Hyperspectral Recognition and Early Warning of Rice Diseases and Insect Pests Based on Convolution Neural Network

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Abstract. The traditional method of disease and pest recognition uses SVM to classify and recognize the image. Because of the large training convergence error, the recognition accuracy is not high. In view of the above problems, the paper studies the method of rice hyperspectral pest identification and early warning based on convolution neural network. By reducing the dimension of the collected spectral image, we can get more image information and extract image features. Based on alexnet, the structure of convolutional neural network is designed. The recognition database was established by collecting the spectrum images of rice diseases and insect pests, and the convolution neural network was trained by transfer learning, so as to realize the recognition and early warning of rice diseases and insect pests. The experimental results show that the convergence error of the method based on convolution neural network is small and the recognition accuracy is higher.

Keywords: Convolution neural network · Rice diseases and insect pests · Hyperspectral imaging · Recognition and early warning methods

1 Introduction

For agricultural production, the outbreak of crop diseases and insect pests has a great impact on the yield. However, the traditional detection methods mainly rely on personal experience and visual observation of the traditional methods of pest control, with high rate of misjudgment and poor real-time performance, which can not meet the needs of pest control. It is a new demand for the development of agriculture to find an accurate, fast, efficient and automatic method for identification and detection. With the development of information technology, image processing technology has been applied to the detection of crop diseases and insect pests, which has become one of the main ways to replace artificial identification. In addition, through the combination of artificial intelligence and other emerging knowledge, the detection of crop diseases and insect pests has the accuracy, convenience and intelligence, which brings a lot of convenience for the detection of crop diseases and insect pests, and increases the timeliness [1].

Hyperspectral resolution remote sensing is a technology to obtain a lot of very narrow spectral continuous image data in the visible, near infrared, mid infrared and thermal infrared band of electromagnetic spectrum, which can be used for ground

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object recognition. As a new technology, hyperspectral remote sensing develops rapidly, and its application in agriculture has also been studied deeply. Plant reflectance is related to physiological and biochemical characteristics, light, background and surrounding environment. The spectral characteristics of plants in visible and near-infrared bands are related to the growth and morphological characteristics of specific plant species [2]. After crops are damaged by diseases and insect pests, the leaf color, leaf and plant properties, physical structure, pigment content, etc. will change, which may lead to changes in spectral information. Hyperspectral technology provides a potential solution for the detection of the degree of pests.

Convolutional neural network is a variety of multi-layer perceptron. Compared with general neural network, convolutional neural network can directly process the two-dimensional matrix of image, and has outstanding performance in image processing [3]. Based on the above analysis, this paper will study the hyperspectral recognition and early warning method of rice diseases and insect pests based on convolution neural network.

2 A Method of Hyperspectral Recognition and Early Warning of Rice Diseases and Insect Pests Based on Convolution Neural Network

2.1 Rice Hyperspectral Dimensionality Reduction

In order to realize the hyperspectral recognition and early warning of rice diseases and insect pests, this paper uses the high-resolution spectral imaging system of UAV to collect the rice spectral image of the object area. After the rice spectral image is collected, because of the large amount of spectral data information collected, each spectral curve can be regarded as high-dimensional vector information, and multiple spectral curves constitute a high-dimensional vector space. In order to obtain the detail data of hyperspectral image, the dimension of hyperspectral image is reduced.

The multiscatter correction of hyperspectral image is carried out before dimension reduction. Multiple scattering correction is mainly to eliminate the scattering effect caused by the uneven distribution of particles and particle size. It can effectively eliminate the shift and shift of a line caused by the scattering effect between samples and improve the signal-to-noise ratio of the original absorbance spectrum. The calculation formula of multiple scattering correction is as follows [4]:

$$\begin{cases} \bar{x} = \dfrac{1}{n}\sum_{i=1}^{n} x_i \\ x_i = a_i + \bar{x} b_i \\ (x_i, MSC) = \dfrac{x_i - a_i}{b_i} \end{cases} \tag{1}$$

