PNN based crop disease recognition with leaf image features and meteorological data

Shi Yun[1], Wang Xianfeng[1], Zhang Shanwen[1], Zhang Chuanlei[2*]

(1. *Department of Electronics and Information Engineering, Xijing University, Xi'an 710123, China*;
2. *School of Computer Science and Information Engineering, Tianjin University of Science and Technology, Tianjin 300222, China*)

Abstract: An automatic crop disease recognition method was proposed in this paper, which combined the statistical features of leaf images and meteorological data. The images of infected crop leaves were taken under different environments of the growth periods, temperature and humidity. The methods of image morphological operation, contour extraction and region growing algorithm were adopted for leaf image enhancement and spot image segmentation. From each image of infected crop leaf, the statistical features of color, texture and shape were extracted by image processing, and the optimal meteorological features with the highest accuracy rate were obtained and selected by the attribute reduction algorithm. The fusion feature vector of the image was formed by combining the statistical features and the meteorological features. Then the probabilistic neural networks (PNNs) classifier was adopted to evaluate the classification accuracy. The experimental results on three cucumber diseased leaf image datasets, i.e., downy mildew, blight and anthracnose, showed that the crop diseases can be effectively recognized by the integrated application of leaf image processing technology, the disease meteorological data and PNNs classifier, and the recognition accuracy rate was higher than 90%, which indicated that the PNNs classifier trained on the disease feature coefficients extracted from the crop disease leaves and meteorological data could achieve higher classification accuracy.

Keywords: image processing, crop disease recognition, disease meteorological data, morphology, probabilistic neural networks (PNNs)

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1 Introduction

There are many kinds of crop diseases, if not been controlled well, they would cause quality decline of agricultural production and seriously yield losses and even threaten food security in the agricultural industry worldwide[1]. A number of studies have documented the economic loss associated with disease[2,3]. Also, the periodically outbreak of crop diseases often leads to large scale crop death and consequent famine. For a long time, the governments of all countries in the world have been aware that the crop disease detection is extremely critical for sustainable agriculture. For crop disease management, the diseases need to be detected at their early stage to control their spread speed[4,5]. So far, the observation by the experts' naked eye based on the disease symptoms on the crop leaves is the main approach adopted in practice for detecting and identifying the crop diseases. This method usually relies on the in–field visual identification by the agricultural technicians and it requires continuously monitoring, which might be prohibitively expensive in large farms.

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Biographies: Shi Yun, Lecturer, Research interests: pattern recognition and its application to crop disease recognition. Email: 741725347@qq.com; **Wang Xianfeng**, Associate Professor, Research interests: image processing and its application to crop disease recognition. Email: wangxianfengxj@163.com; **Zhang Shanwen**, PhD, Professor, Research interests: manifold learning and its application to crop disease recognition. Email: wjdw716@163.com.

***Corresponding author: Zhang Chuanlei**, PhD, Professor, Research interests: pattern recognition and machine learning. Mailing address: Tianjin University of Science and Technology, 1038 Dagu Nanlu, Tianjin, 300222, China. Tel: +86-22-60270083, Email: 97313114@tust.edu.cn.

Automatic detection of the crop disease is an essential research topic as it may provide benefits in monitoring the large crop fields and it can automatically detect the disease symptoms as soon as they appear on the crop leaves. Therefore, it has great realistic significance to design a fast, automatic, inexpensive and accurate method to detect the crop diseases. The development of visual technologies and the popularity of digital products provide support for the crop disease recognition using image processing techniques[6,7]. Automatic recognition and diagnosis of the crop diseases based on the leaf image symptoms is effective, which could reduce the reliance on the technical personnel in monitoring large rural fields of crops and eliminate the mistakes made by the people who might be short of professional knowledge[8]. The disease recognition features extracted from color moments can be used for diseased leaf classification using the various clustering algorithms. Recently, the research topic of the crop disease recognition based on diseased leaf has received considerable interest from the computer vision and pattern recognition community. Detecting the crop diseases by the shape, texture and color of diseased leaf images also has been discussed in many previous research papers[9-13]. It is very important to extract the disease region[14,15]. The crop disease can be graded by calculating the quotient of disease spot and the spot area[16]. Leaf segmentation can reduce the computational load and storage space without degrading the final recognition results[17-19]. However, the recognition rates by many current crop disease recognition methods are not satisfactory for the crop disease automatic recognition system, due to the complex, dynamic and irregular features of the crop disease leaves. In this paper, a crop disease recognition method is proposed by combining the statistical features of the crop diseased leaf images and the meteorological data. The contribution of the paper includes: 1) a new crop disease recognition method is proposed; 2) the proposed method takes into account both the diseased leaf features and the meteorological data; and 3) the comparison experiments with the traditional crop disease recognition methods shows that the proposed method is more effective and feasible for the crop disease recognition.

