CLASSIFICATION OF LEAF DISEASE USING CNN

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Abstract—In the field of agricultural information, the automatic identification and diagnosis ofmaize leaf diseases is highly desired. To improve the identification accuracy of maize leaf diseases and reduce the number of network parameters, the improved GoogLeNet and Cifar10 models based on deep learning[10]are proposed for leaf disease recognition in this paper. Two improved models that are used to train and test nine kindsof maize leaf images are obtained by adjusting the parameters, changing the pooling combinations, adding dropout operations and rectified linear unit functions, and reducing the number of classifiers. In addition, the number of parameters of the improved models is significantly smaller than that of the VGG and Alex Net structures. During the recognition of eight kinds of maize leaf diseases, the GoogLeNet model achieves a top - 1 average identification accuracy of 98.9%, and the Cifar10 model achieves an average accuracy of 98.8%. The improved methods are possibly improved the accuracy of maize leaf disease, and reduced the convergence iterations, which can effectively improve the model training and recognition efficiency.

I Introduction

Maize is an important food and feed crop. Its plantarea and total output are the largest in the world except for rice and wheat [1]. However, in recent years, the number ofspecies of maize diseases and the degree of harm they cause have increased, mainly due to changes in cultivation systems, the variation of pathogen varieties, and inadequate of plant protection measures. Generally, there are eight typesof common leaf diseases, including Curvularia leaf spot, Dwarf mosaic, Gray leaf spot, Northern leaf blight, Brown spot, Round spot, Rust, and Southern leaf blight [2-6]. Mostseriously, maize leaf disease is hazardous and will affect maize production and people's lives.

Maize leaf diseases have various symptoms. It maybe more difficult for inexperienced farmers to diagnosediseases than for professional plant pathologists [7]. As a verification system in disease diagnostics, an automatic system that is designed to identify plant diseases by the plant's appearance and visual symptoms could be of great help to farmers. Many efforts have been applied to the quickand accurate diagnosis of leaf diseases. By using digital image processing techniques, support vector machine (SVM), neural networks, and other methods, we can detect and classify leaf diseases [8]. An SVM - based multi - classifier was proposed by Song et al. and was applied to identify a variety of maize leaf diseases. The best recognition accuracy was 89.6%. The method of classification using SVM is only applicable to small samples, for a large numberof samples, it cannot achieve high recognition accuracy.

II Literature Survey

L. Chen and L.Y. Wang proposed a method for the identification of maize leaf diseases based on image processing technology and a probabilistic neural network (PNN) [9]. The best recognition accuracy of this method was90.4%. However, for the PNN classifier, the identification accuracy and speed of this method decrease as the number of training samples increases. A method of maize leaf disease identification based on adaptive weighting multi-classifier fusion was proposed by L. F. Xu [10]. Seven common typesof maize leaf disease were tested by this method. The average recognition rate was 94.71%. N. Wang . [11] Z. Qi et al. [11]and F. Zhang [11] proposed different methods using digital image processing techniques based on Fisher discriminant, Retinex algorithm combined with principal component analysis (PCA) and SVM[8], and quantum neural network(QNN) and combination features for identification of maize leaf disease. The highest recognition accuracy of these studies was 95.3%, but fewer maize diseases were involved in these methods. Different methods are used to identify maize diseases and the best recognition accuracy was 95.3%,which cannot meet the current requirements for high recognition accuracy. Therefore, in the follow-up study, we should focus on how to improve identification accuracy.

Deep learning has made tremendous advances in thepast few years.It is now able to extract useful feature representations from a large number of input images. Deep learning provides an opportunity for detectorsto identify crop diseases in a timely and accurate manner which will not only improve the accuracy of plant protection but also expand the scope of computer vision in the field of precision agriculture. Y. Lu et al. [9] used different pooling operations, filter sizes, and algorithms to identify 10 common rice diseases. The proposed convolutional neural networks (CNNs) - based model achieved an accuracy

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of 95.48%. C. Dechant et al. [11] trained CNNs to automatically identify the northern leaf blight of maize. This approach addressed the challenge of limited data and the myriad irregularities that appear in images of field-grown plants. The identification scheme achieved an accuracy of 96.7%. Some researchers can improve the identification accuracy of plant diseases to a certain extent by using different convolution neural network models and changing the ratio of training set size to testing set size [9]. These studies have obtained better results, but more parameters and longer training convergence times have a negative effect on the recognition rate. To obtain a highly maize leaf disease identification accuracy, it is highly significant to design a recognition model with fewer parameters and higher recognition accuracy.

