A Leaf Recognition System for Classifying Plants Using RBPNN and pseudo Zernike Moments

A.H. Kulkarni
Associate Professor Department of Information Science & Engineering, GIT, Belgaum

Dr. H.M.Rai
Ex-Professor- National Institute of Technology, Kurukshetra

Dr. K.A.Jahagirdar
Associate. Professor, University of Agricultural Sciences, Dharwad

R.J.Kadkol
Asst. Professor, Department of Information Science & Engineering, GIT, Belgaum

Abstract- Plants are among the earth's most useful and beautiful products of nature. Plants have been crucial to mankind's survival. The urgent need is that many plants are at the risk of extinction. About 50 % of ayurvedic medicines are prepared using plant leaves and many of these plant species belong to the endanger group. So it is very necessary to set up a database for plant protection. We believe that the first step is to teach a computer how to classify plants. Leaf /plant identification has been a challenge for many researchers. Several researchers have proposed various techniques. In this paper we have proposed a novel framework for recognizing and identifying plants using shape, vein, color, texture features which are combined with pseudo Zernike movements. Radial basis probabilistic neural network (RBFNN) has been used as a classifier. To train RBFNN we use a dual stage training algorithm which significantly enhances the performance of the classifier. Simulation results on the Flavia leaf dataset indicates that the proposed method for leaf recognition yields an accuracy rate of 95.12%

Key words: Dual stage training algorithm, Radial basis probabilistic neural network, pseudo Zernike movements, Vein features, color moments.

I. Introduction

It is possible to identify many of our native plants by looking at their leaves. Strictly speaking, identification should involve examination of the flowers (petals, sepals, stamens etc), which are less variable than leaves. However, in most cases, it is possible to make an identification using just a few features of the leaves. Compared with other methods, such as cell and molecule biology methods, classification based on leaf image is the first choice for leaf plant classification. Sampling leaves and photoing them are low-cost and convenient. One can easily transfer the leaf image to a computer and a computer can extract features automatically using image processing techniques and can recognize the plant /leaf using machine learning techniques.

II. Feature Extraction

The following geometric features which have been used in leaf identification system are described as follows

2.1 Shape features

Aspect ratio: Aspect ratio also called as eccentricity is defined as ratio between length of the leaf minor axis (w) and the length of the leaf major axis. It is notated as

Aspect ratio =w/l (1)

Circularity: Circularity is ratio involving area of the leaf (a) and square of perimeter (p) of the leaf. It can be notated as

Circularity=a/p^2 (2)

Irregularity: Irregularity or dispersion is defined as ratio between the radius of the maximum circle enclosing the region and the minimum circle that can be contained in the region. This feature is of paramount importance when the shape of the leaf is irregular. It is notated as

$$\text{Irregularity} = \frac{\max\left(\sqrt{(x_i-\bar{x})^2+(y_i-\bar{y})^2}\right)}{\min\left(\sqrt{(x_i-\bar{x})^2+(y_i-\bar{y})^2}\right)} \quad (3)$$

The Eq. 3 defines the ratio between the radius of the maximum circle enclosing the region and the minimum circle that can be contained in the region. Therefore, the valve will increase as the region broadens.

Solidity**:** Solidity is defined as ratio between the area of the leaf and the area of its convex hull. It is denoted as

$$\text{Solidity} = \frac{\text{area of leaf}}{\text{area of convex}} \quad (4)$$

Convexity**:** Convexity is defined as ratio between the convex hull perimeter of the leaf and the perimeter of the leaf .It is denoted as

Convexity=perimeter/convex perimeter (5)

2.2. Vein features

Vein features will be extracted by means of morphological operations performed on the gray scale image of the leaf. There are three different kinds of vein features which are computed as follows:

V1=A1/A (6)

V2=A2/A and (7)

V3=A3/A (8)

Here V1, V2, and V3 characterize the features of the vein; A1, A2, and A3 signify the total pixels of the vein, and A denotes total pixels present on the leaf.

