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An Efficient Leaf Recognition Algorithm for Plant Classification Using Support Vector Machine

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Abstract—**Recognition of plants has become an active area of research as most of the plant species are at the risk of extinction. This paper uses an efficient machine learning approach for the classification purpose. This proposed approach consists of three phases such as preprocessing, feature extraction and classification. The preprocessing phase involves a typical image processing steps such as transforming to gray scale and boundary enhancement. The feature extraction phase derives the common DMF from five fundamental features. The main contribution of this approach is the Support Vector Machine (SVM) classification for efficient leaf recognition. 12 leaf features which are extracted and orthogonalized into 5 principal variables are given as input vector to the SVM. Classifier tested with flavia dataset and a real dataset and compared with k-NN approach, the proposed approach produces very high accuracy and takes very less execution time.**

Keywords- Digital Morphological Features (DMFs); Leaf Recognition; Support Vector Machine;

I. INTRODUCTION

Plants play a vital role in the environment. There will be no existence of the earth's ecology without plants. However, recently, several species of plants are at the danger of extinction. In order to protect plants and to catalogue various species of flora diversities, a plant database becomes very essential. There is huge volume of plant species worldwide. In order to handle such volumes of information, development of a rapid and competent classification technique has become an active area of research [1]. Moreover, along with the conservation feature, recognition of plants has also become essential to exploit their medicinal properties and using them as sources of alternative energy sources like bio-fuel. There are various ways to recognize a plant, like flower, root, leaf, fruit etc. 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]. 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. This data is very vital in identifying the various classes of plants. Ji Xiang, Huang and Xiao Feng [6] carried out their investigation 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 employed to discriminate with each other.

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.

This paper implements a leaf recognition algorithm using easy to extract features and high efficient recognition algorithm. The main phases involved in this research are feature extraction and the classification. All features are extracted from digital leaf image. 12 features are orthogonalized by Principal Components Analysis (PCA) [11] and are given to the classifier. The classifier used in this approach is Support Vector Machine [12, 13] for its fast speed and simple structure.

II. LITERATURE SURVEY

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-

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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.

Xiao-Feng Wang et al., [15] proposed a technique of recognizing leaf images depending on shape features through a hypersphere classifier. Initially, the author employed image segmentation to the leaf images. Then, eight geometric features are extracted including rectangularity, circularity, eccentricity, etc., and seven moment invariants for classification. Ultimately, a moving center hypersphere classifier is presented to handle these shape features. Thus, there are more than 20 classes of plant leaves productively classified. The average correct recognition rate is up to 92.2 percent.

III. LEAF RECOGNITION APPROACH

This approach consists of three phases namely image pre processing, feature extraction and classification.

3.1. Image Pre-Processing

This is the feature extraction phase involved in this recognition approach.

A. Units

The leaf image is obtained through scanners or digital cameras. All leaf images are in 800 x 600 resolutions. 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.

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

where R, G, B correspond to the color of the pixel, respectively.

B. 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. An instance of image pre-processing is illustrated in Figure 2.

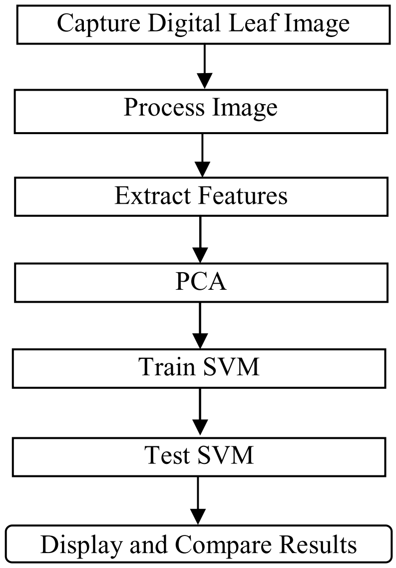

Figure 1. Flow diagram of proposed scheme

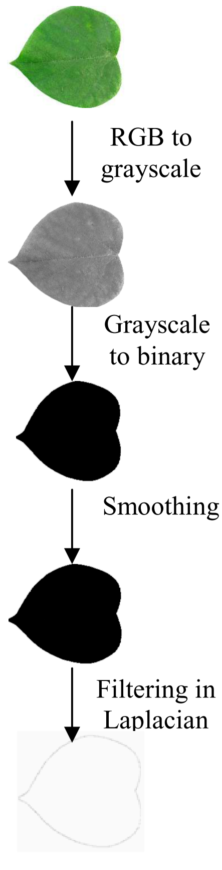

Figure 2. Pre-Processing Phase

To make boundary as a black curve on white background, the "0" "1" value of pixels is swapped.

3.2. Feature Extraction

This approach uses a 12 common Digital Morphological Features (DMFs), derived from 5 basic features, so that a computer can obtain feature values quickly and automatically (only one exception).

