Major crop pests identification research based on Convolutional Neural Network

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Abstract. There are many kinds of crop pests in China and they are prone to disasters. Agricultural pests pose a serious threat to crop growth, so how to effectively identify crop pests is crucial. With the development of computer vision technology and artificial intelligence, the combination of computer vision technology and classification and identification of pests has become a hot and difficult point for experts at home and abroad. In this paper, based on the bag-of-words model and the GoogLeNet model, 2200 pest images collected were used as experimental samples to study the identification of crop pests. The experimental results show that the average classification accuracy of the traditional bag-of-words model is about 56.41%, and the GoogLeNet model recognition accuracy can reach 96.35%. The GoogLeNet model based on transfer learning has higher precision and stronger anti-interference ability than the traditional bag-of-words model.

1. Introduction
Crop pests have always been one of the most important agricultural disasters in China. The occurrence area of crop pests in China has been increasing year by year, and has climbed from more than 2 billion acres in 1980 to nearly 7 billion acres in 2016. In China's major agricultural production areas, the economic losses caused by pests alone will reach tens of millions of yuan per year[1]. At present, the prevention and control of agricultural pests are mainly divided into three methods of biological, chemical and physical machinery[2]. However, traditional large-scale spraying of pesticides will cause waste of drugs, and at the same time bring harm to the ecological environment. The residue of pesticides may even endanger human health. The best solution is to aim at the species and the site of the pests, and to reduce pesticide pollution while effectively controlling pests. Therefore, people should be eager to study the identification and classification of crop pests.

Pattern recognition technology based on computer vision can effectively reduce the cost of recognition, and can significantly improve the recognition speed and efficiency[3]. Compared with manual method, the automatic identification of crop pests by convolutional neural network can reduce labor costs, improve work efficiency, avoid environmental pollution caused by excessive use of pesticides, and ensure food safety. In the transformation and upgrading of precision agriculture, it is of great theoretical and practical significance to promote Chinese agricultural production from labor-intensive traditional agriculture to intelligent precision agriculture.
In recent years, pattern recognition technology has developed rapidly. Scholars at home and abroad have published a large number of related researches, which provide a certain theoretical basis for pattern recognition of pests. At present, the machine recognition of crop pests is mainly based on images. The image-based recognition methods are roughly divided into four categories. One is based on invariant moments. For example, Diao Zhihua et al. introduced invariant moment theory into shape feature extraction, defined the shape feature of wheat leaf disease images extracted from the instantaneous parameters of 7 Hu invariant moments and applied to the designed wheat disease intelligent recognition system to obtain a high recognition rate[4]. The second is based on fuzzy clustering. For example, Vinushree et al. used KFCM to judge the density of insects in plants[5]. The third is support vector machine. For example, Wu Xiang used the corner detection to clip the original image, then segmented the Otsu algorithm's clipping image, and extracted the image features of the pest target in the segmented image by SURF algorithm. Finally, the recognition of 10 types of pest images such as Pieris rapae was realized by the SVM classifier[6]. Fourth, based on neural networks, such as Gassoumi et al. used a neural network method to classify insects in the cotton ecosystem and achieved 90% accuracy[7].

The Convolutional Neural Network (CNN) is a feedforward multi-layer neural network, which is a kind of supervised learning. It is good at dealing with related machine learning problems of images, especially large images. Through a series of methods, CNN can reduce the image with massive data recognition dimensions and finally enable it to be trained. CNN was first implemented by LeNet, which was proposed by LeCun in 1998[8]. LeNet is a classic convolutional neural network used to identify handwritten digits (the MNIST database). Although its network structure is small, it contains convolutional layer, pooling layer, and fully connected layer, which constitute the basic components of a modern CNN. In 2014, Szegedy et al. proposed GoogLeNet that can extract more features with the same amount of computation to optimizing training results[9]. In recent research work, convolutional neural networks have been widely used in image recognition for face detection and license plate recognition. However, the image recognition of pests is more complex and more difficult than other machine vision applications due to the small size, wide varieties, and large differences among species. The research on the application of convolutional neural network in pest image recognition has yet to be done.

