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An Effective Tea Leaf Recognition Algorithm for Plant Classification Using Radial Basis Function Machine

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Abstract: *A leaf is an organ of a vascular plant, as identified in botanical terms, and in particular in plant morphology. Naturally a leaf is a thin, flattened organ bear above ground and it is mainly used for photosynthesis. Recognition of plants has become an active area of research as most of the plant species are at the risk of extinction. Most of the leaves cannot be recognized easily since some are not flat (e.g. succulent leaves and conifers), some does not grow above ground (e.g. bulb scales), and some does not undergo photosynthetic function (e.g. cataphylls, spines, and cotyledons).In this paper, we mainly focused on tea leaves to identify the leaf type for improving tea leaf classification. Tea leaf images are loaded from digital cameras or scanners in the system. This proposed approach consists of three phases such as preprocessing, feature extraction and classification to process the loaded image. The tea leaf images can be identified accurately in the preprocessing phase by fuzzy denoising using Dual Tree Discrete Wavelet Transform (DT-DWT) in order to remove the noisy features and boundary enhancement to obtain the shape of leaf accurately. In the feature extraction phase, Digital Morphological Features (DMFs) are derived to improve the classification accuracy. Radial Basis Function (RBF) is used for efficient classification. The RBF is trained by 60 tea leaves to classify them into 6 types. Experimental results proved that the proposed method classifies the tea leaves with more accuracy in less time. Thus, the proposed method achieves more accuracy in retrieving the leaf type.*

Keywords: *Leaf Recognition, Dual Tree Discrete Wavelet Transform (DT-DWT), Digital Morphological Features (DMFs), Radial Basis Function (RBF).*

I. Introduction

Leaf is the most important organ in a plant. Plant leaf features are important for the plant species identification.[1]Plant recognition is an essential and challenging task. Leaf recognition plays an important role in plant classification and its key issue lies in whether the chosen features are constant and have good capability to discriminate various kinds of leaves. The recognition procedure is very time consuming. Computer aided plant recognition is still very challenging task in computer vision because of improper models and inefficient representation approaches. The main aim of plant recognition is to evaluate the leaf geometrical morphological and Fourier moment based features.

Recently, computer vision and pattern recognition techniques have been applied towards automated process of plant recognition [2].The classification of plant leaves is a vital mechanism in botany and in tea, cotton and other industries [3], [4]. Additionally, the morphological features of leaves are employed for plant classification or in the early diagnosis of certain plant diseases [5].

Preprocessing is a technique in which an image includes removal of noise, edge or boundary enhancement, automatic edge detection, automatic contrast adjustment and the segmentation. As multiple noise damages the quality of nature of the images, improved enhancement technique is required for improving the contrast stretch in leaf images. Image enhancement is basically improving the interpretability or discernment of information in images for human viewers and providing enhanced input for other automated image processing techniques [22, 23]. During this process, one or more attributes of the image are altered. Selection of attributes and the way they are modified are specific to a given task.

Denoising has become an basic step in image analysis. Noise suppression and the preservation of actual image discontinuity is essential in image denoising in order to detect the image details and suitably alter the degree of noise smoothing. Fuzzy feature is used in single channel image denoising to enhance image information. This feature space helps to distinguish between important coefficients, which depends on image discontinuity and noisy coefficients [6]. The size of image plays an important role in order to transmit the image in lesser time and with the allotted bandwidth. DT-DWT has been successfully used in many applications such as image denoising, texture analysis, compression, and motion estimation.

The extraction of leaf features from a plant is a key step in the plant recognition process [7, 8]. This feature extraction process creates a new challenge in the field of pattern recognition [9] [10]. The data acquisition from living plant automatically by the computer has not been implemented. The main phases involved in this research are feature extraction and the classification. All features are extracted from digital leaf image. Radial Basis Function(RBF) is used for efficient classification.

The paper can be organized as follows. Section II describes the related works involved regarding leaf recognition. Section III describes about the proposed methodology. Experimental results are illustrated in Section IV and Section V deals with the conclusion.

II. Related Works

Stephen Gang Wu et al., [11] employ Probabilistic Neural Network (PNN) with image and data processing techniques to implement general purpose automated leaf recognition for plant classification. They implemented a leaf recognition algorithm using easy-to-extract features and high efficient recognition algorithm. They mainly concentrate on feature extraction and the classifier. Features are extracted from digital leaf image. Except one feature, all features can be extracted automatically. The features are orthogonalized by Principal Components Analysis (PCA).As to the classifier; they used PNN for its fast speed and simple structure.

