

Review of Plant Identification Based on Image Processing

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Abstract Plant recognition is closely related to people's life. The operation of the traditional plant identification method is complicated, and is unfavorable for popularization. The rapid development of computer image processing and pattern recognition technology makes it possible for computer's automatic recognition of plant species based on image processing. There are more and more researchers drawing their attention on the computer's automatic identification technology based on plant images in recent years. Based on this, we have carried on a wide range of research and analysis on the plant identification method based on image processing in recent years. First of all, the research significance and history of plant recognition technologies are introduced in this paper; secondly, the main technologies and steps of plant recognition are reviewed; thirdly, more than 30 leaf features (including 16 shape features, 11 texture features, four color features), and then SVM was used to evaluate these features and their fusion features, and 8 commonly used classifiers are introduced in detail. Finally, the paper is ended with a conclusion of the insufficient of plant identification technologies and a prediction of future development.

1 Introduction

Plant can be seen everywhere around us. There are a wide variety of plants on earth, for instance, more than 250,000 species of plants have been named and recorded according to statistics. Plant plays an important role e.g. it can conserve soil and water, improve the climate. Especially for humans, plant provides us with the various foods. In fact, each kind of plant has unique characteristics e.g. morphology, habits, economic values. In order to study the plant effectively, plant classification and identification are of great importance.

At present, there are many methods of plant classification, such as plant genetics method, plant chemotaxonomy method, and plant cytotaxonomy method. Plant classification is not only the basis of Botany, but also is the foundation of plant ecology, plant genetics, plant medicine and life science. It makes a very important role in plant resources protection, development and utilization.

However, only researchers can use these methods of classification or identification. And these methods mainly depend on people's subjective judgment, which affects the accuracy of classification. Therefore, it is hard to meet the needs that people want to quickly identify plant anywhere.

With the development of digital image processing and pattern recognition, the technology of target recognition based on image processing has already entered people's life, such as face recognition, fingerprint recognition, etc. These techniques provide enough theoretical basis and technical preparation for plant recognition based on image processing.

Therefore, in recent years, study on plant recognition based on image processing has been quietly rising, and more and more popular in the international researchers. This method is rapid and is not dependent on the person's

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subjective judgment. It can effectively make up the insufficiency of artificial recognition method, improves work efficiency and the accuracy of plant recognition. This fast and simple method can help people to get to know the plant more quickly and better.

And it is found that the distribution of the articles published in these years of the plant identification from Fig. 1. More and more researchers are concerned about the field of plant identification.

In the paper, our topic focuses on leaf feature extraction and classifier in plant recognition based on image processing. We list most of the existed features and provide a simple test for performance evaluation and summarize main classifiers rather than contemplate to go into details of particular algorithms or describe results of comparative experiments.

The rest of paper is organized as follows. The framework of plant recognition is introduced in Sect. 2. Section 3 reviews existed image features including shape, texture and color features; commonly used classifiers are introduced in Sect. 4. In Sect. 5, we propose the existing problems needed to be resolved later and point out some potential research areas in future. Finally, we make a conclusion for the paper.

2 Framework of Plant Recognition Based on Image Processing

First of all, we would like to explain the feasibility or rationality of plant recognition based on image processing. The characteristics of plant leaf, flower, fruit, stem, branches, and other organs are usually employed for plant classification. In fact, plant recognition based on image processing also employs these characteristics.

However, compared with the flower, fruit, stem, branches, and other organs, plant leaves exist in most of the year and can be easily collected. Plant leaves contain a lot of essential feature information, such as the leaf blade, margin, texture and other information. Meanwhile, these features can be directly observed, and also can be captured efficiently and accurately by digital equipment to obtain the corresponding digitized images. Leaf is an ideal organ for image-based plant recognition.

Image-based plant recognition is similar with existing biometric-based image recognition. In this section, plant recognition based on leaf images is taken for example to

describe the entire framework of plant recognition based on image processing, as shown in Fig. 2.

Its framework is mainly composed of three steps: image preprocessing, feature extraction, and pattern classification. The image, obtained by camera or other devices, usually has some restrictions or interference with noises. Before feature extraction, it is necessary to carry on image preprocessing including image denoising, image segmentation, image enhancement, etc.

Figure 3 is the typical processes of plant leaf image preprocessing. If color information is not considered, color images are also transformed into gray image because gray images are processed more easily and quickly than color images. Because the captured image usually has random noises, image filtering (e.g. median filter) is necessary. After image filtering, the gray image is segmented by binary segmentation. The outline of plant image can be generated as a result of retaining the maximum connected region and removing leafstalk and holes.

After image preprocessing, we will extract the feature of leaf images. Generally speaking, leaf feature consists of shape information, texture information, and color information. Shape information can be extracted by computing various shape descriptors (e.g. Fourier descriptor, invariant moments, and other shape parameters). Texture information is extracted by computing some statistical features (e.g. co-occurrence matrix, histogram, entropy, consistency, smoothness, etc.). Color information is usually extracted from such color spaces as RGB or HIS.

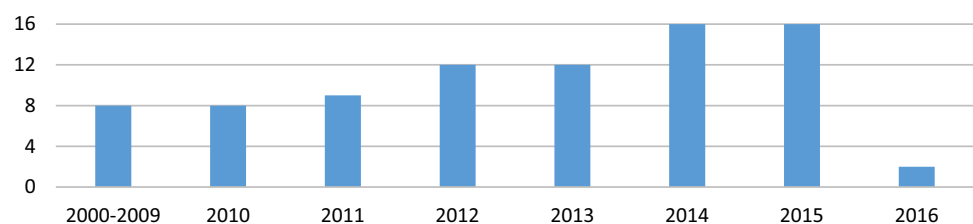
In the stage of image classification, all extracted features are taken as the feature vector. And then these vectors are classified by the classifier. Finally, the recognition results are obtained.

Seen from above framework, it is found that feature extraction and classifier are key techniques, which have a major impact on the recognition result. Hence, 31 kinds of leaf features (including 16 kinds of shape feature, 11 texture features, 4 color features), and 8 commonly used classifiers will be reviewed in detail.

3 Image Features

The feature is a kind of object that is different from other objects' corresponding characteristic, or a collection of these characteristics and features. And it is the data that can

Fig. 1 Distribution of the existed papers



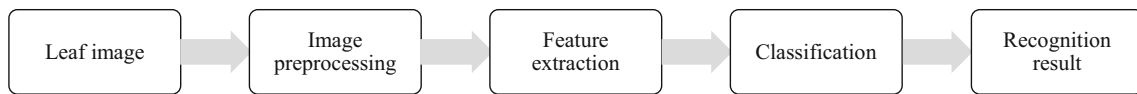


Fig. 2 Framework of plant recognition based on image processing

Fig. 3 Typical processes of plant leaf image preprocessing

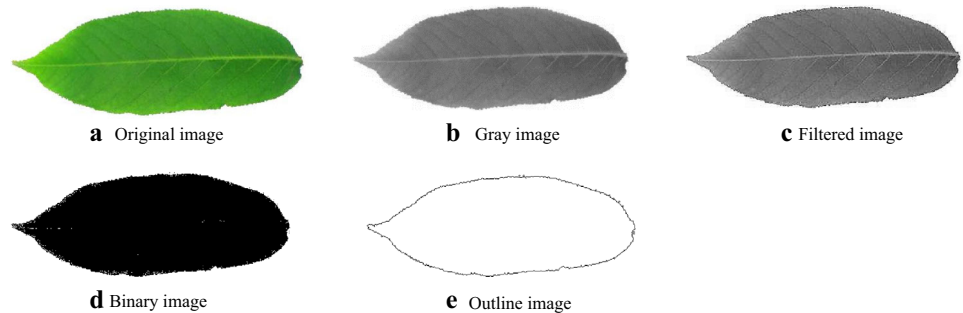


Table 1 Some commonly-used variables

Variable	The meaning of it
W	The width of the exterior rectangle
L	The length of the target region that is the minimum enclosing rectangle length of the target region
P	The perimeter of the target region, counting the number of pixels consisting the target image boundary
A	The area of the target region which represents the number of pixels in the target image
(\bar{x}, \bar{y})	The centroid coordinate of the target region
$P(i, j)$	The probability of the gray element i and j appear respectively, $i, j = 0, 1, 2, \dots, G - 1$
G	The number of gray levels
$p(z_i)$	The corresponding histogram, $i = 0, 1, 2, \dots, G-1$
z_i	Represents the gray level of random variables
M	The length of an image
N	The width of an image
u	The mean of color

