Recognition of Crop Disease and Pesticide Suggestion using Convolution Neural Network

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Abstract

The development of an economy's agricultural sector is directly proportionate to the growth of that economy's potential for innovation, which in turn is directly related to the progress of that agricultural sector. The primary purpose of this investigation is to apply deep learning models to the process of constructing Plant Disease Detection and Classification Networks (PDDC-Net). The Preprocessing step also involves the elimination of various kinds of noise, which ultimately leads to the standardization of the pictures that are a part of the dataset. In addition, the PDDC-Net puts the operation into practice by using a residual network based convolutional neural network (ResNet-CNN) for the purpose of feature extraction and classification. This work not only performs the disease detection, but also performs the pesticide suggestion, which mostly helpful to farmers as well as e-agriculture applications. This allows the operation to be carried out more effectively. This contributes to ensuring that the operation is carried out correctly. The PDDC-Net model that was suggested obtained an accuracy rate that was adequate for the detection and classification of plant leaf diseases, as shown by the outcomes of the tests that were carried out.

Keywords: Convolutional Neural Network, Plant Disease Detection and Classification Networks, residual network based convolutional neural network

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 [1]. 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 [2] 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 [3]. 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 [4]. 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 [5]. 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 [6]. 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 [9]. 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 [8]. 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 [9]. At present, agricultural workers often use books and network, contact local experts, and use other methods to protect and manage crop diseases [10]. But for various reasons, misjudgements and other problems often occur, resulting in agricultural production is deeply affected.

Rest of the paper is organized as follows: Section 2 details about literature survey, section 3 details about the proposed methodology, section 4 details about the results with discussion, and section 5 concludes article with references.

2. Literature Survey

In [11] proposed based on lightweight convolution neural networks applying the channel wise attention (CA) mechanism. Shuffle Net V1 and V2 are chosen as the backbones, and squeeze-and-excitation (SE) blocks are considered as a CA mechanism to improve the Shuffle Net architecture. The proposed model is verified by an open dataset which includes 4,062 grape leaf images from four classes, including 3 diseased classes and 1 healthy class. In [12] developed many applications for the automatic identification of crop diseases. These applications could serve as a basis for the development of expertise assistance or automatic screening tools. Such tools could contribute to more sustainable agricultural practices and greater food production security. To assess the potential of these networks for such applications, they survey 19 studies that relied on CNNs to automatically identify crop diseases. In [13] developed to perform plant disease detection and diagnosis using simple leaves images of healthy and diseased plants, through deep learning methodologies. Training of the models was performed with the use of an open database of 87,848 images, containing 25 different plants in a set of 58 distinct classes of [plant, disease] combinations, including healthy plants. In [14] proposed a real-time system to identify the type of disease present in a crop based on leaf images using machine learning. A deep convolutional neural network architecture is proposed to classify the crop disease, and a single shot detector is used for identification and localization of the leaf. These models are deployed on an embedded hardware, Nvidia Jetson TX1, for real-time in-field plant disease detection and identification. In [15] proposed two main reasons: (i) The natural destructions such as drought, flood, famine, and earthquake. (ii) Pest and pathogens. About 98% of the destruction in crops are caused by pathogens and pests. The remaining 2% of the destruction is due to natural disaster in the surroundings. The rural farmers are severely affected by the crop production problems. In crop's life cycle, leaf plays a major role in getting the information about the growth and production of the plant. In this paper, the proposed system works on the pre-processing of the dataset. The leaf images are collected from the plant village dataset.

In [16] proposed an additional method to classify the diseased leaves using the transfer learning on top of convolutional neural network model to improve the efficacy of image processing while applying deep learning. In [17] studied investigated the potential of deep learning techniques for precision agriculture in the last decade. However, despite the range of applications, several gaps within plant disease research are yet to be addressed to support disease management on farms. In[18] developed model can recognize 13 different types of plant diseases out of healthy leaves, with the ability to distinguish plant leaves from their surroundings. According to our knowledge, this method for plant disease recognition for the first time. In [19] developed model is implemented using python version 3.7.3 and the model is equipped on the deep learning package called Keras, TensorFlow backed, and Jupiter which are used as the developmental environment. In [20] proposed an overview of papers has been finished utilizing machine learning and its advanced learning techniques, as well as image pre-processing and segmentation techniques, to detect and classify various diseases and pests.

