Rice blast recognition based on image processing and BP neural network

Jingjing Kang, You Ma, Maohua Xiao*, Zhixiang Feng, Ziang Deng, Sanqin Zhao

College of Engineering, Nanjing Agricultural University, Nanjing 210031, China

Abstract: Determining disease rapidly and accurately is key to the accurate monitoring of agricultural conditions and timely prevention of agricultural output decrease. Rice, an important crop in China, has been seriously affected by different diseases, among which rice blast is one of the principal damages. In order to solve the problem of poor accuracy of rice blast disease identification and low efficiency of manual detection, a method of rice blast disease identification based on image processing and BP neural network was proposed. The typical lesion images were obtained by image clipping, then the image segmentation was performed by the combination of color image components, and the features of 14 features of color feature, shape and texture were extracted. The characteristic parameters of four types of rice blast - white spot, brown spot, acute and chronic blast, were selected as the input values of BP neural network, and the optimal number of hidden layer nodes was determined experimentally several times to identify the lesion area. After the network was trained, the training set was obtained, and finally the test sample set was imported for identification. The experimental results show that the recognition rate of typical feature extraction was 85.06%, which can effectively classify the rice blast.

Keywords: rice blast; disease identification; image processing analysis; BP neural network

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1. Introduction

Rice is one of China's major food crops. However, it has been deeply threatened by rice blast fungus. Rice blast occurred in rice cultivation countries, causing great losses every year, so detection and control of rice blast is of great significance to the development of agriculture in China. The traditional method of disease identification mainly relies on manual detection, which has low recognition speed, high intensity and low accuracy. Besides, highly experienced identification personnel are needed to meet the technical requirements, and it is not suitable for detection in a wide range and multi-period. On the other hand, artificial testing needs comparison analysis with the disease database, which takes a long time and is difficult to achieve real-time monitoring and timely prevention and control. Therefore, to achieve rapid diagnosis of rice blast, automatic detection of disease prevention is of great significance.

In recent years, with the development of computer technology, many scholars at home and abroad have begun to study the method of disease identification based on computer network and image analysis technology and some results were achieved. Pydipati et al. (2006) used the generalized two-moment discriminant classifier to identify citrus diseases in 2006. Sanyal et al. (2008) used the neural network to identify the rice blast, flax spot and normal leaves with the recognition rate of 89.26%. Song et al. (2011) used YCbCr color space technology to classify the disease spots according to the texture features of maize disease. Meanwhile, the feature of lesion was extracted by using the spatial gray layer of the matrix. The BP neural network was used to classify maize diseases. In 2015, Wang et al. proposed BP network on the basis of image processing, RBF neural network, GRNN and PNNs to effectively identify and diagnose plant diseases. Jayme et al. (2016) proposed a disease identification method on the basis of color transformation,

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* **Corresponding author: Xiao, M.,** College of Engineering, Nanjing Agricultural University, Nanjing 210031, China. Email: xiaomaohua@njau.edu.cn

color histogram and paired classification system, which has an obviously effect in terms of recognition technology. Liu et al. (2009) studied the identification of rice blast by comprehensively using the image processing technology and the neural network identification method of multi-layer perception. Hua combined linear dimension reduction technology and BP neural network on the thermal infrared face image recognition research, a high thermal infrared face image recognition rate achieved in 2010. In 2013, Hu proposed a method for plants color image segmentation on the basis of improved C-V model and multi-channel feature fusion based on YUV and wavelet packet. Jia et al. (2013) put forward the identification of cucumber diseases based on the lesion shape and neural network, which showed excellent results. These studies have achieved some effects on disease identification, but they still need to be improved in recognition accuracy and feature extraction parameters selection.

In this paper, a large number of rice blast disease images were collected at Jiangpu Farm, Nanjing Agricultural University, and an identification method combining image processing and BP neural network was proposed. The method found the typical characteristics of disease image by using the image processing and analysis technology, and they were used as the input of the neural network to identify the disease image. Without affecting the recognition accuracy, the method could save the time of image recognition, hence the rice blast can be diagnosed rapidly and accurately.

