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Plant Disease Detection Method Based on Computer Vision Technology

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Abstract: Aiming at the basic problems that plague crop growth in traditional agriculture, a method of identifying weeds using machine vision and applying chemical agents with selective variables was proposed. Collected visible light images of plant diseases, pre-processed the images, segmented the images using an instruction value composed of R, G, and B color components as a threshold, and wrote an algorithm to misjudge the background image after segmentation as a background. Pixels were used for information recovery; according to the analysis of the change in color characteristics after the occurrence of lesions, sample lesions were extracted using the two color features of G / R and G / B; the results of the damage degree of diseased leaves measured using image processing technology The analysis was performed and compared with the results of the plant disease degree determined by the paper card method in the traditional classification standard. The experiments show that the selected 7 characteristic parameters are used as the input of the neural network, and the number of types of cucumber leaf diseases that need to be identified is used as the output to build a BP neural network model. By adjusting various parameters in the BP neural network, the parameters with the best recognition effect are selected to train the network. The trained network is used to identify the plant disease image. As a result, the disease can be identified well, and the recognition rate is 93.5%.

1. Introduction

Crop disease refers to the damage to normal physiological functions of crops due to infection by other organisms or unsuitable environmental conditions. After the disease of a crop, its metabolism will change to a certain extent. This change can cause changes in the crop cells and the external appearance of the crop, making the crop behave abnormally. Such external changes are called symptoms [1]. There are two types of crop diseases: invasive and non-invasive diseases. The former is caused by the infection of pathogenic microorganisms, such as rust of crops: the latter is caused by unfavorable environmental conditions, such as deficiencies caused by nutrient deficiency, pollution caused by harmful gases in the environment Sexual diseases and weed diseases caused by the weed's wild growth. Most of the diseases of crops can cause systemic symptoms, but the main harmful parts of crops are different because of the different pathogens that cause them [2-3]. Although the symptoms are diverse, most of the disease symptoms will be more or less manifested on the leaves of crops, which will cause changes in the color, shape and texture of the leaves and the distribution of disease spots and streaks. Therefore, this provides the possibility for the non-destructive detection and diagnosis of crop diseases using computer vision technology [4-5]

Foreign research on weed recognition has begun since the 1980s, and a lot of research has been done on computer vision-based weed recognition technology: Singh, V. et al. Five simple dimensionless form factors, such as shape and roughness, were evaluated, and these form factors were considered to be very effective for identifying plants without the need for high-speed computers and large storage capacity [6-7]. Golhani, K, et al. Used plant texture information to identify two grass weeds and two broad-leaved weeds, and found that the uniformity, inertia, and angular quadratic product ratio of texture feature quantities obtained from the gray level co-occurrence matrix When the plants are divided into grasses and broad-leaved species, the accuracy is 93% and 85%, but when the four grasses are completely separated, the accuracy is between 30% and 77% [8-9]. Weed recognition technology based on machine vision has become one of the research hotspots abroad, and there have been special discussions in international ASAE, SPIE, and precision agriculture conferences [10]. China's machine vision technology started late, and its application in weed recognition is still in the exploratory stage. Zhang, Y et al. Used computer processing technology to analyze the characteristic amount of weeds at the seedling stage of corn, and the bimodal method was used to filter out the soil background. Weeds were identified based on the projected area, leaf length, and leaf width, and the location and growth of the weeds were determined. Condition [11].

It is possible to use computer vision and image processing technology to identify and control weeds in crops. Apply herbicides in weed-growing areas, and use no herbicides in weed-free areas, or apply small doses of herbicides to the entire plot and normal doses of weeds to the weeds. Different controls adjust the spraying of different medicaments and classify and eliminate them, so as to achieve fine spraying and variable input. Relevant experts also demonstrated that it is feasible to use a machine vision system composed of a large number of sensors to identify weeds. In addition, the results of herbicide spraying comparison tests conducted by foreign scholars show that: assuming a uniform spraying of herbicides at a rate of 100%, The variable spraying method with intermittent spraying of the herbicide when the nozzle is closed can save 10 % of herbicide, and the variable spraying method of spraying different doses of herbicide according to the weed density can save 45% of herbicide [12]. This not only improves the scientific and technological level of agricultural development and reduces grass damage, but also has very important practical significance for protecting the environment and saving input costs.