2 Materials and methods

2.1 Image collection

The images of cucumber leaves infected with diseases of downy mildew, blight and anthracnose were taken by Canon A640 digital camera in manual adjustment of focus, macro mode, auto white balance and aperture and resolution. Under moderate intensity sun light, leaf images were collected and their meteorological data was recorded once every two days from the early beginning of the disease to the medium–term. In order to make the color of the leaf images close to their natural one, we set the camera white balance before shooting. Camera flash mode was disabled and all other settings remained the same to make sure that all the leaf images were captured under the same conditions. The diseased cucumber leaves were cut before capturing and an A4 size white paper was placed below the disease leaves as background to eliminate the disturbance of other complex background for the subsequent disease recognition rate. More than 300 diseased leaf images of the three kinds of cucumber diseases were taken, and the meteorological data such as seasonality, date, temperature, relative humidity and drought were recorded[13]. All of the leaf images were input to computer in JPG format. The meteorological data of the cucumber leaf disease were stored in ACCESS database. The Leaf images were processed and analyzed with the operating system Windows XP and image processing software Matlab7.x. For each kind of three cucumber leaf disease, 50 images were selected randomly as the training set and the remaining 50 images as the testing set.

2.2 Disease spot image segmentation

Before extracting the features from the diseased leaf images, the leaf should be segmented from the background image. The main goal of leaf spot segmentation is to partition an image into regions. Region growing algorithm is employed to separate the spots from the diseased leaf images[20-23]; it is a simple region–based image segmentation algorithm and determines whether the pixel neighbors should be added to the region by examining the neighboring pixels of initial seed points. The detailed steps are described as follows:

1) Design a matrix $N\times(N+2)$ to store the regional adjacency statistics, with ith row to storage region, R_i list of adjacent regions, number of adjacent regions, as well as R_i flag bits, N is the number of the regions;

2) Spot regions are automatically selected according to a certain rule. The rule used in this paper is that the seed regions have high similarity as its adjacent regions;

3) Mark the seed regions. If there are unmarked regions, for each seed region, its adjacent region list is scanned. For each non–seed adjacent region p of a seed region, check all of their adjacent regions. For the region p, if the marked adjacent regions have the same tag, mark the region p using the tag value; if its marked adjacent regions have different tags, compute the difference of mean color between region p and its adjacent regions and then choose the region tag with minimum mean color difference to mark region p. If the region p is marked, it will be removed from the seed region adjacent region list, and the number of region p of adjacent regions decreases 1. The number of pixel and color mean will be recalculated in the seed region, the unmarked region in the adjacent regions are added to seed region's seed region list and the number of seed region will be updated accordingly.

4) Repeat step (3) until all regions are marked and each of them is classified into the seed region's adjacent regions.

5) Establish the marked regions and generate the disease spot images.

2.3 Extracting the statistical features of the crop diseases

Statistical features of color, shape and texture are extracted from each diseased leaf image.

1) Color features. The segmented color spot image is converted into RGB image; then the RGB image is converted to HIS (H, I and S represent hue, saturation and brightness of the spot images). From RGB space, YCbCr images (Y, Cb and Cr represent the luminance, blue color and red color components) can be obtained. Then, R, G and B are normalized to obtain the color coordinates r, g and b. In the color space, the variation caused by environmental factors, like sunlight intensity, can be eliminated. Twenty four color classifying features are extracted by computing the mean and variance of every color component of R, G, B, r, g, b, H, I, S, Y, Cb and Cr. All of the 24 features can form a color feature vector L_1.

2) Shape features. The edge and disease spot area can be obtained after edge detection and segmentation. The classifying features of the crop disease spot are extracted by Equation (1), which are represented by eccentricity S_{ecc}, roundness S_{cir}, complexity S_{com} and shape S_{foc}, respectively[2,12].

$$S_{ecc}=\frac{L_{long}}{L_{short}},\ S_{cir}=\frac{R_{incricle}}{R_{excricle}},\ S_{com}=\frac{P^2}{Area},\ S_{fac}=\frac{4\pi\cdot Area}{P} \tag{1}$$

where, L_{long}, L_{short} are the length of long and short axis, respectively; $R_{incricle}$ and $R_{excricle}$ are radius of the circle and circumcircle of disease spot area, respectively; P is the circumference of a lesion and $Area$ is the square of the spot.