2.3. Color features/moments

Color moments are measures that can be effectively used to discriminate images based on their features of color. Color moments [1] are also very helpful to distinguish Color based image analysis techniques. The information of Color distribution in a image can be extracted by using the low order moments. Let P_{ij} is the ith Color channel at the jth image pixel. The four Color moments can be defined as :

Mean:

The first color moment can be interpreted as the average color in the image, and it can be obtained by using the following formula

$$\mu = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} P_{ij} \quad (9)$$

Standard Deviation:

The second color moment which is the standard deviation, is calculated by taking the square root of the variance of the color distribution

$$\sigma = \sqrt{\left(\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(p_{ij}-\mu\right)^2\right)} \quad (10)$$

Skewness

The third color moment is the skewness. It measures how asymmetric the color distribution is, and thus it gives measure about the shape of the color distribution. Skewness can be obtained with the following formula:

$$\theta = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(p_{ij}-\mu\right)^3}{MN\sigma^3} \quad (11)$$

Kurtosis

Kurtosis is the fourth color moment. It gives information about the shape of the color distribution. More distinctively, kurtosis is a measure of how flat or tall the distribution is in association to normal distribution

$$\gamma = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(p_{ij}-\mu\right)^4}{MN\sigma^4} - 3 \quad (12)$$

2.4. Texture Feature

An image texture is a set of metrics computed in image processing intended to enumerate the apparent texture of a leaf image. Leaf Image Texture gives information regarding the spatial arrangement of color or intensities in a leaf image or selected region of a leaf image. The recognition of explicit textures in an image is achieved principally by modeling texture as a two-dimensional gray level variation. The resultant two dimensional arrays are called as Gray

Level Co-occurance Matrix (GLCM). After applying GLCM we obtain a feature set which describe the Angular Second Moment, Entropy, Correlation and Contrast of a given image.

2.5. Pseudo Zernike Moments

Moment based techniques have been effectively used in quite a few image processing problems and they are a significant and fundamental tool for generating feature descriptors. Pseudo-Zernike moments provide enhanced performance as compared to Zernike and Hu moments as feature descriptors in terms of their exhibited error rate. [9] .The radial polynomials pseudo Zernike moments use the following

$$S_{nm}(r) = \sum_{s=0}^{n-|m|} \frac{r^{n-s}(-1)^s(2n+1-s)!}{s!(n-|m|-s)!(n+|m|+1-s)!} \quad (13)$$

We can write them in the similar form as Zernike moments with the help of pseudo-Zernike polynomial $\hat{V}_{pq}(r, \varphi)$ as

$$Z_{pq} = \frac{(p+1)}{\pi} \int_0^{2\pi} \int_0^1 \hat{V}^*_{pq} f(r,\varphi)\, r dr d\varphi, \qquad r \geq 1 \quad (14)$$

where $\hat{V}_{pq} = S_{nm}(r) e^{iq\varphi}$

Also we can express S_{nm} in terms of its coefficients the similar way as with radial polynomials, in coefficient form as

$$R_{nm}(r) = \sum_{k=m}^{n} C_{nmk} r^k \text{ with} \quad (15)$$

$$C_{nmk} = \frac{(-1)^{n-k}(n+k+1)!}{(n-k)!(k+m+1)!(k-m)!} \quad (16)$$

III Proposed System

This paper implements a plant recognition algorithm by using easy to extract features like shape, vein, color, texture features which are combined with pseudo Zernike movements. The focal improvements are on feature extraction techniques that include pseudo Zernike movements and the dual stage learning algorithm for training the classifier namely Radial Basis Function neural network. The block diagram of the proposed technique is shown in Figure 1.Here in this research work 32 dissimilar leaf types from the well know Flavia dataset is for recognizing the input leaf.

