IoT Agricultural Pest Identification Based on Multiple Convolutional Models

*Yaru Zhang**

School of Information & Communication Engineering, Beijing Information Science and Technology University, China
zhangyaru@bistu.edu.cn

Abstract

This topic focuses on the corresponding research and simulation of multiple convolutional models for the detection methods of leaf pests and disease identification. Currently, crop pest identification in China mainly relies on field observation by farmers or experts, which is less accurate, time-consuming and extremely expensive, and not feasible for millions of small and medium-sized farms. To improve the recognition accuracy, crop pest recognition is performed by a convolutional neural network (CNN) after combining the plant leaf collection dataset, which has the features of automatic image feature extraction, strong generalization ability, and high recognition rate, and combined with the advantage of similarity by transfer learning, a crop pest recognition algorithm based on the comparison of multiple convolutional neural networks is implemented. After comparison experiments, the algorithm has 99.8% accuracy in the test set and can accurately distinguish seven health states of apples and grapes. This algorithm can help agricultural workers to conduct agricultural activities more scientifically, which is important for improving crop yield and agricultural intelligence.

Keywords: Pest and disease detection, CNN, Transfer learning, VGG, ResNet

1 Introduction

Agriculture is one of the major economic bases in China, and the pests and diseases of crops have always affected the yield and quality of crops. However, traditional pest detection mainly relies on human observation and experience judgment, and the production efficiency and economic efficiency do not reach the ideal goal, so the application of image recognition technology to agricultural pest identification is a very important part of agricultural economic development [1]. At present, visual image recognition technology based on deep learning is widely used in the field of classification, segmentation, and detection of diseases, promoting the development of intelligent identification and prevention of agricultural diseases [2-4], while the combination of agricultural Internet of Things and sensors, wireless transmission technology, and remote automatic control technology is getting closer and closer, making it possible for the algorithm to observe the growth environment and growth process of crops in real-time, so as to obtain at any time to get away without the growth status, pest and disease occurrence, and the change of data when the pest and disease occur, etc [5-7]. Therefore, a reasonable disease detection system is important to ensure that crops are less or free from pests and diseases during the growth process, to ensure the quality of their fruits and the safety of the growing environment, to promote the production of agricultural products, and to avoid the waste of resources and pesticide pollution.

2 Technical Principles

2.1 CNN Model

The CNN is a deformation of the development branch of a neural network. The weight parameter assignment structure, which simplifies the complexity of the network, allows image data to be directly used as layer input, avoiding the process of complex image data pre-processing. The CNN network processing of 2D image data is equivalent to a special multilayer perceptron [8-9]. This perceptron model has a high linear invariance, which ensures that the information does not change during translation, scaling, tilting, or other forms of deformation of the expressive feature information dimension data. The CNN discussion focuses on the implementation of convolutional operations to train multi-layer network structures using real input image data. It can be combined with image data spatial information to learn and extract image features adaptively. The root of deep learning is the iterative update type CNN, which extracts and integrates data feature information through the lowest level input image data, and iterates into different levels of operations sequentially, each iteration has corresponding digital filters to realize the training data reading function, and finally obtains the predicted result output [10-12].

Convolutional neural networks have powerful feature learning and feature expression capabilities. The structure of a CNN consists of a convolutional layer, a pooling layer, and a fully connected layer. The main function of the convolutional layer is to extract features from the input image information, the pooling layer compresses the extracted features, and the fully-connected layer completes the final classification task [13-15]. The structure of the CNN model is shown in Figure 1.

