Cloud Platform System for the Diagnosis of Typical Tea Plant Diseases Based on Neural Network

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Abstract. Based on the analysis and investigation of the traditional artificial diagnosis of typical tea tree diseases, it was found that the artificial diagnosis had low efficiency and high error rate, so the typical tea tree diseases could not be caused by the timely and correct use of pesticides, thus reducing the yield of tea tree. Aiming at the above problems, this paper mainly studied the cloud platform system for the diagnosis of typical tea tree diseases based on neural network. This system is a typical tea tree disease intelligent diagnosis cloud platform system based on Java EE standard 3-layer B/S structure. The system realized the intelligent diagnosis of typical diseases of tea tree, as well as the maintenance and browsing of relevant knowledge information, so that users could consult the detailed information of diseases, and combined with the diagnosis results output by the system, take effective prevention measures, providing strong support for tea tree production. By testing the neural network, the average diagnostic accuracy of the four experiments is 83.5%. The experimental results show that it is feasible to use neural network to diagnose typical tea plant diseases.

Keywords: Neural Network, Tea Tree Typical Diseases, Disease Diagnosis, Diagnosis Cloud Platform System

1. Introduction

As a necessity of Chinese people's life and a traditional high-quality export agricultural product, tea plays an irreplaceable role in the national economy and occupies a very important position in the international market[1]. At present, the European Union and other developed countries implement technical trade barriers by formulating pesticide residue limit standards in tea, expanding inspection projects, and introducing technical regulations, standards and conformity assessment procedures, which restrict the export of Tea products in China[2-3]. Therefore, in the tea planting process, how to diagnose and prevent the typical diseases of tea trees to reduce the loss and make the tea quality meet the quality requirements of high-end markets in Europe and America is a very important and urgent subject[4].

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Production practice has proved that only by timely and accurate control and prevention at the initial stage of disease occurrence can a large amount of tea production and tea quality decline be avoided\cite{5}. It is of great practical significance to promote the stable development of tea production and increase farmers’ income if typical diseases of tea trees can be accurately diagnosed and the incidence of diseases can be effectively controlled\cite{6}. At present, computers have entered the vast rural areas\cite{7}, and the use of computer technology to provide consulting services for farmers has been widely adopted\cite{8}, and is deeply loved by farmers. Therefore, it is an inevitable trend to adapt to the development of The Times to develop and design an effective disease diagnosis system that can be easily used by farmers with the help of computers\cite{9-10}.

Tea tree disease diagnosis essence is a typical fault diagnosis problem, but the tea tree typical disease diagnosis compared with the general equipment fault diagnosis, because of the tea has the characteristics of life, its disease characteristics is general equipment complex, symptoms and diagnosis methods described is the research emphasis and difficulties of tea plant diseases diagnosis and hot spots. Artificial neural network (Ann) is highly nonlinear, highly adaptive and self-learning, and can simulate the information processing, storage and retrieval functions of human brain to different degrees. It is suitable for solving the complex problem of disease diagnosis. In this paper, the neural network model is used to establish the nonlinear relationship between diagnostic parameters and diseases to realize the diagnosis of typical tea plant diseases.

2. Neural Network

2.1. BP Neural Network

(1) Additional momentum method

The additional momentum method not only considers the effect of the error on the gradient, but also the influence of the change trend on the error surface, so as to avoid the oscillation in the training process and accelerate the convergence speed. Based on BP algorithm, the additional momentum method adds a value proportional to the previous weight change to each weight change, and generates new weight change according to BP algorithm. The weight regulation formula with additional momentum factor is:

\[
\Delta b_i(k + 1) = (1 - mc)\eta\delta_i + mc\Delta b_i(k)
\]

\[
\Delta w_{ij}(k + 1) = (1 - mc)\eta\delta_i p_j + mc\Delta w_{ij}(k)
\] (1)

Where \(k\) is the number of training times and MC is the momentum factor, which is generally set at about 0.95. The essence of the additional momentum method is to transfer the influence of the last weight change through a momentum factor. When the momentum factor is zero, the weight change is only based on the gradient descent method. When the momentum factor is \(L\), the new weight change is set as the last weight change, while the change based on gradient method is ignored.

