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Deep Learning Using Research on Recognition Model of Crop Diseases and Insect Pests in Harsh Environments

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Abstract

Agricultural diseases and insect pests are one of the most important factors that seriously threaten agricultural production. Early detection and identification of pests can effectively reduce the economic losses caused by pests. In this paper, convolution neural network is used to automatically identify crop diseases. In this paper, the CNN model is used for training. After the combined convolution operation is completed, it is activated by the connection into the ReLu function. The experimental results show that the overall recognition accuracy is 86.1% in this model, which verifies the effectiveness. The results show that the system can accurately identify crop diseases and give the corresponding guidance. Finally, the simulations revealed that the proposed ResNet CNN resulted in superior performance as compared to NB, SVM and RF.

Keywords: Agricultural diseases, insect pests, deep learning model.

1. Introduction

As a superpower with more than 20% of the world's total population, China has been facing the problem of insufficient arable land resources. According to the survey data of the Ministry of Agriculture, the proportion of cultivated land in China is even less than 10% of China's land area. According to statistics data, the mountainous area accounts for about two-thirds of the total land area in China, while the plain area accounts for only one-third. About one third of the country's agricultural population and arable land are in mountainous areas. This situation has resulted in the relatively poor production conditions of agriculture, forestry, and animal husbandry in China. According to the statistics of the Food and Agriculture Organization of the United Nations, the per capita cultivated land area in China is less than half of the world average level and shows a decreasing trend year by year. Once the natural disasters cause agricultural production reduction, it will seriously affect the output of agricultural products and agricultural development. So how to develop agriculture stably, especially in the complex environment, is extremely important for China.

Although with the development of science and technology, agricultural production is progressing. But due to various natural factors and non-natural factors, the yield of crops has not been greatly improved. Among the various factors, the largest proportion is the problem of crop diseases and insect pests. According to statistics, the area of crops affected by pests and diseases in China is as high as 280 million km2 every year, and the direct yield loss is at least 25 billion kg [1]. In recent years, this problem is on the rise and seriously threatens the development of planting industry. Timely diagnosis and prevention of crop diseases has become particularly important. At present, agricultural workers often use books and network, contact local experts, and use other methods to protect and manage crop diseases. But for various reasons, misjudgements and other problems often occur, resulting in agricultural production is deeply affected.

At present, the research on crop diseases is mainly divided into two directions. The first one is the traditional physical method, which is mainly based on spectral detection to identify different diseases.

Different types of diseases and insect pests cause different leaf damage, which leads to different spectral absorption and reflection of leaves eroded by diseases and healthy crops. The other one is to use computer vision technology to identify images. That is to say, the characteristics of disease images are extracted by using computer related technology, and the recognition is carried out through the different characteristics of diseased plants and healthy plants.

In recent years, the rapid development of artificial intelligence has made life more convenient, and AI has become a well-known technology. For example, AlphaGo defeated the world champion of Go. Siri and Alexa as voice assistants of Apple and Amazon are all applications of artificial intelligence technology represented by deep learning in various fields. As the key research object of computer vision and artificial intelligence, image recognition has been greatly developed in recent years. In agricultural applications, the goal of image recognition is to identify and classify different types of pictures, and analyze the types of crops, disease types, severity and so on. Then we can formulate corresponding countermeasures to solve various problems in agricultural production in a timely and efficient manner. To further ensure and improve the yield of crops and help the better development of agriculture.

With the rapid development of deep learning [2], especially in image recognition [3], speech analysis, natural language processing and other fields, it shows the uniqueness and efficiency of deep learning. Compared with the traditional methods, deep learning is more efficient in the diagnosis of crop diseases in the field of agricultural production. The deep learning model can monitor, diagnose, and prevent the growth of crops in time. Image recognition of crop diseases and insect pests can reduce the dependence on plant protection technicians in agricultural production, so that farmers can solve the problem in time. Compared with artificial identification, the speed of intelligent network identification is much faster than that of manual detection. And the recognition accuracy is getting higher and higher in the continuous development. The establishment of a sound agricultural network and the combination of Internet and agricultural industry can not only solve the problems related to crop yield affected by diseases and insect pests, but also be conducive to the development of agricultural informatization [4].

However, due to the rugged terrain of the mountain environment, the surrounding interference factors are greater. Therefore, the image acquisition is more difficult than the general environment. In addition, the camera and network transmission needed for image recognition and processing will also have a certain impact. Therefore, it is more difficult to carry out intelligent recognition in mountainous areas. This paper tries to build the Internet of Things platform in the complex environment of mountainous areas and carry out the research on the identification model of crop diseases and insect pests. The purpose of this model is to improve agricultural informatization, deal with the harm of pests and diseases to crops and improve crop yield.