In the above formula, $\bar{x}$ is the average spectrum,x_i is the collected hyperspectral image, n is the number of images, a_i is the translation amount of hyperspectral curve, b_i is the relative offset coefficient, (x_i, MSC) is the corrected spectrum. After the hyperspectral correction of rice, in order to eliminate the measurement impact caused by spectral rotation, derivative algorithm is used to deal with Hyperspectral [5]. The derivative is calculated as follows:

$$\frac{dy}{d\lambda} = \frac{q_j - q_i}{\Delta\lambda} = \frac{q_j - q_i}{j - 1} \tag{2}$$

In the above formula, q is fluorescence intensity, spectral wavelength difference $\Delta\lambda$, and hyperspectral wavelength i, j. After the hyperspectral dimension reduction processing, through the dimension reduction processing can synthesize all aspects of rice Hyperspectral Information, and make the information not overlapping. In this paper, wavelet transform is used to reduce the dimension of rice hyperspectral.

The function $\psi(t)$ of the basic wavelet is shifted ε, and the inner product operation is ξ performed with the signal $x(t)$ to be analyzed at different scales [6]:

$$WT_x(\xi, \varepsilon) = \frac{1}{\sqrt{\xi}} \int_{-\infty}^{+\infty} x(t)\psi * \left(\frac{t - \varepsilon}{\xi}\right) dt \tag{3}$$

In the above formula, $WT_x(\xi, \varepsilon)$ is the hyperspectral image after dimension reduction processing. After the hyperspectral processing of rice, the characteristics of the hyperspectral skin image are extracted.

2.2 Extraction of Hyperspectral Image Features

In this paper, vegetation index is used to extract spectral features. Vegetation index is a combination of two or more wavelengths of surface reflectance to enhance a specific feature or detail of vegetation. According to the information of spectral characteristics of plants, for the main chemical components of plant leaves, pigment, water, carbon and nitrogen, we can extract broad-band green degree, narrow-band green degree, light utilization rate, canopy nitrogen, drought or carbon decay, leaf pigment, canopy water content. These vegetation indexes can simply measure the number and growth status of green vegetation, chlorophyll content, leaf surface canopy, leaf cluster, canopy structure, the utilization efficiency of vegetation for incident light in photosynthesis, the relative content of nitrogen in vegetation canopy, the carbon content of cellulose and lignin in dry state, the pigment related to stress in vegetation, and the canopy The real-time diagnosis of vegetation growth can be realized by monitoring the content of water content and so on. The available vegetation index is shown in the table below [7] (Table 1).

Table 1. Practical vegetation index

Serial number	Name	Descriptions
1	NVDI (Normalized Difference Vegetation Index)	The difference between the scattering of green leaves in the near-infrared band and the absorption of chlorophyll in the red band was increased
2	Simple Ratio Index	The ratio of the scattering of green leaves in the near-infrared band to the absorption of chlorophyll in the red band
3	Enhanced Vegetation Index	Enhanced NVDI to address the effects of soil background and atmospheric aerosols on dense vegetation
4	Atmospherical1y Resistant Vegetation Index	Enhance NVDI to better solve the effects of atmospheric scattering
5	Sum Green Index	Sensitivity of global light scattering in the green band range to canopy clearance
6	Photochemical Reflectance Index	It is useful for estimating leaf carotenoids (especially yellow pigment), leaf stress and carbon absorption efficiency

The convolution neural network structure is designed after extracting the curve features of rice hyperspectral image.

2.3 Structure Design of Convolution Neural Network

The structure of convolutional neural network designed in this paper is similar to the classical model alexnet, which is a very typical convolutional neural network model. Alexnet is an eight layer network model, mainly composed of one input layer, five volume layers, three full connection layers and one classification layer. In addition, the first five convolution layers and the first two full connection layers will be followed by the activation layer, using the activation function relu. The activation function is as follows [8].

$$f(x) = \max(0, x) \tag{4}$$

In the process of feature extraction of relu function, the amount of calculation is less, and as an activation function, it will affect some neurons, enhance the sparsity of neural network, speed up the convergence of neural network, and reduce the dependence between parameters. In the convolution neural network designed in this paper, the first activation layer and the second activation layer will be followed by the normalization layer. The specific parameters are shown in the table below [9, 10] (Table 2).