*Corresponding Author: Yaru Zhang; E-mail: zhangyaru@bistu.edu.cn
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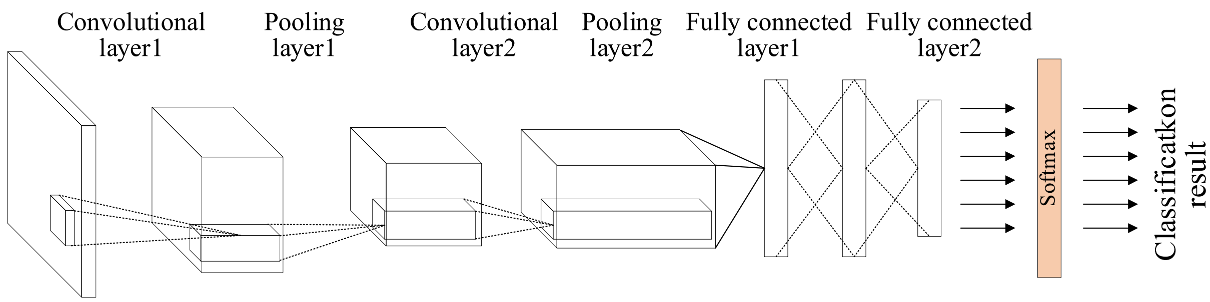


Figure 1. CNN model structure diagram

2.2 VGGNet Model

Visual Geometry Group (VGGNet), which won second place in the classification task as well as first place in the recognition task in ILSVRC 2014, is an upgraded version of AlexNet with a cleaner structure and deeper network layers than AlexNet [16-17]. Its core idea is to use cascaded convolution to reduce the number of parameters and thus improve performance. Cascaded convolution uses three 3×3 convolutional layers stacked up to cover the same perceptual field and can approximate a 7×7 convolution. However, cascaded convolution employs far fewer parameters, resulting in significant performance advantages in both training time and runtime. VGGNet improves feature extraction by increasing the depth of the model. The number of channels per convolution layer is doubled layer by layer, allowing feature information in the image to be extracted more comprehensively [18]. The most classic and frequently used ones are VGG16 and VGG19, whose network structures are shown in Figure 2.

