# Identification of the agricultural pests based on deep learning models

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*Abstract*—**Pest identification is an important part of farming. It is crucial to accurately identify crop pests. In this background, based on the convolutional neural network, this paper collected 71 types of 35,000 images of pests, using the Inception-v3 and Inception-v4 model in GoogLeNet to build pests recognition model. Finally, based on several evaluation indicators, we combine the traditional methods for comparison and effect verification. The results show that the deep learning model is the best model for identifying pests and diseases in all the models involved in this study. Among them, the Inception-v4 support vector machine classification method has the highest accuracy, the overall classification accuracy rate is 97.3%, and the Inception-v3 classification accuracy is the second. The research can provide references for the identification of agricultural pests.**

***Keywords-identification; pest; deep learning model; GoogLeNet***

## I. INTRODUCTION

Traditional artificial identification of pests is mainly based on the appearance characteristics and life habits of pests such as morphology, texture and judged by the prior knowledge of farmers. However, there are tens of thousands of kinds and large quantities of agricultural pests. It takes a lot of time to identify them manually. At the end of the 20th century, the concept of "precision agriculture" was put forward internationally[1].

China is a large agricultural country with abundant agricultural production resources, but the climate conditions are complex and diverse, and agricultural biological disasters occur frequently and seriously[2]. Every year, agricultural pests cause great losses[3]. From 2006 to 2015, the area of diseases and pests is ranged from 460.35 billion to 5075.3 billion $hm^2$, with an average actual loss of grain of 196.549 million tons[4], which the loss caused by pests was more serious. The main agricultural disasters in China are caused by crop pests, which have the characteristics of many kinds, great influence and the frequency of disasters. The disasters caused by crop pests interfere with the crop growth and lead to the decline in crop yield. Therefore, it is necessary to control agricultural pests[4]. Accurate pest identification is the precondition for pest control and pesticide application[5], but if it only relies on manual identification, it will be inefficient and high labor cost.

In recent years, with the rapid development of computer networks, image recognition technology based on computer vision has been widely used in the field of agricultural pest control, which can effectively reduce the cost of recognition and significantly improve the speed and efficiency of recognition[3]. The identification results of the convolutional neural network are accurate and efficient. By using the convolutional neural network, the automatic identification results of crop pests can identify the types of pests and apply pesticides accurately, which has far-reaching significance for improving China's grain production capacity and food security.

At present, recognition based on machine vision has attracted great attention of scholars all over the world and has become one of the hot research directions. Gasoumi et al. used the neural network method to classify pests in the cotton ecosystem, and achieve 90% accuracy[6]. Liang Wanjie et al. proposed a method of rice stem borer pest identification based on convolutional neural network, elaborated data preprocessing, data set construction, identification model structure design and model development and implementation technology[7]. In 2016, the Google team proposed Inception-ResNet-v2 based on the Inception-v3 model in GoogLeNet combined with the inspiration from Microsoft ResNet, and achieved the best result in ILSVRC image classification benchmark test[8]. Using Inception structure can make full use of computing resources while increasing the depth and width of the convolutional neural network, which make the difficulty of model training will not increase too much. And it can replace the last fully connected layer of other convolutional neural network with the global average pooling layer. Therefore, the research of convolutional neural network based on the GoogLeNet model in crop pest identification has important theoretical and practical significance[7].

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## II. INCEPTION MODEL

### A. Convolutional neural network

The convolutional neural network is a kind of backpropagation (BP) neural network, which extracts the features of objects through the interaction of the feature extraction layer and feature mapping layer. Each layer of the convolutional neural network consists of a number of small size feature maps, and the volume operations in the upper layer to lower layer are performed using a specific size filter with the upper-layer data. The most important structure of the convolutional neural network is the convolutional layer, which can extract effective features and reduce the time complexity of the images. The pooling layer is usually connected by the convolutional layer to map the features, merge similar features and greatly reduce the number of features. The pooling layer can reduce network parameters and allow the trained features to have a certain generalization ability to avoid network overfitting. Normally, the neuron nodes of each layer are connected to the upper part of the area, which has two advantages. One is that the weight coefficients can be shared and the structural parameters can be greatly reduced. The other is to preserve the position relation of local features and ensure that the position relation of local features is preserved(see Figure 1).

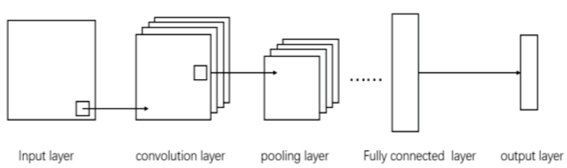


Figure 1. Convolutional neural network.

