Recognition of Crop Pest Diseases Based on Multi-scale Artificial Intelligence

Sihai Li

***Abstract*—Agricultural production has become a key factor for the well-being of citizens and stability of the world economy. However, pest diseases in the fields will reduce the production of crops and pose a threat to food security. In order to solve this problem, farmers have to use more advanced pest recognition systems to identify the types of pest diseases quickly rather than making judgement based on their own observation. This paper presents an artificial intelligence recognition model based on multi-scale convolutional neural network called LH-DenseNet. In this model, the advanced deep convolution network model DenseNet is used as the basic framework, and the large-scale public dataset ImageNet is used to train the convolution neural network's powerful feature extraction ability by applying various data enhancement strategies. Extracting and integrating the global and detailed features of images can improve the accuracy of pest classification. Thus, it can enhance the potential of deep learning in the field of agriculture, allowing more autonomic and systematic systems emerge.**

***Index Terms*—Agricultural production, pest diseases, pest recognition, multi-scale convolutional neural network, LH-DenseNet.**

I. Introduction

Agricultural development is significant to the improvement of people's livelihood and economic development. Crop diseases and pests have always been an important factor affecting crop production. The first step of pest control is to identify the species of pests and diseases accurately and quickly. For a long time, the identification and monitoring of agricultural pests and diseases are mainly based on expert diagnosis and farmers' judgment based on planting experience. However, due to the complexity of pest problem in agriculture and relatively few professionals in related aspects, it is difficult to make a timely response to control pests. In addition, relying on farmers' experience may lead to delay or misjudgment of pest issue. The image recognition method for classifying and monitoring crop diseases and pest problems has the advantages of high accuracy, good real-time performance, and little damage to plants. In recent years, with the continuous development of agricultural modernization, more advanced technology and equipment are employed in agricultural production. Moreover, with the rapid development of artificial intelligence, especially its excellent performance in the field of pattern recognition, technologies such as deep learning have gradually become the focus of research in the field of agricultural modernization.

As one of the deep learning models, deep convolutional neural network has made excellent achievements in the field of image classification by using modules such as convolution kernel, activation function, pooling layers, and dropout. The performance of deep convolutional neural network on public datasets such as ImageNet [1] and CIFAR-10 [2] has exceeded human levels, and it has excellent feature extraction ability. With the increasing amount of data and the development of computer's calculating ability, deep learning has gradually become the mainstream method in image classification, object detection, and other fields. Deep learning has become a new research hotspot in the field of agriculture because of its great potential in industry, transportation, and other fields.

In previous studies, Ruan et al extracted a total of 55 color and texture features from 142 wheat grain images and used a 4-layer BP neural network to predict the percentage of wheat scabbed kernels. The maximum and average errors of prediction were 5.14% and 1.93%, respectively. Ahmad, et al [3] used 6 color-related features to establish a model to classify different fungal and disease damages of soybean seeds. The classification accuracy ranged from 30% to 97%, which provided color-sensitive disease extraction related features. thought. Story *et al.* [4] photographed lettuce leaves in a controlled environment. The growth of lettuce was detected by combining the morphological characteristics, color characteristics and texture characteristics of lettuce plants. In the control experiment, calcium-deficient plants were found one day earlier than manual observation. Wang Yanping *et al.* [5] performed morphological expansion and erosion operations on tomato binary images, separated the diseased parts from the photographed images, and used a 3-layer BP neural network for classification. The recognition accuracy of 30 tomato fruit samples was obtained. more than 90%. Wang Jianlun [6] used the combination of Canny operator and OTSU operator to separate the leaves from the cluttered background, and optimized the segmentation results through the shape discrimination method. Between 72.5% and 83.75%. Then, the segmented leaves were identified by K-nearest neighbor clustering, and the leaf area after 3D reconstruction was used to improve the accuracy of pest and disease discrimination. Fan Zhenjun [7] used 1650 potato and citrus images as a dataset, and extracted the pest and disease areas of the image by using Grab-cut and ORB+SIFT feature points, and then used HSV color features and UPLBP features as features and used K-nearest neighbor clustering. Class and SVM were used for classification to obtain the discriminant results, and the recognition accuracy of the four diseases was between 92.59% and 96.3%.