2. Methods

2.1. Bag-of-words model (BOW model)
In recent years, with the development of computer vision technology and artificial intelligence technology, the bag-of-words model has been widely used in computer vision. In the image classification technology based on the BOW model, the three parts of feature extraction, visual dictionary construction and classifier training are generally included. The SIFT feature extraction adopted in this study mainly extracts global or local invariant features from a given image set to obtain the representation of the image. The construction of the visual dictionary is mainly to cluster the extracted image features, and the cluster center is used as a visual word, and the set of all cluster centers is the visual dictionary of this construct. Classifier training is an operation aimed at the image classification task. The classification and recognition of the image can be performed by the trained classifier.

2.2. Convolutional Neural Network(CNN) - transfer learning of the GoogLeNet model
This study uses the Inception-v3 model in GoogLeNet for transfer learning. The transfer learning of model refers to using tens of millions of images to train an image recognition system. When we encounter a new image field, we can transfer the original image recognition system to a new field, and the same effect can be achieved with less image training in the new field. It is difficult to find sufficient training data on crop pests. However, through transfer learning, the models trained from other data sources can be modified and improved to apply to similar fields, thus greatly alleviating the
problems caused by insufficient data sources. The GoogLeNet model used in this experiment was based on the ImageNet dataset training. At present, there are more than 14 million images in the ImageNet dataset, covering more than 20,000 categories. Among them, there are 3,998 species in the animal category, including some insect pests. Therefore, the model trained with the ImageNet Dataset is feasible in the pest identification of this project. The transfer learning will get better results, and the training time is less. The basic idea is to use the pre-trained GoogLeNet model to find a layer in the model that can output reusable features, and then use the output of the layer as an input feature to train those smaller neural networks that require fewer parameters.

3. Results and analysis

The training results of the traditional bag-of-words model can be seen from the Figure 1. The average classification accuracy of 7 species, such as pomacea canaliculata, gryllidae, henosepilachna vigintiotochomaculata, thrips, cnaphalocrocis medinalis, trialeurodes vaporariorum and acrida cinerea, was over 80%. The classification accuracy of cnaphalocrocis medinalis was 97%. However, the classification accuracy of cutworm, Spodoptera litura, Rhynchocoris humeralis, cletus punctiger dallas and achatina fulica was relatively low. The average classification accuracy of the traditional bag-of-words model can reach 56.41%.

![Figure 1](image)

This study used the Inception-v3 model in GoogLeNet for transfer learning, which was trained by the ImageNet dataset. The Figure 2 shows the identification of two example crop pests, planthopper and prodenia litura, using the Inception-v3 model transferred to mobile phones. The judgment result in the Figure 2 of planthopper means that the probability of being planthoppers is 0.6094699, and the probability of being whitefly is 0.33967218. That is, the recognition result of this image is planthoppers, and the judgment result is correct. In the same way, the judgment result in the figure of prodenia litura means that the probability of the pest being prodenia litura is 0.98734725, and the judgment result is also correct. It can be concluded from the training results that the GoogLeNet model has a high correct rate, and the effect of transfer learning is good. The overall mean recognition accuracy can reach 96.35%.
Figure 2. The result of identifying 2 kinds of crop pests with GoogLeNet model.

Comparing the above training results, it can be found that the traditional bag-of-words model is susceptible to complex background and other factors, which is not conducive to determining the correlation between features and information redundancy, and is not conducive to subsequent classifier training. The GoogLeNet model is based on ImageNet dataset, which has large amount of data, a wide range of image categories, including most pests, and then using our pest dataset for transfer learning. Compared with the traditional bag-of-words model, the model we trained has higher precision and better anti-interference ability.

4. Conclusion
In this study, 2200 pest images collected were used as experimental samples. We mainly adopted neural network as our research idea. Based on the Tensorflow deep learning framework, an image database of crop pests was established through image flipping, random clipping and zero-padding, color jittering and saliency image segmentation in Pycharm. Through transfer learning, the features of crop pests were extracted from the optimized GoogLeNet model, and a classifier for crop pests image recognition was established. The experimental results show that the average classification accuracy of the traditional bag-of-words model can reach more than 56.41%, and the GoogLeNet model recognition accuracy can reach 96.35%. The GoogLeNet model has higher precision and stronger anti-interference ability than the traditional bag-of-words model.

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