DiseSniper： A potato disease identification system based on the ResNet model

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***Abstract*—Potato is one of China's most promising high-production cash crops. However, the frequent occurrence of potato diseases and insect pests directly leads to a considerable crop reduction or low yield, restricting the agricultural economy's development. A variety of potato diseases and insect pests dramatically impact potatoes' quality and production and pose a significant threat to human health. Therefore, it is necessary to use image processing methods to detect potato leaves' growth state at early stages. This study mainly implements the accurate identification of potato blight through the analysis of RGB images and is divided into three parts: data set construction, model construction, and system development.**

First, this study collected the images of potato blight from the Internet as part of the data set. Blurred and unidentifiable images were removed during data set construction. Then we consulted agricultural experts on crop disease to label the disease types of potato disease image data to construct the labeled potato disease data set.

Second, various image filtering algorithms were used to enhance the input image data. A potato blight recognition model was built based on deep learning algorithms. Specifically, the Restnet50 model was used to train the blight classification model. The convolution operation was performed on the input image of 3 channels containing 50 Conv2D functions to distinguish the types and the degree of diseases.

Finally, the disease identification software, DiseSniper, was developed based on the trained model. The system was constructed by the agile development software engineering method. Specifically, the software's front end was designed using PyQT5 and implemented the algorithm in the software. Based on the image data set of potato leaves, the accuracy of the test data set reaches more than 98%.

Keywords—machine vision, potato diseases, algorithm, deep learning

I. Introduction

As one of the most promising high-yield cash crops in the 21st century, the potato industry has been developing continuously and rapidly. The expansion of potato planting areas promotes the development of world agriculture and ensures food security. Potatoes can be directly used as people's daily staple food or as raw materials for food processing. Many diseases may come along during potato growth, including late severe blight, early blight, leaf curl disease, etc. These diseases occur in multiple stages of potato growth. If adequate measures are not taken to prevent and control such conditions, it may lead to low yield, restricting agricultural economic development. Most farmers rely on their experience and subjective judgment to determine potato diseases with treatment methods in the agricultural production process. However, this method has certain limitations as one's knowledge and expertise in identifying and treating the disease may not be deep and comprehensive. Sometimes, the symptoms of potato diseases cannot be observed in time, missing the best treatment period of the illness.

In recent years, with the development of machine vision technology, it has been applied in various fields, such as pavement crack detection and crop disease detection. Machine vision technology has been used to monitor the quality of crop diseases and insect pests. Potato research mainly concentrated on late blight disease recognition, early blight, and apparent features of anthrax and other diseases, while coverage of potato diseases is relatively low.

II. Relate work

Cruz et al.[1] developed a vision-based program to detect Olive Quick Decline Syndrome symptoms on leaves of Olea europaea L. infected by Xylella fastidiosa, named X-FIDO. They proposed a novel algorithm for fusing data at different levels of abstraction to improve the system's performance. The algorithm discovers low-level features from raw data to

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automatically detect veins and colors that lead to symptomatic leaves. The program detects OQDS with a true positive rate of 98.60% in testing, showing great potential for image analysis for this disease. DeChant et al.[2] developed an automated, high-throughput system for detecting NLB in field images of maize plants. Using an uncrewed aerial vehicle to acquire high-resolution images, they trained a convolutional neural network model on lower resolution sub-images, achieving 95.1% accuracy on a separate test set of sub-images. Fuentes et al.[3] presented a deep-learning-based approach to detect diseases and pests in tomato plants using images captured by camera devices with various resolutions. They trained and tested the systems end-to-end on a significant Tomato Diseases and Pests Dataset containing challenging images of diseases and pests, including several inter-and extra-class variations. Experimental results show that the system can effectively recognize nine different types of diseases and problems, with the ability to deal with complex scenarios from a plant's surrounding area. Liu et al.[4] proposed an improved convolutional neural network for apple leaf disease identification. It combined batch normalization and center loss function based on the VGG16 model. Batch normalization is used to normalize the input data of the convolutional layer, which accelerates network convergence. In contrast, using the center loss function in conjunction with the softmax loss function makes the network have more cohesive features, thereby improving apple disease classification accuracy. Lu et al.[5] proposed a novel rice diseases identification method based on deep convolutional neural network techniques. Using a dataset of 500 raw images of diseased and healthy rice leaves and stems captured from experimental rice fields, the model achieves an accuracy of 95.48% on rice disease datasets.