2. Image acquisition and classification

2.1. Image acquisition

To let the experimental setting better reflect the real world with simulated conditions, a set of real-time acquisition experiments was designed. The shooting was under the natural light, using white paper as background to increase the contrast between the background and the leaves so that the leaves can be presented in a much clearer way. The experiment was conducted in August 2017 at Jiangpu Experimental Farm of Nanjing Agricultural University. After the image was taken, shearing was carried out, and the lesion area was taken as the sample. A total of 164 samples of four blast types were collected and 160 valid samples were collected. The image format processed in the experiment was JPG and the size was 600 × 150 pixels.

The camera used in this study was Zenmuse Z, with a single focal length and a camera distance of 0.2 meter. Camera image file format is JPG, image resolution is 4000×3000.

2.2. Disease image characteristics

In this paper, four different types of rice blast (Jia & Ji, 2013) were identified, and the characteristics of which are shown in Table 1.

Table 1. Four blast characteristics.

Disease name	Shape characteristics	Color and texture features
Chronic leaf blast	Fusiform	Center: gray; Edge: brown; Peripheral: yellow halo
Acute type leaf blast	Nearly round or oval	Dark green; gray moldy layer
Brown-spot leaf blast	Dots	brown
White-spot type leaf blast	Dots	white

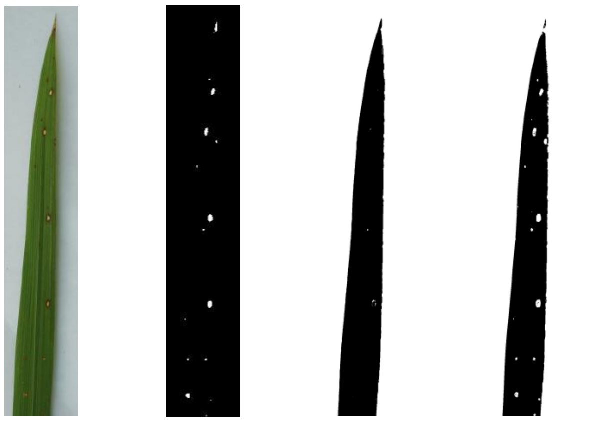
Before disease image feature extraction and disease identification, it is necessary to separate the lesion from the diseased leaf image for subsequent feature extraction and recognition. Image segmentation can use iterative selection threshold method, the minimum mean square error method and the maximum between-class variance method (Zhang, Wang, & Xue, 2012).

In this study, according to the existing image segmentation algorithm, combining the histogram of image background and lesion color features and RGB components, the maximum inter-class variance method was used to segment the three colors components (R-G) (G-B) (2R-G-B). After binarizing the three combinations, it was found that only the lesion area was left after (R-G) segmentation, and the segmentation effect was obvious, which could facilitate the extraction of morphological parameters (Fig. 1.). Therefore, the maximum between-class variance method was selected for segmentation of (R-G) component combination.

3. Feature extraction

3.1. Color characteristics

Pictures taken under natural light have noise and other effects, so image preprocessing is required before feature extraction Zhang, Mao, &Qiu, 2009). Image preprocessing can reduce the interference of other factors on the recognition and improve the recognition accuracy



a. Original map b. R-G Segmentation map c. G-B Segmentation map d. 2G-R-B Segmentation map

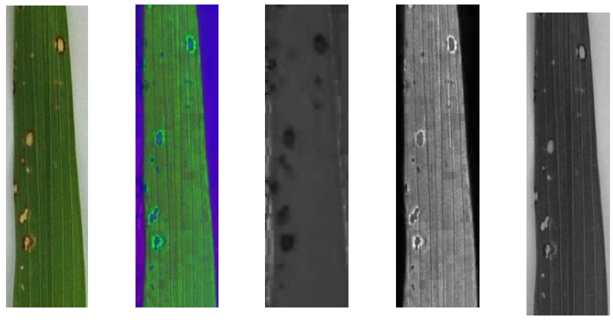
Fig. 1. Figure of segmentation comparison.

