



# AN EFFECTIVE MODEL FOR PREDICTING LEAF DISEASES WITH DEEP LEARNING THROUGH CONVOLUTIONAL NEURAL NETWORKS

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**Abstract:** One of the most significant elements that pose a significant risk to agricultural productivity is the presence of leaf diseases. Finding and naming diseases and pests as soon as they appear is one of the most effective ways to cut down on the financial damage they incur on the farmer. In this study, a convolutional neural network was utilized to automatically detect illnesses that might affect crops. Here we have taken an image dataset containing more than 20,000 images. Training is carried out with the help of the Inception-ResNet-v2 model. The direct edge in the cross-layer and the multi-layer convolution in the residual network unit of the model. Following the completion of the combined convolution process, it is triggered by the connection into the ReLu function. The experimental results suggest that this model achieves an overall recognition accuracy of 98.0%, which substantiates the claim that it is successful. Following the completion of this model's training, we developed and deployed the UI of agricultural disease and insect pest identification. After that, we began the real testing process. The findings demonstrate that the system is capable of correctly identifying crop illnesses so that the farmer can choose to suitable method to overcome the crop from the identified disease.

**Index Terms -** Leaf disease prediction, Deep learning, Convolutional neural network, Illness.

## I. INTRODUCTION

At the moment, researchers focusing on agricultural diseases are mostly moving in two different ways. The first way is the classic physical method, which identifies various illnesses mostly by spectral detection. This method has been around for a very long time. Different kinds of illnesses and insect pests produce different kinds of damage to leaves, which in turn leads to different kinds of spectral absorption and reflection from healthy crops and those that have been damaged by diseases. The second option is to recognize pictures via the use of computer vision technologies. That is to say, the features of disease pictures are extracted via the use of technology connected to computers, and the recognition is accomplished through the use of the distinct characteristics that sick plants and healthy plants share.

The recent years have seen a fast growth of artificial intelligence (AI), which has resulted in life being more convenient, and AI has become a well-known technology in recent years. Take, for instance, the game of Go, where AlphaGo prevailed against the reigning world champion. Deep learning is an application of artificial intelligence technology that is used in a variety of disciplines, including Apple's Siri and Amazon's Alexa, which serve as voice assistants for their respective companies. Image recognition, which serves as the primary focus of research in the fields of computer vision and artificial intelligence, has seen significant

advancements in recent years. In the context of agricultural applications, the purpose of image recognition is to recognize and categorize various kinds of photographs, as well as to do analyses of the various types of crops, diseases, and severity levels. After that, we will be able to devise appropriate countermeasures to deal with the myriad of issues that arise throughout agricultural production in a timely and effective way. with the purpose of further ensuring and improving the production of crops and contributing to the greater growth of agriculture.

With the fast progress of deep learning notably in image recognition voice analysis, natural language processing, and other domains, it demonstrates the one-of-a-kindness and efficacy of deep learning. Deep learning is a more effective technique for diagnosing plant illnesses than the more conventional approaches that have been used in the past. This pertains to the sector of agricultural production. The model that uses deep learning can monitor, diagnose, and stop the development of crops at the appropriate moment. Image identification of crop illnesses and insect pests might lessen farmers' reliance on plant protection technicians in agricultural production, allowing them more time to find and implement appropriate solutions to any issues that arise. The pace of manually detecting anything is far slower than the speed of identifying something using an intelligent network, which is lot quicker than identifying something artificially. In addition, the precision of the recognition is always improving thanks to the ongoing development. Not only can the establishment of a reliable agricultural network and the combination of the Internet and the agricultural industry help solve problems related to crop yield that are caused by diseases and insect pests, but they can also help foster the growth of agricultural informatization.

However, because of the mountain environment's rough topography, the surrounding interference factors are stronger. This is a challenge for radio astronomers. As a result, acquiring a picture is a more challenging task than dealing with the overall surroundings. Additionally, the camera and network transmission that are essential for picture identification and processing will have some degree of influence on the situation. Mountainous regions provide a greater challenge for the implementation of intelligent recognition because of this reason. The purpose of this article is to conduct research on the identification model of agricultural diseases and insect pests, as well as construct a platform for the Internet of Things that can function in the challenging environment of mountainous regions. This model's ultimate goal is to result in an improvement agricultural informatization, reducing the damage caused by diseases and pests to crops, and increasing crop yields are all important goals.