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Sihai Li is with High School Affiliated to Renmin University of China, Beijing, China (e-mail: lisihai1424@gmail.com).

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In recent studies, several scholars used deep learning to propose solutions to boost the efficiency of spraying pesticide in the fields based on Unmanned Aerial Vehicles [8] and Wireless Sensor Networks [9]. Some scholars summarize the development and modification of deep learning in drone technology during the past decade [10,11], including drone structure, multiple sensor development, and innovation in spot area spraying. In addition, some scientists take advantage of deep learning and use it in the field of robotics and artificial intelligence to reduce the land pollution in agricultural fields [12]. According to Venkata [13], the connections between image processing systems and drones are analyzed, and he proposes some solutions for improving pesticide spraying using artificial intelligence. Moreover, some new technologies such as nanotechnology and global positioning system are used to improve the efficiency of pest management [14]. In short, deep learning is crucial for modern development of agriculture in many aspects. Kawasaki et al. used convolutional neural networks to classify 800 cucumber leaves (including 300 disease A, 200 disease B, and 300 healthy). The experiment used random rotation and cropping to preprocess the data, and used 4 Folded cross-validation measures how well the network is trained. It is proved by experiments that image segmentation is not performed on the dataset collected by the author, and the classification accuracy rate of more than 90% is achieved by using CNN. Cruz *et al*. [15] used a neural network to classify 100 healthy pictures, 99 specific pictures and 100 pictures of other diseases. Models trained on related datasets are used for transfer training to solve the problem of less data. At the same time, a method is proposed to inject manually extracted shape and texture features into fully connected layers during training to help the network integrate features. When evaluating the network, the accuracy rate, recall rate, Matthew correlation coefficient and other indicators were selected. Mohanty *et al*. [16] used 54,306 images taken in a laboratory environment to classify a total of 26 diseases in 14 crops, and the classification accuracy was as high as 99.35%. YangLu [17] used neural networks to classify 500 rice leaves in 10 classes and demonstrated the superiority of this structure over previously built machine learning classifiers. In 2017, Zhou Yao [18] used the YOLO network to count insects on the induction plate of the greenhouse, with an accuracy rate of more than 92%. Liu Haibo [19] collected and constructed a data set of 7040 tomato diseases and pests in 10 categories. The classification accuracy of the shallow network and the VGG16 model is compared, and the corresponding network is ported to the mobile phone for testing.

Although deep learning methods have strong robustness to complex and diverse datasets, on the one hand, training a network with strong generalization ability relies on a large number of diverse datasets; on the other hand, reasonable image preprocessing is also It can effectively improve the recognition effect of deep learning [20]. Reasonable image preprocessing is to highlight the required features in the image to facilitate subsequent segmentation and classification. Due to the complex lighting conditions of crops in the natural environment, and the changes of shooting hardware, the obtained pictures may have problems such as excessive noise, overexposure, underexposure, and low contrast. Therefore, filtering the collected images to remove noise, histogram equalization and other preprocessing operations will greatly help to improve leaf segmentation, recognition speed and classification accuracy. In addition, images similar to the original images can be obtained through image preprocessing, used as dataset augmentation in deep learning. Image filtering is to obtain or exclude relevant information by calculating the adjacent pixel values of the picture, which can achieve functions such as image denoising, image smoothing, and extraction of image edge features. The principle of mean filtering is equivalent to averaging eight pixels around each pixel to replace the center point. This processing method can make the amplitude of each pixel in the image approximately equal, making the image smoother, the algorithm is simple, and the processing The speed is faster, but for noisy images, the mean filter often does not work well. The directly collected images of crop diseases and insect pests often contain complex backgrounds or occlusions. Eliminating the background or extracting areas of interest in the image can effectively improve the image recognition accuracy [20].