(Song et al., 2010; Zhang et al., 2011). After the image segmentation was completed, the image feature needs to be extracted, and the common image features are shape features, color features, texture features (Ruiz et al., 2011). The color characteristic is a kind of comprehensive feature which describes the superficial nature of the image or the scene in the image area. The color characteristics of four different types of rice blast are irrelevant to the brightness of the image, which can effectively suppress the noise and have significant differences. Therefore, the color characteristics can be used as the main characteristics of rice blast automatic identification. In addition, since some components of HSI and YCbCr space can effectively suppress noise (Qi, Ma, & Zhang, 2006), the RGB color space was converted into the HSI and YCbCr color space in the paper in order to find the color features that can effectively distinguish different types of rice blast lesions (Gonzalez & Woods, 2004).

In HSI space, the influence of the luminance component can be eliminated from the color information (hue and saturation) carried by the color image, and its components are shown in Fig. 2.

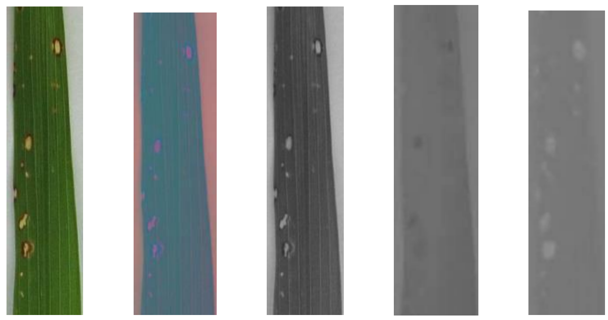
The YCbCr color space component diagrams are shown in Fig. 3

Analysis of Figs. 2 and 3 reveals that the HSI and YCbCr spaces can effectively suppress the noise generated by natural light shooting and the influence of the light intensity unevenly; the influence of light is relatively small, and the boundary between the lesion and the background is clear. Therefore, each component of H, S, I, Y, Cb, and Cr were extracted as a parameter of a color feature.



a. Original b. HSI space map c. H component d. S component e. I component

Fig. 2. HSI space map.



a. Original b. YCbCr space map c. Y component d. Cb component e. Cr component

Fig. 3. YCbCr space map.

3.2. Morphological characteristics

In this paper, the ovality, eccentricity, squareness and complexity were selected as morphological features to be extracted based on the shape features of the four rice blast diseases, which are in the shapes of spindle, near circle, ellipse and circle. The specific extraction process was as follows: the maximum inter-class variance method was used to segment the (R-G) color component combination to obtain a binarized image containing only the lesion. After morphological operation of the image after segmentation, the area (the number of pixels), the long axis of the ellipse, the minor axis of the ellipse, the eccentricity, the minimum circumscribed circle area of the target area (the number of pixels after canny operator edge detection), and other morphological characteristics were extracted. And the morphological characteristics such as ovality, centrifugation rate, rectangle and complexity were obtained. Parameter symbols are shown in Table 2.

(1) Ovality (E):

$$E = \frac{S}{\pi ab} \tag{1}$$

(2) Rectangle (*Rec*):

$$Rec = \frac{S}{S_{\min}} \tag{2}$$

(3) Complexity (*C*):

$$C = 1 - \frac{4 \times \pi \times S}{P^2} \tag{3}$$

The shape characteristics of the four rice blast lesions extracted from the experiment are shown in Table 3.

Table 2 Parameter symbol description.

Parameter	Definition
S	Area of the target area (the number of pixels in the area)
a	The size of the long axis of the target area
b	The size of the short axis of the target area
e	Centrifugation rate
$S_{\min}$	The smallest external rectangular area of the target area
p	Target area perimeter (the number of boundary pixels)

Table 3 Four rice blast lesion shape characteristic value list.