This thesis combines the diagnostic theory of plant diseases with modern information technology through this thesis. Through the interdisciplinary research, the exploratory research on the diagnosis of plant diseases and pathogenic fungi is carried out. For the identification of plant diseases, on the one hand, for leaf diseases with typical symptoms, based on image information of the diseases in the visible light range, an automatic recognition system for cucumber leaf diseases based on computer vision was constructed; hyperspectral imaging using a combination of images and spectra Technology, to achieve the diagnosis of cucumber leaf diseases. On the other hand, for diseases with insignificant symptoms or root diseases, BP neural network technology is introduced, and neural networks are used to identify the picture of diseases and insect pests in microscopic details that cannot be perceived by the human eye, realizing the early stage of Cucumber leaf spot disease. Detection.

2. Proposed Method

2.1 Plant Disease Detection

(1) BP neural network

There are multiple layers of neurons in the neural network that are connected to each other. When the neurons in the previous layer are excited and excited, they will pass to the neurons connected to the next layer. After the potential of the neuron is stimulated to a certain value, it is activated. The most widely used and effective algorithm in neural networks is the Error Back Propagation Training, which is the BP network algorithm.

BP network is generally divided into three layers: input layer, hidden layer and output layer, as shown in Figure 1. When the mathematical expression relationship of the input and output data is unknown, it can clarify the mapping relationship between them through autonomous learning and store it in the network. Backpropagation is generally used in BP networks to learn parameters, and to minimize network errors, the fastest gradient information is usually used to find parameter combinations.

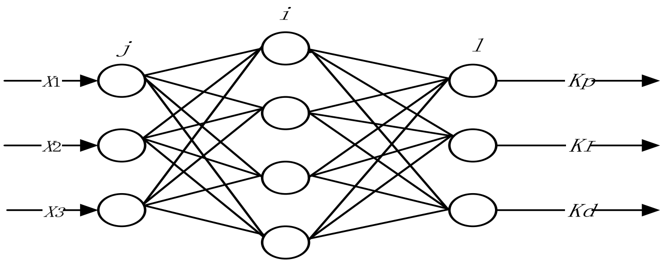

Figure 1. 3-layer BP neural network model

(2)The BP network model can be divided into four parts: input-output model, stimulus function model, error calculation model, and self-learning model. Let the input signal be X_i and the output signal be Y_i. The connection weight between the input neurons i and j, i and i is W_{ij}, and the connection weight between the hidden neurons is T_{ij},, and f is a non-linear effect. Function, q is the threshold value of the neural unit, t_{pi} is the expected output value of the i neuron node, h is the learning factor, Θ_i is the calculation error of the output node i, O_j is the calculation output of the output node j, and a is the momentum factor.

Node output model:

$$Q_j = f(\sum W_{ij} \times X_i - q_j) \tag{1}$$

Hidden node output model:

$$Y_j = f(\sum T_{ij} \times Q_j - q_k) \tag{2}$$

The function model is the stimulus function, which is generally selected as the Sigmoid function. The value is continuously calculated in (0, 1):

$$f(x) = 1/(1+e^{-x}) \tag{3}$$

The error calculation model is a function representing the magnitude of the error between the output data and the expected value:

$$E_p = \sum (t_{pi} - O_{pi})^2 \tag{4}$$

The BP neural network in the learning process connects the weight matrix W_{ij} between the upper and lower nodes. The model that is continuously learned according to the error is:

$$\Delta W_{ij}(n+1) = h \times \Theta_i \times O_j + a\Delta W_{ij}(n) \tag{5}$$

(2) Optimization of BP network model

The optimization of the learning factor h automatically adjusts the learning factor by changing the step size according to the size of the output error. Achieve reduced or accelerated convergence.

$$h = h + a(E_p(n) - E_p(n-1)) / E_p(n) \tag{6}$$

Where a is the step size of the adjustment, and the value range is [0,1].

The number of hidden nodes is one of the key factors affecting network performance. Too few hidden nodes will reduce the network's fault tolerance. Too many hidden nodes will increase the learning time of the network. In serious cases, the network will fail to converge. Generally, some linearly related hidden nodes are selectively deleted. The deletion of nodes is generally based on certain criteria. For example, the threshold and weight of a node to the next node fall within the range of ± 0.1 and ± 0.05. Then this node can be deleted.

2.2 Design of BP Neural Network for Cucumber Leaf Disease Recognition

(1) Color feature structure

First introduce color space, which is generally called color model in computer vision. It is the arrangement of colors in three-dimensional space. At present, the most commonly used color models in image processing are RGB color space and HIS color space.

