Tea Plant Disease Recognition Based on Convolutional Neural Network

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Abstract
In order to explore the identification of tea plant diseases based on Convolutional Neural Networks (CNN), a convolutional neural network model is constructed by combining K-means clustering algorithm with CNN through collecting tea leaves from natural growth field in xx experimental field, and the running environment is designed to simulate the model. The obtained data are analyzed. In the analysis of the influence of K value selection on accuracy, it is found that when K value increases gradually and the accuracy increases slowly to K=128, the accuracy of convolutional neural network model tends to be stable and the amplitude decreases slowly. Therefore, the value of K is 128 from the comprehensive point of view of calculation. When comparing the size of different patch image blocks, it is found that the accuracy of the three K values is similar near 9*9, 11*11 and 13*13. Finally, from the comprehensive point of view, when the patch image block is 11*11, the effect will be better. Comparing with the traditional neural network algorithm, it is found that the recognition rate of the convolution neural network model for tea plant diseases is much higher than that of the traditional algorithm, and the recognition rate of the convolution neural network for disease categories is as high as 96.65%, while the recognition rate of the traditional neural network algorithm is lower than that of the CNN method. When the number of iterations is analyzed, it is found that when the number of iterations of the convolutional neural network model in this study is 100, the average correct rate is higher and the training time is basically appropriate. Therefore, through the study of tea plant disease identification in this study, it can be found that the application of convolutional neural network to tea plant disease identification accuracy will be greatly improved, with higher robustness, and meet the experimental expectations. Although there are some shortcomings in the experimental process, it can still provide a reference for the later identification of tea plant diseases.

Key words: CNN, Number of Iterations, Tea Plant Diseases, Convolution Layer

1. Introduction

With the rapid development of society, the pace of science and technology is accelerating, which accelerates the process of global informatization, and promotes the process of industrial chain development in the world. It has played a great role in promoting the global economy, such as clothing, food, housing and transportation. Tea, as one of the main crops in China, is planted mostly in mountainous areas of provinces south of the Yangtze River in China. Its leaves are larger and are carefully cultivated by people [1]. In the process of tea plant growth, the leaves will inevitably be disturbed by insects, causing them to encounter diseases, which ultimately affect the growth of tea plants and the quality of tea [2, 3]. There are more than 40 kinds of common tea plant diseases, most of which play an important role in leaf growth. In order to control these diseases, it is necessary to identify and classify them first [4]. Therefore, the identification and control of tea plant diseases will greatly improve the quality of tea and benefit the growth of tea plants, which is also a research hotspot of scholars.

Deep learning is a new multi-layer neural network algorithm. Convolutional neural network is a kind of feed-forward neural network algorithm with high efficiency and deep structure [5]. CNN has the ability of representation learning and can carry out shift-invariant classification for input information according to its...
hierarchical structure, so it is also called Shift-Invariant Artificial Neural Networks (SIANN). CNN can imitate the construction of biological visual perception mechanism, and can also conduct supervised learning and unsupervised learning [6, 7]. Many scholars have done research on related crops. Xin Yang and Tingwei Guo try to enhance plant resistance to pathogens by studying plant resistance genes, and develop recognition and scoring system based on leaf image to monitor and predict plant diseases [8]. Amanda Ramcharan et al. (2017) used transfer learning training deep convolution neural network to identify bare lymphocyte syndrome (BLS), red mite disease (RMD), green mite disease (GMD), cassava brown streak disease (CBSD) and cassava mosaic disease (CMD). Finally, it is found that the field image recognition method based on transfer learning provides a fast, economical and easy deployment method for digital plant disease detection [9]. S. Arivazhagan et al. (2018) proposed a method based on in-depth learning to identify leaf diseases of mango plants. Five different leaf diseases of mango, including anthracnose, black spot, leaf leprosy, leaf squamous disease and leaf burning disease, are identified. The recognition accuracy of the proposed CNN model for mango leaf diseases reaches 96.67%, which shows the feasibility of its real-time application. Muhammad Attique Khan et al. (2018) detected and classified various fruit diseases based on correlation coefficient and deep feature (CCDF), and extracted features of selected diseases such as apple sore and eggplant disease [10]. The results of qualitative analysis show that this method is superior to the existing methods in improving classification accuracy. Wan-jie Liang et al. (2019) proposed a new method for rice blast recognition based on CNN. The CNN model is trained and tested by collecting multiple sample data sets. The results show that the higher-order features extracted by CNN have stronger recognition ability and effectiveness than those extracted by traditional manual methods such as local binary pattern histogram (LBPH) and wavelet transform (Haar-WT) [11]. Trung-Tin Tran et al. (2019) used artificial neural network model to identify, classify and predict malnutrition of tomato plants. Two different models based on convolution neural network are analyzed to classify and predict the symptoms of nutritional deficiency in order to improve crop yield and prevent tomato diseases caused by nutritional deficiency [12].