Thus, the shape feature vector is $L_2=[S_{ecc}, S_{cir}, S_{com}, S_{fac}]$.

3) Texture features. The crop disease will make the texture of diseased leaf different from the normal ones in thickness and layout, etc. The texture feature of the diseased leaf images includes 5 features, i.e., energy, contrast ratio, moment of inertia, correlation and entropy of lesion area, which are computed by the gray level co–occurrence matrix calculation. The computation is as follows[12,24]:

$$\begin{gathered}T_{ene}=\sum_{i=0}^{255}\sum_{j=0}^{255}p(i,j)^2,\ T_{con}=\sum_{i=0}^{255}\sum_{j=0}^{255}(i-j)^2p(i,j),\\ T_{inv}=\sum_{i=0}^{255}\sum_{j=0}^{255}\frac{p(i,j)}{1+(i-j)^2},\ T_{cor}=\sum_{i=0}^{255}\sum_{j=0}^{255}\frac{ijp(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y},\\ T_{ent}=\sum_{i=0}^{255}\sum_{j=0}^{255}p(i,j)\log_2[p(i,j)]\end{gathered} \tag{2}$$

where, σ_x, σ_y and μ_x, μ_y are variances and mean values in the x and y components, respectively; $p(i,j)$ is the normalized gray–level co–occurrence matrix; i and j are the pixel gray value of the disease spot image.

Thus, the texture feature vector is $L_3=[T_{ene}, T_{con}, T_{inv}, T_{cor}, T_{ent}]$.

These above statistical features extracted from the color, shape and texture of each spot image constitute a classification feature vector of a diseased leaf image, denoted as [L_1, L_2, L_3] with 24+4+5=33 dimensionalities.

2.4 Aggregation of meteorological data

Due to the complex natural environment in the field, the crop spot classifying features of the shape, texture, color between the same kind of crop disease leaves vary a lot, which often result in the low recognition rate and low robustness if only crop diseased leaf image is employed for the disease recognition purpose. For this reason, many crop disease recognition methods have not been applied to the real crop disease recognition system. Many studies have shown that any kind of the crop disease depends on a certain environmental conditions, such as season, climate and weather, geography, soil and others. It is important to understand the meteorological data and make use of it to recognize the crop disease. For example, bacterial angular leaf spot of cucumber often occurs from late April to early May, gets the peak in late May to early June, suitable temperature within 22-24ºC at the relative humidity 70% above; Being rainy, warm, low lying wet and continuous farming could easily raise the crop disease incidence and prevalence; Some crop leaf diseases often occur during the rainy season; Some crop leaf diseases occur when it is high temperature and drought. In March, the blight disease easily infects seedlings of woody flowers such as rose, and disease occurs mainly on the leaves and the phenomenon becomes serious with the temperature rising. In April, some leaf disease is in the early stage of infection, such as Euonymus, rose to blight and black spot disease. If we know the meteorological data of the crop diseases, we can make use of them in the crop disease predicting and recognition. For this reason, it is important to collect meteorological data associated with the crop disease and establish a meteorological data table for every type of disease (Table 1) and quantitative (discrete) the information sheet which reflect the natural environmental conditions. For example, for seasonal factor, it can be divided into multiple levels (e.g. 36 intervals) all year round. Another solution for seasonal factor is that the growing period can be broken down by half month. For rainfall season, it can be divided into small, medium, large levels (Table 2). Furthermore, using the rough set attribute reduction method, the unimportant attributes can be removed from the information table[25-26]. Thus, the classification feature vector of the meteorological data L_4 of the crop disease is obtained.