### B. Inception-v3 and Inception-v4

This study uses the Inception-v3 model and the Inception-v4 model in GoogLeNet for transfer learning. Model migration refers to an image recognition system that uses tens of millions of images to train. When we encounter a new image field, the original image recognition system can be migrated to a new field, and the same effect can be achieved in the new field with fewer images. Model migration can also be combined with deep learning to distinguish the transferable degrees at different layers, and those levels with higher similarity are more likely to be migrated. For the problem of crop pests, it is more difficult to find enough training data. However, through transfer learning, the models trained from other data sources can be improved and applied to similar fields, thus the problem caused by the lack of data sources can be greatly alleviated. The basic idea of transfer learning is to use the pre-training GoogLeNet model to find the layers that can output reusable features in the pre-training model, and then the output is used as input feature to train the smaller neural network which needs fewer parameters.

The Inception-v3 model and Inception-v4 model used in this paper have been greatly improved, including convolution decomposition. Specifically, $7 \times 7$ convolution is decomposed into two one-dimensional serial convolutions, and $3\times3$ convolution is decomposed into two one-dimensional serial convolutions ( $1\times3$ and $3\times1$). In this way, the computation can be accelerated, the network depth can be further increased, the nonlinearity of the network is increased, and the Residual Blocks structure in ResNet is added to the Inception-v4 model which can improve the convergence speed of the model training.

## III. MODEL VALIDATION

### A. Image segmentation accuracy

The segmentation accuracy used in this paper is the ratio of the intersection and union of the binary foreground segmentation mask graph and the real foreground segmentation mask graph.

$$p=\text{mean}\left(\frac{A\cap B}{A\cup B}\right) \tag{1}$$

Where p is the accuracy rate, A means the binary foreground segmentation mask graph, and B means the real foreground segmentation mask graph.

### B. Model training accuracy

Cross entropy (loss value): Cross entropy is the distance between the actual value (probability) and the predicted value (probability), that is, the smaller the value of the cross entropy, the closer the two probability distributions.

$$H_{(p,q)} = -\sum_x p(x)\log q(x) \tag{2}$$

Where p is the predicted value of the probability distribution, q is the actual value of the probability distribution, and H(p,q) is the cross entropy.

## IV. THE RESULTS AND ANALYSIS

### A. cross entropy

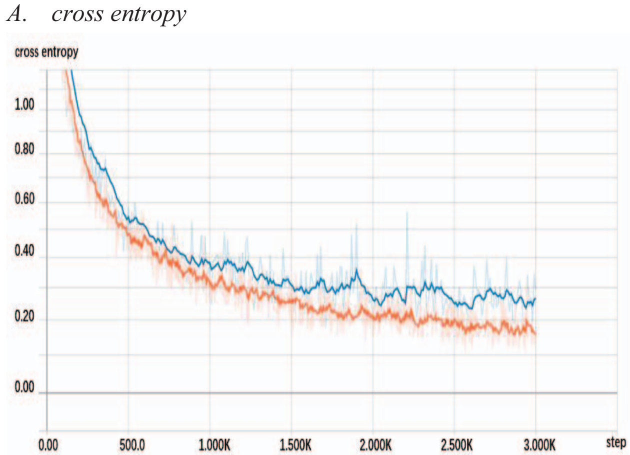


Figure 2. cross entropy

In Figure 2, the cross entropy of the model decreases as the number of steps increases. During this period, the accuracy rate has a small fluctuation, but after 2500 steps, it finally stabilizes at around 0.18. It indicates that the accuracy is steadily increasing.

### B. *Different pests*

We used Inception-v4 model to identify 71 kinds of pests, and the total number of samples reached 35000(some of them are shown in Figure 3).

