RESEARCH ON THE SEGMENTATION OF RICE LEAF BLAST SPOTS BASED ON COLOR SPACE AND PSO-IMPROVED BP NEURAL NETWORK

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Abstract - Rice blast is one of the four major diseases of rice. Once that happens, the yield will be greatly reduced. Image segmentation is the key link of rice blast identification, and its real-time and accuracy have a great impact on the accuracy of rice blast identification. Affected by factors such as crop texture distribution, complex background and blurred disease spots, there is currently no efficient and high-accuracy image segmentation method for rice leaf blast. In this study, by analyzing the colour characteristics of rice blast lesions, the 2R-G+B colour space component is innovatively used as the input feature of the neural network, which has excellent results, and Particle Swarm Optimization (PSO) is used to optimize the back propagation (BP) neural network. Finally, the model is trained and tested. The results show that the method using PSO to improve BP can achieve an average image segmentation similarity of 93.97%, which has obvious advantages compared with other existing image segmentation models. The method has a fast iteration speed, and at the same time, it effectively avoids the neural network falling into a local minimum, and provides an effective new method for the existing rice leaf blast image segmentation technology.

Keywords: BP neural network, Color space feature, Lesion segmentation, PSO, Rice leaf blast.

1. Introduction

Rice blast is one of the most harmful diseases in rice production, commonly known as "rice fever". According to the different parts of the disease, it can be divided into seedling blast, leaf blast, ear blast and knot blast. In popular years, production is generally reduced by 10% to 20%. In severe cases, it can reach 40% to 50%, or even stop production, threatening the country's food security [1,2].

The traditional identification and diagnosis of rice blast mainly rely on the comparison and judgment of relevant disease spot images provided by manual or professional books, and this method is time-consuming, inefficient and low in accuracy. With the wide application of digital image processing technology in agricultural production, the research on image segmentation of rice blast is more and more important to help farmers detect and control the disease as soon as possible [3]. At present, a large number of scholars have carried out scientific research on image segmentation, which is mainly divided into two categories—traditional image segmentation methods and deep learning-based image segmentation methods. The former includes the edge detection method, graph theory method, threshold method, clustering method. The latter includes fully convolutional network (FNN), deep convolutional neural network (DCNN), back propagation neural network (BP) [4,5].

The neural network has good self-learning, self-organization and self-adaptation [6]. It can deal with uncertain systems and has gradually been applied in the field of agriculture, attracting more and more scholars' attention in the field of agriculture. YOGESHWARI M. et al. [7] proposed a new technique to detect plant leaf diseases with DCNN. Using improved fast fuzzy C-means clustering (IFFCMC) and adaptive Otsu (AO) thresholding to segment the preprocessed images, and extracting GLCM features from the segmented images, the final system achieved an accuracy of around 97.43%. Zhang W. et al. [8] proposed a method for accurate segmentation of plant images under artificially biased light based on convolutional neural network (CNN). The results of the test set showed that the segmentation accuracy of plant images with dichromatic light can reach 91.89%. ASHWINKUMAR S. et al. [9] proposed an automated model. The optimal mobile network-based convolutional neural network (OMNCNN) was used to analyze plant leaf diseases in different stages including preprocessing, segmentation, feature extraction and classification. The experimental results showed that the maximum accuracy of this

OMNCNN model was 0.985. Zhang M. et al. [10] established a high-precision hybrid leapfrog algorithm (SFLA)-pulse coupled neural network (PCNN) model for potato lesion image segmentation and realized the adaptive optimization of PCNN parameters. The image of potato late blight was segmented and the segmentation accuracy was 95.41%. Wang Z. et al. [11] proposed a segmentation method based on an improved fully convolutional neural network (FCN) to accurately segment the lesion area of maize leaves. At the same time, in the test set image segmentation experiment, the IOU index reached 91.23%. AO Z. et al. [12] used a point-based convolutional neural network (CNN) to separate stems and leaves, and then segmented the point cloud into individual maize plants based on morphological features, overcoming challenges of individual organ-level phenotypic trait extraction in maize from field lidar data. Ma J. et al. [13] developed a convolutional neural network (CNN)-based greenhouse cucumber disease identification system for cucumber downy mildew and complex background noise, combined with the regional growth algorithm, and realized the segmentation of greenhouse cucumber disease spot images. The segmentation accuracy reached 97.29%. Yue Y. et al. [14] introduced a maximum entropy decision-making mechanism based on the pulse coupled neural network model (PCNN). Among the six components of R, G, V, H, S and V, the component with the largest entropy value was selected as the processing object, which improved the segmentation accuracy and effect of plant disease spot images.