To identify the specific cotton diseases and pests under research, as well as overall performance based on the various metrics used. Our findings endorse that machine learning and its advanced learning techniques provide outperform ordinally utilized image processing techniques in phrases of exactness and other viable methodologies.

3. Proposed Methodology

Agriculture is one of the most important sources for human sustenance on Earth. Not only does it provide the much necessary food for human existence and consumption but also plays a major vital role in the economy of the country. But Plant diseases have turned into a dilemma as it can cause significant reduction in both quality and quantity of agricultural products. Nowadays farmers are facing many crucial problems for getting better yield cause of rapid change in climate and unexpected level of insects, to get better yield, need to reduce the level of pest insect. Several millions of dollars are spent worldwide for the safety of crops, agricultural produce, and good, healthy yield. It is a matter of concern to safeguard crops from Bio-aggressors such as pests and insects, which otherwise lead to widespread damage and loss of crops. In a country such as India, approximately 18% of crop yield is lost due to pest attacks every year which is valued around 90,000 million rupees. Conventionally, manual pest monitoring techniques, sticky traps, black light traps are being utilized for pest monitoring and detection in farms. Manual pest monitoring techniques are time consuming and subjective to the availability of a human expert to detect the same. Disease is caused by pathogen which is any agent causing disease. In most of the cases pests or diseases are seen on the leaves or stems of the plant. Therefore, identification of plants, leaves, stems and finding out the pest or diseases, percentage of the pest or disease incidence, symptoms of the pest or disease attack, plays a key role in successful cultivation of crops. In general, there are two types of factors which can bring death and destruction to plants: living(biotic) and nonliving (abiotic) agents. Living agent's including insects, bacteria, fungi, and viruses. Nonliving agents include extremes of temperature, excess moisture, poor light, insufficient nutrients, and poor soil pH and air pollutants.

In recent years, deep learning has made breakthroughs in the field of digital image processing, far superior to traditional methods. How to use deep learning technology to study plant diseases and pests' identification has become a research issue of great concern to researchers.

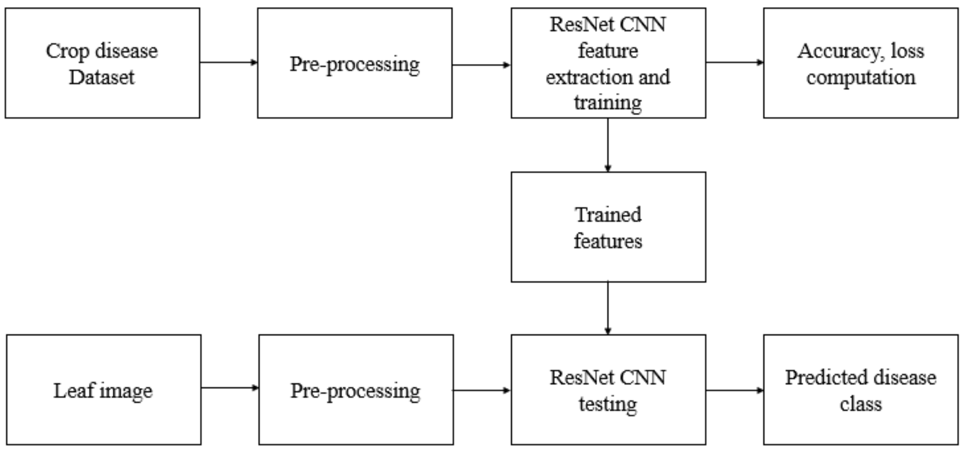

Figure 1: Block diagram of proposed system.

