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Design and Research on Identification of Typical Tea Plant Diseases Using Small Sample Learning

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Abstract: Tea plants are susceptible to diseases during their growth. These diseases seriously affect the yield and quality of tea. The effective prevention and control of diseases requires accurate identification of diseases. With the development of artificial intelligence and computer vision, automatic recognition of plant diseases using image features has become feasible. As the support vector machine (SVM) is suitable for high dimension, high noise, and small sample learning, this paper uses the support vector machine learning method to realize the segmentation of disease spots of diseased tea plants. An improved Conditional Deep Convolutional Generation Adversarial Network with Gradient Penalty (C-DCGAN-GP) was used to expand the segmentation of tea plant spots. Finally, the Visual Geometry Group 16 (VGG16) deep learning classification network was trained by the expanded tea lesion images to realize tea disease recognition.

Keywords: Small sample learning; Tea plant disease; VGG16 deep learning

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1. Introduction

The background of tea plant disease pictures in natural scenes is complex and the illumination is uneven, which greatly affects the accuracy of disease recognition. To improve the recognition accuracy, the primary task is to carry out accurate segmentation [1]. The quality of segmentation directly affects the subsequent recognition process. With the rapid development of computer science and technology, machine learning and image-processing methods have been widely used in plant disease recognition [2]. Due to the large amount of training data required for training deep networks, and the few tea plant disease test sites, it is difficult and expensive to collect different tea plant disease data in the field. The problem of insufficient training data could be solved by directly using deep networks to identify tea plant diseases [3]. Therefore, addressing the challenges of natural scene variation and small sample sizes is the key focus of this paper.

2. Segmentation of disease spots

The background of diseased tea plant images taken in natural scenes is complex, which affects the accuracy of disease recognition. The segmentation method was used to remove the healthy leaves and background in the image and retain the disease spots, which was conducive to the subsequent disease recognition. Common image segmentation methods include unsupervised clustering, threshold segmentation, and supervised machine learning [4,5]. The following introduces several common segmentation methods for lesions and the comparison of segmentation results.

2.1. Threshold segmentation

Threshold segmentation is a kind of image segmentation technology, which applies to images with different gray levels occupied by the target and background. It is based on an assumption of gray-level images, that is, under a certain index, the target part and the background part are very different [6]. In the process of segmentation, the quality of the selected threshold directly affects the segmentation effect, so how to select the optimal threshold is the key to threshold segmentation [7]. The following describes the iterative method of threshold selection.

The principle of determining the optimal segmentation threshold through the iterative method is as follows: select the median gray value of the grayscale image as the initial threshold, divide the image into two parts, calculate the average gray value of the two parts before and after segmentation, take the minimum median difference of the two average gray values as the goal, determine the optimal segmentation threshold through continuous iteration, and use the optimal threshold to segment the image to obtain the segmentation effect [8].

2.2. Otsu method

The Otsu method was proposed by the Japanese scholar Otsu in 1979 and is also known as the maximum inter-class variance method. The principle of the Otsu method for image segmentation is as follows: the gray value of pixels in the image is divided into two categories C and D by randomly selected threshold T, and the optimal threshold T is determined by continuous iteration with the target of the maximum inter-class variance of the C and D regions. The optimal iterated threshold T is used to segment the image to obtain the segmentation effect.

The advantage of threshold segmentation is that the method is simple and easy to understand, and it is not affected by the change of image contrast and brightness under certain conditions [9]. The disadvantage of this method is that when processing images with complex backgrounds, the segmentation effect is low. To obtain the optimal threshold, it is necessary to traverse all pixels and calculate the mean value and variance, which requires a large amount of calculation and low efficiency.

2.3. Graph-cut algorithm

In the algorithm based on Graph-cut, the image segmentation problem can be equivalent to the binary label problem, and the foreground and background are determined by different labels to achieve the purpose of image segmentation [10]. Given a set of image pixels I, the goal of Graph-cut is to assign a label $f_i \in \{t,1\}$ to each pixel $i \in I$ in the image, where label 1 is the foreground and label 0 is the background.

Taking the composition of a 3 × 3 image as an example, based on the constructed graph, the image segmentation problem can be transformed into the problem of finding the minimum cut set, and the minimum cut set of the graph can be obtained by the maximum flow/minimum cut algorithm. The global optimal image segmentation results are obtained.

3. Data augmentation

When using the deep learning method to identify tea plant diseases under small sample conditions, overfitting problems will occur. In recent years, deep convolutional generation adversarial networks have been used to generate samples and expand the number of samples [11]. Since deep convolutional generative adversarial networks (DCGANs) cannot generate samples of specific categories, plaque samples of different categories can be generated by adding conditional labels [12]. This paper makes use of the advantages of the Wasserstein GAN with Gradient

Penalty (WGAN-GP) loss function to add gradient penalty (GP) to the discriminator network to prevent issues such as gradient collapse or gradient disappearance and improve the stability of the network.

Generative adversarial networks (GANs) are a new generative model. It consists of two parts, namely generative neural network G and discriminator neural network D. The relationship between the two is antagonistic. The generator and the discriminator are two sides of each other. The generator generates similar target samples by learning the data distribution of the original target [13]. The function of the discriminator is to judge whether the input sample is the real sample or the generated target sample.