be extracted after measurement or processing. For the image, each image has its own features that can be distinguished from other types of images, some are natural features that can be intuitively felt, such as edge, brightness, color and texture etc.; some can be obtained after transforming or processing, such as variable moments, the histogram and others. In terms of plant leaf recognition, mainly from the leaf shape, texture and color of the three characteristics are studied.

Here, we first list some of the commonly used variables that appear in the following formula in Table 1.

3.1 Shape Feature

Shape is an important feature of the image description. The accurate extraction of shape features is based on the image segmentation. After the object is segmented from the

image, it consists of the boundary and the region pixels surrounded by the boundary. Therefore, the shape feature description can be roughly divided into two categories: the boundary based features and features based on regions. The following will be a detailed introduction.

3.1.1 Aspect Ratio

Aspect ratio denotes the ratio of width to length of the external rectangle of leaf contour. It is defined by

$$R_{Ar} = \frac{W}{L}, \tag{1}$$

References [1–9] employed this feature when proposing advanced leaf recognition based on leaf contour and centroid for plant classification. And in the process of plant identification, this feature was also used as one of the feature vectors for classification in Refs. [10–26].

3.1.2 Circularity

Circularity is defined by

$$C = \frac{P^2}{4\pi A}, \quad (2)$$

where A is the area which represents the number of pixels in the target image, P is the perimeter by counting the number of pixels consisting the target image boundary. They are respectively defined by

$$A = \sum_{i,j} I(i,j), \quad (3)$$

$$L = N_e + \sqrt{2}N_o, \quad (4)$$

where $I(i, j)$ is the pixel of the image. Perimeter is to view each pixel as a point, the up, down, left and right side of the each point's neighbour point distance is 1, the diagonal direction distance is $\sqrt{2}$, the even-numbered chain code number is N_e and the odd-numbered chain code number is N_o according to the eight-direction chain code calculation.

The circularity feature was used in Refs. [1–5, 27–30] when proposing a method which combined some shape features, color moments, and vein features to retrieve leaf images. And in Refs. [15, 20, 25], they used the feature of circularity when investigating the use of a machine-learning algorithm called SVM for the effective classification of leaves in digital images.

3.1.3 Area Convexity

Area convexity is also called convexity, solidity, which is the ratio between the area of the target and the area of its convex hull. And its equation is

$$R_{Aconv} = \frac{A}{A_C}, \quad (5)$$

where A_C is the area of its convex hull (it means the smallest convex set containing all points in an object).

The feature of convexity was used in Refs. [2, 4, 6–8] when they proposed an approach to recognize plant leaves. And a simple and computationally efficient method for plant species recognition using leaf images was presented in Refs. [13, 16–20, 22, 24]. In Refs. [26–28, 30–35], they proposed a new method for leaf recognition system where both local descriptors and this feature were employed.

3.1.4 Perimeter Convexity

Perimeter convexity is also called convex perimeter ratio which is defined as the ratio between the perimeter of the target and the perimeter of its convex hull. And the equation is

$$R_{Pconv} = \frac{P}{P_C}, \quad (6)$$

where P_C is the perimeter of its convex hull.

This feature was used in Refs. [4, 8, 12, 16, 17, 20] when they carried out some related research for leaf recognition. And Refs. [22, 27, 28, 30, 32, 34–36] also employed the feature of convex perimeter ratio when proposing a simple method based on bisection of leaves for recognition.

3.1.5 Rectangularity

Rectangularity describes the similarity between the target region and its rectangle. It's defined as

$$R = \frac{A}{A_R}, \quad (7)$$

where A_R is the area of the rectangle (the minimum enclosing rectangle of the target region).

References [3–5, 8, 9] employed this feature when using classifiers with image and data processing techniques to implement a general purpose automatic leaf recognition for plant classification. And this feature was used when Refs. [16, 21–25, 37] investigated an expert system for automatic recognition of different plant species through their leaf images.

3.1.6 Compactness

Compactness is defined as

$$R_{com} = \frac{P^2}{A}, \quad (8)$$

References [17, 18, 22, 23] employed this feature when describing an optimal approach for feature subset selection to classify the leaves based on leaf images. And the feature of compactness was used when proposing a novel framework for recognizing and identifying plants in Refs. [31, 32, 34, 35, 37].

3.1.7 Hu's Invariant Moment

Hu's invariant moment mainly describes the outline of the target region and is defined as Eqs. (9)–(20).

$$\phi_1 = \eta_{20} + \eta_{02} \quad (9)$$

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \quad (10)$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \quad (11)$$

$$\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \quad (12)$$

$$\begin{aligned} \phi_5 = & (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\ & + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \end{aligned} \quad (13)$$

$$\phi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \tag{14}$$

$$\phi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{30})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \tag{15}$$

$$\phi_8 = 2\left\{ \eta_{11}[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] - (\eta_{20} - \eta_{02})(\eta_{30} - \eta_{12})(\eta_{21} - \eta_{03}) \right\} \tag{16}$$

$$\phi_9 = [(\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12}) + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})] \times (\eta_{20} - \eta_{02}) + 2\eta_{11}[(3\eta_{21} - \eta_{30})(\eta_{30} + \eta_{12}) - (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})] \tag{17}$$

$$\phi_{10} = [(3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12}) - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})] \times (\eta_{20} - \eta_{02}) - 2\eta_{11}[(\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12}) + (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})] \tag{18}$$

$$\phi_{11} = (\eta_{04} + \eta_{40} - 6\eta_{22})^2 + 16(\eta_{31} - \eta_{13})^2 \tag{19}$$

$$\phi_{12} = (\eta_{04} + \eta_{40} - 6\eta_{22})[(\eta_{20} - \eta_{02})^2 - 4\eta_{11}^2] + 16\eta_{11}(\eta_{31} - \eta_{13})(\eta_{20} - \eta_{02}) \tag{20}$$

And the normalized central moment is

$$\eta_{pq} = \frac{u_{pq}}{u_{00}^\gamma}, \tag{21}$$

where the $(p + q)$ th moments of the image $f(x, y)$ is

$$u_{pq} = \sum_x \sum_y (x - \bar{x})^p (y - \bar{y})^q f(x, y), \tag{22}$$

and γ is

$$\gamma = \frac{p + q}{2} + 1, \quad (p + q = 2, 3, \dots), \tag{23}$$

References [4, 15, 25, 27] used this feature when proposing an efficient classification framework for leaf images with complicated background. And the feature of the Hu invariant moment was also employed in Refs. [34, 38–41] when presenting a system for recognizing plant based on leaf images.