Table 1 Meteorological data table of the cucumber leaf disease

Disease category	Meteorological information						
	Date	Temperature	Humidity	Rainfall	Light	Symptoms	…
Downy mildew	4.10	30	25%	Medium	General	Obviously	
Blight	7.10	22	25%	Large	Weak	Not obvious	
Anthracnose	6.10	25	80%	Small	Strong light	Heavy	

Table 2 Discretization of the information

Disease category	Meteorological data						
	Date	Temperature	Humidity	Rainfall	Light	Symptoms	…
Downy mildew	1	3	1	2	1	2	
Blight	2	2	1	3	0	1	
Anthracnose	2	2	5	1	3	3	

2.5 Normalize the extracted features

For a diseased leaf image, its statistic feature vector L_1, L_2, L_3 of color, texture and shape can be obtained, and its meteorological feature vector L_4 can also be obtained. Then we combine these features into a united classifying feature vector L=[L_1, L_2, L_3, L_4] with 24+4+5+5=38 dimensionalities. It should be emphasized that the dimensions and the value ranges of L_1, L_2, L_3 and L_4 are different from each other, which means that the features should be normalized. Suppose there are m training diseased leaf images, we can form an m×38 feature matrix, denoted as follows

$$\begin{bmatrix} L_{1,1}, L_{1,2}, \ldots, L_{1,38} \\ L_{2,1}, L_{2,2}, \ldots, L_{2,38} \\ \vdots \\ L_{m,1}, L_{m,2}, \ldots, L_{m,38} \end{bmatrix} \tag{3}$$

where, each row [$L_{i,1}$, $L_{i,2}$, …, $L_{i,38}$] indicates a feature vector of a diseased leaf image formed by L_1, L_2, L_3 and L_4.

The normalized feature matrix is expressed as follows:

$$\begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_m \end{bmatrix} = \begin{bmatrix} x_{1,1}, x_{1,2}, \ldots, x_{1,38} \\ x_{2,1}, x_{2,2}, \ldots, x_{2,38} \\ \vdots \\ x_{m,1}, x_{m,2}, \ldots, x_{m,38} \end{bmatrix} \tag{4}$$

where, $x_{i,j} = L_{i,j} / \sqrt{\sum_{k=1}^{m} L_{k,j}^2}$.

In Equation (4), each row represents a normalized leaf image feature vector. Through Equation (4), the range of each feature $x_{i,j}$ is restricted from 0 to 1 to make sure that feature is unified. So the problem of scale variance is solved, which also means that the feature vector ensure the scale invariance.

2.6 Probabilistic neural networks (PNNs) classifier

Probabilistic neural networks (PNNs) classifier provides a general solution for pattern classification problems by following an approach developed in statistics, called Bayesian classifier. The classifier is capable of handling a multi–class problem, which decomposes a multi–class classification problem into dichotomies[27-29]. The typical PNN classifier consists of four layers, i.e., input layer, pattern layer, summation layer and output layer. (1) The input layer unit does not perform any computation and simply distributes the input to all neurons in the pattern layer. (2) The pattern layer is fully connected to the input layer, with one neuron for each pattern in the training set. The weights are set equal to the different training patterns. Each neuron performs a dot product of the sample X and the pattern j stored as a weight vector w_j, named $y_j=X\cdot w_j$. A radial transfer function $\exp[(y_j-1)/\sigma^2]$ is calculated, and the result is fed into the summation layer. (3) The summation layer neurons compute the maximum likelihood of pattern X being classified into the class by summing and averaging the output of all neurons that belong to the same class. The pattern layer is selectively connected to the summation units depending on the class of patterns. There is one neuron for each class, and each neuron sums the outputs from the pattern layer neurons. (4) The output layer neuron yields a binary output value corresponding to the best class choice for the specific sample. The output layer compares the weighted votes for each target category accumulated in the pattern layer and uses the largest vote to predict the target category.

It is assumed that X is an unknown testing sample and there are 3 kinds of input feature vectors as the training samples, and the number of the feature vectors in each class is k_1, k_2 and k_3, respectively. Each input vector is associated with one of the 3 classes. From Equation (4), each feature vector has 38 elements. The architecture of the adopted PNN classifier is shown in Figure 1. In pattern layer, there are 3 kinds of classes; in summation layer, $Y_{ij} = e^{-\|X-X_{ij}\|^2/\sigma}$, where σ is the smoothing parameter, and $g_i(i=1,2,3)$ is expressed as follows:

$$\begin{aligned} g_1 &= w_{1,1}Y_{1,1} + \ldots + w_{1,k1}Y_{1,k1} \\ g_2 &= w_{2,1}Y_{2,1} + \ldots + w_{2,k2}Y_{2,k2} \\ g_3 &= w_{3,1}Y_{3,1} + \ldots + w_{3,k3}Y_{3,k3} \end{aligned} \tag{5}$$

The class of X is evaluated by $Max(g_1, g_2, g_3)$.