Wang et al., [12] first investigated the representation efficiency of 3D DT-DWT for video and proposed a DDWT-based scalable video coding scheme without motion estimation (DDWTVC) [13]. Better coding efficiency in terms of PSNR and visual quality are reported compared with 3D SPIHT which also does not use motion compensation.

Xiao Gu et al., [14] proposed a novel approach for leaf recognition by means of the result of segmentation of leaf's skeleton based on the integration of Wavelet Transform (WT) and Gaussian interpolation. And then the classifiers, a nearest neighbor classifier (1-NN), a k -nearest neighbor classifier (k-NN) and a radial basis probabilistic neural network (RBPNN) are employed, based on Run-length Features (RF) obtained from the skeleton to identify the leaves. Ultimately, the efficiency of this approach is illustrated by several experiments. The results reveal that the skeleton can be effectively extracted from the entire leaf, and the recognition rates can be significantly improved.

Jyotismita Chaki et al., [15] proposed an automated system for recognizing plant species based on leaf images. The leaf images corresponding to three different plant types are analyzed using two different shape modeling techniques. The first modeling is based on the Moments-Invariant (M-I) model and the second on the Centroid Radii (C-R) model. The first four normalized central moments have been considered for the M-I model and studied in various combinations namely in joint 2-D and 3-D feature spaces for producing optimum results. An edge detector has been used for the C-R model to identify the boundary of the leaf shape and 36 radii at 10 degree angular separation have been used to build the feature vector. A hybrid set of features involving both the M-I and C-R models has been generated and explored to find whether the combination feature vector can lead to better analysis. Neural networks are used as classifiers for discrimination.

III. Methodology

The tea leaf recognition method used in the proposed approach consists of three phases namely image pre processing, feature extraction and classification. The steps used in the recognition of tea leaf system is shown in the Fig.1.

3.1. Image Pre-Processing

The input tea leaf images undergo several processing steps as follows.

A. Converting RGB Image To Binary Image

The tea leaf image is obtained through scanners or digital cameras. An RGB image is firstly converted into a grayscale image. Equation 1 is used to convert RGB value of a pixel into its grayscale value.

$$gray=0.2989*R+0.85870*G+0.1140*B \qquad (1)$$

Where R, G and B corresponds to the color of the pixel, respectively.

B. Fuzzy Denoising Using Dual Tree Discrete Wavelet Transform

Here the denoising is done through Fuzzy shrinkage rule. In image denoising, where a trade-off between noise suppression and the maintenance of actual image discontinuity must be made, solutions are required to detect important image details and accordingly adapt the degree of noise smoothing. With respect to this principle, use a fuzzy feature for single channel image denoising to enhance image information in wavelet sub-bands and then using a fuzzy membership function to shrink wavelet coefficients, accordingly.

Dual Tree Discrete Wavelet Transform (DT-DWT) is used as a fuzzy denoising algorithm which provides both shiftable sub-bands and good directional selectivity and low redundancy.

The 2-D dual-tree discrete wavelet transform (DT-DWT) of an image is employed using two critically-sampled separable 2-D DWT's in parallel .[16] The advantages of the dual-tree DWT (DT-DWT) over separable 2D DWT is that, it can be used to employ 2D wavelet transforms which are more selective with respect to orientation.