In summary, through the above scholars’ research on crop diseases, there is no identification of tea plant diseases. Therefore, a convolution neural network model is constructed in this study by combining K-means clustering algorithm with CNN. A running environment is designed to simulate it. Through the statistics and analysis of the data obtained, a new idea is provided for the identification of tea plant diseases in the later stage.

2. Methodology

2.1. Artificial Neural Network

Artificial neural network abstractly simulates the basic characteristics of human brain in identifying things. It is an intelligent bionic model of artificial neurons inspired by biological neurons [13]. For the neural network, its complete structure mainly includes hidden neuron structure and functions to be activated. For human and animal organisms, the neurons in the body include cell bodies, dendrites, axons, prominences and other input components, signal transduction segments and output terminals. According to the human neural network as the prototype, ANN algorithm abstracts the neural network and several algorithms are designed to construct the hidden layer and the features needed in the model. In addition, there will be weight connection between input layer and hidden layer. Weight represents the merits and demerits of the characteristics of the neural network. If the weight is large, it means that there is a greater impact on the results. If the weight is small, it means that there is a less impact on the results [14]. The multilayer perceptron is shown in figure 1.

![Figure 1. Multilayer perceptron](image)

2.2. BP Neural Network

In the neural network, BP neural network is a classical three-layer neural network, which consists of input layer, hidden layer and output layer. BP neural network is a multi-layer feedforward network which can reduce
the network error to the maximum, so as to achieve the effect of network optimization. Back propagation is a process of transferring errors in the structure of neural networks in the opposite direction of information forward transmission. Gradient descent method is used to adjust the weights of each layer and reduce the errors step by step [15-17]. The core of BP is to minimize the error based on gradient. Formula 1 is as follows.

\[ L(e) = \sum_{j=1}^{k} \phi(e_j) = \frac{1}{2} \sum_{j=1}^{k} (y_j - y_j')^2 \]  

(1)

In the formula, \( y_j' \) represents the expected output and \( y_j' \) represents the actual output. The structure of BP neural network is shown in figure 2.

![BP neural network mechanism](image)

**Figure 2.** BP neural network mechanism

In figure 2, x, y and z represent the input layer, the hidden layer and the output layer of the neural network respectively. Each node represents a neuron. The layers of the neural network communicate with each other through the weight coefficients of the nodes. If the forward propagation result of the BP neural network information satisfies the expected effect, the network learning process is completed and the algorithm stops learning. If the expected result is not completed, the weight of each layer is adjusted by error back propagation to continue the learning process [18]. If the result of BP neural network is not up to expectation, the definition of output error \( E \) is shown as follows.

\[ E = \frac{1}{2} (d - P)^2 = \frac{1}{2} \sum_{i=1}^{n} (d_i - P_i)^2 \]  

(2)

BP neural network also has some shortcomings, such as local minimization, slow convergence rate, uncertainty of structure selection and so on. These structural problems are unavoidable. Therefore, in order to achieve more efficient, faster and more accurate recognition of tea plant diseases, the structure of convolutional neural network in deep learning algorithm is used to study this classification.