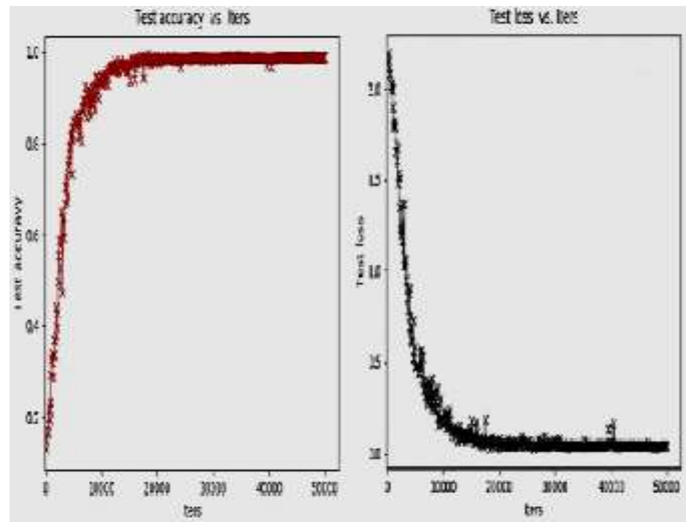
III Proposed Model

In this study, two improved deep convolution neural network models, GoogLeNet and Cifar10, are presented to increase the recognition accuracy of maize leaf diseases and improve the traditional identification methods with long convergence times and large numbers of model parameters.The two models that are used to train and test 9 kinds of maize leaf images are obtained by adjusting the model parameters, changing the pooling combinations, adding the dropout operation and rectified linear unit (Relu) function, and reducing the number of classifiers. Finally, the experimental results are compared with those of the unmodified model.

A Google Model

The initial learning rate of the original GoogLeNet model is 0.001, using the ‘‘step’’ method to attenuate the learning rate. After 100000th iterations and classified by the three classifiers, the top - 1 testing accuracy are 98.8%, 98.6%, 98.2%; top - 5 testing accuracy are 99.6%, 99.6%, 99.6%; the loss of the system is 15.8%. Fig.1 (a) shows the changes of partial top - 1 test accuracy and Fig.1 (b) shows the curve of the system loss. We can see that the top - 1 identification accuracy and system loss gradually converge after 40000th iterations. The training time and the convergence time of theoriginal model are longer. The original model also has a larger number of parameters.

The first classifier of the GoogLeNet model is used to perform 50000th iterations on 9 samples of the maize leaf dataset in this test. After each 100th iteration, the top - 1 accuracy and the model loss are measured. Fig.2 (a) shows the changes in top - 1 test accuracy and Fig.2 (b) show the curve of the model loss. In this study, the initial learning rateof the GoogLeNet model is 0.001, and the ‘‘step’’ method attenuates the learning rate by 0.96 times every 2000th iterations. As seen from Figure, after 10000th iterations, the top - 1 testing accuracy gradually tends to 1, the loss gradually approaches 0, and both states are stable. Experiments show that the average top - 1 accuracy is 98.9%and the loss is 1.6%, after using the improved GoogLeNet model to train and test the maize leaf image dataset.



(a) (b)

Fig 1: Experimental results of the original GoogLeNet model.