## II. LITERATURE SURVEY

Research is ongoing in several areas, including those concerned with the detection and control of agricultural diseases and insect pests. The advancement of technology has led to the creation of a variety of sensor networks and autonomous monitoring systems that have been suggested.

Image sensors are one other kind of solution that may be used in conjunction with monitoring traps that are utilized for the purpose of capturing pests . The authors O. López, M. Rach, H. Migallon, M. Malumbres, A. Bonastre, and J. Serrano are conceived and constructed a system that has a low power consumption and is powered by a battery. The system is based on wireless image sensors. The setting and remote adjustment of the frequency of recording and sending trap pictures of sensors is something that can be done by the trapping application.

In addition, acoustic sensors play a role in the monitoring system. The authors N. Srivastav, G. Chopra, P. Jain, and B. Khatter are provide a method that may be used to identify red palm weevil (abbreviated RPW) using them. The noise that is made by the pest may be automatically caught with the assistance of an acoustic device sensor. When the sound level of the pests reaches a certain threshold, the system will send a notification to the customer informing them that an infestation is taking place in the designated region. It was helpful for farmers to save time and energy by allowing them to monitor every portion of their field on their own, which also increased the efficiency of their work. When the predetermined threshold value is exceeded, each of the acoustic sensors will report the amount of noise that they are experiencing. These sensors will all be linked to the base stations.

In addition, there have been applications of machine learning in the agriculture sector, such as research on plant diseases and pests and other related topics. The challenge of accurately diagnosing plant diseases has been tackled using a variety of different machine learning strategies that have seen widespread use. In (Potato leaf diseases detection and classification system [8]), a Neural Network-based approach is suggested for evaluating potato health using leaf image datasets.

In addition, the experimental study described in (Application of neural networks to image recognition of plant diseases [9]) was carried out, the primary objective of which was to develop an imaging-based diagnosis system for plant diseases. Four distinct kinds of neural networks were trained based on color, shape, and texture variables collected from a disease picture dataset. The findings demonstrated that a neural network that is based on image processing may boost the accuracy of identifying plant diseases.

Image processing technologies might also be used to identify the scab disease that affects potatoes (Scab diseases detection of potato using image processing [10]). This is an added benefit. To begin, photographs taken at a variety of potato farms were gathered together. Following the completion of image enhancement, picture segmentation was carried out in order to obtain the target area. In the end, a histogram-based method of analyzing the target area was used so that the phase of the illness could be determined.

### III. METHODOLOGY

In the proposed methodology, the main aspect is to identify the illness of 3 different types of leaves. Here we have taken an image dataset from kaggle where it contains more than 20 thousand of images which have been used for training the model. Convolutional Neural Networks a deep learning model is used here to train the model. Training is carried out with the help of the Inception-ResNet-v2 model where in it is the popular model having 164 layers deeper network and can classify images into 1000 categories. Model has been created with dataset partitioned in to Training set, validation set and Test dataset. Model has been trained to identify the leaf diseases for three categories of leaves of potato, pepper and tomato. Model is well trained and generating a good accuracy in predicting the leaf diseases on which it is trained. CNN is the popular algorithm for image analysis in deep learning, so we have chosen this algorithm to implement this model. A technique for evaluating the health of plants using leaf image datasets is presented here. This approach is based on a neural network. In addition, to the experimental study that was carried out, the purpose of which was to develop a method for the identification of plant diseases using photographs.