RGB color space is the most basic color model in image processing. It is established on the basis of color matching experiments. The main idea of the RGB color space is that the human eye has three color-sensing cells: red, green, and blue. Their maximum photosensitivity falls in the red, blue, and green regions, respectively. The synthesized spectral response is the viewing curve. It can be inferred that any color can be formulated with three primary colors of red, green and blue. For the quantitative measurement of color, Grassman proposed the three-tone matching axiom. The three possible cases of color matching are shown in formulas (7), (8) and (9):

$$c[C] = n[N] + p[P] + q[Q] \tag{7}$$

$$c[C] + n[N] = p[P] + q[Q] \tag{8}$$

$$c[C] + n[N] + p[P] = q[Q] \tag{9}$$

[C] is the unknown color light, [N], [P], [Q] is the three primary color light, and c, n, p, q are the matching coefficients.

(2) Network model design

The input and output data in the BP neural network are determined based on the analysis of the research problem. Cucumber leaf disease recognition based on BP neural network, the input vector is the feature parameter extracted from the cucumber leaf disease feature, and the output vector is the corresponding cucumber disease category. In theory, to complete a non-linear mapping from input to output, as long as there are enough nodes in the hidden layer. Therefore, this paper chooses a 3-layer network to solve the problem of cucumber leaf disease identification.

The BP neural network was used to classify and identify the leaf diseases of cucumber. The hierarchical structure of the BP neural network was determined according to the effective parameters and the types of diseases. A suitable learning algorithm was designed to train the network, and finally the classification and recognition results were obtained. Network training requires a sufficient number of samples so that the connection weights between the neurons in the neural network can be better modified and the accuracy of the recognition can be improved.

For the eigenvalues, the difference between the eigenvalues will affect the accuracy of the network, causing large numerical information to eat up small information.In order to eliminate this effect, the input of the BP neural network using the S excitation function should be at f0,11 Between, so the normalization process of the feature vector is required, and the normalization formula is:

$$g(x,y)=\frac{2\left[f(x,y)-\min\ f(x,y)\right]}{\max\ f(x,y)-\min\ f(x,y)}-1 \tag{10}$$

Where *f (x, y)* is the original data set, min*f (x, y)* is the minimum matrix of each row, max*f (x, y)* is the maximum matrix of each row, and *g (x, y)* is normalized matrix.

Steps of BP network design for cucumber leaf disease recognition: Determine the number of input layer nodes the number of input layer nodes is the number of selected feature parameters. From the feature extraction and feature parameter analysis in the previous chapter, we know that there are 7 feature parameters selected, so the number of neuron nodes in the input layer is 7. The number of output nodes is determined.The number of output nodes is the number of categories that need to be classified.Because it is necessary to identify three leaf diseases of cucumber, such as leaf spot, early blight and gray mold, and diseases that do not belong to these three, the output is The number of layer neurons is 4. Determining the number of nodes in the hidden layer the choice of the number of nodes in the hidden layer is very important to the BP network, which determines the learning ability of the BP network. The number of nodes is too small, the network learning time decreases, the weights are inaccurate, and the network recognition rate is low. Too many nodes will increase the recognition accuracy, but the network training time will be too long. According to the results, the number of hidden layer nodes is determined based on the results and the error meets the requirements. When selecting the number of hidden layer nodes, general empirical formulas are commonly used for calculation, and the formula is as follows:

$$s=\sqrt{(0.43mn+0.11m^2+2.45n^2+0.72m+0.35n+0.45)} \tag{11}$$

Where n is the number of inputs, m is the number of outputs, and s is the number of hidden layers sought. In this paper, n is 7, m is 4, and the calculated s is 12. Therefore, the test range of the number of nodes in the hidden layer is 11.15.

3. Experiments

3.1 Experimental Data Set

The test samples were mainly cucumber leaves (also including a small amount of tomato leaves) stained with rust that favored warm and humid environments. The samples were taken from the self-testing experimental farm. During the experiment, 30 samples were collected from the experimental farm each time (20 of them were stained with rust and 10 were stained with leaf spot). A total of seven samples were collected.

3.2 Experimental Environment

Image processing and feature extraction are mainly performed on MATLAB 2014b. MATLAB is a combination of Matrix and Laboratory. It is a very powerful engineering language for data analysis, engineering and scientific drawing, digital image signal processing, graphical user interface design, modeling, and simulation development. .