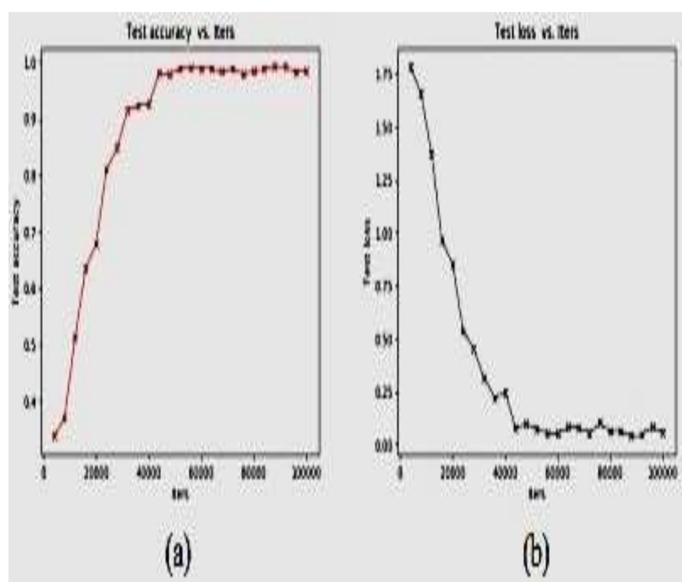


Fig 2: Experimental results of the improved GoogLeNet model.

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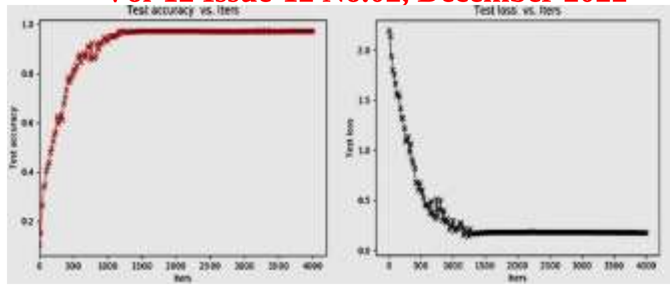
B Cifar10 Model

The Relu function and dropout operation will be added between the two fully connected layers of the Cifar10 model. Relu function can adaptively learn the parameters ofthe rec tifier and increase accuracy with negligibleadditional cost. For an input x, the Relu activation function.

$elu(x) = 0, \text{ if } x \leq 00, \text{ if } x > 0$

The dropout operation works by randomly suppressing a certain number of neurons. The suppressed neurons are temporarily not involved in the forward communication of the network. Optimizing the model-related parameters and then initializing the three pooling combinations: Max - Max - Ave (By taking the maximum of the kk neighbourhood in the feature graph, max-pooling can calculate the maximum value of the non-overlapping rectangular area for each convolution kernel output. The mean pooling is averaged over all the sampling points in the locally accepted domain. It is possible to reduce the error of the variance of the estimated variance increases due to the limited size of the neighbourhood, which can retain more image background information.). Considering the fact that different dropout parameters will affect the recognition accuracy, in this test, the relationship between the dropout probability value and the testing accuracy of the improved model is studied. The maximum testing accuracy of the model is 97.8% when the dropout probability value is 0.65. We fix this value and then experiment with four pooling combinations of three convolutions: Max/Ave/Ave, Max/Max/Ave, Max/Max/Max, and Ave/Ave/Ave. The learning rate of this model is fixed at 0.0002. The accuracy and the loss of the model is measured after every 20th iteration, for a total of 50000th iterations. The model's testing accuracy and loss curves are shown in graph. As seen in graph, the preferred pooling combination is Max - Max - Ave. The originalmodel's testing accuracy and loss are shown in Fig.3. The improved models' testing accuracies are shown in Fig.4 .



(a) (b)

Fig 3: Experimental results of the original Cifar10 model.