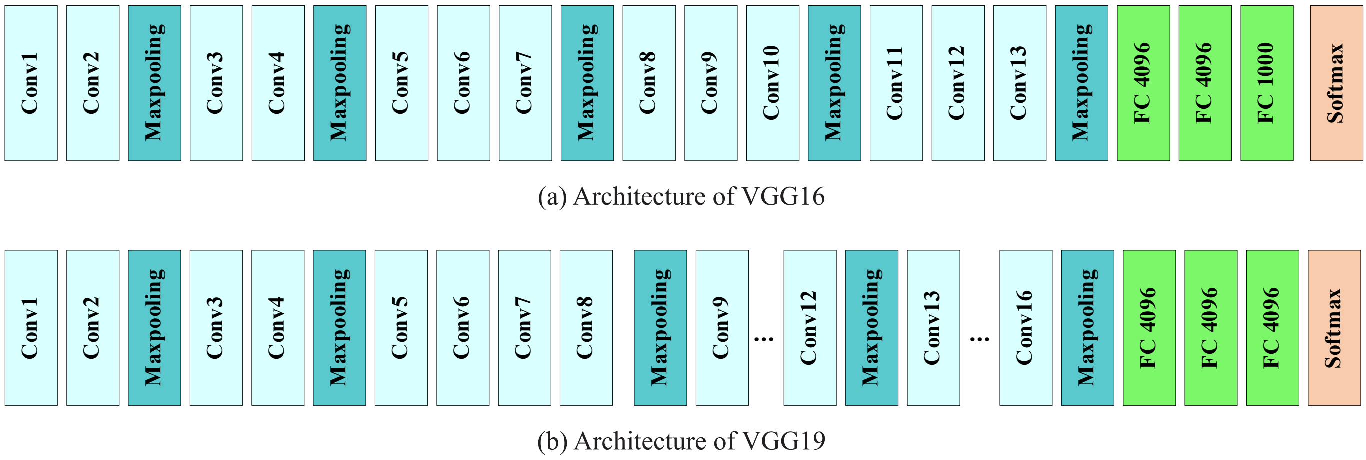


Figure 2. Network architecture

2.3 ResNet Model

In deep learning, the CNN learn image features by layer-by-layer abstraction for feature extraction, and as the network goes deeper, the network gradually loses the feature detail information in the shallow layers, which leads to gradient dissipation and gradient explosion, resulting in a decrease in the accuracy of the training set [19-20]. The proposed residual network, Deep Residual Network (ResNet), adds residual connections to make the feature information of different layers pass to each other, which alleviates the gradient disappearance problem and deepens the network while ensuring the classification performance of the image [21-23]. The structure of ResNet is shown in Figure 3. Each residual component consists of two convolutional layers and a shortcut link, which is represented by the curved arrow in Figure 3. As the network gets deeper and deeper, it becomes more and more difficult to learn features. If a shortcut link is added, the learning process changes from learning features directly to adding some features to the previously learned features to

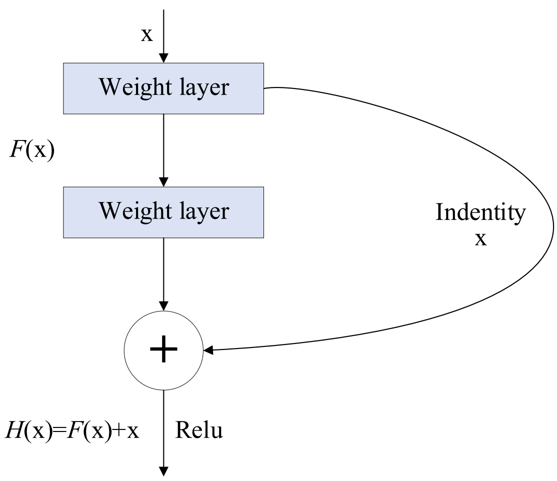


Figure 3. Structure of Residual module

obtain better features [24]. In the previous case, the features were learned independently layer by layer, but now it becomes such a model $H(x) = F(x) + x$, where x is the feature at the beginning of the shortcut link, and $F(x)$ is the fill and increase of x, which becomes the residual. Therefore, the goal of learning is to change from learning the complete information to learning the residuals, and the difficulty of learning quality features is greatly reduced.

The loss function is used to evaluate the extent to which the predicted value of the model is different from the true value. In the traditional ResNet network, the Cross-Entropy of each sample is weighted and averaged as the final loss function value [25]. The formula for calculating the cross entropy is as in Equation (1), (2).

$$CE = \begin{cases} -\log(p) & if\ y=1 \\ -\log(1-p) & otherwise \end{cases}. \tag{1}$$

$$Loss = \frac{\sum CE(p,y)}{m}. \tag{2}$$

Where p denotes the probability that the model predicts y=1; y is the label value; CE (p, y) is the cross-entropy of each sample; and m is the number of samples in Eq. (1). Loss is the final loss function value in Eq. (2).