3.1.8 Irregularity

Irregularity refers to the ratio of the radius of the inscribed circle and circumcircle radius of the target region. It's defined as

$$R_S = \frac{r}{R}, \tag{24}$$

where r is the target region's inscribed circle radius, R is the target region's circumcircle radius.

In Refs. [14, 22, 29, 31, 32, 37], they employed this feature when presenting a measure based on plant leaf images for classifying the different types of plants.

3.1.9 Eccentricity

Eccentricity is defined as

$$e = \frac{R_{max}}{R_{min}}, \tag{25}$$

where R_{max} is the maximum distance of the centroid to the target boundary and R_{min} is the minimum distance of the centroid to the target boundary.

This feature was employed by Harish et al. [16] when they used morphological features and Zernike moments to identify and classify plant leaves. Elhariri et al. [20] used this feature when presenting a classification approach based on RF and LDA algorithms for classifying the different types of plants. Zhao et al. [22] used this feature when proposing a measure based on identifying plant blade samples combined with bark recognition. Aakif et al. [26] employed this feature.

3.1.10 Length/Perimeter

Length/perimeter is defined as

$$R_{LP} = \frac{L}{P}. \tag{26}$$

This feature was used in Refs. [3, 5, 8, 9] when using some morphological features and vein features to identify and classify the plant leaves. And in Refs. [12, 16, 21, 24, 27], they employed this feature when proposing advanced leaf recognition based on leaf contour and centroid for plant classification.

3.1.11 Narrow Factor

Narrow Factor is defined as

$$R_{NF} = \frac{D}{L_p}, \tag{27}$$

where D is the longest distance between any two points of the target region, and L_p is the target region's long axis length.

Wu et al. [3] employed this feature when using PNN to implement a general purpose automatic leaf recognition for plant classification. Singh et al. [5] used this feature when putting forward three techniques of plants classification for

solving multiclass problems. And the feature of narrow factor was used in Refs. [16, 21, 27].

3.1.12 Perimeter Ratio of Physiological Length and Width

Perimeter Ratio of Physiological length and width is defined as

$$R_{PR} = \frac{P}{L + W}. \tag{28}$$

Wu et al. [3] used this feature when employing PNN with image to implement a general purpose automatic leaf recognition. Singh et al. [5] employed this feature when presenting three techniques of plants classification for solving multiclass problems. This feature was employed by Harish et al. [16] when using morphological features and Zernike moments to identify and classify plant leaves. Bijalwan et al. [21] used this feature when conducting some researches for plant recognition.

3.1.13 Zernike Moment

Zernike Moment is defined as

$$Z_{pq} = \frac{p+1}{\pi} \sum_x \sum_y f(x, y) \cdot V_{pq}^*(x, y), \tag{29}$$

V^* is the complex conjugate of V ,

$$V_{pq}(x, y) = U_{pq}(r \cos \theta, r \sin \theta) = R_{pq}(r) e^{jq\theta}, \tag{30}$$

$$R_{pq}(r) = \sum_{s=0}^{(p-|q|)/2} (-1)^s \frac{(p-s)!}{s! (\frac{p-|q|}{2} - s)! (\frac{p+|q|}{2} - s)!} \rho^{p-2s}, \tag{31}$$

where $n = 0, 1, 2, \dots; j = \sqrt{-1}, p - |q|$ is the even, r is the radius, θ is the angle between r and the x -axis. And

$$V_{pq}(y, x) = V_{pq}(\rho, \theta) = R_{pq}(\rho) \cdot e^{jq\theta}, \tag{32}$$

p is 0 or a positive integer, $p - |q|$ is the odd, $|q| \leq p$.

Wang et al. [38] employed this feature when proposing an efficient classification framework for leaf images with complicated background. Kadir et al. [13] used this feature for classification of leaf images. This feature was employed by Wang et al. [25] when they did some researches based on PCNN. When Kulkarni et al. [17, 18] presented a novel framework for recognizing and identifying plants, they used the feature of pseudo Zernike movements, which is defined as

$$Z_{pq} = \frac{(p+1)}{\pi} \int_0^{2\pi} \int_0^1 \dot{V}_{pq} \cdot f(r, \phi) r dr d\phi, r \geq 1, \tag{33}$$

where

$$\dot{V}_{pq} = S_{nm}(r) e^{iq\phi}, \tag{34}$$

$$S_{nm}(r) = \sum_{s=0}^{n-|m|} \frac{r^{m-s} (-1)^s (2n+1-s)}{s! (n-|m|-s)! (n+|m|+1-s)!} \tag{35}$$

3.1.14 Generic Fourier Descriptor

Generic Fourier Descriptor (GFD), also called GFT, is defined as

$$GFD_s = \left\{ \frac{PF(0,0)}{2\pi r^2}, \frac{PF(0,1)}{PF(0,0)}, \dots, \frac{PF(0,n)}{PF(0,0)}, \dots \right. \\ \left. \times \frac{PF(m,0)}{PF(0,0)}, \dots, \frac{PF(m,n)}{PF(0,0)} \right\}, \tag{36}$$

where PF is

$$PF(\rho, \varphi) = \sum_r \sum_i f(\rho, \theta) \cdot e^{j2\pi(\frac{r}{R}\rho + \frac{i}{T}\varphi)}, \tag{37}$$

$0 < r < R, \theta_i = i (2\pi/T) (0 < i < T), 0 < \rho < R, 0 < \phi < T, R$ is the radial frequency resolution and T is the angular frequency resolution,

$$r = \sqrt{(x - \bar{x})^2 + (y - \bar{y})^2}, \tag{38}$$

$$\theta = \arctan \frac{y - \bar{y}}{x - \bar{x}}, \tag{39}$$

Kadir et al. [29, 31, 32] used this feature when carrying on classification of the leaf image. Aakif et al. [26] employed this feature for plant recognition.

3.1.15 Elliptical Eccentricity

Elliptical eccentricity refers to the eccentricity of the ellipse of which has the same standard second central moment of the target region. And it is defined as

$$e = \frac{c}{a}, \tag{40}$$

where c is the ellipse half focal length and a is semi-major axis of the ellipse.

Hossain et al. [6] employed this feature when presenting a simple and computationally efficient method for plant species recognition using leaf images.

3.1.16 Center Distance Sequence

Center distance sequence (CDS) is defined as

$$CDS = \{D(x_i, y_i) | 0 < i < P - 1\}, \tag{41}$$

where $D(x, y)$ is

$$D(x, y) = \sqrt{(x - \bar{x})^2 + (y - \bar{y})^2}. \tag{42}$$

Wang et al. [42] used this feature when they proposed a novel method for plant recognition based on the leaf image.

3.2 Texture Feature

Texture is comprised of many closely woven elements, and is periodic. Texture of the image is the image gray scale and color change, namely the gray scale and color space in the form of a certain change of figure (model), is a true regional characteristics inherent. The texture of the image describes the features of smooth, sparse, and so on. There are three kinds of commonly used methods for texture description: statistics method, structure method, frequency spectrum method. Here texture features are introduced one by one.

3.2.1 Energy

Energy is also called the second moment that reflects the degree of uniformity of the gray image, and it is defined as

$$En = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P^2(i, j), \tag{43}$$

The feature of energy was used in Refs. [7, 13, 15, 17, 18] when they studied the framework for the identification and detection of plant leaf images. And in Refs. [31, 32, 37, 43–49], this feature was employed to build the plant identification system.