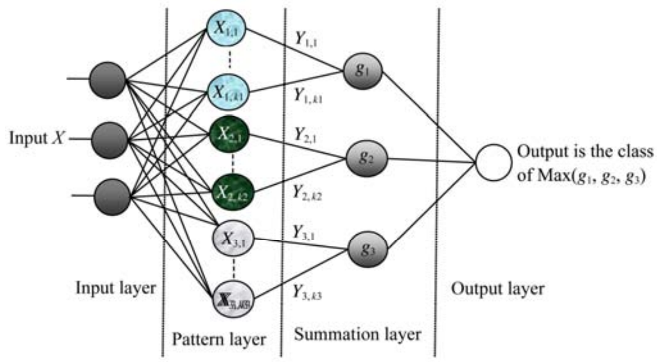

Figure 1 Architecture of probabilistic neural networks

3 Results and discussion

3.1 Experimental results

To verify the effectiveness of the proposed method, the recognizing experiments were carried out on the cucumber diseased leaf dataset of downy mildew, blight and anthracnose. For each kind of disease, 100 leaf images were collected, in which 50 images were randomly selected as the training dataset to train the PNNs classifier and the remaining were used to test the algorithm's performance. In order to reduce computation time for image processing, firstly, the lesion region of each color leaf image was segmented from each cucumber leaf disease image, and each segmented spot image size was normalized to 128×128 (As shown in Figure 2 A, B and C). Then enhancement of the image will be performed, and color image was converted to RGB, with contour extraction of components, corrosion and dilation for G component. By region growing algorithm, the spot image was separated from the leaf image, and the complete disease spot image was obtained (Figure 2 a, b and c). Then this disease spot image worked as a template and was combined to the original image to generate leaf disease spot of color image. The RGB image could be easily converted to other color model. Figure 3 shows the color components of R, G, B, H, I, S, Y, Cb and Cr of downy mildew spot image.

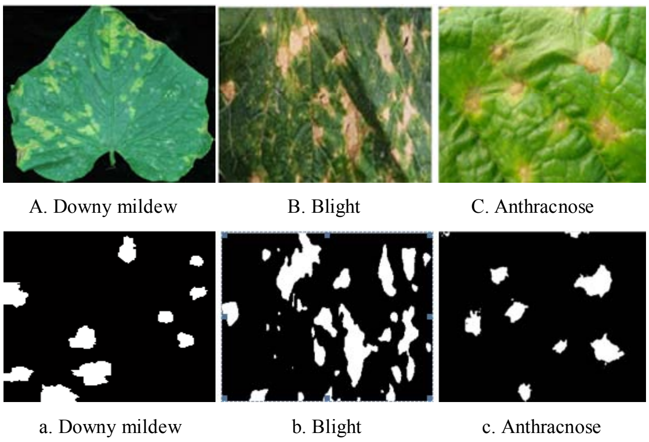

Figure 2 Cucumber diseased leaf images and their segmented spots

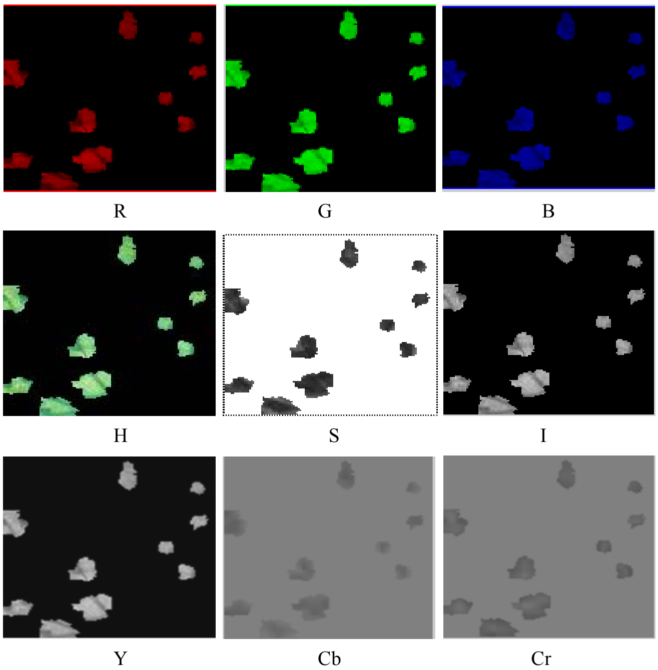

Figure 3 Downy mildew spot image and their color components of R, G, B, H, I, S, Y, Cb and Cr

By computing the statistical features of color, shape and texture of each diseased leaf image, 24+4+5=33 features could be obtained, expressed also as [L_1, L_2, L_3]. From the information of seasonality, climate, meteorology, geography, soil and disease occurrence conditions which are close to natural environment, a meteorological data table was obtained. Then, with the rough set based attribute reduction algorithm, 5 key attributes were selected from the information tables, i.e., seasonality, temperature, humidity, rainfall and drought, which constitute a feature vector L_4 for classification purpose.