3 Framework Design

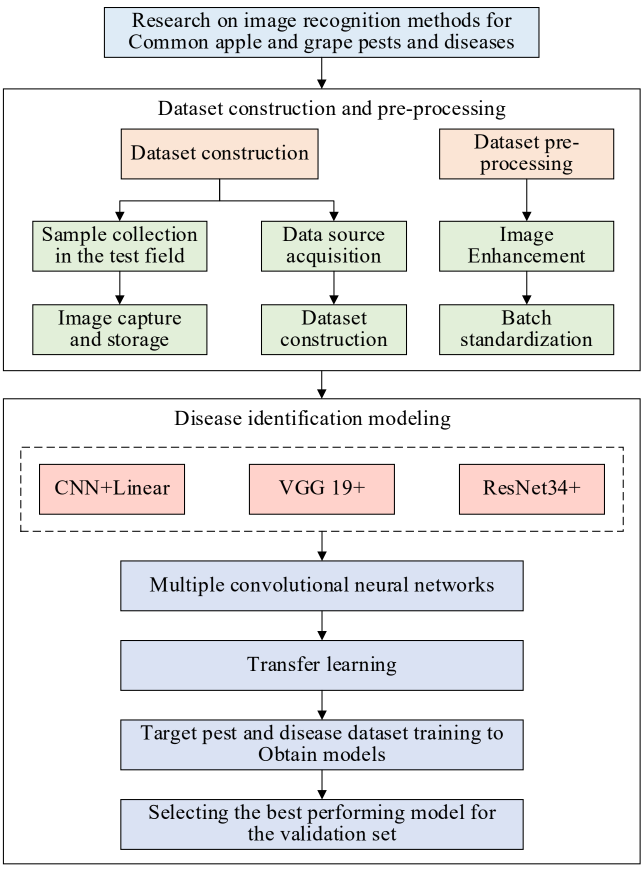


Figure 4. Technology roadmap

In this project, we conducted a study on the identification of crop foliar diseases based on the comparative analysis of multiple convolutional neural networks for the classification problem of seven types of apple and grape foliar diseases, including:

(1) Constructing multiple convolutional neural network models for apple and grape pest identification research. Among them, the residual structure of ResNet34 does not have the problem of gradient disappearance or explosion due to the increase of model depth; the performance of the model is improved at several levels, such as saving arithmetic power, improving robustness, improving generalization, and improving accuracy.

(2) Collecting the causes and influencing factors of black star disease, black rot, and green blight of apples and grapes, and expanding the data set to further feedback on the model to improve the accuracy.

The research route is shown in Figure 4.

4 Experimental Results and Analysis

4.1 Data Set

The dataset used in the experiment was obtained from the Beijing Data Center, which contains 4639 images of healthy and diseased apple leaves and was divided into training and testing sets. Black_rot, Grape_Leaf_blight and Grape_healthy are divided into seven categories of 500, 494, 220, 1315, 940, 333, and 837 images, respectively, for a total of 4639 images, and 1213 images for the test set.

In the dataset, Apple_scab represents apple leaves suffering from black star disease, as shown in Figure 5.

Figure 5. Black star disease apple leaf diagram

Apple_Black_rot represents a leaf with apple black rot, as shown in Figure 6.

Figure 6. Map of apple leaves with black rot

Cedar_apple_rust represents a leaf with apple cedar rust, as shown in Figure 7.

Figure 7. Map of cedar rust apple leaves

Apple_healthy stands for healthy apple leaves, as shown in Figure 8.

Figure 8. Healthy apple leaf diagram

Grape_Black_rot represents leaves suffering from grape black rot, as shown in Figure 9.

Figure 9. Map of black rot grape leaves

Grape_Leaf_blight represents leaves affected with grape bruise disease, as shown in Figure 10.

Figure 10. Leaf diagram of grape bruise disease

Grape_healthy stands for healthy grapes, as shown in Figure 11.

Figure 11. Map of healthy grape leaves

4.2 Experiments

4.2.1 Data Pre-processing

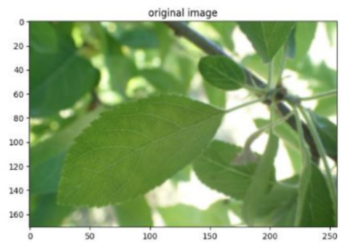
The original images often contain a lot of useless information, and preprocessing the dataset is an important task to weaken the influence of useless information on the network model. The statistical analysis of the seven types of datasets used in this paper shows that the datasets have a limited amount of data and have the problem of unbalanced data distribution, and some samples with too little data will hurt the training of the model [26-27]. In this section, reasonable pre-processing operations are performed on the existing datasets, and the datasets are trimmed employing image cropping and inverse color transformations. For the characteristics of agricultural images, the dataset images are operated as follows:

(1) Image cropping

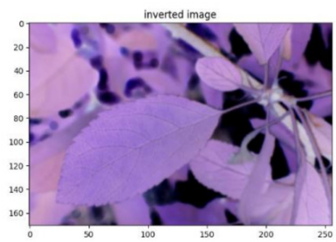
The specification size of agricultural images is generally non-uniform, which is not conducive to the input of network models. After observation and analysis, most of the main information of the image is concentrated in the middle (171, 256) region of the image, so the image is cropped before input to the network model, and the middle part of the image region is selected to simplify the dataset while retaining the main information. Finally, the image is compressed or expanded to meet the fixed size of the input image required by the neural network model.

