***Detection of Crop Disease Using Optimization Model in Biodiverse Environment***

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# Abstract:

Diseases of the crop and insect pests are among the main causes of crop loss which is danger for agricultural production. Disease recognition is more difficult on the field because it has a complex background and different light intensity. Initial recognition and pests identification can significantly reduce the financial losses caused by pests. Using convolution neural networks, crop diseases can be automatically identified. The identification of a disease is often based on signs such as lesions or spots found in various slices of a plant. The size, color and the amount of these spots can define in great detail the disease that has killed the crop. Public data set is use as data set. Experimental environment Model works on is biodiverse environment.

**Keywords:** Crop diseases, Deep learning, Detection, Convolutional neural network, Biodiverse, environment, Optimization.

# Introduction:

Farming and rearing of animals and plants for the purpose of producing food, material, medicinal plants and other products to maintain and improve human life is called agriculture. Farming was one of the key elements of sedentary human civilization, in which domesticated species produced surpluses of food that made it possible for people to live in cities. Rural science is the study of farming.

Statistical data indicate that mountains cover about two-thirds of China's land area, while plains make up approximately one-third. Around one-third of the country's agricultural population resides in hilly regions.[1] Due to this situation, agriculture, forestry, and animal husbandry rank among the poorest performing sectors in China. According to statistics from the Food and Agriculture Organization, there is a consistent decline in China's GDP per cultivated acre compared to the world average each year. A decrease in agricultural output due to natural disasters can have severe repercussions for farm production and agricultural development. This issue has been escalating in recent years, posing a significant threat to crop production in China. A stable agricultural sector is crucial, especially in a complex environment.[2] It is crucial to diagnose and prevent crop diseases promptly. Agricultural workers utilize books and networks, consult local specialists, and employ various methods to manage and control these diseases. However, due to various factors, errors occur, and agricultural production is consistently impacted by different challenges.

Image processing is now commonly used by a wide range of individuals who have access to digital cameras and computers. With minimal investment, one can easily enhance contrast, identify edges, assess strength, and apply various numerical techniques to images. Although these methods can be highly effective, many users tend to manipulate images with enthusiasm, often unaware of the fundamental principles behind even the simplest image-processing functions. While this approach may be suitable for some, it often leads to significantly degraded results that fall short of the potential outcomes achievable with a deeper understanding of how image-processing systems function.

Image processing is a method of signal processing that utilizes an image input, such as a photograph or a video frame. This operation can yield either a new image or a collection of parameters and characteristics associated with the original image. Image processing encompasses two key aspects:

1. Enhancing the visual appeal of an image for human viewers.
2. Preparing an image for feature and structure measurement.

There are 3 Types of transformation in Image processing [3]

1.1 Image to image transformations

1.2 Image to information transformations

1.3 Information to image transformations

It is possible to decode, slice, and rebuild images from raw CT or MRI data as well as produce computer graphics, animations, and virtual reality.

To identify insect pests and crop diseases, deep neural networks are gradually applied. A deep neural network mimics the structure of biological neural networks using learnable factors to exchange the connections between neurons in an artificial neural network to simulate the brain.[4]

The convolutional neural network, a subset of the feed forward neural network, is one of the most widely used deep neural network topologies. The history of convolutional neural networks as we know it began in 2012 with the release of the AlexNet model. The effectiveness of convolutional neural networks is further demonstrated by AlexNet's success. Since then, convolutional neural networks have experienced rapid development and have been widely used in a variety of industries, including smart homes, financial supervision, medical diagnostics, and text and speech recognition.

There are three key elements to convolutional neural networks. using a convolution layer for feature extraction. Feature selection is done via the convergence layer, sometimes referred to as the pooling layer. Reducing the number of characteristics results in reducing the number of parameters. The entire connection layer is responsible for producing the characteristics and Summary output. A function of nonlinear activation ReLU is employed in conjunction with a convolution procedure in the convolution layer.

The input layer, which the computer perceives as a matrix's input, is visible in the image on the left. The convolution layer follows, with ReLU serving as its activation function. There is no activation function in the pooling layer. It is possible to mix pooling and convolution layers many times. It is possible to construct the models in a variety of ways by combining a convolution layer with another convolution layer or a convolution layer with a pool layer. On the other hand, the most popular CNN mixes many pooling layers with convolution layers. A comprehensive connection layer serves as a classifier in the last phase, translating the learned feature representation to the label space.

1. **Literature Review:**

Deep architectures refer to groups of functions that correspond to each other. complex pathways. Deep Learning algorithms operate by parameterizing suchetypes. designing and adjusting the parameters of circuits to optimize them as closely as possible. a specific goal for training. While previously considered challenging to teach In the realm of complex structures, many effective algorithms have been suggested. In the past few years. We examine a few of the theoretical justifications for deep. designs, along with a few of their real-world achievements, and suggest avenues for further research to tackle the existing obstacles.[5]

A technique for teaching a neural network using pictures of 10 different crops. The AI Challenger Competition 2018 provided the images. The ReLu function activates the system. Adam optimization algorithm is utilized in this paper. In a classification problem, the evaluation metric used is top 1 accuracy. The test findings showed that the system achieved an 86.1% accuracy in recognition overall. It could also recognize pests and diseases affecting crops. Future efforts in this study will focus on enhancing the model's accuracy and expanding the dataset.[6]