3.2.2 Entropy

Entropy reflects the complexity or non-uniformity of the image texture, and it is defined as

$$Ent = - \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} p(i, j) \log_2 p(i, j), \tag{44}$$

sometimes we also calculate the sum of entropy and the entropy difference are described as

$$S_{Ent} = - \sum_{i=0}^{2G-2} P_{x+y}(i) \log P[P_{x+y}(i)], \tag{45}$$

$$D_{Ent} = - \sum_{i=0}^{G-1} P_{x+y}(i) \log [P_{x+y}(i)], \tag{46}$$

and

$$P_{x+y}(k) = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i, j); \quad |i + j| = k, \tag{47}$$

In Refs. [7, 13, 15, 17, 18, 20, 23, 31, 32], they proposed a texture extraction method combing a non-overlap window local binary pattern (LBP) and Gray Level Co-Occurrence Matrix (GLCM) for plant leaves classification. And in Refs. [37, 43, 44, 47–50], they proposed a new method for a leaf recognition system where both local descriptors and this feature were employed.

3.2.3 Contrast

Contrast is also called the inertia moment and reflects the image clarity, and it is defined by

$$Con = \sum_{i=1}^G \sum_{j=1}^G (i - j)^2 P(i, j), \tag{48}$$

In Refs. [7, 13, 15, 17, 18, 20, 23, 31, 32], they employed this feature when using texture features and discriminant analysis to identify leaf images. And Refs. [37, 43, 44, 47–50] used the feature of contrast when putting forward a method for plant leaf classification based on the neighborhood rough set.

3.2.4 Correlation

Correlation is used to measure the similarity of the elements of a co-occurrence matrix element to the row or column, and it is defined as

$$Cor = \frac{\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} ijP(i, j) - u_1 u_2}{\sigma_1^2 \sigma_2^2}, \tag{49}$$

and

$$u_1 = \sum_{i=0}^{G-1} iP(i, j), \tag{50}$$

$$u_2 = \sum_{j=0}^{G-1} jP(i, j), \tag{51}$$

$$\sigma_1^2 = \sum_{i=0}^{G-1} (i - u_1)^2 \sum_{j=0}^{G-1} P(i, j), \tag{52}$$

$$\sigma_2^2 = \sum_{j=0}^{G-1} (j - u_2)^2 \sum_{i=0}^{G-1} P(i, j), \tag{53}$$

This feature was employed when studying for detection and classification of plant leaf images in Refs. [7, 13, 15, 31, 43–46]. And in Refs. [37, 48, 50], this feature was used for plant leaf classification. Sometimes *cor1* and *cor2* are used that defined as

$$Cor1 = \frac{Hxy - Hxy1}{\max[P_x(i) \log P_x(i), P_y(j) \log P_y(j)]}, \tag{54}$$

$$Cor2 = (1 - e^{(-2)(Hxy2-Hxy)})^{0.5}, \tag{55}$$

where Hxy , $Hxy1$, and $Hxy2$ are

$$Hxy = - \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j) \log[P(i,j)], \tag{56}$$

$$Hxy1 = - \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j) \log[P_x(i)P_y(j)], \tag{57}$$

$$Hxy2 = - \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P_x(i)P_y(j) \log[P_x(i)P_y(j)], \tag{58}$$

And in Refs. [17, 18, 20, 23, 47], this feature was used when they investigated an expert system for automatic recognition of different plant species through their leaf images.

3.2.5 Average

Average is a measure of the average luminance of the texture, and it is defined by

$$\mu = \sum_{i=0}^{G-1} z_i p(z_i), \tag{59}$$

The feature of average was used when developing a method to identify and classify medicinal plants from their leaf images using texture analysis of the images as a basis for classification in Refs. [44, 45, 50]. And the feature of sum average was used in Refs. [15, 46] when they proposed a method for the extraction of shape, color and texture features from leaf images and trained an classifier to identify the exact leaf class, and the sum average is

$$S_{Average} = \sum_{i=0}^{2G-2} iP_{x+y}(i) \tag{60}$$

3.2.6 Inverse Difference Moment

Inverse difference moment is also called homogeneity and is defined as

$$IDM = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{P(i,j)}{1 + (i - j)^2}, \tag{61}$$

In Refs. [7, 13, 15, 20, 23, 31, 32], they used this feature when developing a method to identify and classify plants from their leaf images using texture analysis. And this feature was employed when presenting a

method for plant species identification using images in Refs. [44, 46, 47, 50].

3.2.7 Standard Deviation and Variance

Standard deviation is a measure of average texture contrast and it's defined as

$$\sigma = \sqrt{\mu_2(z)}, \tag{62}$$

the n order moments of the mean value μ is

$$\mu_n = \sum_{i=0}^{G-1} (z_i - \mu)^n p(z_i), \tag{63}$$

and sometimes variance and sum-variance are calculated as follows,

$$Variance = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i - \mu)^2 P(i,j), \tag{64}$$

$$S_{Var} = \left\{ i + \sum_{i=0}^{2G-2} P_{x+y}(i) \log[P_{x+y}(i)] \right\}^2 P_{x+y}(i), \tag{65}$$

Bashish et al. [45] used this feature when studying a framework for detection and classification of plant leaves and stem diseases. This feature was employed by Janani and Gopal [15] when they proposed a method for the extraction of shape, color and texture features from leaf images. Elhariri et al. [20] used this feature when presenting a classification approach based on RF and LDA algorithms for classifying different types of plants.

3.2.8 Maximum Probability

Maximum probability is the strongest response to the gray level co-occurrence matrix measure, and it is defined by

$$P_{max} = \max_{ij} [P(i,j)], \tag{66}$$

Pydipati et al. [50] employed this feature when using color texture features and discriminant analysis to identify the citrus disease. Zhang et al. [44] employed the feature of maximum probability when putting forward a method for plant leaf classification. Shabanzade et al. [7] proposed a new method for leaf recognition system where both local descriptors and this feature were employed.

3.2.9 Uniformity

Uniformity is defined as

$$U = \sum_{i=0}^{G-1} p^2(z_i), \tag{67}$$

Pydipati et al. [50] employed this feature when using color texture features and discriminant analysis to identify the citrus disease.

3.2.10 Entropy Sequence

Entropy sequence (EnS), proposed by Ma [51], is defined by

$$EnS[n] = -p_1[n] \log_2 p_1[n] - p_0[n] \log_2 p_0[n], \tag{68}$$

where $p_1[n]$ and $p_0[n]$ represent the probability when $Y_{ij}[n] = 1$ and $Y_{ij}[n] = 0$ in the output $Y[n]$ separately.

Wang et al. [42] employed this feature when they proposed a novel method of plant recognition based on leaf images, and they [25] also used this for plant recognition.

3.2.11 Hog

Histogram of oriented gradient (Hog) feature is object detection feature descriptor in computer vision and image processing. It constitutes the feature of the gradient direction histogram of the local region of the image. Hog feature and SVM classifier have been widely used in image recognition.

Nilsback et al. [52] employed this feature when investigating to what extent combinations of features could improve classification performance on a large dataset of similar classes. Xiao et al. [53] used the feature of this when they studied the recognition of the plant leaf. Qing et al. [54] presented a method to recognize plant leaves employing HOG as the feature descriptor.

3.3 Color Feature

Color features are most stable and reliable of visual features. Compared with geometric features, it has better performance on robustness as it is insensitive to the size and direction of sub objects in images. Color moments are a simple but effective color feature. In the following, some common color features are introduced simply.