A. Basic Geometric Features

Five fundamental geometric features are obtained in this approach.

1) Diameter: The diameter is the longest distance between any two points on the margin of the leaf. It is represented as D.

2) Physiological Length: The only human interfered segment of the proposed algorithm is that, the two terminals of the main vein of the leaf should be marked through mouse click. The distance between the two terminals is the physiological length. It is represented as Lp.

3) Physiological Width: Drawing a line passing through the two terminals of the main vein, one can plot infinite lines orthogonal to that line. The number of intersection pairs between those lines and the leaf margin is also infinite. The longest distance between points of those intersection pairs is defined at the physiological width. It is represented as Wp. As the coordinates of pixels are discrete, two lines are considered as orthogonal if their degree is 90◦ ± 0.5˚C.

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

5) Leaf Perimeter: Leaf perimeter is represented as P, leaf perimeter is computed by counting the number of pixels comprising of leaf margin.

B. 12 Digital Morphological Features

Based on 5 basic features introduced previously, 12 digital morphological features used for leaf recognition are defined [17].

1) Smooth factor: The effect of noises to image area is used to illustrate the smoothness of leaf image. Smooth factor is 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) Aspect ratio: It is the ratio of physiological length Lp to physiological width Wp, thus Lp/Wp.

3) Form factor: This feature illustrates 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.

4) Rectangularity: Rectangularity illustrates the similarity between a leaf and a rectangle. It is defined as LpWp/A, where Lp represents physiological length, Wp denotes the physiological width and A is the leaf area.

5) Narrow factor: Narrow factor is the ratio of the diameter D and physiological length Lp, thus D/Lp.

6) Perimeter ratio of diameter: Ratio of perimeter to diameter, denoting the ratio of leaf perimeter P and leaf diameter D, is computed by P/D.

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

8) Vein features: The morphological opening is performed on grayscale image with falt, disk-shaped structuring element of radius 1,2,3,4 and substract remained image by the margin [25]. The results look like the vein. Thus, following 5 feature are called vein features. Areas of left pixels are represented as A_{v1}, A_{v2}, A_{v3} and A_{v4} respectively. Then, the last 5 features: A_{v1}/A, A_{v2}/A, A_{v3}/A, A_{v4}/A, A_{v4}/A_{v1}.

Thus, the feature acquisition steps are carried out and then, the data analysis step has to be performed.

3.3. Proposed Classification Scheme

A. Principal Component Analysis (PCA)

In order to minimize the dimension of input vector of SVM, PCA is used to orthogonalize 12 features. The main aim of PCA is to present the information of original data as the linear integration of certain linear irrelevant variables. PCA alters 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. In this paper, the contribution of first 5 principal components is 93.6%. To balance the computational complexity and accuracy, we adopt 5 principal components. When using the proposed algorithm, in order to obtain the values of components in the new coordinate system, the mapping f: $R^{12} \rightarrow R^5$ is used.

B. Classification using Support Vector Machines

Support Vector Machine (SVM) is a type of classifier that is a group of associated supervised learning technique utilized especially for the purpose of classification. SVM will generate a separating hyperplane in the space, one that increases the boundary between the two data sets. In order to establish the boundary, two parallel hyperplanes are produced, one on every side of the separating hyperplane between the two data sets. For SVM, a data point is denoted as a p dimensional vector, and it is needed to differentiate whether it can split such points with a p-1dimensional hyperplane. This is called a linear classifier.

As support vector machines are linear classifier that has the ability to discover the optimal hyper plane that increases the separation among patterns, this characteristic feature creates SVMs as a potential significance for classification purposes. Initially, the whole data set is partitioned into training (F1) and testing (F2) data randomly. The features in F1 are trained using SVM classifier and Features in F2 are predicted.

Linear classification indicates that the decision surfaces are linear functions of the input vector and therefore are defined using dimensional hyperplanes within the dimensional input space. The best linear classification surface function of characteristics space can be described by the following equation:

$$g(x) = \sum_{j=i}^{n} a_j y_i k(x, x_i) + b \tag{2}$$

where (x_i , y_i) are the two types of sample collection partitioned in the sample space, b represents the classification threshold, and $k(x, x_i)$ is being the nonlinear kernel function that replace characteristics space and meet Mercer conditions. The best linear classification surface function is obtained by striking the best resolve a_i where $i = 1, 2, \dots, n$ of the following function $Q(a)$.

$$g(x)g(x) = \sum_{j=i}^{n} a_j y_i k \quad (3)$$

$$\max_{a} Q(a) = \sum_{i=0}^{n} a_i - 0.5 \sum_{i=0}^{n} \sum_{j=0}^{n} a_i a_j y_i y_j k(x_i, x_j) \quad (4)$$

$$\sum_{j=i}^{n} a_j y_i = 0 \quad (5)$$

$i = 1, 2, \dots, n$ and $0 \leq a_i$.