In the process of identifying crop diseases and pests, the overall appearance of crops and the detailed features of leaves play an important role in the diagnosis of crop diseases and pests. In this paper, an artificial intelligence pest recognition model based on multi-scale convolutional neural network called LH-DenseNet is proposed. The advanced deep convolutional network model DenseNet is adopted as the basic framework, and the large-scale public open dataset ImageNet is used to train the powerful feature extraction ability of convolutional neural network by applying various data enhancement strategies. The overall and detailed features of the image were extracted and integrated to improve the accuracy of pests and diseases classification.

Fig. 1. The sample pictures of crop pest diseases.

II. Dataset and Methods

We used neural network models to classify 61 types of pest diseases in the dataset. The data set used in this paper is the "Crop Pest Diseases Dataset 2018" from the Global AI Challenge (challenger.ai), which contains 10 species of crops, including apple, cherry, corn, grape, potato, peach, citrus, strawberry, tomato and pepper, and 27 kinds of pest diseases. Some pest diseases are also classified according to the degrees that the plants are harmed. There were 61 categories in total, and the dataset includes a total of 47,637 color photographs.

The image dataset is randomly divided into three parts according to the proportion of training set (70%), validation set (10%) and test set (10%). The training set and validation set both provide real labels, while the test set only provides online testing without label data.

Due to the large imbalance of the data set, when using the stochastic gradient descent method, during the training process, some categories with a large number contribute more to the gradient descent, while some categories have less impact on the gradient due to their scarcity. This results in a smaller loss function value when the network discriminates the result as a larger number of data when the two data features are not much different. In order to solve the problem of data imbalance, there are the following three solutions. The first is to reduce the pictures of a large number of categories to a similar proportion to the few pictures. Although this method reduces the degree of imbalance between the data, it loses a lot of information about the majority of pictures, which affects the accuracy of the test. The second is to expand a few pictures to the same number as most categories by means of data augmentation. Compared with the first method, although the original information in the training set is not lost, we usually perform data augmentation for all categories. On the other hand, the data set of a few categories may be expanded too much, resulting in data redundancy and limited network performance improvement.

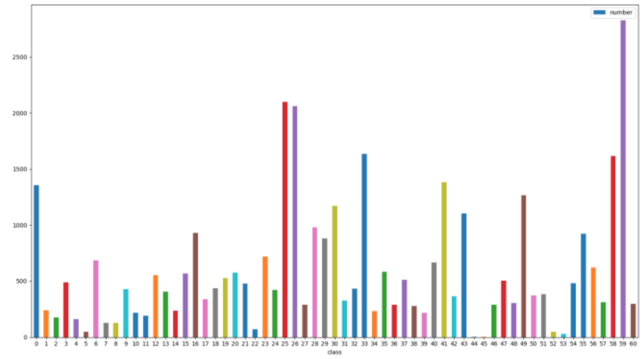

Fig. 2. The sample distribution of crop's pest diseases dataset.

The third method is the method adopted in this experiment, that is, the method of combining model fusion and self-service sampling, which not only ensures the balance between data when training a model, but also makes full use of the pictures in the training set. The specific steps are as follows: adopt self-help bagging method to the pictures of the severe and general types of diseases in the training set. Each time the number of extractions is 1 to 1.2 times that of the minority class data set, so as to obtain a relatively balanced data set in different degrees of development of the disease.

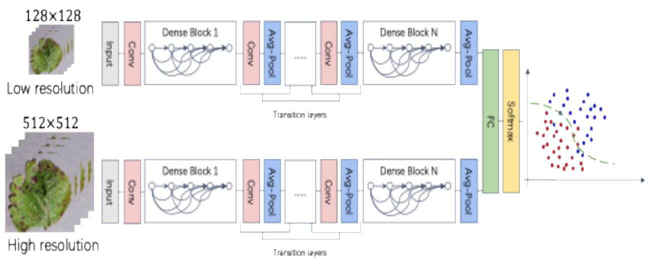

Fig. 3. The sample pictures of crop pest diseases.

