Research on plant diseases and insect pests identification based on CNN

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Abstract. Plant diseases and insect pests are common factors affecting plant growth, which is directly harmful to the quality of agricultural production. In order to identify and classify plant diseases and insect pests, in this paper, a detection method based on convolutional neural network (CNN) is proposed. Specifically, this paper first introduces the processes of plant diseases and insect pests data collection, and then the methodology for training detection model based on CNN is described. Finally, a series of comparative experiments are conducted to demonstrate the effectiveness of our model, and experimental results show our model achieves competitive performance on plant diseases and insect pests dataset.

1. Introduction
In agricultural production, the problem of pests and diseases can directly affect the quality of crop production. Therefore, detecting plant diseases and insect pests plays an important role in improving crop yield and promoting economic growth. The citrus which serves as an important part of people's daily consumption of fruits contains limonoids, carotenoids and flavonoids, which has antimutagenic and antioxidant properties. The citrus is able to effectively alleviate negative impact from diseases, and is increasingly becoming one of the most consumed agricultural products in people's daily life. According to the characteristics of citrus crop, it will have certain periodic diseases and insect pests during the planting process ranging from scarab, leaf curl moth pests to ulcers. Without human intervention, these diseases and insect pests will cause low citrus yield and poor fruit quality, which will do harm to the economic benefits of agriculture to a certain extent.

Since 2012, Alexnet [1] has made great achievements in Imagenet dataset for image classification, and the deep learning technique based on deep neural network has achieved breakthrough success in various applications and become the benchmark method in many fields, such as autonomous driving, natural language processing, medical image processing and etc. Before the popularity of deep learning technique, most traditional image-based classification works adopt two-stage strategies [2]. In the first stage, a variety of manual feature extraction techniques (e.g. histogram, optical flow, SIFT) are employed to extract features from input image; in the second stage, classification models based on machine learning (e.g. SVM, random forest) were applied on these manual features and then made the predication. The performance of traditional methods to a great extent depends on manual feature extraction techniques, which is limited by the prior knowledge of model designers. In contrast, the approaches based on deep learning, especially the convolution neural network, use multiple and stacked
convolution layers to automatically obtain the richer features of input image [3], thus enabling the model to achieve excellent performance.

Inspired by superiority of deep learning technique, in this paper, a classification method based on CNN is proposed for plant disease image recognition, to be specific, the processes of how to collect plant diseases image dataset are introduced. Then, different methods including traditional image processing methods and CNN-based model are applied on dataset to citrus diseases. Finally, a more accurate approach to identify citrus pests and diseases is verified, which provides an important basis for the accuracy of citrus pest identification and disease level determination.

2. Experimental platform construction and image acquisition and processing

2.1. Experimental data acquisition

The quality of the collected images has great effect on segmentation accuracy, directly impacting on the accuracy of classification and recognition results. Considering the characteristics of the growing area of citrus plants in China, this paper chooses a pomelo orchard in a certain area in China as the image collection site. In terms of data collection, an orchard automatic picking robot is used as a carrier, and a camera is directly mounted on the automatic picking robot to take pictures of plant leaves and collect images. The acquisition of citrus leaf images is the basis of the design system of this paper. The image acquisition process is shown in Figure 1:

![Image Acquisition Process](image.png)

**Figure 1.** Image acquisition process.

The image acquisition system mainly includes two parts: pickup robot and industrial camera. The method of collecting leaf images is to remotely control the automatic picking robot in the orchard to automatically walk, stop and take pictures, and transfer the images to a computer to enter the processing steps after the system.

2.2. Plant disease sample pre-process

In this paper, the leaves of pomelo presenting a variety of diseases and insect pests, and the characteristics of diseases and pests were simply extracted and classified. In this paper, the disease types, parts, colors and spots of pomelo leaves were simply taken as the characteristics. Because we focus more on the entire training process, we chose the simplest way to complete the feature extraction. In addition, there are many ways to extract features, such as LBP (Local Binary Patterns), HOG (Histogram of Oriented Gradient), and so on.

The selected insect pests and diseases images were divided into 4 kinds of diseases, such as ulcer disease leaf, anthracnose leaf, black spot disease and yellow dragon disease leaf. The specific disease is shown in Figure 2:
The feature information of the leaves of honey pomelo pests and diseases is shown in Table 1.

**Table 1. Comparison of characteristics of typical pests.**

| A kind    | B part | C colour | D spot |
|-----------|--------|----------|--------|
| ulcer     | blade  | tan      | null   |
| anthrax   | blade  | taupe    | null   |
| black spot| fruit  | dark     | appear |
| kadron    | blade  | yellow   | null   |

3. **Plant diseases and insect pests identification selection model: Introduction to ResNet**

Convolutional neural networks are similar to traditional neural networks in that they can self-optimize through learning. Each neuron receives an input and performs an operation. From the input original image vector to the final output class score, the entire network still represents a single perceptual score function. The last layer will contain class-related loss functions, and all the tricks developed on traditional neural networks still work for convolutional neural network. CNN is able to encode the characteristics of images into the single architecture and directly output final prediction, which is more suitable for image classification picture tasks.