3.3 Experimental Steps

Computer vision systems for plant disease detection using color images have been constructed to collect images of haw disease. The background of the field of view of the CCD camera is a test bench built with a blue flat plate. The leaves of plant diseases were placed on the experimental bench flatly, and were in the field of view of the CcD camera.

When you start collecting plant disease images, you first need them. Adjust the light intensity to only turn on the four fluorescent lamps used in the experiment, adjust the aperture and focus of the CCD camera to an appropriate setting, and fine-tune the camera's focus so that the image of the plant disease leaf sample can be clearly captured by the CC'D camera and collected through the image The card conversion and transmission are clearly displayed on the display of the industrial computer. For each leaf sample, the image is captured by a CCD camera, and plant disease information is obtained. These information are described using R (red), G (green), and B (blue) color spaces. The frame grabber inserted in the PCI slot of the industrial computer is used to receive, convert, and transmit this information. The three digital color signals of R, G, and B under the NTSC system from the CCD camera are received by the image acquisition card and converted into 8-bit color digital images, which are transmitted to the memory of the industrial computer and saved.

Based on the accurate segmentation of the lesion, the multivariate feature parameters of the lesion image are extracted, including the R mean, G mean, B mean, r mean, g mean, b mean, H mean, and I mean 9 color feature parameters such as S and mean, 5 texture feature parameters such as moment of inertia (or contrast), correlation, angular second-order moment (energy), inverse moment, entropy, etc., shape complexity, eccentricity, shape parameters, Four shape feature parameters such as circularity constitute the feature vector representing the lesion information, and a standardized digital image feature database of cucumber leaf diseases is established.

The function of the cucumber leaf disease automatic diagnosis system is to input the image of tomato leaf disease, use the constructed system to perform image preprocessing, lesion segmentation, and lesion feature extraction, and finally use the constructed disease pattern. Recognition algorithm to identify diseases.

4. Discussion

4.1 Training and Testing of BP Networks

(1) This paper uses the neural network toolbox in MATLAB software to implement the analysis and design of BP neural network. First, select training samples, and select 150 pictures of cucumber leaf diseases. The 7 feature parameters selected in Chapter 4 are used as the input of the BP neural network model, and the training sample feature values are shown in Table 1.

Table 1. Training samples of cucumber leaf disease recognition network

Energy	Moment of inertia	Correlation	Area	Roundness	Elongation ratio
0.1043	0.7435	1.7273	152	2.3452	1.1323
0.2912	0.4123	2.8910	122	2.4432	2.3412
0.0820	1.2341	1.2312	147	2.2341	1.2643
0.1535	0.7002	2.5453	326	2.7281	2.9832

Select "learngdm" as the learning function and the initial value of the learning rate as 0.05. The error performance function is the variance "mse" between the network output and the actual output. The target expected error is set to 0.01 and the maximum number of trainings is 2,000. Therefore, the condition for stopping training is to reach the expected error of the target or the maximum number of trainings. The neural network training was performed using the training samples of the crown leaf disease as input, and the test set was used for testing. The result is best when the hidden layer node is 12, the BP neural network model can reach a preset level, and the network error change graph can be shown in Figure 2 and reaches convergence after 146 iterations.

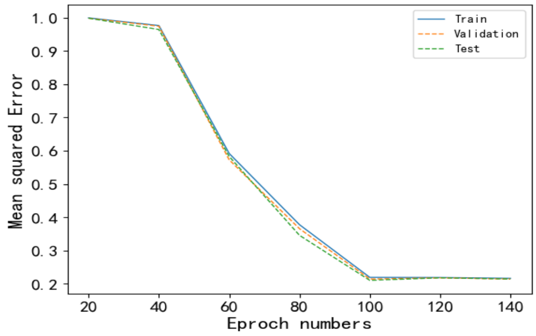

Figure 2. BP network convergence diagram

(2) In the cucumber leaf disease images collected in this paper, 200 images of each disease were selected, and 50 images of each disease were randomly selected as test samples. The recognition rate of the network reached 93.5%, and the other recognition rate was 90.3%. Although the number of iterations of the second network is less than the first one, considering the training times and relative errors of each network, this paper chooses the first BP neural network to realize tomato leaf disease recognition. The results of the neural network are shown in Figure 3.