3.3.1 Mean of Color

Mean is a most common feature of the data. For color of images, mean can be used for describing the average of color, it is defined as

$$\mu = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N P(i,j), \tag{69}$$

Kadir et al. [14, 29, 31, 32, 43] used mean of color as an color feature in their leaf retrieval system. In Refs. [15, 37] employed this feature for medicinal plant recognition based

on their leaves. Narayan et al. [36] also used it for plant classification. Kulkarni et al. [17, 18] used RBPNN as a classifier and mean of color as the feature for leaf recognition. In 2015, Refs. [23, 35] used this feature for plant classification under complex environments.

3.3.2 Standard Deviation of Color

Standard deviation of color is described as

$$\sigma = \sqrt{\frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N [P(i,j) - \mu]^2}, \tag{70}$$

Kadir et al. [14, 29, 31, 32, 43] employed the feature of standard Deviation of color when they carried out some research on plant recognition. And in Refs. [15, 17, 18, 23, 35–37], this feature was used when proposing a method for the extraction of shape, color and texture features from leaf images and training an classifier to identify the exact leaf class.

3.3.3 Skewness of Color

Skewness of color describes the shape information about the color distribution and it is the measure of the color symmetry. It is defined as

$$\theta = \frac{\sum_{i=1}^M \sum_{j=1}^N [P(i,j) - \mu]^3}{MN\sigma^3}, \tag{71}$$

where σ is the standard Deviation of color.

Kadir et al. [14, 29, 31, 32, 43] used the feature of skewness of color when they studied on plant recognition of leaf images. And when reporting the results of experiments in improving performance of leaf identification system, the feature of skewness of color was used in Refs. [15, 17, 18, 23, 35–37].

3.3.4 Kurtosis of Color

Kurtosis of color describes the shape distribution of information about color, and it is a measure of the extent of a normal distribution with respect to sharpen or flat. It is defined as

$$\gamma = \frac{\sum_{i=1}^M \sum_{j=1}^N [P(i,j) - \mu]^4}{MN\sigma^4}, \tag{72}$$

The feature of kurtosis of color was used by Kadir et al. [14, 31, 43] when they conducted some researches on plant recognition of leaf images. And this feature was employed in Refs. [15, 17, 18, 23, 35–37] when proposing a method

for the extraction of shape, color and texture features from leaf images.

3.4 Feature Evaluation

This paper introduces a variety of features (including shape, texture and color, a total of 31), and a list of their applications in much of the literature. In order to make a further understanding of these features, we evaluate them. And the recognition rate of this index is used to measure the effectiveness of the feature. We are following through a series of experiments to evaluate the characteristics.

In experiments, Flavia [55] dataset was used to test our methods. SVM was used as a classifier for this experiment. In order to ensure the reliability of the experiment, we conducted 20 random experiments on each feature. For the sample selection, we made the training samples and test samples as close as possible to the number of 1:1.

As shown in Table 2, the accuracy of each feature was listed, and the recognition rate was expressed by the mean and variance for each one. In order to get a more intuitive understanding, we drew a line chart to display.

As shown in Fig. 4, there are 26 characteristics, and they are all single valued. Their number is shown in Table 1. And the next, multiple value features are shown in Fig. 5. Their numbers 1–6 are corresponding to 27–32 in Table 1.

We found a single single-value feature recognition rates were generally low from Figs. 4 and 5. In view of this, we tried their pairwise fusion to see whether their recognition rate would be improved when using two single-value features. These eight features were the best eight in the single-valued feature.

In addition to the features of each group only ten random tests, the experiment set is basically the same with the above experiment. Table 3 is some features of their shorthand. The eight features of the best recognition rate in the single valued feature are selected and the experimental results are obtained after pairwise fusion are shown in Table 4.

From Fig. 6, their number is shown in Table 4. It was found that the recognition rate of two features was better than the recognition rate of single valued features. Through the contrast experiment, we found that the recognition rate was increased at the same time as the characteristic value was added. And this led us to select the fusion of multiple features as the input feature in the future.

4 Classifiers

Classification is a very important method of data mining, which is based on the existing data to learn a classification function or construct a classification model (that is, we usually refer to the classifier). The function or model can make the record data in the database map to a given category one, which can be applied to forecast the data. In a word, the classifier is generally referred to classifying samples in data mining methods, include the decision tree, logistic regression, naive bayes and neural network algorithm and so on. Construction and implementation of a classifier great experience through the following steps:

- (a) Select samples (including positive samples and negative samples), all the samples are divided into two parts of training and testing samples;

Table 2 Accuracy of each feature

Numbers	Feature	Accuracy	Numbers	Feature	Accuracy
1	Perimeter Convexity	3.8894 ± 0.0001	17	Standard Deviation of color	8.7615 ± 0.4996
2	Perimeter Ratio of length and width	3.8945 ± 0.0228	18	homogeneity	9.5035 ± 0.6791
3	Compactness	3.9457 ± 0.0522	19	Average	10.8393 ± 0.8804
4	Circularity	4.5394 ± 0.2000	20	Eccentricity	12.5230 ± 0.4225
5	Kurtosis of color	4.9027 ± 0.4328	21	Irregularity	12.5281 ± 0.2535
6	Energy	6.4380 ± 0.1404	22	Skewness of color	12.9017 ± 0.3991
7	Uniformity	6.4483 ± 0.1626	23	Length/perimeter	13.1422 ± 0.8514
8	Contrast	6.4943 ± 0.3088	24	Correlation	13.5261 ± 0.8047
9	Area Convexity	7.4616 ± 0.3651	25	Narrow Factor	18.0040 ± 0.4092
10	Rectangularity	7.4616 ± 0.3711	26	Elliptical eccentricity	18.5056 ± 0.4437
11	Maximum probability	7.7942 ± 0.3746	27	CDS (50)	31.4329 ± 0.7593
12	Zernike Moments	8.1883 ± 0.3800	28	Hu (12)	46.2671 ± 0.8827
13	Standard deviation	8.3930 ± 0.3451	29	Hu (7)	47.7840 ± 0.8317
14	Mean of color	8.4442 ± 0.2846	30	GFD (26)	65.0204 ± 1.2766
15	Entropy	8.6438 ± 0.5708	31	Ens (37)	75.0511 ± 0.8432
16	Aspect ratio	8.7256 ± 0.4225	32	HOG (81)	91.9140 ± 1.0235

Fig. 4 Accuracy of each single valued feature

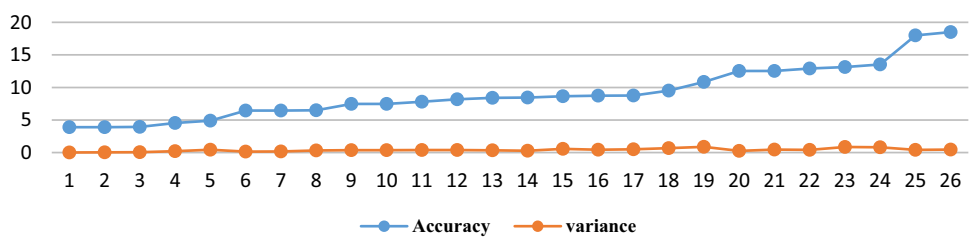


Fig. 5 Accuracy of each multiple value feature

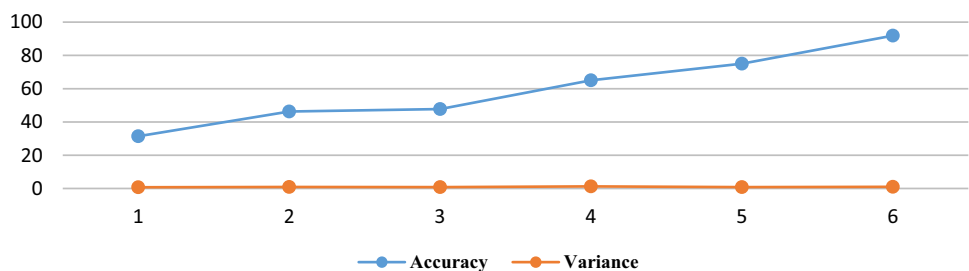


Table 3 Some features of shorthand

Feature name	Shorthand	Feature name	Shorthand
Average	Ave	Length/perimeter	LeP
Eccentricity	Ecc	Correlation	Cor
Irregularity	Irr	Narrow Factor	NaF
Skewness of color	Ske	Elliptical eccentricity	Ell

- (b) Perform the classifier algorithm on the training sample, and generate a classification model;
- (c) Perform the classification model on the test sample, and generate predictions;
- (d) According to forecasts, calculate the necessary assessment and evaluate the performance of the classification model.