Due to different crop species, their disease characteristics are quite different. The existing research analysis shows that due to factors such as crop texture distribution, complex background, and blurred disease spots, there is currently no efficient and high-accuracy image segmentation method for rice leaf blast [15]. Therefore, based on the existing research results of vegetative neural network image segmentation, this study mainly focuses on the leaf plague and proposes a colour space feature-based PSO to improve the BP neural network for the rice leaf plague spot segmentation method. Firstly, based on the RGB colour space, the 2R-G+B colour component map of the image is extracted as the input feature of the neural network. Then the parameters of BP neural network are optimized by PSO. Finally, the BP neural network is trained and tested, and compared with methods such as threshold method, region method and BP network model.

2. Theoretical Background

2.1 BP Neural Network

BP (back propagation) neural network is a concept proposed by scientists headed by Rumelhart and McClelland in 1986. It is a multi-layer feedforward neural network trained according to the error back propagation algorithm, so it is also called the error back propagation algorithm [16]. Because BP neural network has good nonlinear mapping ability, self-learning ability, generalization ability and fault tolerance performance, BP neural network is widely used. Many scholars have applied it to the field of image segmentation.

BP neural network consists of input layer, hidden layer and output layer. Its three-layer network structure is shown in Figure 1. The training process is mainly divided into two stages. The first stage is the forward propagation of the signal, from the input layer through the hidden layer, and finally to the output layer. The second stage is the back-propagation of the error, from the output layer to the hidden layer, and finally to the input layer, adjusting the weights and biases from the hidden layer to the output layer in turn, and the weights and biases from the input layer to the hidden layer. Using the basic algorithm gradient descent method to minimize the difference between the theoretical output value and the actual output value, the weights of the network are continuously optimized. The following is the structure diagram of the BP neural network:

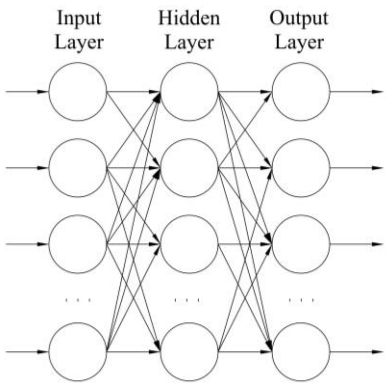


Figure 1: Three-layer network structure diagram of BP neural network

Given a training set: $D = \{(x_1, y_1), (x_2, y_2) \dots (x_n, y_n)\}$, where $x_n \in R^d, y_n \in R^l$. It means that the training sample consists of d attributes and outputs an l-dimensional real-valued variable. From the input layer to the hidden layer, the weight is set to v_{ij} and the threshold is set to λ_j. From the hidden layer to the output layer, the weight is set to w_{jk} and the threshold is set to θ_k. In the BP neural network model, we assume that there are d input neurons, q hidden neurons and l output neurons, and the neuron activation function uses the Sigmoid function here. The output of the i-th input layer neuron is x_i. Therefore, the following variable relationships can be obtained:

The input to the j-th hidden neuron is:

$$\alpha_j = \sum_{i=1}^{d} v_{ij^*} x_i. \quad (1)$$

The output of the j-th hidden neuron is:

$$b_j = g(\alpha_j - \lambda_j). \quad (2)$$

The input to the k-th output neuron is:

$$\beta_k = \sum_{i=1}^{q} w_{jk^*} b_j. \quad (3)$$

The output of the k-th output neuron is:

$$c_k = g(\beta_k - \theta_k). \quad (4)$$

2.2 Particle Swarm Optimization

Although BP neural has strong nonlinear processing ability and good robustness, this algorithm still has some problems such as local minimum value and slow convergence speed [17]. Therefore, PSO, as an effective global search method, can solve this problem [18].