Crop disease datasets are pre-processed and uploaded to Residual Network-CNN ((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.

3.1. Crop disease dataset

The dataset totally contains 15 classes of crop diseases, such as pepper__bell___Bacterial_spot', 'Pepper__bell___healthy', 'Potato___Early_blight', 'Potato___healthy', 'Potato___Late_blight', 'Tomato__Target_Spot', 'Tomato__Tomato_mosaic_virus', 'Tomato__Tomato_YellowLeaf__Curl_Virus', 'Tomato_Bacterial_spot', 'Tomato_Early_blight', 'Tomato_healthy', 'Tomato_Late_blight', 'Tomato_Leaf_Mold','Tomato_Septoria_leaf_spot','Tomato_Spider_mites_Two_spotted_spider_mite. Here, Pepper, Potato, and Tomato are the major crop classes with different disease sub-types.

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, our images must match the input size of the network. If we need to adjust the size of images to match the network, then we can rescale or crop data to the required size.

we can effectively increase the amount of training data by applying randomized augmentation to data. Augmentation also enables to train networks to be invariant to distortions in image data. For example, we 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.

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

There are two ways to resize image data to match the input size of a network. Rescaling multiplies the height and width of the image by a scaling factor. If the scaling factor is not identical in the vertical and horizontal directions, then rescaling changes the spatial extents of the pixels and the aspect ratio.

Cropping extracts a subregion of the image and preserves the spatial extent of each pixel. We can crop images from the center or from random positions in the image. An image is nothing more than a two-dimensional array of numbers (or pixels) ranging between 0 and 255. It is defined by the mathematical function f(x,y) where x and y are the two co-ordinates horizontally and vertically.

Resize image: In this step-in order to visualize the change, we are going to create two functions to display the images the first being a one to display one image and the second for two images. After that, we then create a function called processing that just receives the images as a parameter.

Need of resize image during the pre-processing phase, some images captured by a camera and fed to our AI algorithm vary in size, therefore, we should establish a base size for all images fed into our AI algorithms.

3.3 Proposed ResNet-CNN

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 network, an artificial neural network to imitate the brain, using learnable parameters to replace the links between neurons. Convolutional neural network is one of the most widely used deep neural network structures, which is a branch of feed forward 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.

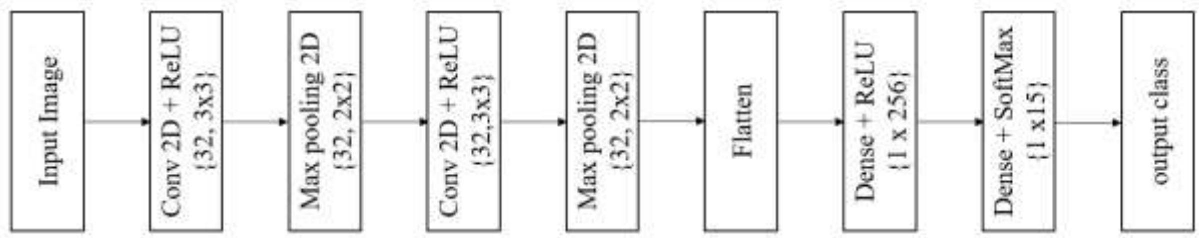

Figure 2: Proposed ResNet-CNN

Convolutional neural networks are generally composed of three parts. Convolution layer for feature extraction. The convergence layer, also known as the pooling layer, is mainly used for feature selection. The number of parameters is reduced by reducing the number of features. The full connection layer carries out the summary and output of the characteristics. A convolution layer is consisting of a convolution process and a nonlinear activation function ReLU. A typical architecture of CNN model for crop disease recognition is shown in Figure 2.

The leftmost image is the input layer, which the computer understands as the input of several matrices. Next is the convolution layer, the activation function of which uses ReLU. The pooling layer has no activation function. The combination of convolution and pooling layers can be constructed many times. The combination of convolution layer and convolution layer or convolution layer and pool layer can be very flexibly, which is not limited when constructing the model. But the most common CNN is a combination of several convolution layers and pooling layers. Finally, there is a full connection layer, which acts as a classifier and maps the learned feature representation to the sample label space.