III. METHODS

A. Data Acquisition and Preprocessing

This study's potato image data set was obtained from the Plant Village website. A total of 2142 RGB images containing three types of potato leaf diseases were obtained from the data set to form the data set of this study. The data set included 1000 early blight, 1000 late blight, and 152 healthy leaves.

Deep neural network models usually need much training data to get better results. In cases of limited data volume, data augmentation can increase the diversity of training samples, improve model robustness, and avoid overfitting. Typical data augmentation methods include flipping, rotation, scaling, random crop, and color jittering. In this study, due to the small amount of data and to ensure that the number of images of three types of potato disease is relatively balanced, data augmentation techniques were used to increase image data. The random crop method performs random cropping with a ratio of 0.6-1.0 under the condition that the aspect ratio remains unchanged. The flip method was used to perform random flipping of images. The Gaussian process was used to perform Gaussian filtering of images, the mean method was used to balance noise, and median filtering was used to perform image filtering. Finally, the number of pictures of each type of disease reached 2000.

Fig. 1. Potato leaves with two disease types and healthy leaves.

B. Modeling

This study used four models, VGG16, GoogLeNet, DenseNet201, and ResNet50, to train and test potato disease data sets.

The VGG convolutional neural network model was proposed by Simonian and Zisserman[6] from the University of Oxford. The model can be divided into six configurations A, B, C, D, E, and A-LRN. The size of the convolutional kernel and the number of convolutional layers in each design are different. The number 16 refers to the number of weighted layers in the network. In the past, this network has shown its unique advantages in image classification and target detection. A convolutional neural network consists of 13 convolutional layers, three fully connected layers, and five pooling layers.

The convolution kernel of VGG16 is 3×3, so the height and width of the previous convolution layer and the next convolution layer are the same. Since the convolution kernel of this network is small and the convolution layer and the pooling layer are constantly overlaid, it is easier to form a deep network structure to learn more about the data set deeply.

GoogLeNet is a new deep learning structure proposed by Christian Szegedy in 2014[7]. The characteristic of GoogLeNet is that it introduces the idea of the Inception module, after which dimensionality reduction is carried out before data input. Convolution operation will be carried out after the number of features is reduced, which reduces many calculation operations and the complexity of calculation. GoogLeNet model adopts various data augmentation methods, such as using BN regularization technology to minimize the redundant network structure and dense matrix with high computational performance for the calculation to better train performance.

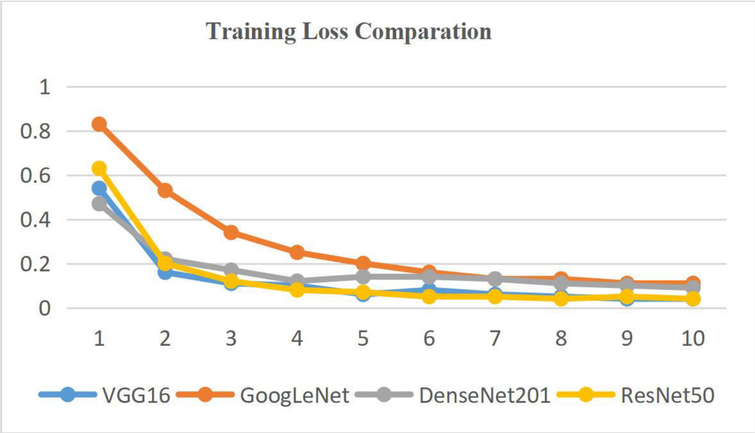

Fig. 2. Comparison of training losses among the four models.