The judgment conditions for training the network using the additional momentum method are as follows:

\[
mc = \begin{cases} 
0 & \text{when } SSE(k + 1) > SSE(K) \cdot \text{error} \_ \text{ratio} \\
0.95 & \text{when } SSE(k + 1) < SSE(K) \\
mc & \text{other}
\end{cases}
\] (3)

Where, \(SSE(K \div 1)\) and \(SSE(K)\) are the squared error sum of the \(K \div 1\) training and the \(K\) training respectively, and error\_ratio is the maximum error ratio, which is generally set at about 1.04.
(2) Adjustment of adaptive learning rate

Another method to solve the problems of slow convergence and oscillation in the training process of standard BP algorithm is the adaptive learning rate method, which can improve the convergence rate by properly selecting the learning rate. The regulation criterion is: check whether the correction value of weight really reduces the error function. When the new error exceeds a certain multiple of the old error, the learning rate will decrease; otherwise, the learning rate will remain unchanged. When the new error is smaller than the old error, the learning rate is increased. This method ensures that the network is always trained at the maximum acceptable learning rate.

3. Experimental Design of Cloud Platform for Disease Diagnosis

3.1. Training Samples

The training samples of the network are extracted from the disease information examples obtained in the knowledge acquisition stage, and the encoded disease information is taken as the training samples of the network through the disease information pretreatment. A total of 324 training samples are obtained, as shown in Table 1.

| Numbering | Onset | Period of onset | Pathological color | Pathological shape | Pathological arrangement | Disease |
|-----------|-------|-----------------|--------------------|--------------------|--------------------------|---------|
| 1         | 1     | 0.842           | 1                  | 1                  | 1                        | 1000000000 |
| 2         | 0.5   | 0               | 0                  | 0.155              | 0                        | 01000000000 |
| 3         | 0.25  | 0.671           | 0                  | 0.155              | 0                        | 00100000000 |
| 4         | 0.5   | 1               | 0.5                | 0.155              | 0.5                      | 00010000000 |
| 5         | 0.5   | 0.347           | 0.833              | 0                  | 0.5                      | 00001000000 |

3.2. Experimental Design

This experiment adopts the N-fold cross validation method. The n-fold cross validation method is to divide the training set into N parts and take turns to take n-1 part as the training data and 1 part as the test data for the experiment. The corresponding accuracy rate will be obtained in each experiment.

The average accuracy of n results is used as an estimate of the algorithm's accuracy. In the experiment, N value was 4. 324 training samples were randomly divided into 4 equal parts, and numbered, respectively T1, T2, T3, and T4. Each training sample was taken as the data test set in turn, and the other 3 pieces were taken as the training set.

4. System Analysis of Disease Diagnosis Cloud Platform

4.1. Species Analysis of Tea Leaf Diseases

In all 160 tea plantations, serious leaf diseases mainly include tea brown leaf spot, tea cloud leaf spot, tea cake disease, tea wheel spot, tea anthrax, tea leaf spot, tea equator disease, tea coal disease, tea red leaf spot and tea white star disease. These 10 kinds of tea leaf diseases occurred in different degrees. In general, tea moire leaf blight and tea anthracnose are the most common, and tea anthracnose occurs seriously in local areas. The incidence of tan spot disease, tea wheel spot disease and tea cake disease
is common and serious in local areas. The incidence of tan spot disease and tea cake disease is 15.3% in City A and 15.9% in city B. Tea leaf spot disease and tea equator disease occurred in local areas and were not common, with the highest incidence of 5.5% in City B. One or more kinds of tea equator diseases occur simultaneously and can be expanded to the whole tea-growing area. Tea coal disease, tea red leaf spot and tea white star disease are also common and serious in local areas.