PSO is a population intelligence algorithm designed by simulating the predation behaviour of birds. In each iteration of the search process, the bird's search direction and speed are adjusted according to the bird's own experience and population communication. That is, the extreme value tracking method is used, and the specific process is shown in the figure:

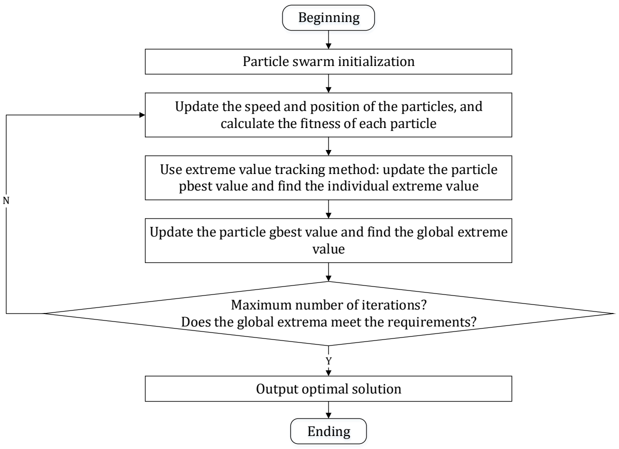


Figure 2: Flow chart of PSO

Through the analysis of existing data examples, it is concluded that the classification model obtained by PSO has better fitting accuracy than the model obtained by commonly used algorithms such as grid search algorithm (GS), cuckoo search algorithm (CS), genetic search algorithm (GA) and other algorithms [19]. Therefore, to ensure the effect of rice disease spot image segmentation in this study, the PSO algorithm is used in this model to improve the BP neural network.

The loss function is an indicator used to evaluate the difference between the predicted value of the model and the actual value. The smaller the value, the better the performance of the model and the higher the stability. Therefore, the fitness function of the PSO algorithm in the process of optimizing the BP neural network adopts the loss function of the neural network, and its formula is as follows:

$$f_i = -\frac{1}{n}\sum_j^n \left[Y_{j,k} \ln y_{j,k} + \left(1 - Y_{j,k}\right)\ln\left(1 - y_{j,k}\right)\right], \quad (5)$$

where n is the number of samples, $Y_{j,k}$ is the k-th real output value of the j-th sample, and $y_{j,k}$ is the k-th predicted value of the j-th sample [20].

2.3 RGB Colour Space

In this study, the leaf blast spots were segmented according to the colour space characteristics of rice disease images, which was due to the obvious difference between the pixels in the rice blast disease spots and the healthy areas [21].

Its colour characteristics are: the centre of the diseased spot area is generally grey-white, and the edge is brown, while the pixels of the healthy rice image are green. Common colour spaces include HSV, YCbCr, CMY and RGB colour spaces. The RGB colour space is based on the three basic colours R (Red: Red), G (Green: Green) and B (Blue: Blue), which are superimposed to different degrees to produce rich and wide-ranging colours.

Since RGB colour space is the most basic and commonly used colour space in image processing, the research on rice disease spot image segmentation in this paper is carried out on the basis of RGB colour space, and the most suitable RGB colour components for this system model are studied.

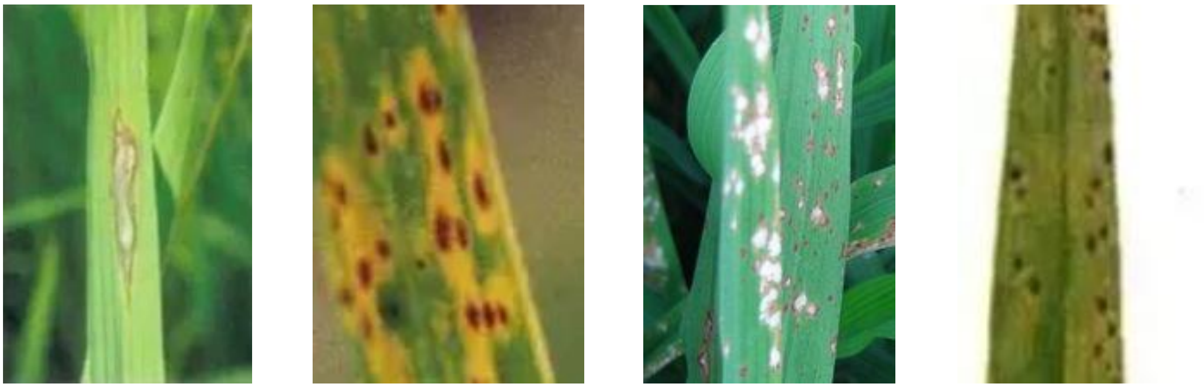
3. The principle of PSO-BP Image Segmentation based on Color Space Features

3.1 Obtaining Training Samples

From the description in 2.3, this model adopts the method based on RGB colour space features to perform image segmentation of rice blast lesions, so as to separate the target lesion area from the background. That is, the diseased area is separated from the normal area of the leaf. Therefore, the essence of the rice image segmentation problem is to classify each pixel of the rice leaf image.