TABLE I. THE TRAINING LOSS COMPARATION OF THE FOUR MODELS

Model	Training Loss									
	1	2	3	4	5	6	7	8	9	10
VGG16	0.54	0.16	0.11	0.1	0.06	0.08	0.06	0.05	0.04	0.04
GoogLeNet	0.83	0.53	0.34	0.25	0.2	0.16	0.13	0.13	0.11	0.11
DenseNet201	0.47	0.22	0.17	0.12	0.14	0.14	0.13	0.11	0.1	0.09
ResNet50	0.63	0.2	0.12	0.08	0.07	0.05	0.05	0.04	0.05	0.04

TABLE II. THE VALIDATION LOSS COMPARATION OF THE FOUR MODELS

Model	Validation Loss									
	1	2	3	4	5	6	7	8	9	10
VGG16	0.16	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01
GoogLeNet	0.29	0.15	0.09	0.07	0.04	0.04	0.02	0.02	0.01	0.02
DenseNet201	0.04	0.08	0.03	0.03	0.01	0.08	0.02	0.04	0.02	0.06
ResNet50	0.01	0.04	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.00

TABLE III. THE PERFORMANCE OF THE FOUR MODELS ON THE TEST SET

Model	ResNet50	VGG16	GoogLeNet	DenseNet201
Test Accuracy	0.98	0.89	0.91	0.81
Test Loss	0.10	0.24	0.24	0.42

DenseNet is a convolutional neural network proposed by He Kaiming et al.[8] in 2017. DenseNet networks can be divided into DenseNet 161, DenseNet 201, and other types, and this study adopts the DenseNet 201 model.

ResNet Convolutional Neural Network was proposed in 2015 by four scholars from Microsoft Research [9] and achieved good results in the ImageNet competition. Depending on the configurations of the convolution layers, the network is divided into ResNet18, ResNet50, and other types. ResNet proposed a residual network mechanism, which can send part of the input data directly to the output, so that part of the original information can be retained. This structure effectively prevents the problem of gradient disappearance during backpropagation so that the depth of the network can reach hundreds or even deeper.

C. Training

This study used four convolutional neural networks (VGG16, GoogLeNet, DenseNet201, and ResNet50) to conduct iterative training on the potato disease image data set. The Epoch was set as 10, the Batch size was 32, the image size was 256×256, and the depth was 3. Table 1 shows the loss values of the four models on the training set in the training process, and Table 2 shows the loss values of the four models on the validation set in the training process. Through the analysis of Table 1 and Table 2, we can see that the loss values on the validation set of the four models are all smaller than the loss values on the training set. This is because we employ regularization operations on the training but not on the validation set. The training set error is calculated and processed in the current Epoch, while the verification set error is calculated after completing the training of the current Epoch. Therefore, the convolutional neural network used in calculating Validation Loss is better than the neural network used to calculate Training Loss. Therefore, in the absence of over-fitting, the loss value on the validation set will be smaller than the loss value on the test set. Figure 2 compares the training error values of the four models in the training process with the increase in training times and the change in model loss values. The abscissa of the figure is the value of Epoch, and the ordinate is the value of Training Loss.

IV. Results

A. Model Validation on Test Set

Table 3 compares the test errors and test accuracy of the four models. The analysis of Figure 2 and Table 3 shows that among the four models of VGG16, GoogLeNet, DenseNet201, and ResNet50, ResNet50 can reduce the training error to a low and stable level more quickly in the iteration process. The ResNet50 convolutional neural network has the highest test accuracy and minimum test error among the four models. Therefore, the ResNet50 model is selected as the final model to be applied in the DiseSniper potato disease identification system software.

B. Software Development

In this study, PyQT5 was used to develop the software's graphical interface. The software can input a single image or multiple images at the same time for potato disease recognition. When a single picture is given as an input, the software will provide the disease type judgment corresponding to the current leaf. In the case of batch input, up to 50 images can be given as an input at a time, and the software will provide statistical results of disease judgment, namely the proportion of various diseases and healthy leaves.

V. Conclusion

A software system named DiseSniper was designed and developed to identify potato disease categories based on potato disease images in this study. The software's input is the RGB picture of potato leaves, and the output is the judgment of the corresponding disease category of the leaves. The software can distinguish potato leaf images of early blight, late blight, and healthy with an accuracy of 98 percent. The judgment model used in the software is a tri-classification model based on ResNet50 training, which is obtained by comparing the four mainstream deep learning models used for image recognition. The current function of the software is not powerful enough, and it can only achieve the classification of three types of blades. Future research will consider adding more training data samples of leaf diseases and enlarging the training data set to realize the accurate variety of potato diseases.

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