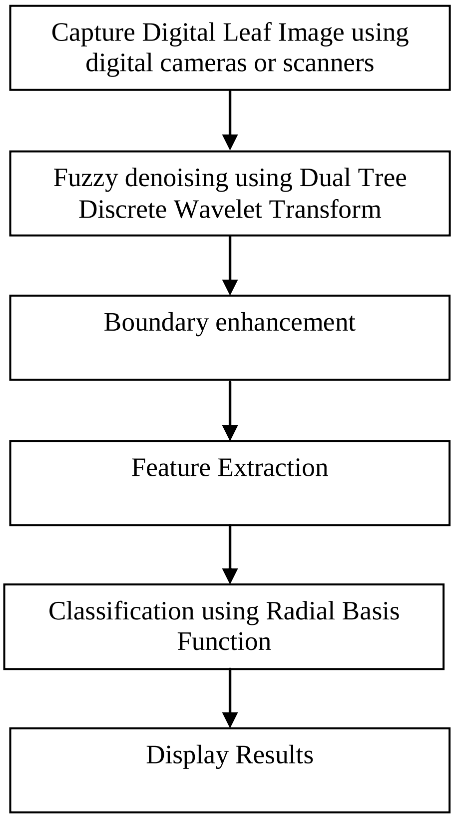

Fig. 1 Steps used in the recognition of tea leaf system

The real part or the imaginary part of DT-DWT [19] produces perfect reconstruction and hence it can be employed as a stand-alone transform. Feature vector can be calculated using magnitude of subbands. The implementation of DT-DWT is easy. An input image is decomposed by two sets of filter banks, (H_0^a, H_1^a) *and* $H_0^b, H_1^b)$ separately and filtering the image both horizontally and vertically. Then eight sub bands are obtained: LL_a , HL_a , LH_a , HH_a , LL_b , HL_b , LH_b and HH_b. Each high-pass subband from one filter bank is combined with the corresponding subband from the other filter bank by simple linear operations: averaging or differencing. The size of each subband is the same as that of 2D DWT at the same level. [20] But there are six high pass subbands instead of three highpass subbands at each level. The two lowpass subbands, LL_b and LL_a , are iteratively decomposed up to a desired level within each branch.

The DT-DWT (K) can be designed in two ways to have required delays. The first is based on Farras filters and the second employs Q-shift (quarter shift) filter design. The key issue in the design of DT-DWT (K) is to obtain (approximate) shift invariance using any of the filter forms.[21]To use a redundant transform for compression seems contradictory to the goal of compression which is to reduce whatever redundancy as much as possible. However if coefficients of a redundant transform are sparse enough, compression can even benefit from the introduced redundancy since most coefficients are nearly zero.

Processing is usually result from a modification of the spatial correlation between wavelet coefficients (often caused by zeroing of small neighboring coefficients) or by using DWT. DWT is shift invariance and will cause some visual artifacts in thresholding based denoising. For this reason, the fuzzy filter is used on the results of the proposed fuzzy-shrink algorithm to reduce artifacts to some extent. First, use a window of size (2 L+1) × (2 K+1) centered at (i, j) to filter the current image pixel at position (i, j). Next, the similarity of neighboring pixels to the center pixel is calculated using the following equation.

$$m(l,k) = \exp\left(-\left(\frac{Y_{s,d}(i,j) - Y_{s,d}(i+l,j+k)}{Thr}\right)^2\right) \qquad (2)$$

$$s(l,k) = \exp\left(-\left(\frac{l^2 + k^2}{N}\right)\right) \qquad (3)$$

where $Y_{s,d}(i,j)$ and $Y_{s,d}(i+l,j+k)$ are central coefficient and neighbor coefficients in the wavelet sub-bands, respectively. $Thr = c \times \hat{\sigma}_n$, $3 \le c \le 4$, $\hat{\sigma}_n$ is estimated noise variance, and N is the number of coefficients in the local window $k \in [-K \ldots K]$, and $l \in [-L \ldots L]$.

According the two fuzzy functions, can get adaptive weight $w(l,k)$ for each neighboring coefficient:

$$w(l,k) = m(l,k) \times s(l,k) \qquad (4)$$

Using the adaptive weights$w(l,k)$, obtain the fuzzy feature for each coefficient in the wavelet sub-bands as follows:

$$f(i,j) = \frac{\sum_{I=-L}^{L} \sum_{K=-K}^{K} W(l,k) \times |Y_{s,d}(i+l,j+k)|}{\sum_{I=-L}^{L} \sum_{K=-K}^{K} W(l,k)} \qquad (5)$$

After finding the fuzzy feature, will form Linguistic IF-THEN rules for shrinking wavelet coefficients as follows:

"IF the fuzzy feature $f(i,j)$ is large THEN shrinkage of wavelet coefficients $Y_{s,d}(i,j)$ is small".

Finally, the output of post-processing step is determined as follows:

$$\tilde{x}(i,j,c) = \frac{\sum_{I=-L}^{L} \sum_{K=-K}^{K} w(l,k) \times \hat{x}(i+1,j+k,c)}{\sum_{I=-L}^{L} \sum_{k=-k}^{k} w(l,k)} \qquad (6)$$

where $\hat{x}$ is the denoised image, which can be obtained using proposed fuzzy-shrink algorithm. After the post processing process the enhanced leaf image is obtained as a result.