Due to the different climatic conditions and disease resistance among rice varieties, the shape, colour and size of the lesions are also different. Therefore, the common rice leaf blast is usually divided into the following four types: chronic type, acute type, white spot type and brown spot type, as shown in Figure 3. Through scientific methods, several pictures of different types of rice blast were collected, including different degrees and types of disease conditions.

Then, the pictures are uniformly processed initially, so that the leaves occupy the entire picture, and each picture is about 600 pixels.



(a) Chronic type *(b) Acute type* *(c) White spot type* *(d) Brown spot type*

Figure 3: Common types of rice leaf blast

In order to effectively achieve the segmentation of the image target area and the background, it is necessary to select and transform the rice leaf image. This study extracts a special set of image features from images based on the RGB colour space.

Starting from the RGB colour feature information of the pixels in the normal area and the lesion area, an array is established to store the classification values of the pixel points of the sample image. If the pixel is a lesion, the classification result is set to 1, and if it is other background colours, it is set to 0. The above image features are extracted and a training sample array is generated, which are used as the feature values of the 1 and 0 sample points of the classification result respectively, and are used to train the BP neural network. Then use the trained neural network model to classify all the pixels in the image to complete the image segmentation.

3.2 Image Feature Extraction

From the above, the extraction of image features is the source of training samples of BP neural network. To achieve effective image segmentation and feature recognition, a series of processing needs to be performed on the original image to obtain a small and fine set of classification features.

This research is based on RGB colour space and uses the Matlab platform for image secondary processing and feature extraction. Specific steps are as follows:

① Enter the command in MATLAB, import the preliminary processing map of rice leaves, extract the colour components of R, G and B channels respectively and display them as grayscale images;

② Calculate the following combined colour component images: R, G, B, R-G, R-B, G-B, 2R-G, 2R-B, 2G-R, 2G-B, 2R-G+2B;

③ Compare the above colour component combination chart, manually select the colour component that can best reflect the colour difference between the diseased area and the normal leaf area.

In this study, 12 rice blast images were randomly selected for feature research, and some of the extracted feature images are shown in Figure 4 (1-3). It can be seen from the characteristics of the image that the difference between the diseased area and the normal area of rice leaf blast in the 2R-G+B component image is the largest, indicating that this colour component combination can effectively suppress the influence of uneven light intensity and noise. Therefore, this study selects the 2R-G+B colour components as the eigenvalues of the neural network training samples.