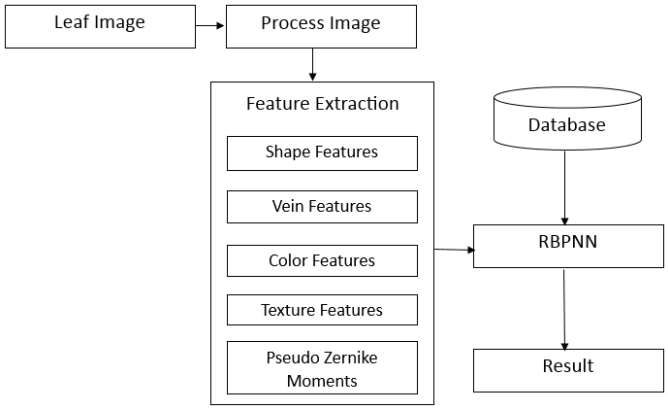

Figure1: Proposed System for leaf recognition

3.1 Radial basis probabilistic neural network

The radial basis probabilistic neural network (RBPNN) model, as shown in Figure 2, amalgamates the benefits of radial basis function neural networks (RBFNN) and probabilistic neural networks (PNN). The conception of a RBPNN involves four different layers: one input layer, two hidden layers and one output layer. The input layer consists of source (i.e., input) nodes. The first hidden layer consists of the hidden centers which are determined by input training sample set and normally is a non-linear processing layer. The second hidden layer discriminatorily sums the outputs of the first hidden layer. The second hidden layer commonly has the equivalent size as the output layer for a labeled pattern classification problem. Universally the weights between the first hidden layer and the

second hidden layer of the network are ones or constants which may include zeros also. Explicitly these weights are commonly set as fixed values and necessarily do not require learning. The last layer is the output layer. Similar to the RBFNN, the selection of the number of neurons in the first hidden layer of the RBPNN is the prime concern for the network performance. By and large, the number of neurons in the first hidden layer is strongly correlated to the efficient performance of the RBPNN.

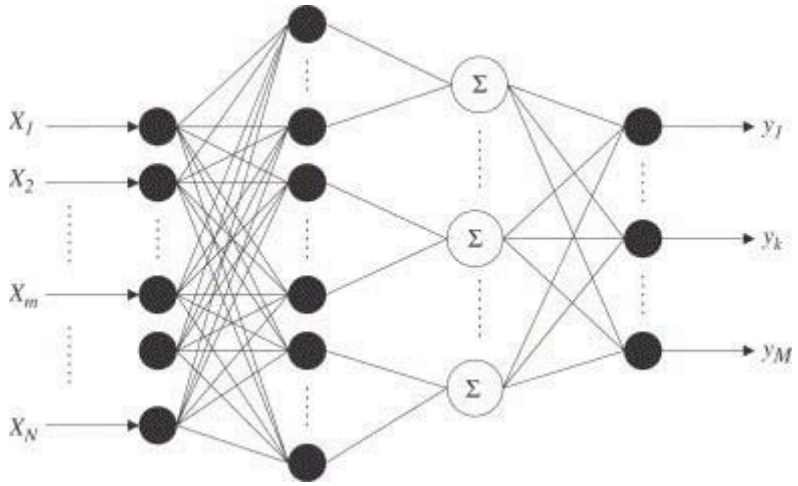

Figure 2: Basic architecture of RBPNN

3.2 RBF neural network classifier design

The design of RBF neural networks classifier is mainly the difficult part of the entire research. In the input layer, the number of input nodes of the neural network is set equivalent to the number of feature vector elements. The number of nodes present in output layer is then set to the number of leaf image classes.

3.3 Dual stage learning algorithm

The training of the RBF neural networks can be made quicker by using a dual stage training algorithm. During the first stage of the training we resolve the output connection weights, which need the result of a set of linear equations that can be completed quickly. During the second stage, the parameters of the basis function which necessarily correspond to the RBF units are also found out using an unsupervised learning technique that requires the result of a set of nonlinear equations. Finally training of the RBF neural networks requires estimation of the output connection weights, centers, and widths of the RBF units.

IV. Experimental Results

To experiment the proposed method, a dataset named Flavia, which can be downloaded from http://flavia.sourceforge.net/, has been used. This dataset contains 32 kinds of plant leafs. Based on this dataset, 40 plants per species were employed to train the network, and 10 plants per species were used to test the performance of the proposed system. For each type of plant, 10 pieces of leaves from testing sets are used to test the accuracy of our algorithm. To calculate the overall accuracy of our system we have used the following formula.

Accuracy= NR/NT where NR is the number of images correctly recognized and NT is the total number of query input images.

From table no 1 we observe that using the pseudo Zernike moments from order 2 to 9 along with 5 shape features, mean of colors, standard deviation of colors , skewness of colors , 16 texture features, 3 vein features resulted in a highest accuracy of 94.52%.

Table 1: Accuracy of leaf image recognition using pseudo Zernike moments from order 2 to 9 and various combinational features.