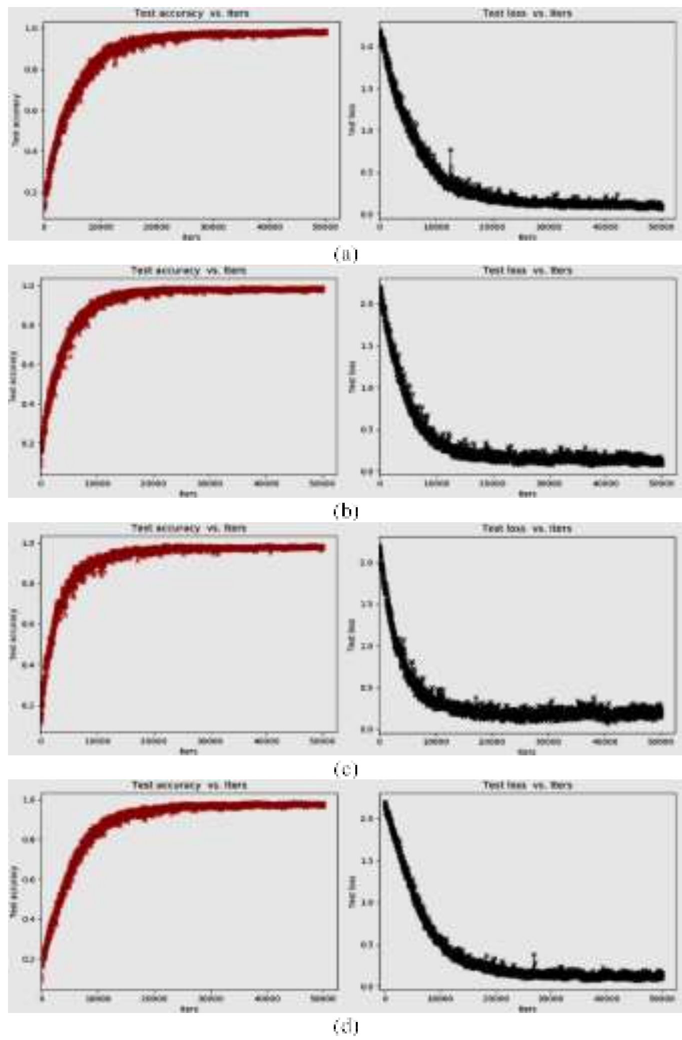


Fig 4: Experimental results of the four pooling layer combinations of the Cifar10 model (a) Max-Ave-Ave. (b) Max-Max-Ave. (c) Max-Max-Max. (d) Ave-Ave-Ave.

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Methodology

A. DATASET:

An appropriate dataset is required at all stages of object recognition research, starting from the training phase to evaluating the performance of recognition algorithms. Atotal of 500 images are collected from different sources, such as the Plant Village and Google websites, including different periods of occurrences of maize leaf diseases, which are divided into 9 different categories. There are 8 categories representing infected maize leaves and a category representing healthy leaves. Eight kinds of maize leaf diseases are shown in Fig.5: Curvularia leaf spot, Dwarf mosaic, Gray leaf spot, Northern leaf blight,Bbrown spot, Round spot, Rust, and Southern leaf blight; these are the main diseases investigated in this study.

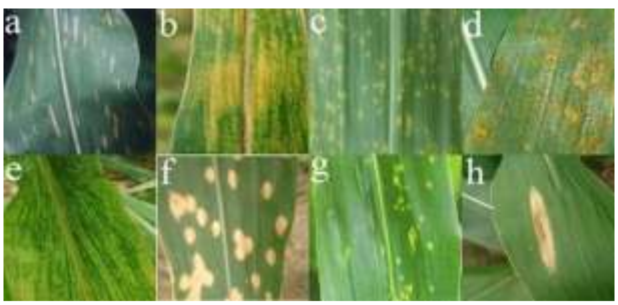

Fig 5: Eight common maize leaf diseases a: Southern leaf blight; b: Brown spot; c: Curvularia leaf spot; d: Rust; e: Dwarf mosaic; f: Gray leaf spot; g: Round spot;h: Northern leaf blight.

B. AUGMENTATION:

Training CNNs requires substantial data. The moredata the CNNs have to learn, the more features it can obtain.Since the original leaf image dataset collected in this study is not sufficient, it is necessary to expand the dataset by different methods to distinguish the different disease categories. After the original images are initialized, additional versions are created by rotating the images 90°, 180°, and 270°; by mirroring each rotated image; by cuttingthe center of the image by the same size; and by convertingall processed images to grayscale. The dataset is expanded by the above methods, which helps in reducing over fitting during the training stage. Partially converted images are shown in Fig.6. In total, the maize leaf dataset contains 3060 images 2248 (80%) for training and 612 (20%) for testing.