(2) Inverse color transformation

The main color of the agricultural images is green, and since the data set of this competition was taken in an orchard, the background color of the pages is also mostly green. Considering that the values of the pixels in the images are too close to each other, an inverse color transformation is considered to enhance image differentiation. The inverse color transformation of an image is to make black pixels white and white pixels black. The generalized inverse color [28] transformation can also be applied to color images, i.e., complementing all pixel points, and the inverse image processing can enhance white or gray details in dark areas. The effect of the inverse color transformation of an image is shown in Figure 12.



(a) Original image



(b) After inverse color transformation

Figure 12. Image inverse color transformation effect

4.2.2 Algorithm Analysis

For better comparative analysis and selection of the best model, we decided to use the combination of using CNN + multiple linear layers, VGG16 + transfer learning, and Resnet34 + transfer learning on the dataset respectively to conduct experiments and observe the experimental effects, the specific steps of the experiments can be summarized as follows: (1) Load images and preprocess them. (2) Construct network models and try multiple convolutional neural networks, such as CNN combined with a variety of linear layers, VGG16 + transfer learning, Resnet34 + transfer learning, etc. (3) Train the model and evaluate and save the model, the specific process is described as follows:

(1) Load images and perform preprocessing

Firstly, the competition dataset is loaded into the program, and with the help of the transforms library function provided in Python, the size of all images is uniformly adjusted to 171×256 and inverse color processing is performed, and finally the dataset is divided into a training set validation set according to the ratio of 7:3, and part of the training set is shown in Figure 13.

Figure 13. Training set images

(2) Neural network structure construction

The CNN+ multilayer linear model, VGG16 model, and Resnet34 model are constructed respectively, where VGG16 and Resnet34 are combined with transfer learning principles to further optimize the model results, and the basic training process of the network structure is as follows: firstly, through the CNN feature extraction module, the images are finally transformed into multidimensional feature vectors after different blocks; Then the dimensionality of the feature vectors is compressed through the Flatten operation compresses the dimensionality of the feature vector and adds the position encoding vector; then the information is fused by Transformer Encoder module, and the input and output vectors of each Transformer Encoder module have the same dimensionality [29-30]; The last Transformer Encoder output vector is globally averaged pooling to a 1×768 feature vector; Finally, the dimensionality is reduced by a fully connected layer and a Softmax classifier is used to achieve image classification.

(3) Train the model and evaluate and save the model

In the process of model training, considering the learning rate, and the influence of the optimizer on the experimental results, a comparison experiment is set to determine the hyperparameters suitable for the model in this chapter. The learning rate is set with three gradients: 0.01, 0.001, and 0.0001, and the optimizer is set with three types: AdamW, Adam, and SGD optimizer. By comparing different combinations of optimizers and learning rates, it was found that the model achieved better results when the SGD optimizer and learning rate were set to 0.0001. However, it is found that the larger the learning rate is, the faster the model converges and the shorter the model training time is, but the problem of low model accuracy also arises. Combining various factors such as model training time and model accuracy, the learning rate was finally set to 0.001.

4.2.3 Evaluation Index and Loss Function

Our research found that the commonly used metrics for convolutional neural networks are Precision (*Pr*), Recall (*Re*), and mean average precision (*mAP*), and to better examine the speed of the model, we also considered the frame rate Frame per second (*FPS*) metric to measure model effectiveness.

(1) *Pr*

The *Pr* indicates how many targets are correctly detected out of the number of samples detected as targets, reflecting the accuracy of the detection results, and is expressed by Equation (3).

$$Pr = \frac{TP}{TP + FP}. \tag{3}$$

Where TP represents the target is a valid blade, and the detection result is a valid blade; FP represents the target is not a valid blade, and the detection result is a valid blade.

(2) *Re*

The *Re* refers to how many targets are detected in all the images containing the targets to be measured, responding to the incompleteness of the detection, as shown by Equation (4).

$$Re = \frac{TP}{TP + FN}. \tag{4}$$

Where FN represents the target is a valid blade, and the detection result is not a valid blade.