C. Boundary Enhancement

The margin of a leaf is highly focused in this pre processing step. Convolving the image with a Laplacian filter of 3 × 3 spatial mask:

$$\begin{matrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{matrix} \qquad (7)$$

Fig. 2.1 Enhanced image

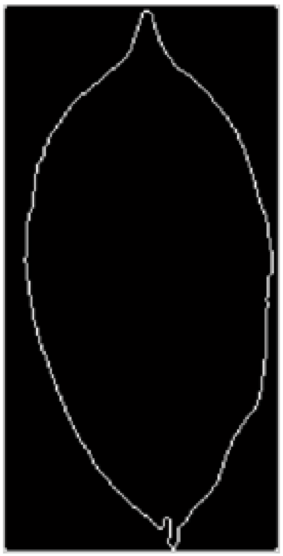

Fig. 2.2 Boundary Enhancement

The Fig. 2 shows the enhanced image and boundary enhancement the proposed tea leaf recognition. To make boundary as a white curve on black background, the pixel values "1" and "0" are swapped.

3.2. Feature Extraction

The proposed approach uses common Digital Morphological Features (DMFs), so that a computer can obtain feature values quickly and automatically The features used for extraction in the proposed method is described as follows.

A. *Physiological Length:*

The distance between the two terminals is the physiological length. It is represented as L_p.The red line in the Fig. 3 indicates the physiological length of a leaf.

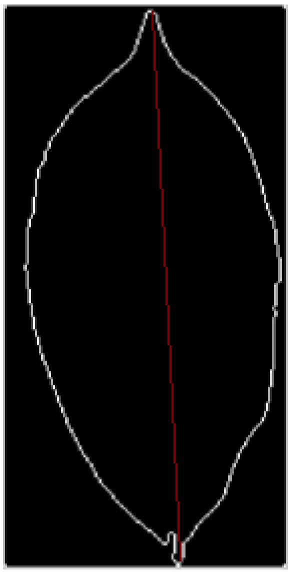

Fig. 3 Physiological length of a leaf

B. *Physiological Width:*

Drawing a line passing through the two terminals of the main vein, infinite lines can be plotted orthogonal to that line. The number of intersection pairs between those lines and the leaf margin is also infinite. At the physiological width, the longest distance between points of those intersection pairs is defined. It is represented as W_p. As the coordinates of pixels are discrete, two lines are considered as orthogonal if their degree is $90^\circ \pm 0.5^\circ$.The red line in the Fig. 4 indicates the physiological width of a leaf.

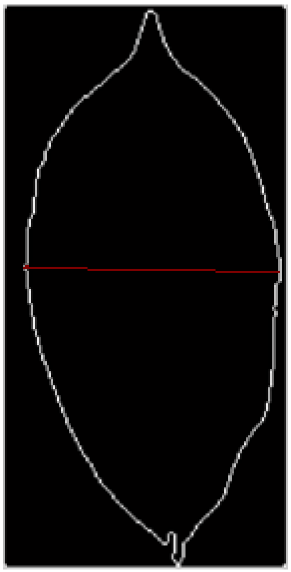

Fig. 4 Physiological width of a leaf

C. *Aspect Ratio:*

The ratio of physiological length L_p to physiological width W_p is called aspect ratio and it is given by,

$$Aspect\ ratio = \frac{L_p}{W_p} \tag{8}$$

D. Serration Angle:

The teeth angle of a leaf can be defined using serration angle.

$$\theta = arc\cos\left(\frac{(a.b)}{|a||b|}\right) \quad (9)$$

Where θ is the serration angle , a is the length of first recognizable teeth from the tip of the angle and b is the breadth of first recognizable teeth from the tip of the angle.

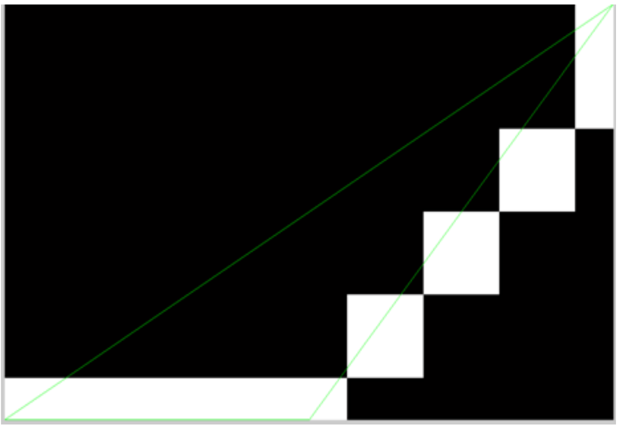

Fig. 5. Serration angle obtained from the tea leaf

The serration angle obtained from the tea leaf using equation 4 is shown in the Fig. 5.