2. Literature survey

López et al. proposed an autonomous monitoring system based on a low-cost image sensor that it can capture and send images of the trap contents to a remote-control station with the periodicity demanded by the trapping application. The images delivered by image sensors would be time-stamped and processed in the control station to get the number of individuals found at each trap. All the information would be conveniently stored at the control station, and accessible via Internet by means of available network services at control station (WiFi, WiMax, 3G/4G, etc.).

Srivastav et al. focused on a pest control and monitoring system for efficient sugarcane crop production, which is a staple crop grown in Pune. The main pests that affect sugarcane are top shoot borer, stalk borer, rood borer and sugarcane wooly aphid. Transmission and reception of field data is through ZigBee 802.15.4 digital communication device standard. The system covers large areas with very low energy consumption.

Athanikar et al. described a neural network-based detection and classification of Potato leaf samples using Segmentation of K-Means Clustering. Algorithms are developed to acquire and process colour images of single leaf samples. Different leaves like healthy and diseased are considered for the study. The classification is carried out using different types of features sets, viz., colour, texture, and area. Classification accuracies of over 92% are obtained for all the leaves samples (healthy and diseased) using all the three feature sets.

Wang et al. recognized method to realize plant image diseases, four kinds of neural networks including backpropagation (BP) networks, radial basis function (RBF) neural networks, generalized regression networks (GRNNs) and probabilistic neural networks (PNNs) were used to distinguish wheat stripe rust from wheat leaf rust and to distinguish grape downy mildew from grape powdery mildew based on color features, shape features and texture features extracted from the disease images.

Samantha et al. proposed image processing methodology to detect scab disease of potato. In this paper first, the captured images are collected from different potato field and are processed for enhancement. Then image segmentation is carried out to get target regions (disease spots). Finally, analysis of the target regions (disease spots) based on histogram approach to finding the phase of the disease and then the treatment consultative module can be prepared by on the lookout for agricultural experts, so plateful the farmers.

Too et al. focused on fine-tuning and evaluation of state-of-the-art deep convolutional neural network for image-based plant disease classificationThus, alleviating the problem of food security. In this experiment, DenseNets has tendency’s to consistently improve in accuracy with growing number of epochs, with no signs of overfitting and performance deterioration.

Mohanty et al. used a public dataset of 54,306 images of diseased and healthy plant leaves collected under controlled conditions, in this work trained a deep convolutional neural network to identify 14 crop species and 26 diseases (or absence thereof). Overall, the approach of training deep learning models on increasingly large and publicly available image datasets presents a clear path toward smartphone-assisted crop disease diagnosis on a massive global scale.

Dyrmann et al. presented a method that is capable of recognising plant species in colour images by using a convolutional neural network. The network is built from scratch trained and tested on a total of 10,413 images containing 22 weed and crop species at early growth stages. This includes images taken under controlled conditions about camera stabilisation and illumination, and images shot with hand-held mobile phones in fields with changing lighting conditions and different soil types. For these 22 species, the network can achieve a classification accuracy of 86.2%.

Sa et al. presented a novel approach to fruit detection using deep convolutional neural networks. The system builded an accurate, fast, and reliable fruit detection system, which is a vital element of an autonomous agricultural robotic platform; it is a key element for fruit yield estimation and automated harvesting. Recent work in deep neural networks has led to the development of a state-of-the-art object detector termed Faster Region-based CNN (Faster R-CNN).

Sladojevic et al. studied the plant disease recognition has been proposed for the first time. All essential steps required for implementing this disease recognition model are fully described throughout the paper, starting from gathering images to create a database, assessed by agricultural

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experts. Caffe, a deep learning framework developed by Berkley Vision and Learning Centre, was used to perform the deep CNN training. The experimental results on the developed model achieved precision between 91% and 98%, for separate class tests, on average 96.3%.

Ahmeb and Wang proposed a crop disease and pest identification model based on deep learning from

3. Proposed system

3.1 Crop Disease Recognition Model

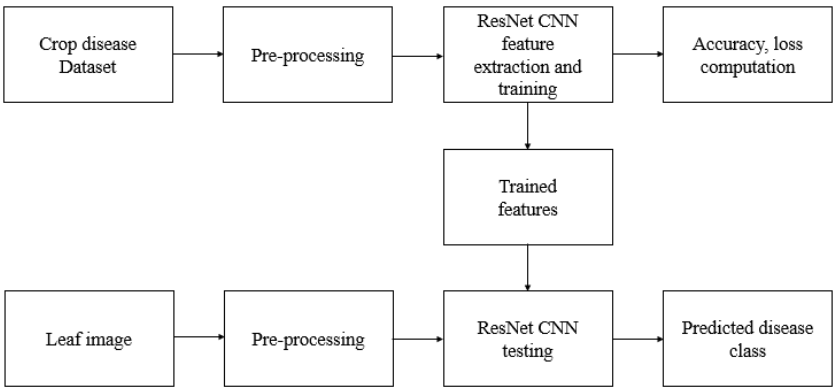

Fig.1: Block diagram of proposed system.