Since the feature value ranges vary greatly, as shown in Table 2 and Table 3, these different types of the feature values need to be normalized.

Table 3 Feature values of cucumber disease extracted from leaf images

Disease feature	Downy mildew		Blight		Anthracnose	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
R	105.48	35.4425	117.42	29.0180	122.42	31.3994
G	90.48	31.1089	102.20	27.8773	110.86	29.2268
B	57.04	22.5125	73.86	29.5794	58.12	29.9044
r	0.4458	0.1497	0.4307	0.0093	0.4329	0.0313
g	0.3667	0.0054	0.3573	0.0068	0.3854	0.0165
B	0.2025	0.0152	0.2293	0.0222	0.1867	0.0387
H	42.30	2.3234	40.36	2.2293	49.30	2.9641
I	37.42	11.9251	39.14	11.8115	35.54	10.5931
Y	30.80	10.7874	36.36	10.5652	35.32	11.5660
Cb	−18.99	5.5888	−17.26	2.4975	−24.79	5.8111
Cr	13.11	3.9907	12.78	3.1735	12.56	3.9735
S_{ecc}	0.8714	0.0363	0.8382	0.0763	0.9086	0.2607
S_{cir}	0.6074	0.9157	0.5026	0.7585	0.4980	0.7086
S_{com}	0.2934	0.0589	0.1480	0.0499	0.3408	0.0871
S_{fac}	0.9572	0.4854	0.8003	0.1419	0.4218	0.9157
T_{ene}	0.1045	0.03155	4.6043	1.5519	0.0689	0.0234
T_{con}	0.0215	0.0240	2.1049	1.4939	0.0154	0.0208
T_{inv}	0.0557	0.0644	0.1132	0.2451	0.1291	0.0627
T_{cor}	0.0004	0.0002	0.0027	0.0012	0.0001	0.0001
T_{ent}	0.6930	0.3351	0.93518	0.6640	0.4859	0.0487

The calculation programs implementing PNNs were written in M–file based on MATLAB software package (MATLAB version 7.0 with neural networks toolbox). All computation was performed on a Pentium IV computer with 256 MB RAM working under MS windows XP. The key design decisions for the neural networks used in disease classification were the architecture and training. The performance of neural networks depends on the sizes of the training set and test set. All 38 fusion features were normalized as the input of PNNs. In PNNs classifier, the smoothing parameter σ takes values from 0.1 to 1 with the increment of 0.1, and the value that obtains the highest accuracy rate was the optimal value[30]. Training and learning functions are mathematical procedures used to automatically adjust the network's weights and biases.

To verify the effectiveness of the proposed method, we compared the results of the proposed method with other four methods: the *K*–means based segmentation, neural–networks–based classification (KM+NN)[8], Support Vector Machines based on hyperspectral reflectance (SVM)[11], Principal Component Analysis and Neural Networks (PCA+NN)[31]. The methods only considered color, shape and texture without meteorological data, i.e., [L_1, L_2, L_3]. For comparison, all methods perform the disease recognition experiment 50 times, recording the highest recognition rates of each algorithm in each experiment and calculating the average values and variances of each method of 50 times experiments. Tables 4 and 5 demonstrate the recognition results of the proposed method on the training set and test set of the three kinds of cucumber diseases, respectively.

Table 4 Recognition results on the training set of three cucumber diseases

Disease	No. of sample	Correctness	Recognition rate/%
Downy mildew	50	47	94.00
Blight	50	47	94.00
Anthracnose	50	48	96.00
Total	150	142	94.67

Table 5 Recognition results on the testing set of three cucumber diseases

Disease	No. of sample	Correctness	Recognition rate/%
Downy mildew	50	45	90.00
Blight	50	46	92.00
Anthracnose	50	46	92.00
Total	150	137	91.33

Table 6 is the average rate of recognition of the five kinds of methods on the test set on the three kinds of cucumber diseases.