The above equation is quadratic function extreme value on condition that inequality, Q (a) is convex function. A convex function is defined as a continuous function whose value at the midpoint of each interval in its domain does not go beyond the arithmetic mean of its values at the ends of the interval. Because its local optimal solution is global optimal solution, the solution is unique. A globally optimal solution is the one in which there are no other possible solutions with better objective function values. Thus the best classification function of SVM is:

$$f(x) = sgn(g(x)) = sgn\{\sum_{(j=1)}^{n} a_j y_j k \quad (6)$$

$$sgn\{\sum_{(j=1)}^{n} a_j y_j k(x, x_i) + b\}\} \quad (7)$$

In order to build a SVM classifier, a kernel function and its parameters is needed. Using a kernel function, SVM's are a substitute training technique for polynomial, radial basis function and multi-layer perceptron classifiers where the weights of the network are determined by solving a quadratic programming problem with linear constraints, instead of solving a non-convex, unconstrained minimization difficulty as in standard neural network training. In this work, Radial basis function $K(x, z) = \exp\left\{-\frac{\|x - z\|^2}{2\sigma^2}\right\}$, kernel function is used, where σ is the width of the function.

IV. Experimental Results

The dataset used in this approach is flavia dataset [16] and real dataset. To each type of plant in flavia dataset, 10 pieces of leaves from testing sets are used to test the accuracy of the proposed algorithm. Numbers incorrect recognition is listed in the last column of Table 1. Real dataset contains 15 tree classes. The tree classes are listed in Table II.

TABLE I. Details about the Leaf Numbers of Different Types of Plants in Flavia Dataset

Scientific Name (Latin)	Common Name	Training Samples	Number of Incorrect recognition
Viburnum awabuki	Japanese Viburnum	58	2
Osmanthus fragrans Lour	sweet osmanthus	55	5
Ginkgo biloba L	ginkgo, maidenhair tree	57	0
Nerium oleander L	oleander	61	0
Podocarpus macrophyllus (Thunb.) Sweet	yew plum pine	60	0

TABLE II. Tree Classes in Real Dataset

Ulmus carpinifolia	Acer
Salix aurita	Quercus
Alnus incana	Betula pubescens
Salix alba 'Sericea'	Populus tremula
Ulmus glabra	Sorbus aucuparia
Salix sinerea	Populus
Tilia	Sorbus intermedia
Fagus silvatica	

The performance of the proposed approach is evaluated using flavia dataset and real dataset the based on the accuracy and execution time of the classifiers.

A. Classification Accuracy

Table III shows the accuracy of the classification algorithms in two datasets. The accuracy of the proposed SVM classification approach is compared with the k-nearest neighbour classification approach. It is observed from the table that the proposed SVM classification approach outperforms the K-NN approach. The accuracy obtained by SVM in flavia dataset is 94.5% whereas the accuracy obtained by the k-NN is 78%. In case off real dataset, the accuracy of k-NN is 81.3% and the accuracy of proposed SVM classification approach is 96.8%.

TABLE III. Comparison of the Classification Accuracy in Two Datasets

Dataset	Accuracy (%)	
	k-NN	***SVM Classification***
Flavia Dataset	78	94.5
Real Dataset	81.3	96.8

B. Execution Time

It is observed from table IV that in flavia dataset, k-NN approach takes 3.6 seconds for execution whereas the proposed approach takes only 0.7 seconds. In real dataset, the k-NN approach takes 4.8 seconds but the proposed SVM classification takes only 1.2 seconds.

TABLE IV. COMPARISON OF THE EXECUTION TIME IN TWO DATASETS

Dataset	**Execution Time (Seconds)**	
	k-NN	***SVM Classification***
Flavia Dataset	3.6	0.7
Real Dataset	4.8	1.2

V. CONCLUSION

A new approach of plant classification based on leaves recognition is proposed in this paper. An efficient machine learning approach for plant leaf recognition is presented in this research. The approach consisted of three phases namely the preprocessing phase, feature extraction phase and the classification phase. The computer can automatically classify 32 kinds of plants via the leaf images loaded from digital cameras or scanners. 12 commonly used Digital Morphological Features (DMFs) obtained from 5 basic features are extracted in the feature extraction phase. SVM classifier is adopted for the classification approach as it has better accuracy, fast training speed and simple structure. 12 features are extracted and processed by PCA to form the input vector of SVM. The performance of the proposed approach is evaluated based on the accuracy and execution time. Compared with k-NN method, the proposed algorithm produces better accuracy and takes very less time for execution. For Further research by incorporating efficient kernel functions the performance of the classifier can be improved.

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