Compared with the classification of plants, BP, KNN, RBPNN and SVM are commonly used. In this paper, the application of classifiers in plant classification is introduced one by one.

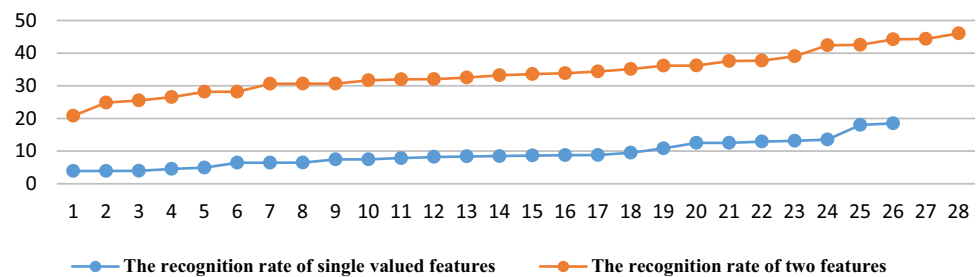
4.1 SVM Classifier

The main idea of Support Vector Machine (SVM) classifier can be summarized as two points: (1) It is analyzed for the linear separable case, and in the case of linear inseparable, through using a nonlinear mapping algorithm that makes linear inseparable samples in the low dimensional input space transform into a high dimensional feature space, which is in order to make it linearly separable, so as to make the high dimensional feature space by using linear algorithm for linear analysis on the nonlinear

Table 4 Accuracy of two features

Numbers	Features	Accuracy	Numbers	Features	Accuracy
1	Ecc + NaF	20.8188 ± 0.6404	15	Ave + Irr	33.5926 ± 1.1992
2	Ske + LeP	24.8311 ± 1.0440	16	LeP + Cor	33.8382 ± 1.4019
3	Ecc + Irr	25.5168 ± 0.6273	17	Ske + Cor	34.3909 ± 0.8467
4	Ave + Ske	26.5404 ± 0.7506	18	Ecc + LeP	35.1279 ± 1.1487
5	NaF + Ell	28.1678 ± 0.9353	19	Ave + NaF	36.1617 ± 1.6846
6	Ave + LeP	28.1781 ± 1.2339	20	Ske + Ell	36.2129 ± 1.1953
7	Ecc + Ske	30.6141 ± 0.6130	21	Irr + Cor	37.5639 ± 0.7025
8	Irr + NaF	30.6346 ± 0.5730	22	Irr + LeP	37.7072 ± 1.0157
9	Ave + Ecc	30.6653 ± 0.9518	23	Irr + Ell	39.0174 ± 1.0164
10	Ave + Cor	31.6786 ± 0.6861	24	Cor + NaF	42.4257 ± 0.7768
11	Ecc + Cor	31.9959 ± 0.7647	25	Ave + Ell	42.5383 ± 1.2103
12	Irr + Ske	32.0163 ± 1.2891	26	LeP + Ell	44.2272 ± 1.0398
13	Ecc + Ell	32.5179 ± 0.5061	27	Cor + Ell	44.3807 ± 0.6601
14	Ske + NaF	33.2036 ± 1.0877	28	LeP + NaF	46.0286 ± 0.8831

Fig. 6 Comparison of experimental results of single valued and fusion features



characteristics of samples possible; (2) It is based on the theory of structural risk minimization, the optimal segmentation hyperplane is constructed in feature space which makes the learning machine get global optimization.

This classifier was applied by Singhet et al. [5] to a database of 1600 leaf shapes from 32 different classes, where most of the classes have 50 leaf samples of similar kind, and obtained 96 % recognition accuracy. Nilsback et al. [52] investigated to what extent combinations of features could improve classification performance on a large dataset of similar classes, and the accuracy reached 88.33 % for the SVM classifier. Watcharabutsarakham et al. [11] proposed a herb leaf classification method for making an automatic categorization, and the experimental results performed 95 % accuracy on ten classes of leaf type with this classifier. This classifier was used by Zhang et al. [56] to discuss the use for recognizing cucumber leaf diseases and got a good accuracy. Tian et al. [57] proposed a new strategy of Multi-Classifer System based on SVM for pattern recognition of wheat leaf diseases and got a higher recognition accuracy of 95.16 %. This classifier was used by Valliammal et al. [37] when they described an optimal approach for feature subset selection to classify the leaves based on GA and KPCA, and the experimental result was up to 92 % accuracy. Prasad et al. [58] used SVM classifier to implement an automated leaf recognition system for plant leaf identification and classification, and 300 leaf features were extracted from a single leaf of 624 leaf dataset to classify 23 different kinds of plant species with an average accuracy of 95 %. Harish et al. [16] used morphological features and Zernike moments to study the classification of plant leaves, and they obtained more than 87.20 % accuracy by using the SVM as a classifier. Narayan et al. [36] got the experiment result of 88 % accuracy when employing the SVM classifier to do some research on the plant recognition. Gang et al. [59] proposed a plant leaf classification technique using shape descriptor by combining Scale Invariant Feature Transform (SIFT) and HOG from the image segmented from the background via Graph cut algorithm, used the SVM classifier and the classification rate was up to 95.16 %. Ahmed et al. [30] conducted some experiments on the plant classification,

and the analysis of the results revealed that SVM achieved above 97 % accuracy over a set of 224 test images. Hsiao et al. [60] conducted a comparative study on leaf image recognition and proposed a novel learning-based leaf image recognition technique via sparse representation (or sparse coding) for automatic plant identification, and the experiment result declared that the SVM classifier obtained 95.47 % accuracy. This classifier was used by Le et al. [61] when they proposed a new plant leaf identification based on KDES, and the experiment result was up to 97.5 % accuracy. Ghasab et al. [23] investigated an expert system for automatic recognition of different plant species through their leaf images by employing the ant colony optimization (ACO) as a feature decision-making algorithm, the efficiency of the system was tested on around 2050 leaf images collected from two different plant databases, FCA and Flavia, and the results of the study achieved an average accuracy of 95.53 %. This classifier was employed by Zhao et al. [22] when they presented a measure based on identifying plant blade sample combined with bark recognition, and the experiments based on 4 kinds of plant of the 120 leaf images and 120 bark images, experimental result showed that the average correct recognition rate of only leaves was 97 %, meanwhile the data of combination with bark feature parameters could be up to 98.5 %. Wang et al. [42] proposed a novel method of plant recognition based on leaf images, and the experimental result showed the proposed method got the better accuracy of 97.82 % than other methods. Priyankara et al. [62] described a leaf image based plant identification system using SIFT features combining with Bag Of Word (BOW) model, and the system is trained to classify 20 species and obtained 96.48 % accuracy level. Kazerouni et al. [63] studied a comparison of modern description method for the recognition of 32 plant species, and got the accuracy of 89.35 %. Quadri et al. [64] discussed leaf recognition of different species of plants using multiclass kernel support vector machine, the SVM classifier was tested with flavia dataset and its accuracy was up to 100 %. This classifier was employed by Wang et al. [25] when they did some researches on the leaf recognition based on PCNN, and the experiment result was 96.67 % accuracy.