Table 2. Structure parameters of convolutional neural network

The sequence number of the layer	The type of layer	The parameters of the layer
1	Convolution layer	11 * 11 * 3 * 64
2	Convolution layer	5 * 5 * 64 * 256
3	Convolution layer	3 * 3 * 256 * 256
4	Convolution layer	3 * 3 * 256 * 256
5	Convolution layer	3 * 3 * 256 * 256
6	Fully connected layer	4096
7	Fully connected layer	4096
8	Fully connected layer	1000
9	Classification layer	—

In the above table, the parameters of the accumulation layer have 4 dimensions, which are expressed as $n_1 * n_2 * n_3 * n_4$, where $n_1 * n_2 * n_3$ is the core size, and n_4 is the number of cores. For the all connected layer n, the number of neurons in its parameters represents the number of neurons. The classification layer here is of softmax type and has no parameters.

In the convolution neural network designed in this paper, the size of the input image is 224 * 224 pixels. The size of convolution core of the first layer convolution layer is 11 * 11 pixels, the step length is 4, and the number of convolution cores is 64. Therefore, after calculation, $\frac{224-11}{4} + 1 \approx 55$, the size of the characteristic image obtained by the first layer convolution layer of 224 * 224 pixels is 55 * 55 pixels, and the number of characteristic images is 64. After the processing of the activation layer and the normalization layer, the characteristic image of 55 * 55 pixels is input to the first pooling layer. $\frac{55-3}{2} + 1 = 27$, the size of the first pooling layer is: 3 * 3 pixels, step size is 2, so after calculation: the size of the feature map obtained through the pooling layer is 27 * 27 pixels. Next, the characteristic image of the 27 * 27 pixel is input into the second convolution layer. The convolution kernel size of the second convolution layer is: 5 * 5 pixels, the step size is 1, two zeros are added around, and the number of convolution kernels is 256. Therefore, $\frac{27-5+4}{1} + 1 = 26$, after calculation, the size of the characteristic graph obtained through the second layer is 26 * 26 pixels, and the number of characteristic graphs is 256. The convolution kernel of the second convolution layer is mainly used to extract the texture information of the visible image. After that, the feature map with the size of 26 * 26 pixels is input to the second pooling layer. The size of the second pooling layer is 3 * 3 and the step size is 2, so after calculation, $\frac{26-3}{2} + 1 \approx 13$, the output size of the second pooling layer is 13 * 13 pixels. Similarly, the third, fourth and fifth convolution layers represent the high-dimensional information of the image. Finally, the feature map with the size of 6 * 6 pixels and the number of 256 is input into three fully connected layers, and finally through the softmax classification layer, the classification results can be obtained. After the structure of convolution neural network is determined, the convolution neural network is trained by using the data set of diseases and insect pests [11, 12].

In this paper, migration learning is used to train the designed convolutional neural network. The training process is as follows:

(1) Select the convolution network which has been trained on the Imagenet dataset;
(2) The mature network is used to extract the features of the image samples, and the 4096 dimension features are extracted from the full connection layer of the 7th layer as the input of the small-scale network to train the small-scale network;
(3) The mature network is used to extract the features of the image samples, and the 4096 dimension features are extracted from the full connection layer of the sixth layer as the input of the small-scale network to complete the small-scale network training;

The trained convolution neural network outputs the recognition results of rice diseases and insect pests according to the fitting results of Gauss function according to the rice diseases and insect pests collection in the recognition database. After the convolution neural network is designed and trained, the rice disease and pest identification database is established.

2.4 Establish the Database of Disease and Pest Identification

In order to accurately identify rice diseases and insect pests with hyperspectral data, it is necessary to establish a database of rice diseases and insect pests identification. Before the establishment of the database, the healthy and pest affected rice should be identified first.