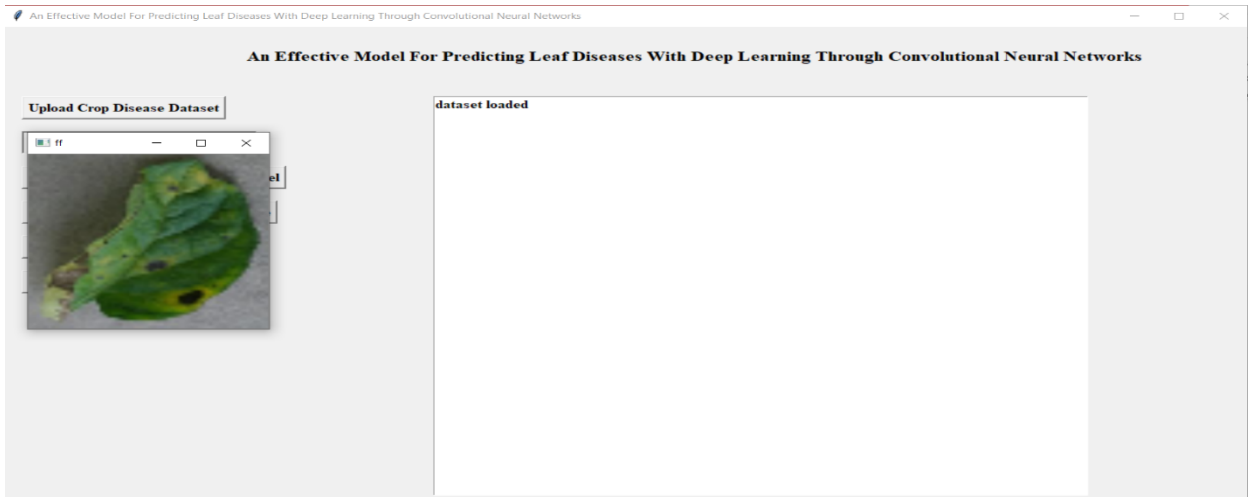
In this paper a deep learning convolution neural network (CNN) is used to predict crop disease and its pests to reduce economical loss in Agricultural field. To build disease recognition model RESNET CNN model is applied which consists of 3 parts

1. **Feature Extraction:** In a Convolutional Neural Network (CNN), the initial layers are dedicated to feature extraction. These layers analyze input data, such as images or multidimensional datasets, to identify distinctive patterns and features.
2. **Feature Selection:** Following feature extraction, a process known as pooling or max pooling is often applied. This operation selects the most significant information from the extracted features, aiding in reducing the computational load and focusing on key aspects of the data.
3. **Activation Function:** The Rectified Linear Unit (ReLU) activation function is applied to the extracted features. ReLU helps in filtering out irrelevant or less important features, ensuring that only relevant and crucial features are passed on to subsequent layers for further processing.
4. **Flatten:** After activation, the features are flattened. This converts the multi-dimensional feature maps into a single-dimensional array, which serves as input for the subsequent layers.
5. **Dense Layer:** The dense layer connects the previous layer to the next layer. It takes the flattened features and applies weights to learn complex relationships within the data. This process refines

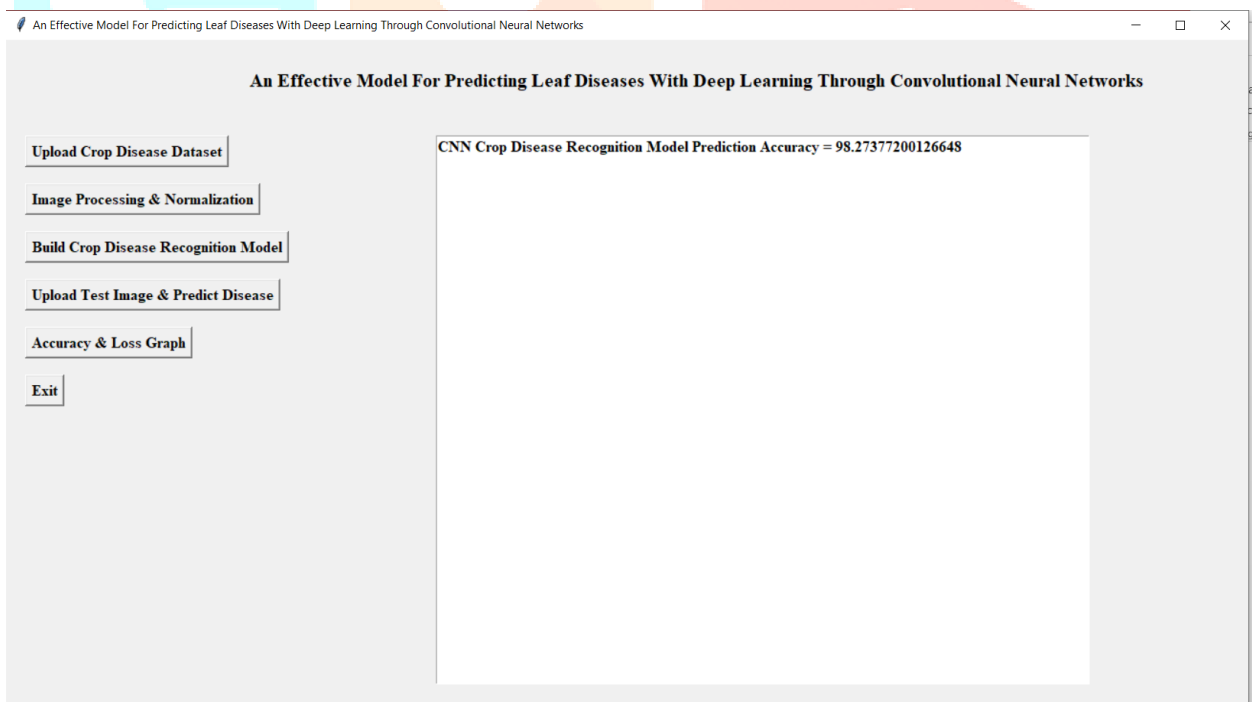
the features further, enhancing their representational power and capturing the most essential characteristics from the dataset. This layer's role is to sequentially distill the input features and enable the network to make accurate predictions based on the learned patterns.