Table.1: Layers description.

Layer Names	No. of filters	Kernel size	Feature size
Conv 2D +ReLU	32	3 x 3	62x62x32
Max pooling 2D	-	3 x 3	31x31x32
Conv 2D+ReLU	32	3 x 3	29x29x32
Max pooling 2D	-	3 x 3	14x14x32

Flatten	-	1x6272	1x6272
Dense +ReLU		1 x 256	1 x 256
Dense + SoftMax		1 x 15	1 x 15

Convolutional neural network mainly solves the following two problems.

1) Problem of too many parameters: It is assumed that the size of the input picture is $50 * 50 * 3$. If placed in a fully connected feedforward network, there are 7500 mutually independent links to the hidden layer. And each link also corresponds to its unique weight parameter. With the increase of the number of layers, the size of the parameters also increases significantly. On the one hand, it will easily lead to the occurrence of over-fitting phenomenon. On the other hand, the neural network is too complex, which will seriously affect the training efficiency. In convolutional neural networks, the parameter sharing mechanism makes the same parameters used in multiple functions of a model, and each element of the convolutional kernel will act on a specific position of each local input. The neural network only needs to learn a set of parameters and does not need to optimize learning for each parameter of each position.

2) Image stability: Image stability is the local invariant feature, which means that the natural image will not be affected by the scaling, translation, and rotation of the image size. Because in deep learning, data enhancement is generally needed to improve performance, and fully connected feedforward neural is difficult to ensure the local invariance of the image. This problem can be solved by convolution operation in convolutional neural network.

4. Results and Discussion

Figure 3 shows the sample images from dataset. Figure 4, Figure 5 Shows the predicted outcomes. In Figure 6, In above graph x-axis represents epoch/iterations and y-axis represents accuracy/loss and green line represents accuracy and blue line represents loss and from above graph we can see with each increasing iteration accuracy is getting better and better and loss getting decrease. Table 1 shows the performance comparison.

Figure 3: Sample dataset.

Figure 4: Crop recognize as Potato healthy.

Figure 5: Crop recognize as Potato early blight.

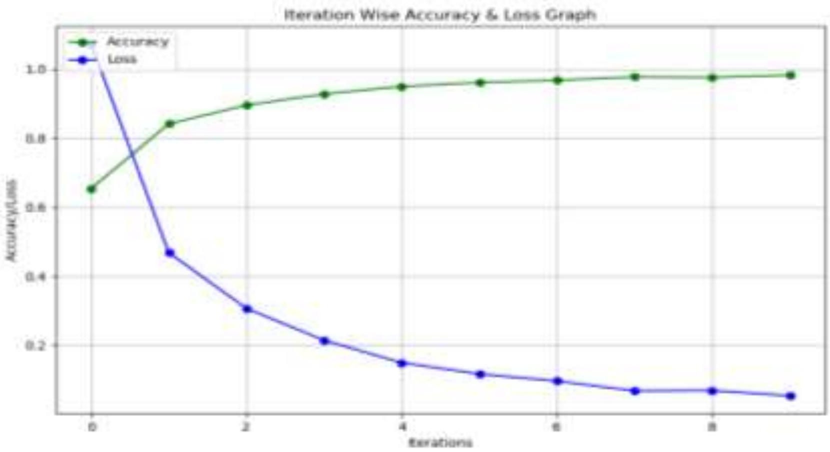

Figure 6: Iteration wise accuracy & loss graph.

Table 1: Performance comparison.

Method	NB	RF	SVM	Proposed
Accuracy (%)	67.37	77.48	78.37	98.28

5. Conclusion

In this work 15 kinds of crop diseases were studied. The model is constructed by using deep learning theory and ResNet-CNN technology. Experiments show that the model can effectively identify the data set, and the overall recognition accuracy is as high as 98.23%. 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.

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