The identification and classification of plant diseases and insect pests in this paper is based on the ResNet model [4]. Aiming at the problem of "accuracy rate declines with the deepening of the network", if the network has reached the optimal level and the network is deepened, the residual between input and output will be pushed to 0. But in most of existed networks, as the increase of neural network layers, the performance of the model will decrease with increasing depth.

In order to solve above challenge and the problem of gradient disappearance, adding new layers to the neural network model, the fully trained model can be more effectively reduced by the ResNet model. At the same time, the ResNet model can reduce the earlier network model. The output is added to the later network layer, which helps alleviate the problem of gradient disappearance and accurately extract plant leaves.
The basic idea of ResNet is to introduce a "shortcut connection" that can skip one or more layers. ResNet proposed a simple yet useful identity mapping, which made the final output is \( y = H(x) = F(x) + x \). Where \( x \) is the original input, and the output is \( y \) which is equivalent to \( F(x) + x \). The identity mapping refers to \( x \) itself, that is, \( x \) in the formula, and the network is to try to learn the residual between input and output, which is \( y - x \), as shown in Figure 3:

![Figure 3. The Mapping of ResNet.](image)

Aiming at the problem of "accuracy rate declines with the deepening of the network", if the network has reached the optimal level and the network is deepened, the residual mapping will be pushed to 0, leaving only the identity mapping. In theory, the network is always in an optimal state The performance of the network will not decrease with increasing depth, which solves the problem of gradient disappearance in the process of pest and disease recognition training.

### 4. Analysis of training data results of ResNet and SVM models

#### 4.1. Analysis of plant disease recognition results based on SVM

In this paper, an orchard automatic picking robot is used as a carrier, and a camera is mounted on the automatic picking robot to take pictures of honey pomelo leaves, then collect and transmit images. 510 leaves with insect pests and diseases are selected as the original image data, and the pests and diseases of pomelo are divided into leaf and fruit diseases. Then, characteristics of the selected leaves (e.g. color, spots) are extracted and used to train classification model.

Through the above process and the eigenvalues listed in Table 1, SVM based pest identification model of pomelo was built, which is to establish the optimal two-class classification of honey pomelo disease identification [5]. The prediction results are shown in Table 2. Finally, the accuracy rate of identifying diseases and insert pests of pomelo leaves based on SVM algorithm was obtained by comparing with the reality.

| Number of samples | Number of errors | Correct rate | Error rate  |
|-------------------|-----------------|--------------|-------------|
| 2040              | 252             | 87.6471%     | 12.36%      |

#### 4.2. Research on the recognition of honey pomelo disease based on CNN

The ResNet neural network model adds new identity mapping to the original CNN, which can effectively reduce the errors generated by training [6]. Moreover, the space of the original model solution is only a subspace of the space of the new model solution. ResNet can well train and learn a large amount of data,
use the learned rules to predict unknown data, or automatically classify samples. In this paper after acquisition of plant disease data, an appropriate network architecture to determine the model structure should be chose. The classic CNN model is composed of 7 layers: input layer, convolution layer, subsampling layer, fully connected layer, output layer, and two convolutional layers also include 2 downsampling layers, a total of 7 layers of network [7].

The output of the convolutional layer enters the input of the fully connected layer. The convolutional layer performs convolution calculations on the input data to extract the data features. The data features extracted by the convolutional layer are placed in the fully connected layer for data classification calculation. The hidden layer further performs data calculation, and the output layer outputs the network data output. At the same time, the training algorithm of CNN also uses BP algorithm, as shown in Figure 4:

![Diagram of network structure of the fully connected layer](image)

**Figure 4.** Network structure of the fully connected layer.

This paper proposes to detect the pomelo insect pests and diseases defect data set based on CNN. The CNN pests and diseases detection method are mainly used to identify the 4 types of honey pomelo pests and diseases, as species, the location, color, and the presence or absence of specks [8]. The loss function adopts the mean square error function, and the decline process of the loss function of one training is selected, as shown in Figure 5:

![Graphs showing the training loss function decline process and recognition accuracy of ResNet](image)

**Figure 5.** The training loss function decline process and recognition accuracy of ResNet.
It can be seen from Figure 5 that when the CNN network model is trained to the fifth generation, the loss of the training function basically reaches the minimum, and at this time, the model's recognition rate of insect pests and diseases has reached a maximum of 95.83%. Compared with the recognition rate of pomelo by SVM, the recognition rate of the first generation of CNN network model was the lowest 89.27%, which was also higher than the recognition rate of SVM 87.65%. Experiments show that compared with previous SVM models, CNN network model is more suitable for identifying plant diseases and insect pests.

5. Conclusion
This paper presents a research on plant diseases and insect pests recognition based on CNN. Taking the pomelo in a fruit garden in a certain country in China as the measured object, the collection of the original image data is briefly explained, the characteristic values of the pomelo are simply classified, and then two different methods of SVM and CNN are introduced. The identification and detection of pests and diseases can be concluded that the CNN based plant pests detection model is much better than the traditional SVM in recognition accuracy, indicating that it is feasible to combine modern artificial intelligence and deep learning methods with agricultural production. It has certain significance for the development of intelligent agriculture in China.

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