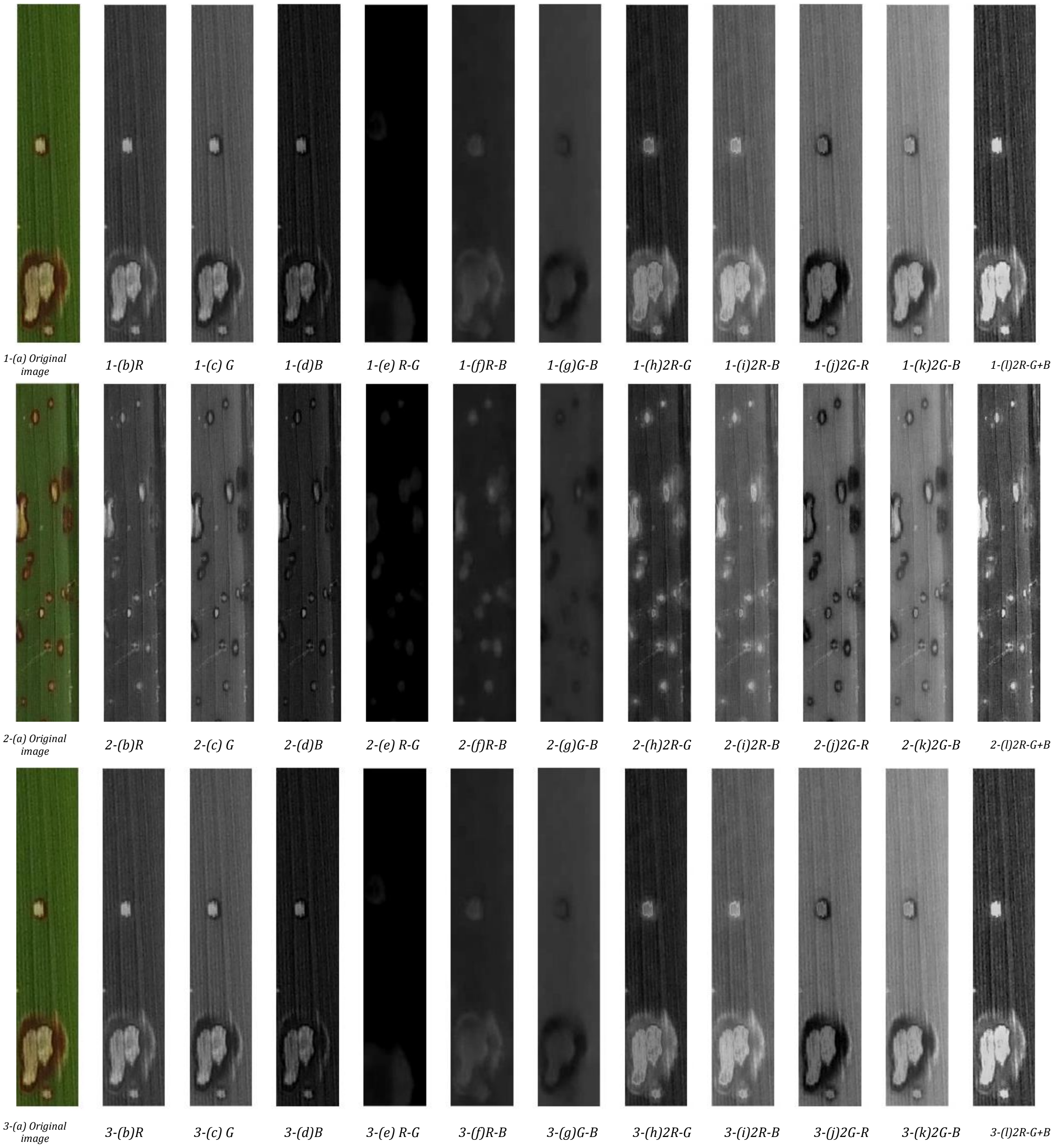


Figure 4: The original image and color component map of the sample

3.3. The Process of PSO-BP Image Segmentation based on Color Space Features

Aiming at the problem that the identification of rice blast is easily affected by the illumination background, blurred lesion boundary and other environmental factors, based on the current lack of research on the efficient and high-accuracy image segmentation method for rice leaf blast, this paper uses the existing BP neural network recognition method with excellent performance, and proposes improvements to its shortcomings to improve the accuracy and stability of image segmentation.

The 2R-G+B colour components is selected as the eigenvalues of the neural network training samples, and a PSO-improved BP algorithm is proposed for rice leaf blast spot segmentation system, which is used for the intelligent segmentation of rice blast images. The specific process is shown in the figure:

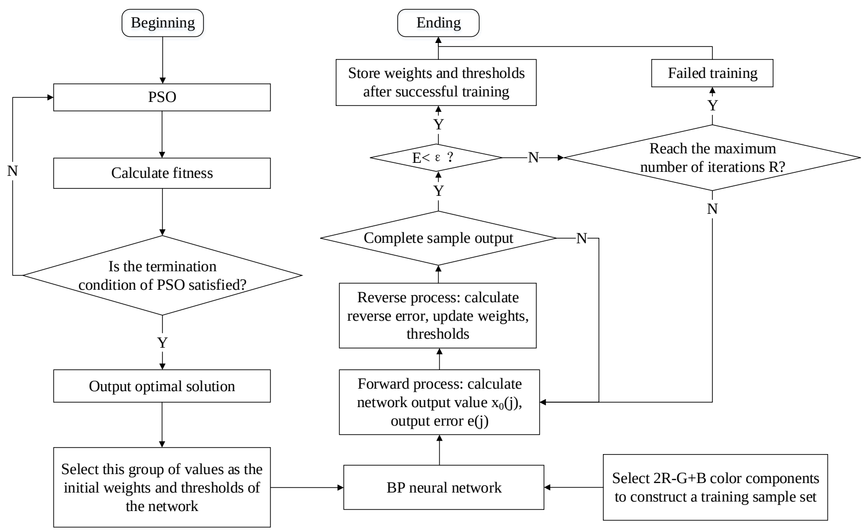


Figure 5: BP neural network model for PSO optimization

The specific steps of the rice leaf blast spot segmentation system based on colour space features and PSO improved back propagation algorithm is as follows:

① Execute PSO;

② Calculate the fitness value of each particle according to formula (5), and obtain the individual extreme value and the global extreme value;

③ If the fitness satisfies the condition or reaches the maximum number of iterations, the PSO ends, and the optimal solution corresponding to the optimal fitness is used as the initialization weight and threshold parameter of the BP neural network; otherwise, go back to step ①;

④ Use the 2R-G+B colour components obtained after the rice leaf image processing to construct the training sample set as the training input value of the BP neural network;

⑤ Execute the forward and reverse processes of the neural network to update the weights and thresholds;

⑥ If the error E meets the requirements, or reaches the maximum number of iterations R, the training is successful, otherwise, go back to step ⑥;

⑦ Store the corresponding weights and thresholds, and output the neural network for image segmentation of rice leaf blast.

This study uses the global search ability of PSO to obtain the global optimal solution of the network to optimize the BP neural network and speed up the network learning speed. At the same time, the 2R-G+B colour component is selected as the eigenvalue of the neural network training sample, which effectively suppresses the influence of uneven light intensity and external noise, and improves the robustness and segmentation accuracy of the neural network. Conversely, the shortcoming of PSO that is prone to the "premature" phenomenon is compensated by the local refinement ability of the gradient descent error backpropagation method [22].

4. Experimental Analysis of Rice Disease Spot Image Segmentation based on PSO-BP Neural Network Model

4.1 Image Preprocessing

According to actual experience, rice leaf blast can be divided into four types. In order to make this research system have good generalization performance, this topic selects these four types as research materials to study the method of disease spot segmentation based on neural networks.

The rice variety is CO39, and the camera was shot with a Canon EOS 200D II and a pixel of 20-25 million under non-glare conditions of natural light. Finally, 60 images of different types of rice blasts were obtained, which were saved in JPG format and preliminarily processed so that the leaves occupy the entire screen, and each image was about 600 pixels.

The image is then processed secondary, using MATLAB as the development environment. After extracting the grayscale image of each RGB channel of each image, select the 2R-G+B colour component grayscale image as the sample feature of the training group, and construct the corresponding sample category array for it. If the pixel is a diseased spot, the classification result is set to 1, and if it is other background colours, it is set to 0. In this experiment, 40 images of each rice blast were randomly selected as the training sample set, and the remaining 20 images were used as the test set. The final training set consists of 160 images, including 96,000 sets of data; the test set consists of 80 images, including 48,000 sets of data.

4.2 Construction and Training of PSO-BP Neural Network

The BP neural network constructed in this experiment consists of three layers: input layer, hidden layer and output layer. It has a strong nonlinear mapping ability and flexible network structure, and the optimization of PSO algorithm enhances the global optimization ability and has a faster iteration speed. Therefore, the use of PSO-BP neural network to construct a rice image segmentation system has a strong advantage over existing methods.

This system uses the global search ability of the PSO algorithm to obtain the global optimal solution of the fitness function, that is, to obtain some optimal initialization parameters of the neural network. After that, it is necessary to determine the number of neural network nodes: from the previous section, the neural network selects 2R-G+B colour components as input features and determines that the number of nodes in the input layer d is 1, and the number of nodes in the output layer is 1. The number q of hidden layer nodes is calculated to be 7 according to formula (6):

$$h = \sqrt{d+l} + q, \tag{6}$$

where h is the number of hidden layer nodes, d is the number of input layer nodes, l is the number of output layer nodes, and q is an adjustment constant between 1 and 10.