Sick leaf num-ber	Ovality				Centrifugation rate				Rectangle				Complexity			
	1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
1	0.52	0.60	0.24	0.39	0.86	0.92	0.65	0.79	0.61	0.60	0.78	0.68	13.07	23.75	10.06	13.20
2	0.42	0.46	0.57	0.33	0.79	0.82	0.90	0.74	0.60	0.75	0.75	0.73	18.43	14.06	21.59	12.15
3	0.37	0.45	0.54	0.26	0.72	0.78	0.89	0.67	0.77	0.64	0.43	0.86	10.80	20.52	72.04	11.99
4	0.35	0.56	0.48	0.36	0.68	0.90	0.84	0.77	0.71	0.61	0.80	0.72	11.32	24.53	21.95	11.19
5	0.43	0.40	0.61	0.35	0.77	0.79	0.90	0.76	0.71	0.68	0.79	0.77	13.70	13.80	17.92	12.10
6	0.42	0.64	0.51	0.37	0.81	0.93	0.86	0.77	0.80	0.76	0.85	0.80	12.31	20.09	16.40	14.25
7	0.41	0.47	0.49	0.29	0.80	0.85	0.86	0.70	0.74	0.74	0.79	0.79	13.07	17.06	13.48	14.51
8	0.66	0.47	0.69	0.42	0.94	0.85	0.95	0.81	0.68	0.61	0.72	0.76	18.81	26.24	28.51	14.70
9	0.40	0.25	0.76	0.25	0.76	0.66	0.97	0.66	0.70	0.65	0.68	0.74	11.99	13.33	34.93	13.43
10	0.50	0.41	0.23	0.24	0.83	0.81	0.63	0.66	0.67	0.61	0.86	0.76	16.07	16.88	11.03	12.15

Note: In the table, 1,2,3,4 indicate acute type, chronic type, white point type and brown point type respectively. Each sample was randomly selected and 10 samples were listed.

3.3. Texture features

Chronic lesions often have the extended brown necrosis of the line and the gray leaves of the moldy layer; acute lesions have brown mold layer on both sides of the mold; the texture of white spots and brown spot type lesions are similar with the leaf texture. Since four types of lesions show significant differences in texture characteristics, gray-level co-occurrence matrix was used to extract the image texture features in this paper. The formula of gray level co-occurrence matrix (Equation (4)) is (pixel gray scale range) (Xia, 2014):

$$P_l = \begin{bmatrix} p_{l,\theta}(0,0) & p_{l,\theta}(0,1) & \dots & p_{l,\theta}(0,j) & \dots & p_{l,\theta}(0,L-1) \\ p_{l,\theta}(1,0) & \dots & \dots & p_{l,\theta}(1,0) & \dots & p_{l,\theta}(1,L-1) \\ \dots & \dots & \dots & \dots & \dots & \dots \\ p_{l,\theta}(i,0) & \dots & \dots & p_{l,\theta}(i,j) & \dots & p_{l,\theta}(i,L-1) \\ \dots & \dots & \dots & \dots & \dots & \dots \\ p_{l,\theta}(L-1,0) & \dots & \dots & p_{l,\theta}(L-1,j) & \dots & p_{l,\theta}(L-1,L-1) \end{bmatrix} \tag{4}$$

where, L is the image gray-scale quantization level; l refers to the distance between the two pixels measure, $P_{l,\theta}(i,j)$ is the number of pairs of pixels along the direction of the distance, $d = (\nabla x, \nabla y)$, the pixel values of these two pixels are i and j, respectively. θ is the direction between pixels. Generally, three directions were chosen. The size of θ can be calculated on the size from the distance d. Therefore, the distance and orientation of two pixels can change l to obtain different combinations to extract different texture features.

After obtaining the gray level co-occurrence matrix calculation results, it was necessary to select the corresponding feature statistics to describe the image texture features. In this paper, four typical characteristic statistics such as entropy (ENT), energy (second order moment, ASM), moment of inertia (CON) and correlation coefficient (COR) (Yuan, Fu, & Yang, 2009) were selected as texture features of the image, and calculated in Equations (5)-(8). $p(i,j)$ is the value of column j in row i of the gray level co-occurrence matrix, and L is the number of gray levels in the image.

$$ENT = -\sum_{i=1}^{L}\sum_{j=1}^{L} p(i,j)\log\{p(i,j)\} \tag{5}$$

$$ASM = \sum_{i=1}^{L}\sum_{j=1}^{L} (p(i,j))^2 \tag{6}$$

$$CON = \sum_{k=0}^{L-1} k^2 \left\{ \sum_{|i-j|=k} p(i,j) \right\} \quad (7)$$

$$COR = \frac{\sum_{i=1}^{L}\sum_{j=1}^{L}(i \times j) \times p(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (8)$$

where, μ_x, μ_y, σ_x, σ_y are, respectively, the expected and variance values of the row matrix element statistics and the expected and variance values of the column matrix element statistics.