### 2.3. Convolutional Neural Network

Convolutional neural network (CNN) is a multi-layer, non-fully connected neural network, which reduces a lot of unnecessary pre-processing work and can directly recognize visual patterns from the original image [19]. Until now, CNN has been widely used in many fields, such as handwritten character recognition, face recognition, eye detection, vehicle detection and robot navigation. However, this neural network has not been applied to the identification of tea plant diseases. The common methods for identifying tea plant diseases are chemical element detection, professional identification, field experiment identification and BP neural network identification, but the process is complicated and the recognition situation is not ideal [20]. However, CNN can recognize the model of change, and the robustness of geometric change is very good. The structure of CNN is shown in figure 3.

Convolutional neural network (CNN) is a kind of network structure that simulates human brain. It is a deep learning algorithm with supervised learning method and multi-level network structure. Compared with other neural networks, CNN has obvious advantages. Convolution layer is the feature extraction layer of CNN, which can enhance the original signal while reducing noise, and realize feature enhancement and filtering. The lower sampling layer aggregates the feature maps of the upper layer by using local correlation, reduces the feature dimension, improves the signal-to-noise ratio, and integrates the local features of a certain region to generate new features. Full-connection layer is a rasterization of input pixel value, which converts two-dimensional feature map into one-dimensional feature queue. Then, through weighted summation of input signal and operation of non-linear activation function, the output feature mapping of full-connection layer is obtained [21].
The number of neurons given by the final output layer is the result of CNN recognition. Compared with the traditional network processing, the convolutional neural network algorithm eliminates many complex and tedious processes, and finally achieves effective image recognition. Therefore, the convolution neural network is used to identify tea plant diseases in this study.

![Convolutional neural network of tea tree](image)

**Figure 3.** Convolutional neural network of tea tree

2.4. Tea Leaf Collection

In this study, the images of the experimental samples are collected from the xx experimental field. The object of image acquisition is tea leaves growing naturally in the field. Samples are collected from March 2018 to March 2019. In the process of image acquisition, the actual growth of the diseased leaves is photographed and sampled from different angles. In the specific shooting details, taking into account the practical application of disease detection algorithm, 451 samples of tea plant disease leaves are screened out after comparison and confirmation by professional and technical personnel. Among them, there are 94 pictures of tea ring spot, 213 pictures of tea anthracnose, 82 pictures of tea moire leaf blight and 62 pictures of tea brown leaf spot. The distribution of data sets is shown in table 1. Typical disease images are shown in figure 1. During the process of sample marking, all disease areas of leaves are marked with a rectangular border (there may be multiple disease areas on a leaf). From table 1 and figure 4, it can be seen that tea disease images have the characteristics of small number, complex background and small proportion of target areas.

<table>
<thead>
<tr>
<th>Disease types</th>
<th>Training set number of pictures</th>
<th>Test set number of pictures</th>
<th>Verification set number of pictures</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pestalotiopsis theae</td>
<td>68</td>
<td>9</td>
<td>18</td>
<td>94</td>
</tr>
<tr>
<td>Tea anthracnose</td>
<td>167</td>
<td>28</td>
<td>18</td>
<td>213</td>
</tr>
<tr>
<td>Tea brown blight</td>
<td>46</td>
<td>16</td>
<td>20</td>
<td>82</td>
</tr>
<tr>
<td>Tea brown leaf spot</td>
<td>29</td>
<td>13</td>
<td>20</td>
<td>62</td>
</tr>
</tbody>
</table>

**Table 1.** Distribution table of tea disease image data set

![Typical image of disease species in tea leaves](image)

**Figure 4.** Typical image of disease species in tea leaves (A. Pestalotiopsis theae; B. Tea anthracnose; C. Tea brown blight; D. Tea brown leaf spot)
2.5. **Tea Tree Convolutional Neural Network (CNN) Model**