(3) Average precision mean

Average Precision (AP) is to reflect the detection accuracy of a single target category and is the area value of the curve enclosed by the precision rate *Pr* and the Re rate. The average precision average *mAP* is the average value of all categories of precision average AP, as shown in Equation (5) and (6).

$$AP = \int_0^1 p(r)dr. \quad \textbf{(5)}$$

$$mAP = \frac{\sum_{i=1}^{k} AP_i}{k}. \quad \textbf{(6)}$$

Where $p(r)$ refers to the P-R curve plotted by Pr and Re values, k represents the number of categories of leaves.

In the classification task, we want to get the probability of each category, and the Softmax function can transform the original output into a probability distribution. In addition, the cross-entropy loss function can compare the probability distribution predicted by the model with the true label distribution and thus train the model. Softmax cross-entropy loss function differs from the SVM classifier in that it can normalize the output components corresponding to each category so that the sum of each component is 1, thus obtaining results that are more consistent with our intuitive understanding of the classification problem [31-33]. Therefore, using the Softmax cross-entropy loss function in the classification task can improve the classification effectiveness and interpretability of the model Equation (7) is the probability calculation formula of Softmax.

$$S_i = \frac{e^{y_i}}{\sum_{j=1}^{c} e^{y_j}}. \quad \textbf{(7)}$$

The cross-entropy loss function is one of the most frequently used loss functions in image classification (including pixel-level classification, such as semantic segmentation, keypoint detection, etc.). Equation (8) is the formula for the cross-entropy loss function.

$$L_c = -\sum_{i=1}^{K} y_i \log(p_i). \quad \textbf{(8)}$$

Where K is the total number of categories, y_i is the true probability that the target belongs to category i. Usually if $i = c$ (c is the true probability of the target) then $y_i = 1$, otherwise $y_i = 0$. p_i is the probability that the target belongs to category i as predicted by the network, i.e., the Softmax classification result of the ith value output by the network.

4.3 Analysis of Experimental Results

Comparing the results of CNN + multiple linear layer combination, VGG16 + transfer learning, and Resnet34 + transfer learning for experiments on the dataset, the experimental test accuracies at the same number of iterations are shown in Table 1, where ResNet34 + transfer learning has less loss and higher validation accuracy and test accuracy than the other methods at the same number of iterations.

Table 1. Comparison of the recognition performance of the three methods

Model	Number of iterations	Loss	Validation accuracy	Test accuracy
CNN+	130	0.184	93.9%	89.8%
VGG16+	130	0.102	96.7%	94.4%
ResNet34+	130	0.003	99.5%	99.8%

The experimental results to achieve the same test accuracy at different numbers of iterations are shown in Table 2. To achieve the same test accuracy, ResNet34 + transfer learning requires the least number of iterations, the highest verification accuracy, and the least loss.

Table 2. Comparison of the recognition performance of the three methods

Model	Number of iterations	Loss	Validation accuracy	Test accuracy
CNN+	500	0.106	96.5%	99.8%
VGG16+	350	0.065	97.8%	99.8%
ResNet34+	130	0.003	99.5%	99.8%

Figure 14 shows the prediction results of an image that correctly describes not only the type of leaf but also the type of pest and disease of the leaf.