4. Tea spot recognition based on the VGG16 network

In the selection of classifier, the advantages of deep learning algorithm compared with traditional machine learning algorithms in image recognition are:

(1) No feature engineering is required: Traditional machine learning algorithms usually need exploratory data analysis on data sets to find out the best features to pass to the algorithm to have a good recognition rate [14]. When deep learning networks are used, only the data set needs to be passed directly to the network to achieve good recognition results.

(2) Strong adaptability and easy conversion: Deep learning can be more easily adapted to different fields and applications, traditional machine learning for image recognition, and low generalization [14]. There are many kinds of tea plant disease images. There are more than 130 kinds in China, with different morphological characteristics. Therefore, using a deep learning network for disease recognition, the effect is better. The following introduces the development history of Visual Geometry Group (VGG) and the recognition process of tea plant disease spots.

5. Experimental results and analysis

5.1. Results of tea plant lesion segmentation

Under the same conditions, the threshold segmentation method, K-means clustering, and Graph-cut algorithm are compared with the supervised support vector machine (SVM). The results show that SVM performs best for segmenting diseased tea leaf images, successfully segmenting all diseased spots with minimal interference and segmentation errors. The Grap-cut algorithm is the second most effective, though it occasionally fails to remove some healthy leaves. The threshold segmentation method and K-means clustering performed well on images with significant foreground-background differences but were less effective on images with minor differences.

5.2. Results of tea plant disease identification

Three typical tea plant diseases selected for this experiment: tea red leaf spot disease, tea grey leaf blight, and tea leaf scab disease, were selected as experimental objects in this experiment. 40 samples were collected for each type of disease, totaling 120 samples. These samples were segmented to create disease spot maps. 20 samples from each category were randomly selected as training data, while the remaining 20 samples from each category were used as the test set. The experimental procedure is outlined as follows.

In this paper, the C-DCGAN + VGG16 method was compared with the traditional machine learning methods. The training set data was put into the C-DCGAN network, and three types of lesion sample images were generated. The recognition results are shown in **Table 1**. As shown in the table, the experiment demonstrates that for small tea plant disease images, using a conditional deep convolutional generative network to augment the data can improve recognition accuracy.

Table 1. The recognition accuracy of tea plant disease images under different methods

Name	Textual method	SVM	Decision tree	K-means
Tea red leaf spot	0.7	0.45	0.3	0.15
Tea grey leaf blight	1.0	0.45	0.6	0.90
Tea leaf scab disease	1.0	0.55	0.15	0.2

5.2.1 Comparison between the extended data method in this paper and the rotating translation extended data method

Under the same conditions:

(1) The lesion training set uses C-DCGAN-GP to expand the data and then uses the extended training set to train VGG16 to obtain recognition accuracy.

(2) The lesion data was extended by rotation and translation at different angles, and then VGG16 was trained with the extended training set to obtain recognition accuracy.

(3) Directly train VGG16 with the lesion training set to get the recognition accuracy.

Comparing the experimental results of a, b, and c. The results show that:

(1) For disease images with small samples, data augmentation can improve the recognition rate of deep networks and prevent overfitting in training deep networks due to insufficient samples.

(2) The average recognition accuracy obtained by expanding tea disease data with the C-DCGAN method in this paper is about 28% higher than that obtained by expanding tea disease data with rotating translation.

5.2.2. Comparing the recognition accuracy of the original tea plant image and the segmented lesion image under different methods

The dataset was modified to include the original images (TLD images) and the segmented disease spot images (DS images) as the training set. Due to the interference from shooting conditions and the complex background of tea plant disease images, the use of C-DCGAN to generate training samples resulted in amplified background noise, which affected the recognition accuracy of the VGG16 network. For all methods, segmentation of disease spots from tea plant disease images significantly improved recognition accuracy. On average, using disease spot images increased the recognition rate by 21.5% compared to using original images.

6. Conclusion

In this paper, a new method for recognizing tea plant diseases from small samples is proposed. The method combines traditional machine learning with deep learning: the Support Vector Machine (SVM) is used to segment disease spots on tea tree leaves, followed by the use of a Conditional Deep Convolutional Generative Adversarial Network (C-DCGAN) to expand the dataset of tea leaf disease spot images. Finally, the improved VGG16 recognition network is employed to obtain the recognition results. The experimental findings are as follows:

(1) The combination of traditional machine learning and deep learning proposed in this paper effectively identifies three types of tea plant diseases. Under the experimental conditions, the identification accuracy for tea red leaf spot, tea grey leaf blight, and tea leaf scab disease was 70%, 100%, and 100%, respectively, with an average recognition rate of 90%, significantly higher than that of traditional machine learning algorithms.

(2) After segmentation, the recognition accuracy was 55% higher compared to direct identification using the original images. Future work will involve expanding the range of tea plant diseases and the number of

samples to further enhance the algorithm's robustness and recognition accuracy across more types of tea disease images.

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Disclosure statement

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