At the same time, the maximum number of iterations of the neural network is set to 3000, and the required training accuracy is set to 10e-5. Input the training set obtained after preliminary processing and secondary processing into the neural network, and then use the weights, thresholds and the above parameters optimized by the PSO algorithm as the initialization parameters of the BP neural network for training, and wait for the output neural network.

4.3 Analysis of Training and Testing Results

The training effect of the PSO-BP neural network in the previous step can be shown by the error convergence curve in Figure 6. It can be seen that the PSO-BP neural network has reduced the error to the required accuracy of 10e-5 at the 13-th iteration, and obtained a very good error accuracy of 2.1655e-06. This shows that the PSO algorithm can effectively improve the shortcomings of the BP neural network which is easy to fall into the local minimum value, improve the stability of the BP neural network and improve the image segmentation performance.

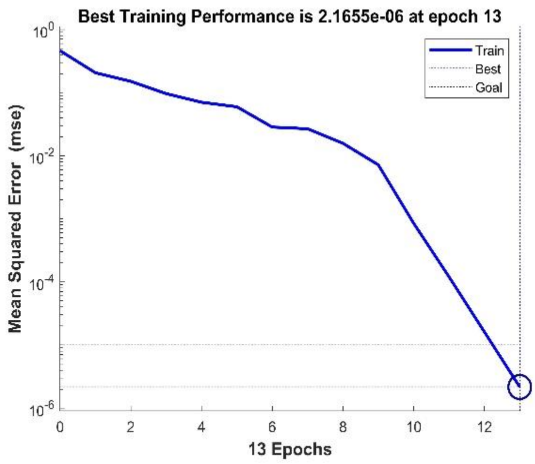
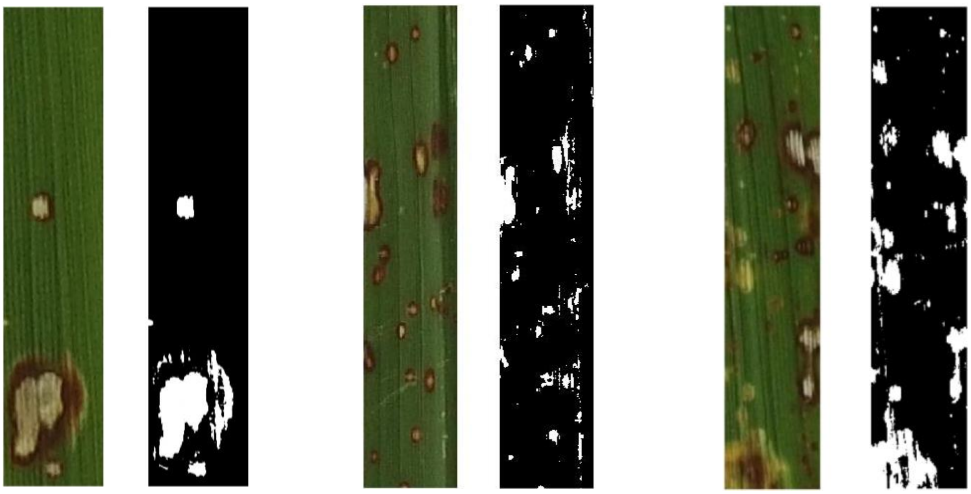


Figure 6: Error convergence curve of PSO-BP neural network

The 80 images and 48,000 sets of data obtained after correlating various types of pictures of rice leaf blast were used as test samples to input the PSO-BP model trained from 160 images and 96,000 sets of data to segment the images of rice disease spots. The obtained partial image segmentation effect is shown in Figure 7 (1~3).



1-(a) Original image *1-(b)GA-BP* *2-(a) Original image* *2-(b)GA-BP* *3-(a) Original image* *3-(b)GA-BP*

Figure 7: Application effect of test sample lesion recognition and segmentation

At the same time, it is necessary to use scientific methods to judge the effect of image segmentation. Here we use the statistical method, Mean Absolute Differences (MAD for short), to count the similarity between the original image of the rice disease spot and the image segmented by the PSO-BP model, as shown in Table 1 [23]. It can be seen that the similarity between the lesion segmentation images of the four leaf blast types and the original image is more than 91%, and the average can reach 93.97%.