4. Disease identification based on BP neural network

4.1. BP neural network

BP neural network consists of input layer, hidden layer and output layer. In the input layer, the characteristic parameters of the disease image to be recognized were input, and the hidden layer contains the complicated laws obtained through training, and the output layer outputs the identification result. The implicit identification rule and function mapping relationship of the research object can be obtained through the learning and training of the neural network model without knowing exactly what the identification rules are. All needed is the application of the network as an extremely complicated function mapping to find out the input the condition parameter and its corresponding output condition parameter (Gonzalezet al., 2008; Chang, Lu, & Li, 2012). Therefore, the BP network has excellent non-linear mapping ability, generalization ability and fault tolerance. Owing to the positive characteristics shown above, BP neural network technology was selected for rice blast disease identification in this research.

4.2. Disease identification process based on BP neural network

In this paper, the image samples were collected and the lesion area was obtained by image cutting. The number of samples after shearing was 480, including 111 white spots, 111 brown spots, 129 acute ones and 129 chronic ones. Some of the invalid samples were removed because some of the spots were not taken clearly. Therefore, it was necessary to remove some invalid samples and obtain 471 effective samples after screening, of which 108 were white spots, 109 were brown spots, 126 were acute and 128 were chronic. And then they were preprocessed and extracted based on Matlab. Combined with the image processing and analysis methods, the typical features of rice blast disease images were selected, and the selected features were used as the input to construct the neural network to identify the types of diseases. The identification process is shown in Fig. 4.

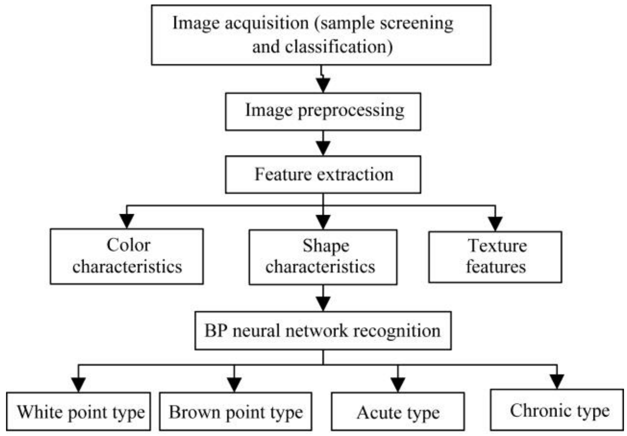


Fig. 4. Disease identification process.

4.3. BP neural network for disease identification

The extracted 14 kinds of characteristic parameters were imported into the neural network, and the parameters of the hidden layer nodes of the neural network were set. After the training set was imported into the neural network for learning, the test set was imported into the test set for recognition. BP network identification structure is shown in Fig. 5.

(1) The design of input layer: find the characteristic which are suitable for disease identification as the input based on the result of characteristic parameter extraction. The input value was limited to (0~1). And the input parameters were normalized to avoid the impact of the magnitude difference and speed up the network convergence.

(2) The number of hidden layer nodes was set to 14, and the incentive function was the log-sigmoid transfer function.

(3) The output layer design: To avoid instability of the output vector, a single vector was chosen as the output, the network output was represented by 1 and 0, 1 was the lesion, while 0 was the opposite. Specifically used (1 0 0 0) (0 1 0 0) (0 0 1 0) (0 0 0 1), which, respectively, stand for white spot type, brown spot type, acute type and chronic type leaf blast.