4.2 KNN Classifier

The adjacent algorithm or k-nearest neighbor (KNN) classification algorithm is one of the simplest methods in the data mining classification technology. K nearest neighbor is that each sample can be represented by its closest K neighbors. The core idea of the KNN algorithm is that if a majority of a sample of the k nearest neighbors in feature space belong to a category, then the sample also belong to this category, and has the characteristics of the samples in this category.

Wu et al. [3] employed 12 leaf features and used this classifier, trained 1800 leaves to classify 32 kinds of plants with an accuracy of 93 % (1-NN), 92 % (4-NN). Du et al. [4] used the KNN classifier, the sample of 200 kinds of images of 20 pieces of the blade was tested with the accuracy of 93 % (1-NN), 92 % (4-NN). Stefan et al. [65] proposed a method for an automatic identification of plant species from low quality pictures of their leaves using mobile devices, and obtained a good recognition rate for the SVM classifier. This classifier was used by Wang et al. [66] when they proposed to improve leaf image classification by taking both global features and local features into account and the experiment result was up to 91.3 %. Li et al. [67] used this classifier to do some research on the plant recognition and the accuracy was more than 96.76 %. The result on a database of 500 plant images belonging to 45 different types of plants with different orientations scales, and translations showed that the proposed method by Bama et al. [68] outperformed 97.9 % of retrieval efficiency. This classifier was used by Zhang et al. [44] to do some research on the plant recognition, experimental results on plant leaf image database demonstrated that the proposed method is efficient and feasible for leaf classification, and got the accuracy of 90.67 %. Shabanzade et al. [7] employed this classifier to study the leaf recognition, and the experimental results showed that using the feature vector containing the local features and global characteristics led us to obtain 94.3 % recognition rate. Zhang et al. [69] proposed a new method for plant leaf recognition and the experiment result was up to 96.63 % by using of KNN. Tian et al. [57] put forward a new strategy of Multi-Classifer system for pattern recognition of wheat leaf diseases and obtained a higher recognition accuracy of 87.13 % with the KNN classifier. Harish et al. [16] used morphological features and Zernike moments to study classification of plant leaves, and they got more than 65.10 % accuracy by using the KNN as a classifier. This classifier was used by Zhang et al. [70] when they presented a SLPA method for plant leaf classification, and the experimental results was up to 96.33 % (on the Swedish leaf dataset), 90.81 % (on the ICL [71] dataset). Amin et al. [72] put forward a scalable

approach for classifying plant leaves using the 2-dimensional shape feature, and got the accuracy of 71.5 % with this classifier. Du et al. [73] used the KNN classifier to do some research on the plant classification and the experimental results demonstrated the recognition rate was 87.14 %. Narayan et al. [36] used 26 characteristics, the KNN classifier is used for the experimental study, and the recognition rate of 85 % is obtained. Arunpriya et al. [19] put forward an ANFIS (Adaptive Neuro-Fuzzy Inference System) for efficient classification, the ANFIS is trained by 50 different leaves to classify them into 5 types and its accuracy was up to 80 % with this classifier. Amlekar et al. [33] employed ANN to study the method of leaf identification, and the recognition rate of 85.54 % is obtained by using kNN classifier. Nidheesh et al. [74] used the geometrical feature to study the recognition method of plant leaves, and the recognition rate of the recognition rate reached 93.17 % (1-NN) by using KNN classifier. Gaber et al. [24] developed a model for plant identification based on their leaf shape, color and texture features, and the accuracy was up to 99.32 %. Wu et al. [75] presented a novel method for leaf recognition and evaluated with extensive experiments on different databases with different sizes by using this classifier. This classifier was used by Zhang et al. [76] when they doing some research on plant leaf recognition based on leaf images. Naresh et al. [77] used this classifier when proposing a symbolic approach for classification of plant leaves based on texture features is proposed. In order to improve the robustness and discriminability of plant leaf recognition further, a fuzzy *k*-NN classifier is introduced for matching by Wang et al. [78], and its experiment result was up to 98.03 % on ICL dataset.

4.3 PNN Classifier

The main idea of the Probabilistic Neural Network (PNN) is to use the Bayes decision rule to make the expectation risk minimum of the error classification, and separate the decision space in the multi-dimensional input space. It is a kind of artificial neural network based on the statistical principle and a feed-forward network model using the Parzen window function as the activation function. PNN absorbs the advantages of the radial basis neural network and the classical probability density estimation, which has a more remarkable advantage in pattern classification compared with the traditional feed-forward neural network. No matter how complex the classification problem, as long as there is enough training data, it can guarantee the optimal solution of the Bayes criterion.

PNN is trained by 1800 leaves to classify 32 kinds of plants with an accuracy greater than 90 % when Wu et al.

[3] conducted some research on the plant recognition. Singh et al. [5] studied the plant identification method. The PNN classifier was used to analyze the sample of 32 kinds of images of 1600 kinds of leaves, and the recognition rate of 91 % was obtained. The method proposed by Hossain et al. [6] had been tested using ten-fold cross-validation technique and the system showed 91.41 % average recognition accuracy with 1200 simple leaves from 30 different plant species. Pednekar et al. [79] implemented general purpose automatic leaf recognition for plant classification and the PNN is trained by 1800 leaves to classify 32 kinds of plants with an accuracy greater than 95 %. Kadir et al. [13] used the PNN classifier for experimental study of the plant classification and the recognition rate was more than 93 %. Uluturk et al. [12] employed PNN that was trained with 1120 leaf images from 32 different plant species which were taken from the flavia dataset, and experiments and comparisons show that method based on half leaf features has reached one of the best results in the literature for PNN with 92.5 % recognition accuracy. Harish et al. [16] employed the shape feature to study the identification method of the plant leaf, the PNN classifier is used for the experiment and the recognition rate is more than 85.6 %. Kadir et al. [14] did the experiment and its result showed that the method for classification gived an average accuracy of 93.75 % when it was tested on Flavia dataset, which contained 32 kinds of plant leaves. Kadir et al. [43] also was in the study of application of neural network in leaf recognition, used PNN classifier for 60 classes leaf samples and obtained the recognition rate of 93.08 %. When Mahdikhanlou et al. [80] using the center distance for leaf identification, they used PNN as a classifier for classification, and recognition rate was about 80 %. When the image recognition method of the leaf was studied by Hsiao et al. [60], the recognition rate was 90 % for the PNN classifier. Nidheesh et al. [74] did some research on the plant recognition and the experiment result was up to 90.31 % with the PNN classifier. This classifier was used by Hasim et al. [81] when they conducted some researches on the plant classification based on plant leaves.

4.4 RBPNN Classifier

Radial basis probabilistic neural network (RBPNN) is a new kind of feed-forward neural networks, which are developed on the basis of the radial basis function neural network (RBFNN) and PNN. RBPNN network structure is also divided into input layer, hidden layer, output layer. But the network with two hidden layers, the first hidden layer is nonlinear processing layer, it implements the nonlinear classification of input or the nonlinear transform of the input samples; the second hidden layer is the

selective summation and clustering on the first hidden layer outputs.