The excellent segmentation effect is inseparable from the selection of the 2R-G+B colour components of the image as eigenvalues. At the same time, the similarity of chronic leaf blast and white spot leaf blast was low, which may be due to the high influence of light and noise. In general, using the 2R-G+B colour components as the input features of the PSO-BP model can achieve a good classification effect and effectively improve the accuracy and stability of image segmentation.

Table 1. Segmentation effects of four types of lesions

Type code of leaf plague	Category of leaf plague	Minimum similarity	Maximum similarity	Number of images
1	Chronic type	91.98%	94.29%	20
2	Acute type	95.12%	97.23%	20
3	White spot type	90.05%	92.31%	20
4	Brown spot type	93.01%	97.75%	20

4.4 Comparative Analysis with other Rice Image Segmentation Algorithms

To verify the effectiveness and practicability of the PSO-BP method based on the 2R-G+B colour component, the experimental results of this method are compared with threshold segmentation method, region segmentation method and neural network segmentation. The experimental results will be random, so various rice image segmentation methods are used to conduct multiple sets of experiments to increase the reliability of the results. The experimental results are shown in Table 2 and Figure 8.

Table 2. Comparison of results of different image segmentation methods

Method	Mean value of segmentation similarity (%)			
	Group 1	Group 2	Group 3	Group 4
Threshold method	54.24	51.35	58.75	55.32
Regional method	53.26	51.26	55.78	56.98
BP network model	81.25	83.14	86.75	85.12
PSO-BP network model	93.14	96.18	91.18	95.38

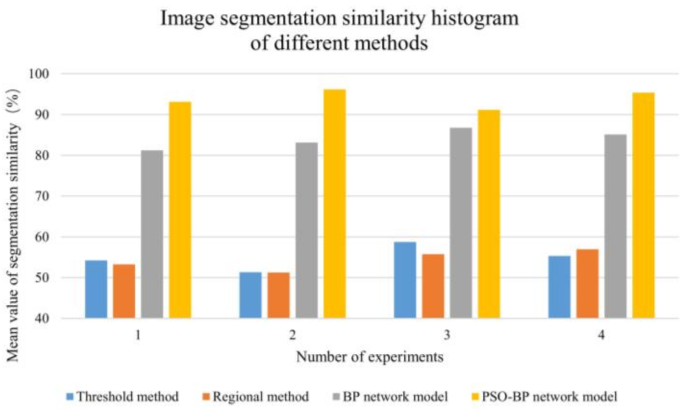


Figure 8: Similarity of trial segmentation

The analysis results in Table 2 can be obtained: the PSO-BP image segmentation method proposed in this paper obtains the highest segmentation similarity. In contrast, it can be seen that since the traditional threshold method is sensitive to noise and has no obvious difference in grayscale, while the regional method is prone to over-segmentation of the image, the segmentation similarity of these two methods is not high. The average was 54.92% and 54.32% respectively. The neural network segmentation method has better self-learning ability and better fault tolerance, so the segmentation accuracy is high. The BP neural network segmentation similarity is above 84.07%, but the segmentation similarity is still not ideal. Compared with the BP neural network, the BP model optimized by the PSO algorithm has a certain improvement in accuracy. This is not only because the PSO method improves the shortcomings of the BP neural network which is easy to fall into the local minimum value, but also because the most suitable colour component 2R-G+B is extracted as the eigenvalue of the neural network. Therefore, the best segmentation effect can be obtained, which greatly improves the stability of the algorithm. In the end, the average similarity can reach 93.97%, which can increase the similarity by 39.65% compared with other methods.

5. Conclusions

Under the background of a lack of research on the segmentation of rice leaf blast spots by the neural network, this paper extracts the 2R-G+B colour component of images based on RGB colour space as the input feature of the neural network, and uses the PSO algorithm to optimize the parameters of BP neural network, and then trains and tests the BP neural network. Compared with the existing image segmentation methods, the conclusions are as follows:

(1) Through experimental tests, it is verified that the PSO improved BP method can achieve an average image segmentation similarity of 93.97%. This has obvious advantages over other existing image segmentation methods, and also provides an effective new method for the existing rice leaf blast image segmentation technology.

(2) This study innovatively combines the 2R-G+B colour components as the input features of the neural network, which effectively reduces the influence of interference such as illumination and noise, and improves the accuracy of neural network classification and the robustness of the system. The correct rate of fault classification in this paper is as high as 96.18%.

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