a binary tree structure [29]. A SVM in each node of the tree is trained using two of the classes. The algorithm then employs probabilistic outputs to measure the similarity between the remaining samples and the two classes used for training. All samples in the node are assigned to the two sub nodes derived from the previously selected classes by similarity. This step repeats at every node until each node contains only samples from one class. The main problem that should be considered seriously here is training time, because aside training, one has to test all samples in every node to find out which classes should be assigned to which sub node while building the tree. This may decrease the training performance considerably for huge training datasets.

3.3. Fourier moments

In order to calculate the Fourier moments of an image, first the centroid of the image is calculated. Rays are now drawn emanating from the centroid toward the boundary. The distance of the centroid from the point of intersection of the rays and the boundary of the image is calculated for each ray and stored. This sequence of lengths is periodic in nature since after every 2 radians the same ray is reached. For this periodic sequence Discrete Fourier Transform (DFT) is calculated. The sequence of radial distances for different images would yield different periodic signals, and therefore different DFTs. Calculation of DFT of the sequence of radial distances makes these moments invariant to rotation since shifting of a sequence or equivalently rotation of an image, corresponds to multiplication of the DFT by an imaginary exponential term, which does not affect its magnitude.

The angle between two successive rays can be varied to increase or decrease number of points in the sequence. By decreasing the angular step more number of points would be extracted which would improve the resolving power of the Fourier moments

3.3.3. Calculating Fourier moments: The definition of Fourier moments suggests that these moments can be calculated using only the boundary pixels of an image. This observation was used to calculate Fourier moments for binary images. This reduced the number of computations required for calculation of Fourier moments and hence made the process significantly faster than both non-orthogonal and Legendre moments.

The first step in computation of Fourier moments was to find out the boundary of the image. These boundary pixels were then used to calculate the centroid of this boundary image. The angles of all boundary points were calculated assuming the origin at the centroid and stored in a vector. Now a loop was used to generate angles, say angle1, from 0 degrees to 360 degrees with a step of 360/512. For each angle generated by this loop, the closest angle from among the stored angle vector values was found. Since each of the angles stored in the angle vector correspond to boundary pixel, so the boundary pixel at an angle of angle-1 is determined. Now the distance of this pixel was calculated from the centroid. This was done for all pixels obtained from the previous steps. This resulted in a sequence of numbers representing the shape of the image. 512-point FFT was calculated on this sequence of radial distances to yield 512 Fourier moments.

The set of moments for samples, which belonged to the same class, were then used to find out a nucleus or mean value of moments for the class. The samples belonging to one class would make a cluster around its nucleus. There would be 32 such clusters. For perfect classification results there should be no overlap between two clusters i.e. for each pair of clusters, the maximum distance of any cluster member from its nucleus must be less than the minimum distance of any cluster member from the other nucleus.

To quantify the success of the Fourier classifiers a confusion matrix was created. The confusion matrix was a 32x32 matrix. The data at position (p,q) in the matrix corresponds to the number of samples of class p which got classified as class q.

4. Results and Conclusion

The proposed techniques are tested on Flavia Database. This consists of 32 classes with 50-60 observation in each class. The closed boundaries are extracted in a Matlab's image processing toolbox. Some samples leaves are shown in figure 6. To Train the SVM-BDT we used 40 leaves from each 32 classes for training and 10 leaves from each 32 classes to test the accuracy of algorithms, so that a total of 1280 leaves are used for training and 320 leaves are used for testing the algorithms. All tests were performed on a personal computer with an intel core 2 duo processor. A 32 class of flavia database is used by the Stephen Gang Wu et al [4] in their work for leaf recognition for plant classification, they achieved 90% accuracy. The proposed SVM-BDT, PNN and Fourier Moment techniques with the same dataset and testing procedure to enables a direct comparison with their results, is shown in Table I. The average correct recognition rate of three classifiers is shown in Figure 7, The SVM-BDT has superior performance i.e. 96%, compare to PNN 91% and Fourier Moment 62%..Snapshot of PNN results also shown in figure 8. which represent the queries leaf image on left side and database image on right side, also identified the botanical name of the sample image with their features value.