Qualitative and quantitative description of "healthy leaves" standard:

(1) There is no insect bite, crawling trace and mechanical damage on the surface of leaves;
(2) The shape of leaves is complete, and there is no sudden change and wilting of leaves caused by external environmental factors such as overheating and supercooling and internal physiological structure mutation;
(3) The SPAD value of chlorophyll was between 35.0 and 50.0;
(4) The net photosynthetic rate was 10.0–30.0, $\mu mol^{-2} \cdot s^{-1}$, CO_2;
(5) The F_v/F_m value of chlorophyll fluorescence parameter is between 0.80 and 0.84;
(6) The growth and development of the whole plant is neat, without excessive growth, and the leaf has no large or small protuberances.

"Leaves with diseases and insect pests" refers to leaves with obvious symptoms of diseases and insect pests or artificially inoculated with diseases and insect pests. After the difference between the rice affected by diseases and pests and the healthy rice is clarified, a discrimination database with the structure shown in the figure below is established (Fig. 1).

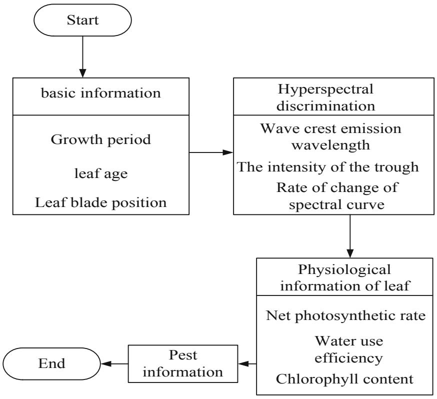

Fig. 1. Identifies the database structure

After the establishment of the discrimination database, the hyperspectral images of rice samples with different diseases and insect pests are collected and input into the database as the recognition standard to realize the recognition and early warning of rice diseases and insect pests.

2.5 Recognition and Early Warning of Rice Diseases and Insect Pests

After dimension reduction and other preprocessing, the collected hyperspectral image of rice is used in the classification layer of convolution neural network to judge whether the rice corresponding to the image is affected by diseases and pests by Gaussian function fitting.

If the hyperspectral point set obtained after dimension reduction is (x_i, y_i), the spectral curve of rice diseases and insect pests is fitted according to Gaussian function.

$$y = \frac{A_0}{\sqrt{\frac{\pi}{2}} \bullet \omega_0} e^{-2\frac{(x-\mu_0)^2}{\omega_0^2}} \tag{5}$$

In the above formula, A_0 is the area of the peak, μ_0 is the position of the peak and ω_0 is the parameter representing the half peak width. The convolution neural network outputs the fitting result of Gauss function after several data iterations. The fitting threshold value of Gaussian function is set as ± 0.1, and the curve whose fitting value is within the threshold value is determined to the rice disease corresponding to the hyperspectral curve of the sample. To complete the identification of rice diseases and insect pests. According to the results of rice diseases and insect pests identified, early warning of rice diseases and insect pests was carried out. So far, the research on Hyperspectral recognition and early warning method of rice diseases and insect pests based on convolution neural network has been completed.

3 Test Experiment

Accurate recognition and early warning of rice diseases and insect pests is an important prerequisite to ensure rice yield. Therefore, this paper studies the hyperspectral recognition and early warning method of rice diseases and insect pests based on convolution neural network. In order to test the performance of this method, this section will design a comparative experiment to complete the performance test of this research method.

3.1 Experiment Content

The experimental area is divided according to different growth periods of rice, and the hyperspectral images of rice collected in the corresponding area are used as the experimental data of this experiment. In order to ensure the authenticity and reliability of the experimental results, the diseases and insect pests of rice in the experimental area were checked manually. The test results are taken as the reference for the experimental test data.

The experimental group is based on support vector machine, and the experimental group is based on convolution neural network. There were two groups in the experiment. The convergence errors of the two methods were compared when using the same sample training set, and the recognition accuracy of healthy rice and pest rice was compared in the practical application. Through the comparison of the above two indicators to evaluate the advantages and disadvantages of the comparison group and the experimental group. Record the experimental data of two experiments, and analyze the experimental results.