E. Segment

The segment of a leaf can be defined as the ratio of first recognizable teeth in the left side from the tip of the angle 'a' to the first recognizable teeth in the right side from the tip of the angle 'b'.

$$segment = \frac{a}{b} \quad (10)$$

F. Segment maximum width to Physiological length ratio

The leaf is divided into 10 segments as shown in the Fig. 6. Each segment width to the physiological length ratio can be determined for all the 10 segments.

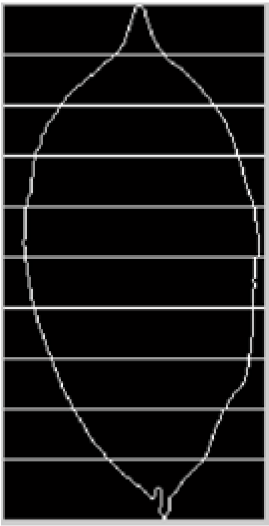

Fig. 6 Segment of a leaf

G. Tip Angle

The angle which is formed from the tip of the leaf to the first recognizable teeth on either side of the leaf is called tip angle.

The tip angle can be calculated using the formula,

$$\theta = arc\cos\left(\frac{(a.b)}{|a||b|}\right) \quad (11)$$

Where θ is the tip angle, a and b are the first recognizable teeth from the tip of the angle on left and right side respectively. The tip angle formed from the tea leaf is shown in the Fig. 7.

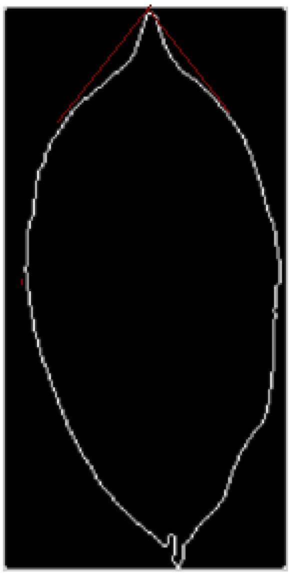

Fig. 7 Tip angle obtained from the tea leaf

3.3. Classification Using Radial Basis Function

A Radial Basis Function Neural Network (RBFNN) is a special type of neural network commonly used for classification, regression, function approximation and data clustering problems. RBFNN uses Radial Basis Function (RBF) as its activation function.[18] Radial Basis Function Neural Network architecture is shown in the fig. 8.

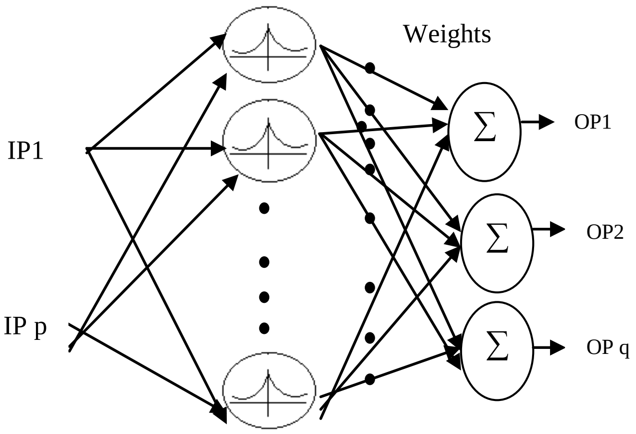

Fig 8. Radial Basis Function Neural Network Architecture

A Radial Basis Function Neural Network has three layers such as the input layer, the hidden layer and the output layer. The input layer in the RBF brings the coordinates of the input vector to each unit in the hidden layer. Activation produced by each unit in the hidden layer using the Radial Basis Function. Then, each unit of the hidden layer processes a linear combination of the activations and creates a classified output in the output layer units. The output depends on the use of the activation function used in the hidden layer and the weights related with the links between the hidden layer and the output layer.