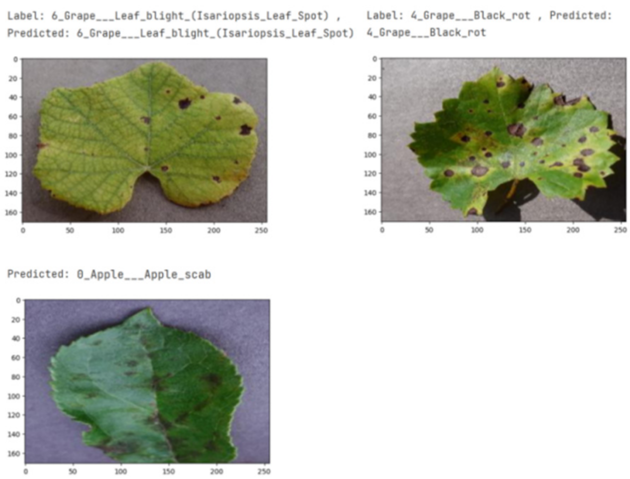


Figure 14. Prediction results of images

In addition, we also plotted the change curve of the loss function and acc change curve for each iteration, as shown in Figure 15 and Figure 16 for the change curve of the loss function and acc change curve of ResNet34 + transfer learning, from which we can see that the loss function and epoch function keep improving as the number of iterations increases.

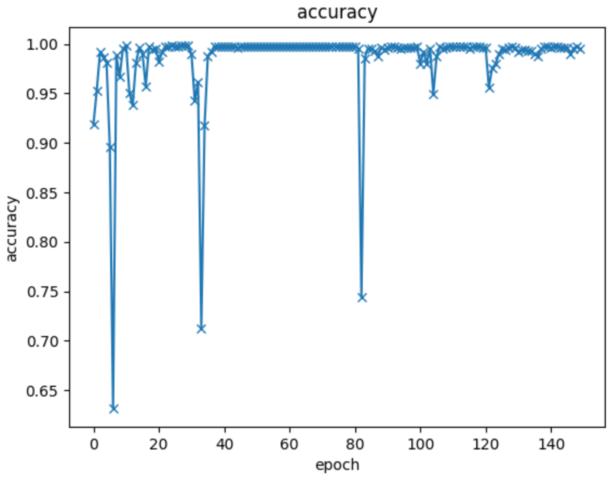


Figure 15. Acc change curve

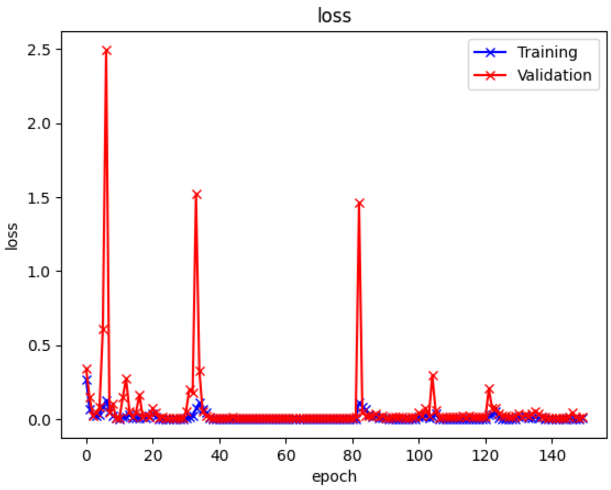


Figure 16. Loss function change curve

5 Conclusion

In this project, a crop pest recognition method based on a convolutional neural network is proposed by studying and simulating multiple convolutional models. This method has the features of automatic extraction of image features, strong generalization ability, and high recognition rate, and it realizes a crop pest recognition algorithm with multiple convolutional neural network comparisons by taking advantage of similarity through transfer learning. After comparison experiments, the algorithm showed 99.8% accuracy in the test set and could accurately distinguish seven health states of apples and grapes. This algorithm is important to help agricultural workers conduct agricultural activities more scientifically, improve crop yields, and enhance agricultural intelligence.

At present, the implemented algorithm model can already distinguish 14 crops and related pests and diseases, and in the future, the research team will introduce more crop leaf data to improve the accuracy and generalization ability of the algorithm model. Also, cutting-edge information on different crop solutions will be collected to provide more scientifically accurate pest and disease control methods to better serve agricultural production. In addition, optimization of the information collection and transmission process is considered to improve the IoT level and interface ease of use and user experience to better meet the needs of a wide range of agricultural workers.

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Biography

Yaru Zhang is an undergraduate student at Beijing Information Science and Technology University. During the undergraduate period, she won the first prize in the Physics Competition for College Students of China, the first prize of "Datang Cup" 5G Technology provincial Competition, and has published a computer software copyright.