4.2. Analysis of Experimental Data

![Figure 1. Gain of disease feature information](image)

As shown in Figure 1, the information gain of 10 disease characteristics in the typical disease information of tea tree. The first five characteristics with the largest visible information gain were the location of the disease, the onset period, the color of the disease, the shape of the disease and the arrangement of the disease. Through the comprehensive analysis of domain knowledge, these five characteristics are finally decided as the input parameters of the diagnostic model. When the training samples are finished in the neural network, network tests are needed to verify the effectiveness of the training network. The following experiment was conducted to test the BP network model with 22 neurons in the hidden layer. Input the sample data into THE BP network, observe the actual output of the network, and analyze the diagnostic accuracy.

Analysis of experimental data, the maximum to the actual output of each sample as final diagnosis, and compare the disease name, found that the diagnosis is correct, but the actual output and desired output exist differences in values, with the diagnosis results and expected results by calculating diagnostic accuracy, this research before 3 samples of the diagnostic accuracy was 80.4%, 83.6%, 86.5%, given the average diagnostic accuracy for 10 samples of output: 83.5%. The test results show that the diagnosis model can get satisfactory results.

According to the above chart analysis, when the number of neurons in the hidden layer is 22, the training effect of the network is the best. The number of training sessions is 200-300, and the training time is about 120 seconds. The training results are ideal. By testing the neural network, the average
diagnostic accuracy of the four experiments is 83.5%, indicating that it is feasible to use the neural network for diagnostic reasoning.

4.3. Prevention and Control Methods

At present, the control of fungal diseases of tea trees is still supplemented by wine-spraying chemical pesticides as the main biological pesticides. When the fungal diseases are serious, tea farmers should avoid using pesticides with high toxicity and high residue as far as possible, and it is a wise choice to choose chemical pesticides with low toxicity and low residue. At the same time, selection of tea varieties with strong disease resistance, the use of induced resistance, biological control and other measures are also strategies to achieve the purpose of disease control.

Improving the resistance of tea plants to pathogenic fungi is a major strategy for the control of fungal diseases of tea plants. Some tea varieties have unique shape, state and physiological structure, showing certain resistance to disease. The surface structure of tea tree is very special, with wax layer, cuticle, vili, stomata, palisade tissue layer, cell wall structure and so on. These characteristics constitute the morphological resistance of tea tree, which plays a physical or chemical defense role in inhibiting the spore germination, growth, invasion and expansion of pathogenic bacteria. Induced resistance, also known as systemic resistance or plant immunity, can improve the resistance of host plants to the subsequent pathogen infection reflected in the defense response. It was found that after certain biological or chemical activator treatment, the activity of oxidase related to defense reaction was increased, the loss of cellulose and coagulation factors was decreased, and the resistance of tea plant to disease was enhanced. Antagonistic endophytic bacteria interact with pathogenic bacteria and endophytic bacteria produce metabolites with antibacterial effect, which is a new strategy to realize biological control of plant diseases. The endophytic bacterium Bacillus subtilis from tea tree, TL2, can be well colonized in tea tree and secrete an antibacterial protein, which has obvious inhibitory effect on hyphae growth, conidia formation and germination of tea rota. There have been many similar studies, such as the screening and application of antagonistic endophytes against pathogenic fungi such as tea anthrax, tea moire leaf blight, red root rot, and branch canker.

5. Conclusions

With the popularization of artificial intelligence science and technology, a variety of agriculture-related diagnostic expert systems emerge at the right moment. However, further theoretical research and application of the existing diagnostic expert system show that it has some problems, such as system heterogeneity, ambiguity, difficulty in acquiring knowledge and vulnerability. In this paper, the diagnosis of typical tea plant diseases based on neural network was studied in the field of tea plant pest. Based on the analysis of the characteristics of the typical disease diagnosis field of tea plant, this paper puts forward a method combining descriptive logic reasoning and semantic reasoning. In the process of inquiring and diagnosing insect pests, the corresponding retrieval formula is constructed according to the user's input to realize the diagnostic reasoning process.

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