Table 6 Recognition results of cucumber diseases in the testing sample set based on the four methods

Method	Recognition rate	Variances
KM+NN	88.89%	2.43
SVM	89.13%	2.06
PCA+NN	89.80%	2.62
[L_1, L_2, L_3]+PNNs	88.46%	1.94
[L_1, L_2, L_3, L_4]+PNNs	91.08%	1.85

3.2 Result analysis

From Table 5, we know that the disease recognition rate of the proposed method is the highest. We find that, during the experiments, the cucumber disease recognition rates of five kinds of methods in moderate disease period were higher than those of light and severe periods. The possible reason is that the disease spot on leaf in early disease period is small and the difference of the leaf from the normal one is not obvious. When the diseases become severe, the leaves are damaged heavily, which makes the disease spot image segmentation difficult, the difference between the obtained classification features are unobvious and disease recognition error rate high. For the traditional methods, in order to improve the recognition rate, more training samples are needed, which requires extra training time cost. In the proposed method, the recognition rate can be improved by integrating the meteorological data of the disease. The experimental results show that the proposed method is more effective and could be potentially used in real field recognition.

4 Conclusions

In order to identify the crop disease, the experts in the crop protection field considered many factors, for example: the disease location, seasonality and onset of external factors, such as natural environment and leaf spot image. However, in traditional leaf image based on disease recognition methods, only the leaf images are considered, and the disease location, seasonality, onset of external factors such as meteorological data were ignored, which resulted in low recognition rates. In this paper, we proposed a method considering not only the classification features extracted from disease image color, shape and texture, but also the crop disease meteorological data including seasonality, location, time, the incidence of external factors such as environmental conditions. From each diseased leaf image, 24 color features, 4 shape features, 5 texture features and 5 meteorological data features were extracted and normalized, which constituted a feature matrix as input to PNN classifier. The experiments were implemented on three kinds of cucumber disease datasets, downy mildew, blight and anthracnose. The correct recognition rate was 91.08%, which demonstrated that integrating leaf image color, texture, shape, and crop disease meteorological data can improve recognition rate.

Actually, there are many factors affecting the development of crop diseases. The incidence of various diseases in different periods has different symptoms. How to use computer vision technology and meteorological data to establish comprehensive and effective crop disease identification methods and systems need to be further studied.

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[References]

[1] Guan Z X, Yao Q, Yang B J, Hu J, Tang J. Application of digital image processing technology in recognizing the diseases, pests, and weeds from crops. Scientia Agricultura Sinica, 2009; 42(7): 2349–2358. (in Chinese with English abstract)

[2] Sun H, Li M Z, Zhang Q. Detection system of smart sprayer: Status, challenges, and perspectives. Int J Agric & Biol Eng, 2012; 5(3): 10–23.

[3] Niphadkar N P, Burks T F, Qin J W, Ritenour M A. Estimation of citrus canker lesion size using hyperspectral reflectance imaging. Int J Agric & Biol Eng, 2013; 6(3): 41–51.

[4] Ananthi S, Vishnu V S. Detection and Classification of Crop Leaf Diseases. International Journal of Research in Engineering & Applied Sciences, 2012; 2(2): 763–773.

[5] Bock C H, Poole G H, Parker P E, Gottwald T R. Crop disease severity estimated visually, by digital photography and image analysis, and by hyperspectral imaging. Critical Reviews in Crop Sciences, 2010; 29(1-3): 59–107.

[6] Tucker C C, Chakraborty S. Quantitative assessment of lesion characteristics and disease severity using digital image processing. J. Phytopathology, 1997; 145(7): 273–278.

[7] Zhang S, Zhang C. Maize disease recognition based on local discriminant algorithm. Transactions of the Chinese Society of Agricultural Engineering, 2014, 30(11): 167–172. (in Chinese with English abstract)

[8] Bashish D A, Braik M, Bani–Ahmad S. Detection and classification of leaf diseases using K–means based segmentation and neural–networks–based classification. Inform. Technol. J., 2011; 10(2): 267–275.

[9] Camargo A, Smith J S. An image processing based algorithm to automatically identify plant disease visual symptoms. Bio. Systems Engineering, 2009; 102(1): 9–21.

[10] Hillnhuetter C, Mahlein A K. Early detection and localization of sugar beet diseases: new approaches. Gesunde Pfianzen, 2008; 60 (4): 143–149.