3.2 Experimental Spectral Image Preprocessing

In view of the large spatial resolution of the original hyperspectral image collected by UAV, before rice pest identification, the original image is simply rough cut. After cutting, the spatial resolution of the spectral image is reduced to 400–900 pixels in width and 200–800 pixels in height. The spatial resolution histogram of the spectral image after rough cutting is shown in the figure below. According to the histogram, the spectral image width is mainly concentrated near 200 pixels, and the height is concentrated near 600 pixels. Therefore, the average hyperspectral image size is normalized to 200×600 pixels to achieve clearer experimental results (Fig. 2).

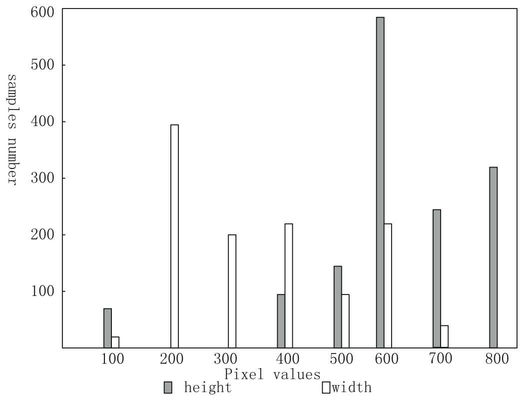

Fig. 2. Width and height histogram of hyperspectral image after rough cropping

After image preprocessing, two experiments were carried out. The data of the two experiments are analyzed and the experimental conclusion is obtained.

3.3 Experimental Results

The convergence error test results of the two methods of the experimental group and the comparison group using the same training set are shown in the figure below.

Compared with the support vector machine and convolution neural network used in the experimental group, the smaller the convergence error in training, the higher the classification accuracy in practical application, and the more stable the performance of the applied method.

It can be seen from the analysis in Fig. 3 that with the increase of training time, the curve decline speed of the control group gradually decreases, and finally tends to be

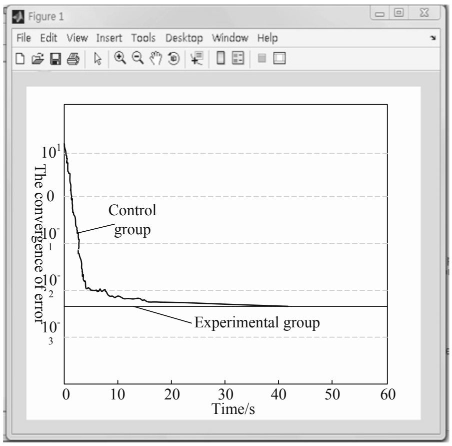

Fig. 3. Error curve during training convergence

flat. E. The results show that the convergence error of SVM is reduced and the classification accuracy tends to be stable. But compared with the experimental group, the convergence speed of the error curve o is slower than that of the control group. According to the theoretical results of training convergence error experiment, the classification accuracy is tested.

The identification results of the two groups of rice pest identification and early warning methods of the comparison group and the experimental group are shown in the table below (Table 3).

Table 3. Identification results of the two methods/strain

Rice growing period	Actual number of plants	Experimental group identification results	Contrast group recognition results
Seedling stage	46	46	53
Tillering stage	15	15	29
Jointing stage	34	34	21
Booting stage	22	21	9
Filling stage	42	40	24

It can be seen from the above table that in different rice growth periods, the number of plants identified by the comparison group method is significantly different from the real number of plants, while the number identified by the experiment group method is less different from the real number. Combined with the error curve in Fig. 3, The application of convolution neural network can improve the accuracy of pest identification, and the results of each stage have strong advantages. In conclusion, the aluminum network based on convolution neural network is better.

4 Concluding Remarks

It is very important to find rice diseases and insect pests in time and accurately for rice planting and development. The traditional identification method of rice diseases and insect pests relies too much on artificial and has low efficiency. Therefore, this paper studies the method of hyperspectral recognition and early-warning of rice diseases and insect pests based on convolution neural network. Through the contrast experiment with the method of recognition and early-warning of rice diseases and insect pests based on support vector machine, the performance of the method studied in this paper is better.

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