Zhang et al. [44] used the RBPNN as a classifier to study the plant recognition, and the experiment result of the recognition rate reached 93.73 %. Husin et al. [82] employed the image processing and neural network classification algorithm to study the plant recognition, and they used the BPNN classifier to obtain the recognition rate of 98.9 %. This classifier was used by Kulkarni et al. [17] to conduct some researches on a system of plant recognition, and the experiment result reached 95.12 % with 1280 leaf images, and the results on the Flavia leaf dataset indicated that the proposed method by Kulkarni et al. [18] for leaf recognition yielded an accuracy rate of 93.82 %. Nidheesh et al. [74] used the geometrical feature to study the recognition method of plant leaves, and the recognition rate of the recognition rate reached 91.18 % by using PNN classifier.

4.5 Hypersphere Classifier

Hypersphere classifier is a kind of classification method to compress the reference samples. By compressing the sample data, effectively reducing the storage space and computing time, and there is no effect on the recognition rate. The basic idea is to use a hypersphere to represent a cluster points (a sample in a high dimensional space is a point, a category corresponds to a set of points in space). We can use a series of hyperspheres to fit the high dimensional space where the point locates. The overall idea is to approximate the number of hyper spheres for each sample, and simultaneously, extends the radius of the hyper sphere to include a number of sample points. Reducing the storage quantity of the hyper sphere so as to eventually contain all the sample points and the multi sample space.

The hypersphere was used as a classifier when Du et al. [4] and Wu et al. [3] did some research on plant classification methods, and they obtained the classification rate of 91 and 92 % respectively. Wang et al. [38] was in the research of the classification of plant leaves under complex background, and the accuracy reached 92.6 % by using this classifier with 1200 leaf images from 20 different classes. Zhang et al. [44] used the hypersphere as a classifier to study the plant recognition, and the experiment result of the recognition rate reached 94.46 %. When the image recognition method of the leaf was studied by Hsiao et al. [60], the recognition rate was 90 % for the hypersphere classifier.

4.6 BP Classifier

Back Propagation (BP) neural network is a multi-layer feed-forward networks consisting of the nonlinear

conversion units, which is composed of the input layer, the hidden layer and the output layer. Under normal circumstances, a three layer BP networks can complete mapping of arbitrary n -dimensional to m dimension, which needs only one hidden layer. When the BP neural network is used as a classifier, the input of the neural network is n components, and that is the n characteristic of plant leaves.

Saitoh et al. [1] collected 20 pairs of pictures from 16 wild flowers in the fields around their campus and obtained a recognition rate of 96 % for this classifier with four features of flowers and two features of leaves. Bashish et al. [45] did some research on plant classification methods, and they obtained the classification rate of 92.7 %. Abirami et al. [47] was in the research of the classification of plant leaves and the accuracy reached 92.6 % by using this classifier. Amlekar et al. [33] employed ANN to study the method of leaf identification, and the recognition rate of 96.53 % is obtained by using BP classifier.

4.7 RF Classifier

Random forest classifier (RF) builds a forest with a random way, the forest is composed of many decision-making trees, and there is no association between each random decision tree forests. After getting the forest, when there is a new sample enters, make every decision tree of the forest to carry on the next judgment to see the sample should belong to which category, and then to see which category is selected the most, predicts the sample for this class.

When Elhariri et al. [20] using RF as a classifier to study the system of plant classification, they obtained the accuracy of 88.82 %. This classifier was employed by Hall et al. [35] to discuss the plant recognition under the complex background, the accuracy was up to 97.3 %.

4.8 k -Means Classifier

The k -average or k -means algorithm is a widely used clustering algorithm. It is the mean of all data samples within the clustering subset as the representative of the clustering. The main idea of the algorithm is through an iterative process to make the data set divide into different categories, and makes the evaluation of clustering criterion function achieve the optimal performance, so that the generated within each cluster is compact. This algorithm is not suitable for processing discrete data, but it has good clustering effect for continuous data.

When Kruse et al. [83] using this classifier to study on the plant identification method, they did some experiments and the classification rate reached 93 %.

4.9 Other Classifiers

In addition to some commonly used classifiers, with the continuous development of plant identification, there have been some new recognition algorithm or rarely used classification methods, these identification methods are listed below.

When Arunpriya et al. [19] studied a new method for the plant classification, the Radial Basis Function (RBF) neural network was trained with 50 different leaves to classify them into 5 types and its result was about 88.6 % accuracy.

Elhariri et al. [20] presented a classification approach based on RF and Linear Discriminant Analysis (LDA) algorithms for classifying the different types of plants, the experimental results showed that LDA achieved classification accuracy of 92.65 % with combination of shape, texture, and vein features. Kruse et al. [83] used LDA to study on the plant identification method, they did some experiments and the classification rate reached 95 %. Kalyoncu et al. [34] was in the research of the classification of plant leaves and the accuracy was more than 70 % by using Linear Discriminant Classifier (LDC).

Lei et al. [84] proposed orthogonal locally discriminant spline embedding (OLDSE-I) and OLDSE-II methods which were applied to recognize the plant leaf and are examined using the ICL-PlantLeaf and Swedish plant leaf image databases, and numerical results show the proposed method can achieve 94.29 ± 2.25 %.

Aakif et al. [26] used the artificial neural network (ANN) to train with 817 samples of leaves from 14 different fruit trees and gives more than 96 % accuracy, and it has also been tested on Flavia and ICL datasets and it gives 96 % accuracy on both the datasets.

Jassmann et al. [85] utilized a convolutional neural network (CNN) in an android mobile application to classify natural images of leaves and got a good result.

Hidden naive bays (HNB) classifier is employed by Eid et al. [86] and several experiments are conducted and demonstrated on 1907 sample leaves of 32 different plant species taken form Flavia dataset, which shows consistently performances of 97 % average identification accuracy.

5 Existing Problems and Future Work

Although a lot of methods of plant recognition based on leaf image were proposed in the past years and some of them have achieved interesting recognition results, some problems still exist and summarized in the following.

Recently there are several datasets in the world, these datasets are built by researchers according to their target. Hence, the kind of plant collected in these datasets is less

and not representative. Because researchers live in different regions, these datasets are vulnerable to geographical restrictions. In addition, because researchers employ their own rules to build the dataset, these datasets do not have a unified rule. Therefore, a fully representative, unified, universally accepted standard database or dataset should be built in the future.

More new features should be explored by numerous techniques. When we propose a novel feature, we should consider whether it is easy to extract, whether it is not sensitive to the noise and whether it has the ability of distinguishing different kinds of plant exactly. In fact, with the change of time and the impact of the environment, the color or shape of the organ maybe change even for the same plant. Therefore, this problem should be taken into consideration in the future.

The existing classifiers are designed from the theory and the application environment of plant recognition is not considered. Then when these classifiers are employed for plant recognition, they do not show their best performance.

For the analysis of experimental results, the researchers use different datasets and the size of data sample is also different in each dataset. This makes it difficult to evaluate the performance of different algorithms or the classifier. Hence, efficient evaluation criteria are necessary for plant recognition. By virtue of the same evaluation criteria, all proposed methods can be evaluated objectively.

6 Conclusion

Plant recognition based on image processing is the result of the development of image processing and pattern recognition. The paper mainly reviews the proposed methods of plant recognition based on image processing in recent years. More than 30 features of plant and 10 kinds of classifier are described in the paper and SVM was used to evaluate the features. Base on the analysis of references, we find out some problems in feature extraction and classification and point out the future work, e.g. building standard dataset, exploring new features, optimizing classifiers, etc.

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Compliance with Ethical Standards

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