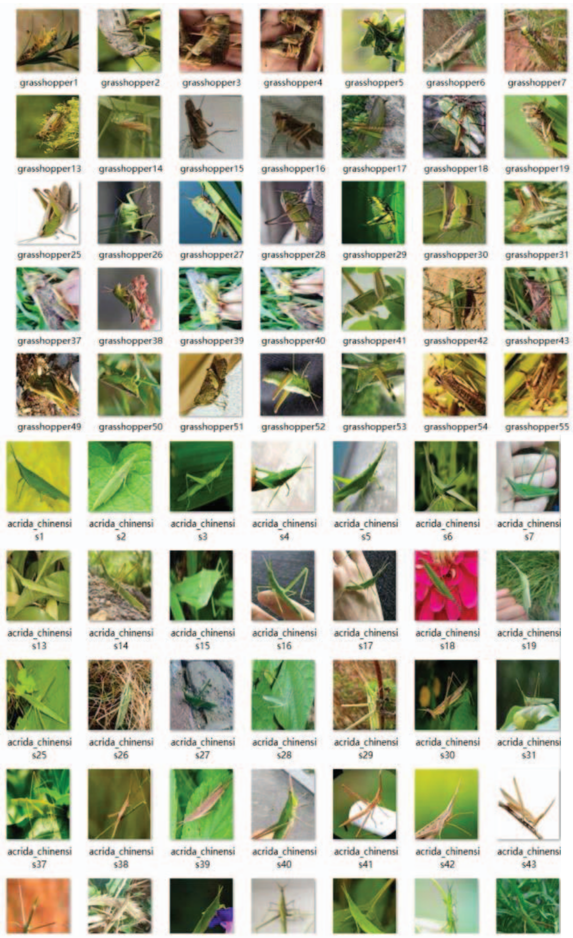

Figure 3. Images of some samples

TABLE I. IMAGE ACCURACY RATE FOR EACH TYPE OF PEST

| Name | Accuracy | Name | Accuracy |
|---|---|---|---|
| silkworm moth | 0.88 | mole cricket | 0.97 |
| whitefly | 0.99 | Geometrid | 0.92 |
| Gypsophila | 0.95 | lappet moth | 0.86 |
| leaf beetle | 0.91 | Limax | 1 |
| Leafhopper | 0.97 | Grasshopper | 0.88 |
| scale insect | 0.92 | Lycaenid | 0.92 |
| carpenter moth | 0.98 | tussock moth | 0.81 |
| Cricket | 0.95 | Millipede | 0.95 |
| Weevil | 0.97 | Armyworm | 0.85 |
| Cutworm | 0.94 | notodontidae | 0.77 |
| plant hopper | 0.85 | Nymphalid | 0.84 |
| Earthworm | 0.95 | psylla | 0.9 |
| Longicorn | 0.99 | white butterfly | 0.87 |
| gall mite | 0.93 | Bark Beetle | 0.92 |
| Eucleid | 0.91 | bagworm moth | 0.91 |
| grasshopper | 0.93 | swallowtail butterflies | 0.93 |
| flatid planthopper | 0.99 | coconut leaf beetle | 0.97 |
| snout moth | 0.75 | snail | 0.96 |
| aphid | 0.95 | tiger moth | 0.94 |
| sawfly | 0.87 | hawkmoth | 0.84 |
| leaf mite | 0.92 | tortricidae | 0.89 |
| thrips | 0.97 | wireworm | 0.98 |
| lace bug | 0.93 | tabby moth | 0.92 |
| grub | 1 | termite | 0.93 |
| red imported fire ant | 0.89 | Red palm weevil | 0.97 |
| scarab | 0.85 | | |

It can be seen from Table I that there is a big difference in the accuracy between different pests. The grub and the limax have the highest accuracy which is 100% in the test, and the pest that has the lowest accuracy is the parasitic moth, and its accuracy is only 75%. The main reason for the result is the influence of patterns and other features. The parasitic moth lacks the distinguishing degree, and the color of the parasitic moth is brown and gray, which is easily confused with the background color. It is difficult to obtain biological edge information, and it causes lower recognition rate. At the same time, due to the seasonal influence, some pests have seasonal differences, which leads to a decrease in the reliability of the samples. In the actual test, there are differences among the pests that are affected by seasons.

### C. *Different models*

TABLE II. THE IMAGE ACCURACY RATE FOR EACH TYPE OF MODEL

| Model | Test samples | Recognized samples | Accuracy |
|---|---|---|---|
| LeNet[8] | 1200 | 1080 | 0.9 |
| CNN [9] | 300 | 281 | 0.9375 |
| SVM[10] | 100 | 89 | 0.8926 |
| BP neural network [11] | 300 | 278 | 0.9267 |
| SSGAN[12] | 3500 | 3301 | 0.9432 |
| Inception-v3 | 5000 | 4781 | 0.9562 |
| Inception-v4 | 5000 | 4865 | 0.973 |

The results show that Inception-v4 has the highest accuracy among the seven models. The accuracy of SVM is the lowest and it's only 89.26%(see Table 2).

Most models have an accuracy between 90% and 95%. Among them, the accuracy of every identified model in the convolutional neural network model is relatively well, and the accuracy of Inception-v3 and Inception-v4 even exceeds 95%.

The reason is that the original traditional extracted features are too simple. Compared with the convolutional neural network, it is not suitable for more complex or high resolution image recognition.

According to the analysis, the Inception-v4 model can achieve more than 99% accuracy for some typical pest images.

## V. CONCLUSION

Using the Inception-v4 model in the convolutional neural network, the identification of 71 types of 35,000 images was tested. The recognition rates of different insects are obtained and compared with SVM and Inception-v3 model. The Inception-v4 model discussed in this paper has the highest precision, reaching 97.3%. The superiority of Inception-v4 model and its application in the identification of pests are fully proved.

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