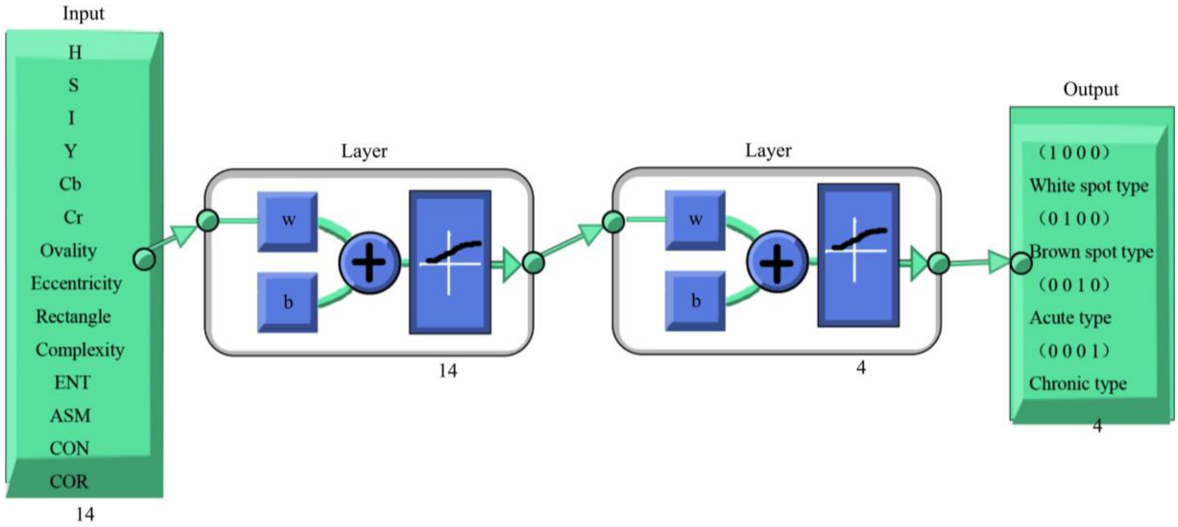


Fig. 5. BP network structure.

4.4. Results and analysis

Seventy-five spots of each lesion were selected as training set for BP neural network training and the remaining samples were used as test samples to classify lesion in neural network. The identification rates of the four kinds of spots are shown in Table 4.

Table 4 Four kinds of lesion recognition results.

No.	Category	Number of tests	Correct number	Accuracy rate
1	Acute type	51	44	86.27%
2	Chronic type	53	49	92.45%
3	White point type	33	30	90.91%
4	Brown point type	34	24	70.59%

Table 4 shows the recognition results of the neural network, in which the recognition rate of both chronic type and white point type lesions reach more than 90%, owing to the high level of the capacity of collective calculation and learning adaptability and strong fault tolerance and robustness as well. These features make the BP neural network capable of getting more ideal experimental results. However, acute and brown spot lesion recognition rate is low, a comprehensive analysis of the reasons is as follows: 1) The samples are not typically representative samples; 2) The size of lesions is too small, leading to greatly reduction of resolution after segmentation, which in turn affects the extraction and final identification of the characteristic parameters; 3) In the late stage of the acute type lesion, the shape feature and the color feature are similar to the chronic type lesion, leading to errors in sample classification. In addition, four types of a disease which are very close in character were studied in this paper. And the environment for image acquisition approached the natural growth state of rice to a great extent. Compared with the previous studies, the image recognition rate is affected by them.

5. Conclusions

In this paper, a large number of blast images were collected and the image segmentation was carried out by the combination of color image components. Eventually, the lesion was identified by BP neural network. Fourteen typical features including H component, S component, I component, Y component, Cb component, Cr component, ovality, eccentricity, squareness and complexity, ENT, ASM, CON and COR were selected from the image color, shape and texture features by image processing and analysis technology. Classification of the recognition was carried out to distinguish four types of rice blast including the white point type, brown point type, chronic type, acute type, and the average identification rate was 90.91%, 70.59%, 92.45%, 86.27%. It was found that BP neural network is more feasible in the diagnosis of rice blast disease. The recognition is fast and of high accuracy. It can lay the foundation for the identification of agricultural diseases in BP neural network. In addition, the image acquisition environment is close to the natural growth state of rice to a great extent, and it can lay a foundation for the real-time detection of rice blast.

Competing Interests

The authors declare that there are no competing interests regarding the publication of this paper.

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