Convolutional neural network algorithm includes multi-layer convolution and pooling layer, which is used to extract the deep features of images layer by layer, and has a good application effect in the field of image recognition. In this study, the sampled images are input into the convolution neural network model of tea plant for training, and a tea plant disease recognition neural network model is constructed by combining K-means clustering algorithm. Then, four types of tea plant disease types are generated under the model recognition. In training, the image blocks are drawn into an eigenvector of 81 dimensions, and K value is 128 in K-means clustering algorithm. Then, under 128 dimensions, 11*11 is used as the weight set by the first convolution layer. With the increase of convolution layer, the processed image is expanded and 120 patches are input to convolution layer for training. Strides is set to 4, and Padding edge pixel is set to SAME, which means that Max-pooling pooling operation is used to carry out edge completion, with size 3*3, and step size 2. The convolution cores of layers 2, 3, 4 and 5 are 5*5-128, 3*3-256, 3*3-256 and 3*3-128, respectively. The step size is 1, and the last three layers are the full connection of two layers 4096 plus one layer of Softmax to output five kinds of prediction results. SGD optimization algorithm is adopted and the learning rate is set to 0.01.

![Diagram](image)

**Figure 5.** Convolutional neural network model of tea tree

![Diagram](image)

**Figure 6.** Convolutional neural network flow chart of tea tree
2.6. Implementation of Convolutional Neural Network

The realization process of the convolution neural network model is as follows. Firstly, the convolutional neural network model constructed in this study is divided into training part and testing part. Among them, Stochastic Training is used in the training part. Firstly, the image is read from the sample image database, and the original image of tea plant disease read from the model is preprocessed and input into the random sample. In order to get a good recognition result, it is necessary to convolute several times and then sample. If the backpropagation adjustment weight does not satisfy the data set by the model, the sample initialization is resumed and this step is continued. After finally reaching the weight set by the model, it is necessary to move on. When the training times reach or are less than the limit error, it will continue. Otherwise, it will return to the stage of sample initialization, which is the training part. In the test part, the test sample is preprocessed first, and then input to the convolution layer for multiple convolutions and sampling. After five consecutive sessions, the full-connection output is performed and the final test is completed. The output classification image is the final classification result. The flow chart of convolutional neural network designed in this study is shown in figure 6.

2.7. Experimental Setup and Operating Environment

This experiment is completed in the environment of Matlab2013a. Windows 7 operating system: Intel (R) Pentium (R) CPU, main frequency 3.00GHz, memory 8GB. Four kinds of images are collected and 451 data samples are used as training samples. All the images of tea plant diseases are used as test samples to verify the structure of convolutional neural network.

3. Results and Discussion

3.1. The Effect of K Value Selection on Accuracy

In the experiment, 32, 64, 96, 128, 256, 512 empirical values are selected. As shown in figure 7, when K is too small, feature extraction is not enough, resulting in a decrease in accuracy. When K value increases gradually, the accuracy of the convolutional neural network model tends to be stable until K = 128. As K value continues to increase, the accuracy changes little, and the amplitude gradually decreases. Therefore, from the comprehensive point of view of calculation, the value of K is 128.

![Figure 7. Effect of K value selection on accuracy rate](image)

3.2. Comparisons of Different Patch Image Block Sizes

In the experiment, four patch sizes are selected from the original disease image data set and K-means clustering is carried out under K=96, 128 and 256 conditions respectively. The experimental results are shown in figure 8. The accuracy of the three K values near 9*9, 11*11 and 13*13 is similar. The reason is that when the patch image block is too small, the pre-training weight feature of the first layer cannot extract the complete lesion feature, which reduces the recognition rate. However, the patch image block of 15*15 is relatively large, which makes the required sample size too small and does not have enough complete and clear learning feature.
information. Therefore, this shows that the inappropriate size of convolution kernel will affect the accuracy of feature extraction in convolution neural network. Therefore, from a comprehensive point of view, when the patch image block is 11*11, the effect will be better.