Figure 3. Recognition results of cucumber leaf diseases

4.2 Identification of Plant Diseases and Insect Pests and Determination of Characteristic Parameters

Table 2. Sum of characteristic parameters in four directions

Groups	Contrast	Correlation	entropy	Smoothness	Kind
wheat	19.7537	3.574304	0.117287	2.596583	30.78095
Chenopodium acuminata	27.1069	3.294021	0.304866	2.662463	79.98601
Bowl of flowers	121.071	2.796139	0.098535	2.446524	25.86
Artemisia sojae	32.9454	3.032386	0.457598	2.731789	120.0498

(1)In the experiment, we compared the 2G-RB of the RGB color system, r, g, b of the rgb color system, and the co-occurrence matrix of the H and S gray bodies of the HIS color system. The human vision knowledge is applied to the machine vision system. The statistics of the HSI co-occurrence matrix are ideal texture features as shown in Figure 4. Twenty samples of wheat, quinoa, bowl bowl flower, sagebrush plant, prickly pear, verbena were selected for analysis, and their five characteristic parameters were extracted to determine the test data. Show.

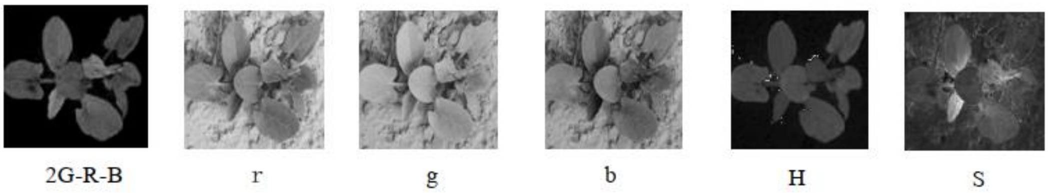

Figure 4. Plant gray image

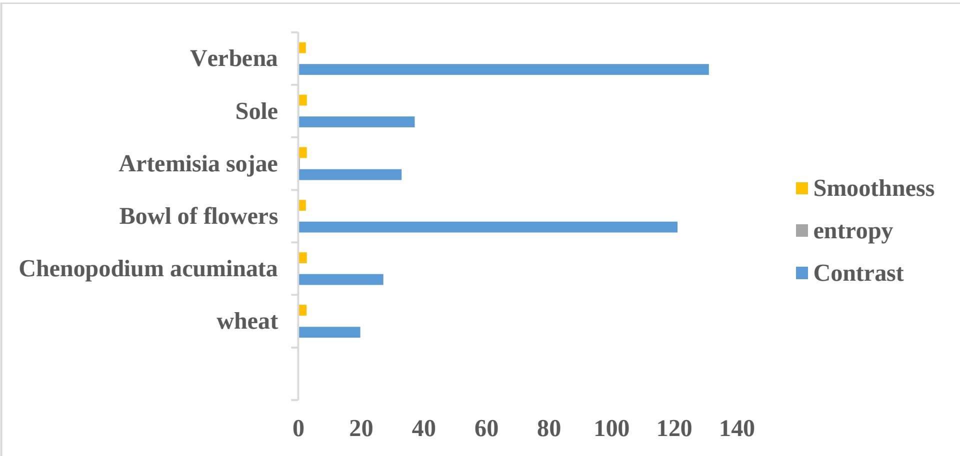

Figure 5. Comparison of characteristic parameters in different directions

(2) There are many algorithms that can be used for identification and classification, but different theories and methods are required for different objects and different purposes. Although the artificial neural network method has developed rapidly in recent years, it can adapt to more complex feature spaces and has many advantages such as self-learning. However, the algorithm complexity is high, and it must be implemented with high-speed parallel processing hardware systems. Starting from practical applications, considering the high real-time requirements of the weed recognition system, an improved nearest neighbor classifier is used in this subject for recognition classification as shown in Figure 6.