Features	**Accuracy**
PZM+ 5 shape features	**87.43%**

PZM + 5 shape features + mean of colors	**90.45%**
PZM + 5 shape features + mean of colors + standard deviation of colors	**91.17%**
PZM + 5 shape features + mean of colors + standard deviation of colors + skewness of colors	**91.98%**
PZM + 5 shape features + mean of colors + standard deviation of colors + skewness of colors + kurtosis of colors	**91.39%**
PZM + 5 shape features + mean of colors + standard deviation of colors + skewness of colors + kurtosis of colors + 16 texture features	**91.90%**
PZM + 5 shape features + mean of colors + standard deviation of colors + skewness of colors + 16 texture features	**91.32%**
PZM + 3 geometric features + 12 texture features	**90.47%**
PZM + 5 shape features + mean of colors + standard deviation of colors + skewness of colors + 16 texture features + 3 vein features	**94.52%**
PZM + 5 shape features + mean of colors + standard deviation of colors + skewness of colors + kurtosis of colors + 16 texture features + 3 vein features	**93.18%**

V. Comparison with Other Systems

To compare our proposed technique with several researches who have used Flavia dataset, we have listed the proposed technique and their results as given in Table.2 Based on the table, the proposed systems that uses pseudo Zernike moments are certainly encouraging for plant identification.

Table.2: Comparison of proposed leaf recognition systems with other Systems

Scheme	Accuracy
Proposed in [3]	71%
1-NN in [4]	93%
k-NN (k = 5) in [4]	86%
RBPNN in [4]	91%
MMC in [2]	91%
k-NN (k = 4) in [2]	92%
MMC in [5]	92%

BPNN in [5]	92%
BPNN in [5]	92%
MLNN in [6]	94 %
Flavia[7]	90%
Zernike moments[8]	93.44%
Proposed method	94.52%

VI. CONCLUSION

We conclude that incorporating pseudo-Zernike moments for feature descriptors is a feasible alternative for classifying structurally complex images. They offer exceptional invariance features and reveal enhanced performance than other moment based solutions. Even if the input is blemished with intense amounts of noise, they still offer a viable and accurate method for leaf recognition. The only negative aspect of pseudo-Zernike moments is their costly computation, which makes them inapt for some problems. Nevertheless they can be computed in parallel and as the computational performance of computers increase, the time necessary for their calculation perhaps won't be a problem in the nearby future. Also, since computation of pseudo-Zernike moments for feature descriptors is time intensive, we have proposed a dual stage training algorithm to train the RBF neural networks which definitely reduces the time intensive problem associated with pseudo-Zernike moments.

REFERENCES

[1] M. Stricker and M. Orengo. Similarity of color images. In In SPIE Conference on Storage and Retrieval for Image and Video Databases III, volume 2420, pages 381-392,Feb. 1995.

[2] O. Miljkovi´c . Image Pre-processing Tool. Kragujevac J. Math. 32 (2009) 97-107.

[3] T. Cervinka, and I. Provazn´ık. Pre-processing for Segmentation of Computer Tomography Images. The Faculty of Electrical Engineering and Communication Brno University of Technology,Department of Biomedical Engineering, 2007.

[4] G. Chen and T. D. Bui, _Invariant fourier-wavelet descriptor for pattern recognition,_ Pattern Recognition, vol. 32,pp. 1083_1088, 1999.

[5] M. Khalil and M. Bayoumi, _A dyadic wavelet a_ne invariant function for 2D shape recognition,_ IEEE Trans.

[6] Yuan Tian Multiple Classifier Combination For Recognition Of Wheat Leaf Diseases Intelligent Automation and Soft Computing, Vol. 15, No. X, pp. 1-10, 2009

[7] Stephen Gang Wu, Forrest Sheng Bao, Eric You Xu, Yu – Xuan Wang Yi – Fan Chang[2007] A Leaf Recognition Algorithm for Plant Classification Using Probabilistic Neural Network , IEEE 7th International Symposium on Signal Processing and Information Technology

[8] Abdul Kadir Experiments Of Zernike Moments For Leaf Identification, Journal of Theoretical and Applied Information Technology 15 July 2012. Vol. 41 No.1

[9] C. H. Teh and R. T. Chin. On image analysis by the methods of moments. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 10(4):496–513, 1988.