[11] Rumpfa T, Mahleinb A K, Steinerb U, Oerkeb E C, Dehneb H W, Plümera L. Early detection and classification of plant diseases with support vector machines based on hyperspectral reflectance. Computers and Electronics in Agriculture, 2010; 74(1): 91–99.

[12] Al–Hiary H, Bani–Ahmad S, Reyalat M, Braik M, ALRahamneh Z. Fast and accurate detection and classification of crop diseases. International Journal of Computer Applications, 2011; 17(1): 31–38.

[13] Gulhane V A, Gurjar A A. Detection of Diseases on Cotton Leaves and Its Possible Diagnosis. International Journal of Image Processing (IJIP), 2011; 5(5): 590–598.

[14] Jayamala K Patil, Raj Kumar. Color Feature Extraction of Tomato Leaf Diseases. International Journal of Engineering Trends and Technology, 2011; 2(2): 72–74.

[15] Chaudhary P, Chaudhari A K, Cheeran A N, Godara S. Color Transform Based Approach for Disease Spot Detection on Crop Leaf. International Journal of Computer Science and Telecommunications, 2012; 3(6): 65–70.

[16] Li G L, Ma Z H, Huang C, Chi Y W, Wang H G. Segmentation of color images of grape diseases using K–means clustering algorithm. Transactions of the CSAE, 2010; 26(Supp 2): 32–37. (in Chinese with English abstract)

[17] Bauer S D, Korc F, Forstner W. The Potential of Automatic Methods of Classification to identify Leaf diseases from Multispectral images. Precision Agric., 2011; 12(3): 361–377.

[18] Valliammal N, Geethalakshmi S N. Crop leaf segmentation using nonlinear *K*-means clustering. IJCSI International Journal of Computer Science Issues, 2012; 9(3): 212–218.

[19] Jaware T H, Badgujar R D, Patil P G. Crop disease detection using image segmentation. World Journal of Science and Technology, 2012; 2(4): 190–194.

[20] Wang N, Wang K R, Xie R Z, Lai J C, Ming B, Li S K. Maize leaf disease identification based on Fisher discrimination analysis. Scientia Agricultura Sinica, 2009; 42(11): 3836–3842. (in Chinese with English abstract)

[21] Song K, Sun X Y, Ji J W. Corn leaf disease recognition based on support vector machine method. Transactions of the CSAE, 2007; 23(1): 155–157. (in Chinese with English abstract)

[22] Yang W, Sun C, Du H, Yang J. Feature extraction using Laplacian maximum margin criterion. Neural Processing Letters, 2011; 33(1): 99–110.

[23] Li G L. Preliminary Study on Automatic Diagnosis and Classification Method of Crop Diseases based on Image Recognition Technology. Beijing: China Agricultural University, 2011; pp.1–64. (in Chinese with English abstract)

[24] Chai A L, Li B J, Shi Y X, Cen Z X, Huang H Y, Liu J. Recognition of tomato foliage disease based on computer vision technology. Acta Horticulturae Sinica, 2010; 37(9): 1423–1430. (in Chinese with English abstract)

[25] Dhaygude S B, Kumbhar N. Agricultural crop leaf disease detection using image processing. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 2013; 2(1): 599–602.

[26] Phadikar S, Sil J. Rice disease identification using pattern recognition techniques. In Proceedings of 11th International Conference on Computer and Information Technology. Khulna, Bangladesh, 2008; pp.420–423.

[27] Burrascano P. Learning vector quantization for the probabilistic neural network. IEEE Transactions on Neural Networks, 1991; 2 (4): 458–461.

[28] Lin S, Kung S Y, Lin L. Face recognition/detection by probabilistic decision–based neural network, IEEE Transactions on Neural Networks, 1997; 8(1): 114–132.

[29] Mao K Z, Tan K C, Ser W. Probabilistic neural–network structure determination for pattern classification. IEEE Transactions on Neural Networks, 2000; 11(4): 1009–1016.

[30] Yang Z, Yang Z, Lu W, Harrison R G, Eftestol T, Steen P A. A probabilistic neural network as the predictive classifier of out-of-hospital defibrillation outcomes. Resuscitation, 2005; 64(1): 31–36.

[31] Wang H, Li G, Ma Z, Li X. Image recognition of crop diseases based on principal component analysis and neural networks. In Proceedings of 2012 8th International Conference on Natural Computation. Chongqing, China, 2012; pp.246–251.