In this paper, we propose LH-DenseNet model based on the DenseNet framework. In the DenseNet, each layer is concatenated with all previous layers in the channel dimension and serves as input to the next layer. Specifically, each layer accepts all layers before it as its additional input. For an L-layer network, the DenseNet contains a total of L(L+1)/2 connections, which is a dense connection. The DenseNet is a direct concatenation of feature maps from different layers, enabling feature reuse and improving efficiency.

When analyzing crop's pest diseases, the DenseNet can extract more global features from low-resolution images and more detailed features from high-resolution images. The global features and detail features of the image play a crucial role in the analysis of pest diseases. For example, through global features, we can analyze the shape, overall outline, size, and other aspects of crops. Through detailed features, we can analyze crop spots, textures, and other aspects. Based on this information, this paper developed the LH-DenseNet model, and used the DenseNet framework to extract the detailed features of crops from high-resolution images and the global features of crops from low-resolution images respectively. Then, the fully connected layer was used to splice and integrate the features. The model can be analyzed using both detailed features and global features, so as to improve the accuracy of analysis.

III. Multi-Scale Crop Pest Diseases Analysis Model

We pre-trained the DenseNet on the large-scale dataset ImageNet and transferred the trained parameters to this model for pest diseases classification training, so as to improve the model's ability of image feature extraction and generalization.

Since most of the images in the dataset were taken with forward uniform light, in order to increase the robustness of the model to complex data in actual use and reduce overfitting, data enhancement was performed on the dataset before training. The data enhancement methods we adopt are image brightness change, random amplification, random rotation, Gaussian noise adding, random cropping, horizontal flip, up and down flip, and Gaussian blur. Through the above data enhancement method, the image quality changes caused by the change of shooting angle, shooting equipment, and environment alteration are simulated, so that the model can learn more image scenes.

IV. Experiments and Results

As shown in Fig. 3, we take the image size resize of 128×128 resolution and 512×512 resolution as the input of the global image model and the detailed image model. We use two DenseNet frames to extract low-resolution image features (L-DenseNet) and high-resolution image features (H-DenseNet), and then use the Fully connected layer to splice and integrate the features. Finally, the Softmax function is used to calculate the classification probability of each class.

During training process, we take advantage of cross-entropy as the loss function. The batch size selected for the training network is 32. The parameter optimization method uses the adaptive moment estimation algorithm (Adam Optimizer), and the initial learning rate is set as 0.0001.

As the experimental results in Table 1 show, our model can better analyze the global features and detailed features of crops by extracting and integrating high-resolution image features and low-resolution image features at the same time, so as to obtain the most accurate diagnosis results. In addition, using high-resolution images to extract detailed features can obtain more accurate results than using low-resolution images to extract global features.

TABLE I: EXPERIMENTAL RESULTS

Methods	Accuracy (%)
L-DenseNet	85.28
H-DenseNet	87.45
LH-DenseNet(Ours)	88.63

V. CONCLUSIONS

The improvement of agriculture is closely related to people's well-being and domestic economic development. However, because of the variety of crop pest diseases, the traditional manual identification and experts' methods are not suitable for the modernization of agricultural development. With the continuous success of artificial intelligence in the field of image recognition and object detection, automatic pattern recognition methods such as machine learning and deep learning have become a new hotspot and trend in agricultural development to identify and monitor pest diseases. In this paper, by developing a multi-scale analysis model of crop pest diseases, the detailed features and global features of the image are used for a more comprehensive analysis, so as to improve the diagnostic accuracy of crop pest diseases analyzed by artificial intelligence and increase the value of artificial intelligence when applying to the fields of pest diseases.

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Sihai Li is with Renmin University of China. His research interests include pest disease control based on artificial intelligence.