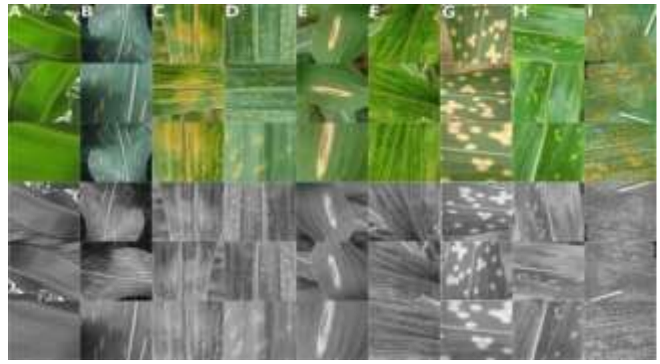

Fig 6: Part of the image samples after the augmentation process Part A shows a healthy maize leaf after rotation, cutting, and grayscale. Part B-I shows eight kinds of maize leaf disease images

C. IMAGE PREPROCESSING AND LABELLING:

To improve feature extraction and increase consistency, the images in the dataset for the deep CNNs classifier are pre- processed before the model is trained. One of the most significant operations is the normalization of image size and format. In this study, all images are resized to 224x224 pixels and 32x32 dots per inch, which are automatically computed by Python scripts based on the Open CV framework.

In the interest of confirming the accuracy of the classes in the dataset, agricultural experts examined leaf images grouped by a keyword search and labeled all the images with the appropriate disease acronym. It is wellknown that it is essential to use accurately classified imagesfor the training and validation dataset. Only in that can may an appropriate and reliable model be developed. In this stage, various classes of the dataset, as well as the training set and the testing set, are marked.

D. CONVOLUTIONAL NEURAL NETWORKS:

Artificial Intelligence has been witnessing a monumental growth in bridging the gap between the capabilities of humans and machines. Researchers and enthusiasts alike, work on numerous aspects of the field to make amazing things happen. One of many such areas is the domain of Computer Vision. The agenda for this field is to enable machines to view the world as humans do, perceive it in a similar manner and even use the knowledge for a multitude of tasks such as Image & Video recognition, Image Analysis & Classification, Media Recreation, Recommendation Systems, Natural Language Processing, etc. The advancements in Computer Vision with Deep Learning has been constructed and perfected with time, primarily over one particular algorithm — a Convolutional Neural Network[16-20].

A Convolutional Neural Network (ConvNet/CNN)[20] is aDeep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics. The Operations done by CNN[8] are: Convolution, Activate Function, Pooling, Dropout, Loss Function.

E. HYPERPARAMETER:

The improved Cifar10 and GoogLeNet models' hyperparameters are shown in Table compared with the original one in Table 2. By changing the base learning rate, it can affect the identification accuracy of the network. All experiments are done using the GPUs. The models are optimized by the stochastic gradient descent (SGD) algorithm. The method of batch training is to divide the training set and the testing set into multiple batches. Each batch consists of training 10 images. The initial learning rateof the Cifar10 model is fixed at 0.0002. The initial learning rate for the GoogLeNet model is 0.001 and decremented by
0.96 times.

V CONCLUSION:

In this study, when identifying 9 types of maize leaves, the two improved deep convolutional neural networkmodels, GoogLeNet and Cifar10, can achieve high identification accuracy, 98.9%, and 98.8%, respectively. When the train-test set is 80 - 20 (80% of the whole dataset used for training, and 20% for testing), the classification algorithms used in this study allow the systems to acquire a diversity of sample conditions with strong robustness. Experiments show that it is possible to improve recognition accuracy by increasing the diversity of pooling operations, the reasonable addition of a Relu function and dropout operations, and including multiple adjustments of the mode lparameters. In future research, we will identify more types of maize diseases and pests and combine new algorithms andother deep learning structures for the training and testing of the model. Meanwhile, in order to enable agricultural producers to make quick and reasonable judgments about crop disease information, the trained model can be combined with mobile devices in a flexible manner.

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