Crop disease datasets are pre-processed and uploaded to ResNet CNN for feature extraction. On the other hand, leaf images are also pre-processed and uploaded to ResNet CNN for testing. The leaf images and the crop disease datasets are compared to the trained features which are already trained with the plant diseases. The extracted features have some loss computation and accuracy. The comparison graph could predict the classes of the plant disease.

3.2 Image pre-processing

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subfield of digital signal processing, digital image processing has many advantages over analogue image processing. It allows a much wider range of algorithms to be applied to the input data — the aim of digital image processing is to improve the image data (features) by suppressing unwanted distortions and/or enhancement of some important image features so that our AI-Computer Vision models can benefit from this improved data to work on.

To train a network and make predictions on new data, your images must match the input size of the network. If you need to adjust the size of your images to match the network, then you can rescale or crop your data to the required size.

You can effectively increase the amount of training data by applying randomized augmentation to your data. Augmentation also enables you to train networks to be invariant to distortions in image data. For example, you can add randomized rotations to input images so that a network is invariant to the presence of rotation in input images. An augmented Image Datastore provides a convenient way to apply a limited set of augmentations to 2-D images for classification problems.

You can store image data as a numeric array, an ImageDatastore object, or a table. An ImageDatastore enables you to import data in batches from image collections that are too large to fit in memory. You can use an augmented image datastore or a resized 4-D array for training, prediction, and classification. You can use a resized 3-D array for prediction and classification only.

3.3 Convolutional Neural Networks

Deep neural network is gradually applied to the identification of crop diseases and insect pests. Deep neural network is designed by imitating the structure of biological neural

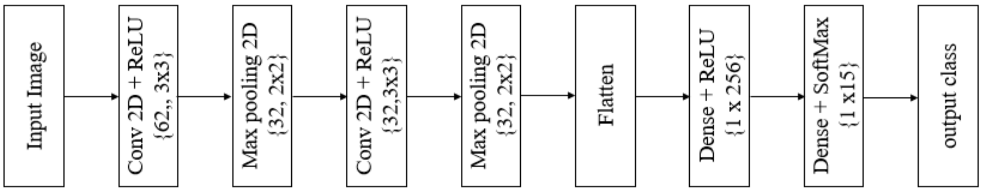

Fig. 2: A typical convolution neural network.

Table.1: Layers description.

Layer Names	No. of filters	Kernel size
Conv 2D +ReLU	32	3 x 3
Max pooling 2D	-	3 x 3
Conv 2D+ReLU	32	3 x 3
Max pooling 2D	-	3 x 3
Flatten	-	-
Dense +ReLU		1 x 256
Dense + SoftMax		1 x 15

network, an artificial neural network to imitate the brain, using learnable parameters to replace the links between neurons [3]. Convolutional neural network is one of the most widely used deep neural network structures, which is a branch of feed forward neural network [4]. The appearance of the deeper AlexNet network [11] in 2012 is the beginning of the modern convolutional neural network. The success of AlexNet network model also confirms the importance of convolutional neural network model. Since then, convolutional neural networks have developed vigorously and have been widely used in financial supervision, text and speech recognition, smart home, medical diagnosis, and other fields.

3.4 DL-CNN

According to the facts, training and testing of DL-CNN involves in allowing every source image via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from [0,1]. Figure 1 discloses the architecture of DL-CNN that is utilized in proposed methodology for CBIR system for enhanced feature representation of word image over conventional retrieval systems.

Convolution layer as depicted in Figure 5.1 is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It’s a mathematical function which considers two inputs like source image I(x,y,d) where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here d=3, since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as F(k_x,k_y,d).

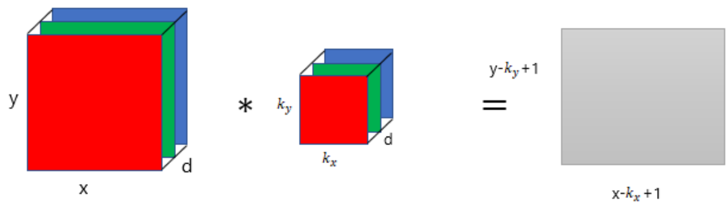

Fig. 3: Representation of convolution layer process.