A large, deep convolutional neural network was developed in order to categorize 1.2 million high-resolution images from the ImageNet LSVRC-2010 competition into 1000 various categories. In the test data, we obtained top-1 and top-5 error rates of 37.5% and 17.0%, significantly outperforming the previous best. The neural network comprises of five convolutional layers, some with subsequent max-pooling layers, and three fully-connected layers, ending with a 1000-way softmax, containing 60 million parameters and 650,000 neurons. In order to speed up training, we utilized non-saturating neurons and a highly efficient GPU implementation of the convolution operation. In order to address overfitting in the fully connected layers, we utilized the "dropout" regularization method, which has shown high effectiveness. We submitted a different version of this model to the ILSVRC-2012 contest and attained a top-5 test error rate of 15.3%, outperforming the second-place entry which achieved 26.2%.[7]

The apple leaf disease dataset (ALDD) was primarily developed in this study using data augmentation and image annotation techniques, with workshop photos and intricate field images. Based on deep-CNNs, a new model for recognizing apple leaf diseases is introduced by combining the Inception structure of GoogleNet with Rainbow. The INAR-SSD model is specifically designed to identify five common apple leaf diseases using a testing dataset of 26,377 images of diseased apple leaves. According to the results, the INAR-SSD model achieves a recognition performance of 78.80 percent mAP on ALDD, with a recognition speed of 23.13 FPS. The results indicate that the INAR-SSD model is a cutting-edge solution for detecting apple leaf diseases early, offering enhanced accuracy and speed compared to previous methods, allowing for real-time identification.[8]

A technique for developing a diagnostic system for mildew disease in pearl millet that merges transfer learning with feature extraction. Deep learning is advantageous for precision agriculture as it enables practical and fascinating data analysis. The expected advantage of the proposal is to support stakeholders (such as researchers and farmers) through the provision of knowledge and information acquired through the process of reasoning. The test findings indicate that accuracy stands at 95.00 percent, recall at 94.50 percent, precision at 90.50 percent, and the f1-score at 91.75 percent, demonstrating a positive performance.[9]

1. **Research Methodology:**

In previous research, a system was developed and integrated into WeChat mini programs. The program can identify the disease on the leaves of crops based on the name of the disease. The first step is to upload an image and send it for backend processing in the system. Once the recognition is finished, the crop with the highest level of similarity will be identified and its name and status will be displayed. Let's take a look at some algorithms that already exist.

**4.1 Existing Algorithm**

4.1.1 Adam optimization algorithm:

Adam is an alternative optimization technique that produces neural network weights that are improved by conducting multiple rounds of "adaptive moment estimation". Adam is a stochastic gradient descent extension that requires less resources and can solve non-convex problems quicker than a lot of other optimization programs. The most effective use of it is to maintain tight gradients over numerous iterations, especially with very large data sets.

Adam combines two popular stochastic gradient techniques, Adaptive Gradients and Root Mean Square Propagation, to develop a novel learning approach.  
 Adam optimization can be used as an alternative to traditional stochastic gradient descent for updating network weights.

In order to speed up convergence, Adam algorithm utilizes both Momentum and Adaptive Learning Rates. Adam is a different optimization method that applies multiple rounds of "adaptive moment estimation" to generate more effective weights for neural networks.

**4.2 Models**

4.2.1 Inception Network:

The Inception network sets itself apart from ordinary convolutional neural networks by employing multiple convolution kernels in its convolutional layer, resulting in a combined depth image as its output. GoogLeNet, the champion of the 2014 ImageNet Image Classification Competition, employed Inception v1.

4.2.2 The ALexNet model:

AlexNet consists of 5 convolutional layers, 3 pooling layers, and 3 fully connected layers. AlexNet not only incorporates the principle and concept of LeNet-5, but also introduces numerous innovative attributes. One option for addressing gradient dispersion issues is to replace the Sigmoid function with the ReLU function. Dropouts are implemented at fully connected layers in order to prevent overfitting.

4.2.3 The LeNet-5 model:

Even though LeNet-5 was introduced early on, it remains a highly effective and comprehensive neural network, especially in applications like recognizing handwritten numbers. The LeNet-5 network is composed of 7 layers including 2 convolutional layers, 2 pooling layers, and 3 fully connected layers. The output is divided into 10 categories and uses an input image size of 32 \* 32.

1. **Data Set:**

Datasets for common illnesses are: 1) Plant Village, an open dataset, now has 54,309 plant leaf disease images, covering 14 different vegetable crops and fruit, including grapes, apple, blueberry, soybean, orange, strawberry, peach, cherries, bell, pepper, corn, raspberry, pumpkin, potato, and tomatoes contains 26 diseases (17 types of fungal disease, four types of bacteria disease, two types of mycosis, two types of viral infections and one types of diseases caused by mite), as well as 12 healthy crop leaf photos. 2)Using the same data set as the 2018 Artificial Intelligence Challenger Competition's Crop Disease Recognition competition, the data set was used to identify diseases in crops [v], with 45,356 images of 27 disease images of 10



Fig 1: Apple Healthy



Fig 2: Potato Blight Fungus



Fig 3: Tomato leaf Mold Fungus

crops (Cherry, Corn, Apple, Grape, Citrus, Peach, Tomato, Strawberry, Pepper, Potato). Dataset is separated into 3 parts: 80% Training set (36,302), 10% Validation Set (4540), 10% Testing Set (4514). The only thing in each picture is the leaves of one crop. Fig. 2 shows some sample pictures. 3)‘Plant Pathology Challenge’ for CVPR(XIII), which includes 3651 high-resolution annotated RGB images of 1200 apple scab symptoms and 1399 symptoms of cedar apple rust and 187 patterns of complex disease (same leaf showing multiple symptoms) and 865 healthy apple leaf.

1. **Conclusion:**

This paper presents a study on using optimization algorithms to detect crop diseases. By means of literature reviews, the Inception-ResNet-v2 model's precision can be improved. Reviews of the literature also demonstrate that the hybrid model performs more accurately than the conventional model, which qualifies it for the detection and identification of insects and plant diseases. The objective of future research is to increase the model's accuracy and broaden the dataset.

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