The results shows that the SVM-BDT has superior performance than the PNN and Fourier moment based classifier, because of its high generalization performance without the need to add a prior knowledge, even when the dimension of the input space is very high, because of using binary decision tree the less number of SVM are required which improve the classification accuracy. PNN also gives good results compared to Fourier moment because PCA reduce the dimension of input vector which improve the speed of PNN and its easy to implement framework, Fourier moment has less accuracy because of much computation work required in calculating the moments for each type of samples.

Figure 6. Sample leaves from flavia database

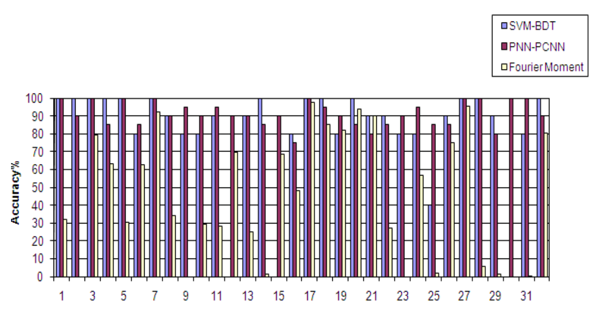


Fig 7.Performance comparisons of SVM-BDT with PNN and Fourier Moment

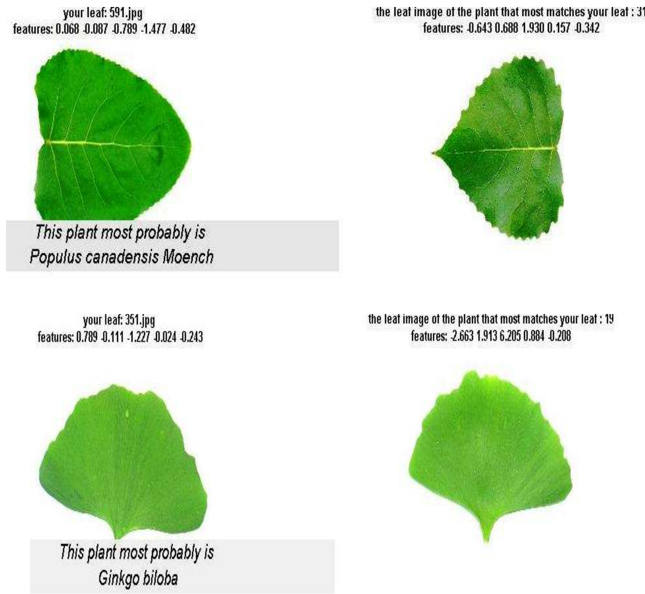


Figure 8 Snapshot of PNN results

Table 1 Comparison of SVM-BDT with PNN and Fourier moment

Classes/Classifiers	SVM-BDT	PNN-PCNN	Fourier Mon
1	100	100	32.2
2	100	90.	0
3	100	100	79.17
4	100	85	63.01
5	100	100	30.36
6	80	85	52.9
7	100	100	92.31
8	90	90	33.9
9	80	95	0
10	80	90	29.23
11	90	95	28.00
12	0	90	69.84
13	90	90	25.00
14	100	85	01.54
15	0	90	68.33
16	80	75	48.21
17	100	100	97.4
18	100	95	85.48
19	80	90	81.97
20	100	85	93.94
21	90	80	90.00
22	90	85	27.27
23	80	90	0.0
24	80	95	56.92
25	40	85	01.85
26	90	85	75.00
27	100	100	95.35
28	100	100	5.45
29	90	80	15.79
30	0	100	0
31	80	100	20.77
32	100	90	80.36

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Authors

KRISHNA SINGH received her B.E. Degree in 1991 from the Department of Electronics & Telecommunication engineering ,Rani Durgawati Vishwavidyalaya India and M.Tech in Electronics Engineering from NIT Allahabad, India. Working as Lecturer in Electronics and Communication Engineering under Directorate of Technical education Bhopal Madhya Pradesh India.since 1994 onward .She is currently a PhD student in the Department of Electrical Engineering,IIT Roorkee India in the Image Processing group. She has published various papers in Journal and conference proceeding.

INDRA GUPTA received her PhD degree from IIT Roorkee India in 1996; she is currently Associate professor in the Department of Electrical Engineering IIT Roorkee India, and published various papers in Journal and conference proceeding.

SANGEETA GUPTA is currently Scientist E in Botany Division Forest Research Institute Dehradun, and published various papers in Journals and conference proceeding.