3.4.1 ReLU layer

Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function G (·) is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function max (·) over the set of 0 and the input x as follows:

$$G(x) = \max\{0, x\}$$

3.4.2 Max pooing layer

This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

3.5 Softmax classifier

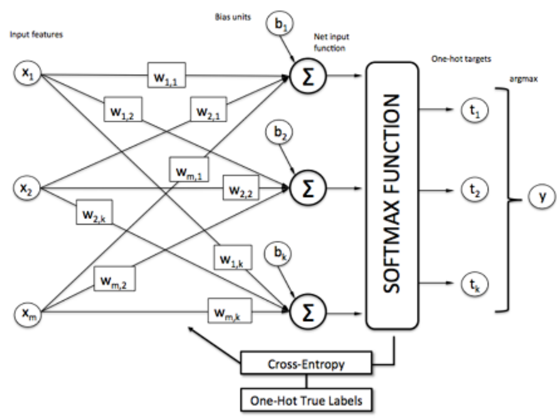

Fig.4: Softmax classifier.

In the above, a picture is given, and we must predict what is the object that is present in the picture. In the normal case, we predict whether the crop is A. But in this case, we must predict what is the object that is present in the picture. This is the place where softmax comes in handy. As the model is already trained on some data. So, as soon as the picture is given, the model processes the pictures, send it to the hidden layers and then finally send to softmax for classifying the picture. The softmax uses a One-Hot encoding Technique to calculate the cross-entropy loss and get the max.

4. Results

This section gives the detailed analysis of simulation results implemented using "python environment". Further, the performance of proposed method is compared with existing methods using same dataset. Table 1 compares the performance of the proposed method with existing methods. Here, the Proposed ResNet CNN resulted in superior accuracy as compared to the existing models. The graphical representation of table 2 is presented in figure 8.

4.1 Modules

1. Feature Extraction: CNN compose of multiple layers and first layer define for feature extraction and this feature will be extracted from given input image dataset or any other multidimensional dataset.
2. Feature Selection: Using this layer features will be selected by applying a layer called pooling or max polling.
3. Activation module: using this module RELU will be applied on input features to remove out unimportant features and hold only relevant important features
4. Flatten: This layer will be defined to convert multidimensional input features into single dimensional input array
5. Dense: This layer can be used to connect one layer to other layer to receive input features from previous layer to new layer to further filter input features in next layer to get most important features from dataset to have best prediction result.

Fig.5: Sample dataset.

Table.2: Performance comparison.

Method	NB	RF	SVM	Proposed
Accuracy	67.37	77.48	78.37	98.28

Fig.6: Crop recognize as Potato healthy.

Fig.7: Crop recognize as Potato early blight.

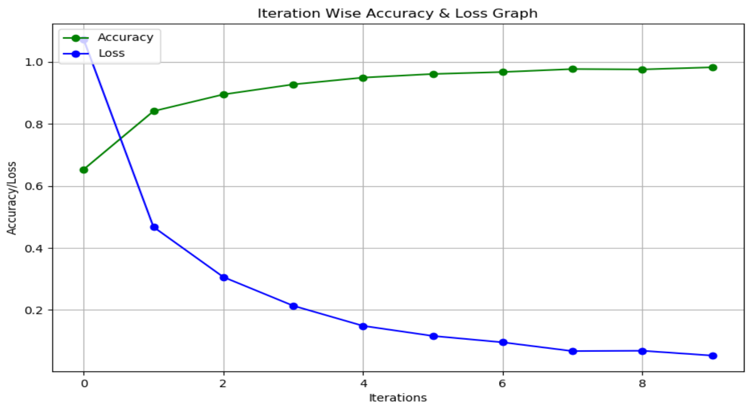

Fig.8: Iteration wise accuracy & loss graph.

5. Conclusion

In this paper 15 kinds of crops were studied. The model is constructed by using deep learning theory and convolution neural network technology. Experiments show that the model can effectively identify the data set, and the overall recognition accuracy is as high as 86.1%. The results show that the recognition accuracy of this hybrid network model is relatively higher than the traditional model, and it can be effectively applied to the identification and detection of plant diseases and insect pests.

In the future work, there are two directions should be improved:

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1) Extended data set. In this paper, only 27 diseases of 10 crop species were studied, and other species and diseases were not involved, such as rice and wheat, and their related diseases. Therefore, the next step is to obtain more crop species and disease images for research.

2) Optimize the model. Through the experiment of this paper, we can see that Inception-resnet-v2 this kind of mixed network has absorbed the corresponding advantage. This model has achieved good recognition accuracy and is worthy of further study and optimization. At the same time, we should design a network model which can classify crop images with higher accuracy.

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