Several learning algorithms available for RBF neural networks . The main applications of RBF is data classification. Majority of the learning algorithms determines the number of units in the hidden layer, the activation functions connected with the hidden units and the weights related with the links between the hidden and output layers.[17] The general mathematical form of the output units in RBF network is as follows:

$$f_j(x) = \sum_{i=1}^{h} w_{i,j}\, r_i(x) \qquad (12)$$

where f_j is the function corresponding to the j^{th} output unit and it is a linear combination of h radial basis functions $r_1, r_2, \ldots\ldots, r_h$.

In this paper, supervised learning algorithm based on gradient descent with momentum is used for training RBF neural networks.

A. Gradient Descent with Momentum

Gradient descent with momentum is implemented to train the RBF neural network to respond to the local gradient and to recent trends in the error surface. Momentum which acts like a low pass filter, permits the network to ignore small features in the error surface. With momentum a network can slide through a shallow local minimum.

Gradient descent with momentum depends on two parameters. The training parameter lr indicates the learning rate and the training parameter mc is the momentum constant that defines the amount of momentum. mc is set between 0 and values close to 1. The value of momentum constant 1 results in a network that is completely insensitive to the local gradient.

GDM can be used to train RBF neural network as long as its net input, weight, and transfer functions have derivative functions. RBF is used to calculate derivatives of performance $perf$ with respect to the weight and bias variables X. The variable can be adjusted based on the gradient descent with momentum,

$$dX = mc * dXprev + lr * (1 - mc) * dperf/dX \qquad (13)$$

Where $dXprev$ is the previous change to the weight or bias. Training stops when any of these conditions occurs:

- If it reaches maximum number of repetitions.
- The maximum amount of time is exceeded.
- Performance is minimized to the goal.
- The performance gradient falls below min_grad.
- Validation functioning has increased more than max_fail times since the last time it decreased.

IV. Experimental Results

The tea leaf recognition is considered in the proposed approach. The dataset used in this approach is UPASI dataset. The performance of the proposed approach is evaluated based on the following parameters: Accuracy and Execution time. The different tea leaves taken in the proposed approach is shown in the Table 1.

TABLE I
DIFFERENT TYPES OF TEA LEAVES TESTED IN THE PROPOSED METHOD

Tea leaf name	Tested Samples	Number of Correct Recognition
TRF 1	58	53
UPASI - 3	61	56
UPASI - 9	57	52
UPASI - 10	55	49
UPASI -17	60	53
UPASI - 22	64	61

Table 2 shows the accuracy of the classification algorithms. The accuracy of the proposed Radial Basis Function classification approach is compared with K- Nearest Neighbour classification approach.

TABLE 2
COMPARISON OF THE CLASSIFICATION ACCURACY

Classification Techniques	Accuracy (%)
Radial Basis Function	86.2
K- Nearest Neighbour	78

It is clearly observed from the table 2 that the proposed Radial Basis Function classification approach outperforms the K- Nearest Neighbour classification approach. The accuracy obtained by Radial Basis Function classification is 86.2% whereas the accuracy obtained by the K- Nearest Neighbour is 78%.

TABLE 3
COMPARISON OF THE EXECUTION TIME

Classification Techniques	Time (seconds)
Radial Basis Function	2.02
K- Nearest Neighbour	3.6

Table 3 reveals the execution time of the classification algorithms. The execution time of the proposed Radial Basis Function classification approach is compared with K- Nearest Neighbour classification approach.

It is observed from the table 3 that the proposed Radial Basis Function classification approach takes only 2.02 seconds for execution where as the K-Nearest Neighbour classification approach takes 3.6 seconds.

V. Conclusion

A new approach of tea leaf classification based on leaf recognition is proposed in this paper. The approach consists of three phases namely the preprocessing phase, feature extraction phase and the classification phase. The image is preprocessed by Dual Tree Discrete Wavelet Transform (DT-DWT) using fuzzy shrinkage rule. The features of leaf are extracted and given as an input to the classifier. Radial Basis Function Neural Network is trained using Gradient Descent with Momentum(GDM). The computer can automatically classify 6 kinds of plants via the leaf images loaded from digital cameras or scanners. The performance of the proposed approach is evaluated based on the accuracy and execution time. The proposed algorithm produces better accuracy and takes very less time for execution. The perfoemance of algorithm can be further improved by incorporating efficient kernel functions and also the performance of the classifiers can be improved.

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