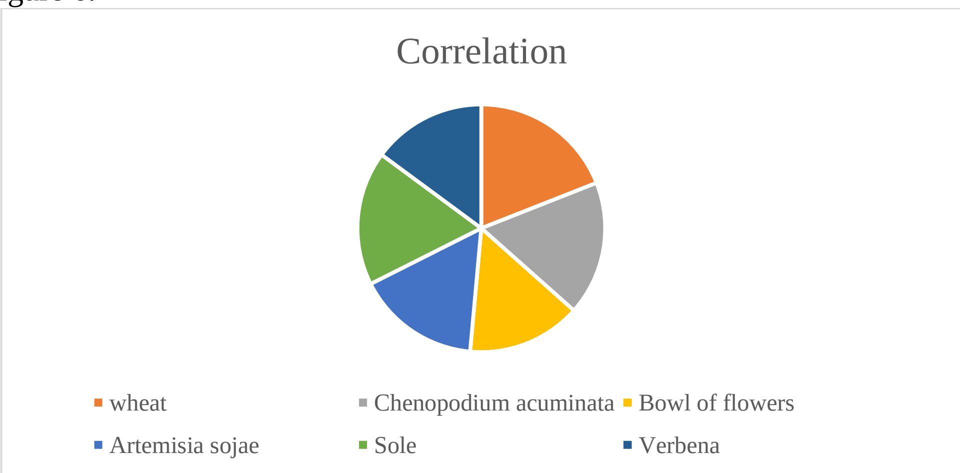

Figure 6. Correlation of impacts of plant diseases

5. Conclusions

Each disease recognition rate is derived from the ratio of the number of correctly identified diseases to the number of tests. It can be concluded from the table that the average recognition rate has reached 93.5%, which has a better classification recognition ability. Some leaf spot and early blight are similar in color and shape, so the recognition rate is relatively low. Gray mold and other several diseases have different sizes and lesions, and the recognition rate is relatively high. If it does not belong to these three diseases, it is other diseases. The results show that the feature parameters extracted in this paper are effective features, and the recognition of BP neural network is effective and feasible. In this paper, using image processing technology and artificial neural network as technical means, starting from the most common crop tomato leaf diseases, preprocessing and image segmentation of tomato leaf disease images, and extracting the texture and shape characteristics of diseased leaves Using the extracted feature parameters as the input of BP neural network, a neural network model is established to realize the recognition of three tomato leaf diseases, which has certain significance in the automatic recognition of tomato diseases.

Spectral technology has made significant progress from information acquisition technology and processing analysis to application model research. With further development, the prospect will be broader: dynamic monitoring through aerospace remote sensing with high space and high spectral resolution. Get crop signs, water and fertilizer status, and disease and insect "symbol maps" in a timely manner, combine with the agricultural expert system to make diagnosis and decision, and truly realize timing positioning and precise operation. With the continuous development and maturity of spectroscopy technology, people have a deeper understanding and understanding of its technical characteristics and instruments, and will be more used in crop quality analysis, quality breeding and biological research. Spectroscopy technology has been widely used in regional and global scales for water monitoring, nutrition diagnosis, plant growth, agricultural yield estimation, quality testing, and ecological environment monitoring. The development of hyperspectral, microwave remote sensing, and multi-angle remote sensing has enabled the estimation of factors such as vegetation index, leaf area index, photosynthetically active radiation, and analysis of vegetation biochemical parameters, vegetation biomass and crop yield estimation, and monitoring accuracy of pests and diseases. Quantitative process. With the improvement and development of spectroscopic technology and supporting technologies, in addition to the spectrometers commonly used in general laboratories, a variety of specialized spectrometers and application software can be developed to meet different needs. In the application of spectral technology, in addition to a comprehensive understanding of the technical characteristics, it is also necessary for the user to have a wealth of professional knowledge in a specific field to reveal the inherent characteristics in the vegetation spectrum and improve the estimation accuracy of various parameters. Tap the maximum potential, bring the advantages of spectral analysis technology to the extreme, and serve modern agriculture to the maximum. At the same time, the organic combination of spectral technology and computer vision technology in the application will produce better results.

Most studies have identified diseases in the visible light range, and the parameter extraction is mostly based on color features and texture features. This method often has complex algorithms, long running time, and the recognition rate is still not high. And more pattern recognition methods (including artificial neural networks) can not be applied to the texture recognition of plant lesions, which affects the accuracy of disease diagnosis. Therefore, it is necessary to find a simpler, faster recognition, and high recognition rate algorithm for extracting the characteristic parameters of different plant diseases. Because of the many types of crop diseases, and their complexity and variability due to different onset times, locations, and degrees of disease, the comprehensiveness of plant disease identification is currently poor, and the application of some research methods to other crops and diseases needs to be further studied. the study. The plant disease diagnosis system is less intelligent. The plant disease diagnosis system used in production still relies on the expertise, technology and experience of the input staff, and the reliability and efficiency of the diagnosis are limited. For most modern production users, the expert system is not yet able to solve the problem of disease diagnosis. Therefore, research on a highly intelligent plant disease recognition system based on expert knowledge and containing a variety of major crops is also one of the current hotspots that need to be studied.

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