Figure 8. The effect of different patch image block size on accuracy

3.3. Comparison and Analysis of Traditional Neural Network Algorithms

From table 2, it can be seen that the recognition rate of convolution neural network model is much higher than that of traditional algorithm, and the recognition rate of convolution neural network is 96.65%, while the recognition rate of traditional neural network algorithm is lower than that of CNN method. Therefore, the experimental results show that the convolution neural network algorithm is feasible and accurate for disease identification.

Table 2. Comparisons between convolutional neural networks and traditional neural networks

<table>
<thead>
<tr>
<th>Disease category</th>
<th>Convolutional Neural Network</th>
<th>Traditional Neural Network</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Recognition rate (%)</td>
<td>Missing detection rate (%)</td>
</tr>
<tr>
<td>Pestalotiopsis theae</td>
<td>95.1</td>
<td>2.5</td>
</tr>
<tr>
<td>Tea anthracnose</td>
<td>97.2</td>
<td>1.8</td>
</tr>
<tr>
<td>Tea brown blight</td>
<td>98.1</td>
<td>1.2</td>
</tr>
<tr>
<td>Tea brown leaf spot</td>
<td>96.2</td>
<td>2.3</td>
</tr>
<tr>
<td>Average value</td>
<td>96.65</td>
<td>1.95</td>
</tr>
</tbody>
</table>

3.4. Analysis of Tea Classification Result by Iteration Number

The weight calculation of convolutional neural network model is an iterative method. The number of iterations has different effects on the accuracy of tea plant disease classification. In this study, the classification of tea plant diseases studied is iterated according to many experiments. On this basis, ideal weight parameters are obtained. From figure 9A, it can be seen that when the number of iterations increases, the accuracy increases rapidly at first, and when the number of iterations increases to 100, the average correct rate decreases with the increase of the number of iterations. From figure 9B, it can be seen that the training time increases with the increase of the number of iterations and is proportional to each other. From figure 9C, it can be seen that there is no direct connection between the test time and the number of iterations. However, the basic trend is increasing. Therefore, when the number of iterations of the convolutional neural network model in this study is 100, the average correct rate is higher and the training time is basically appropriate.
4. Conclusions

In order to explore the identification of tea plant diseases based on convolution neural network, a convolution neural network model is constructed by combining K-means clustering algorithm with CNN through collecting tea leaves from natural growth field in XX experimental field, and the running environment is designed to simulate the model. The data obtained are statistically analyzed. In the analysis of the influence of K value selection on accuracy, it is found that when K value increases gradually and the accuracy increases to K=128, the accuracy of convolutional neural network model tends to be stable. In addition, as the K value continues to increase, the accuracy does not change much, and the range gradually decreases. Therefore, from the comprehensive point of view of calculation, the value of K is 128. When comparing different patch image block sizes, it is found that the accuracy of the three K values is similar near 9*9, 11*11 and 13*13. Finally, from a comprehensive point of view, when the patch image block is 11*11, the effect will be better. Comparing with the traditional neural network algorithm, it is found that the recognition rate of the convolution neural network model for tea plant diseases is much higher than that of the traditional algorithm, and the recognition rate of the convolution neural network for disease categories is as high as 96.65%. However, the recognition rate of traditional neural network algorithm is lower than that of CNN method. When the number of iterations is analyzed, it is found that when the number of iterations of the convolutional neural network model is 100, the average correct rate is higher and the training time is basically appropriate.

In conclusion, through the study of tea plant disease identification in this study, it can be found that the application of convolutional neural network to tea plant disease identification accuracy will be greatly improved, with higher robustness, and meet the expected requirements of the experiment, so as to provide experimental reference for the later tea plant disease identification. However, there are also some shortcomings in the experimental process. For example, the number of image samples collected can continue to increase, which can improve the accuracy of the experimental results, and has more reference value.

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