By following these steps, a CNN effectively transforms input data into a format that enables it to understand and interpret complex relationships within the dataset, ultimately leading to improved prediction results.

#### IV. RESULTS



**Figure1: Image Processing and Normalization**



**Figure 2: CNN model generated and its prediction accuracy is 98%**

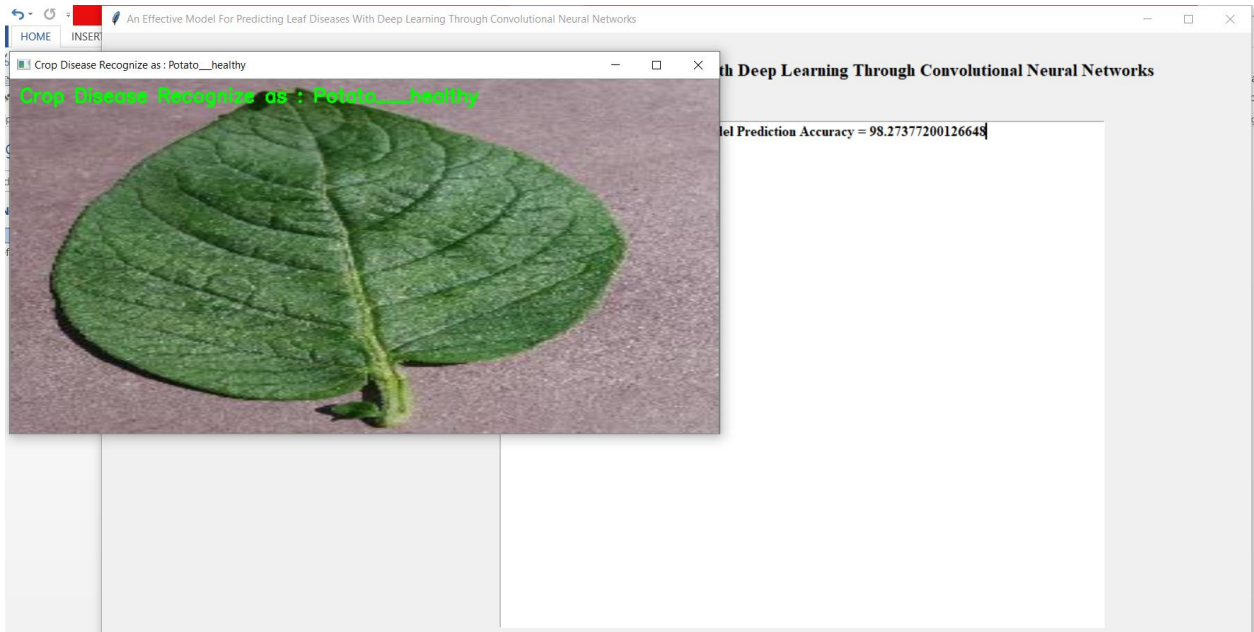


Figure 3: potato leaf predicted as healthy

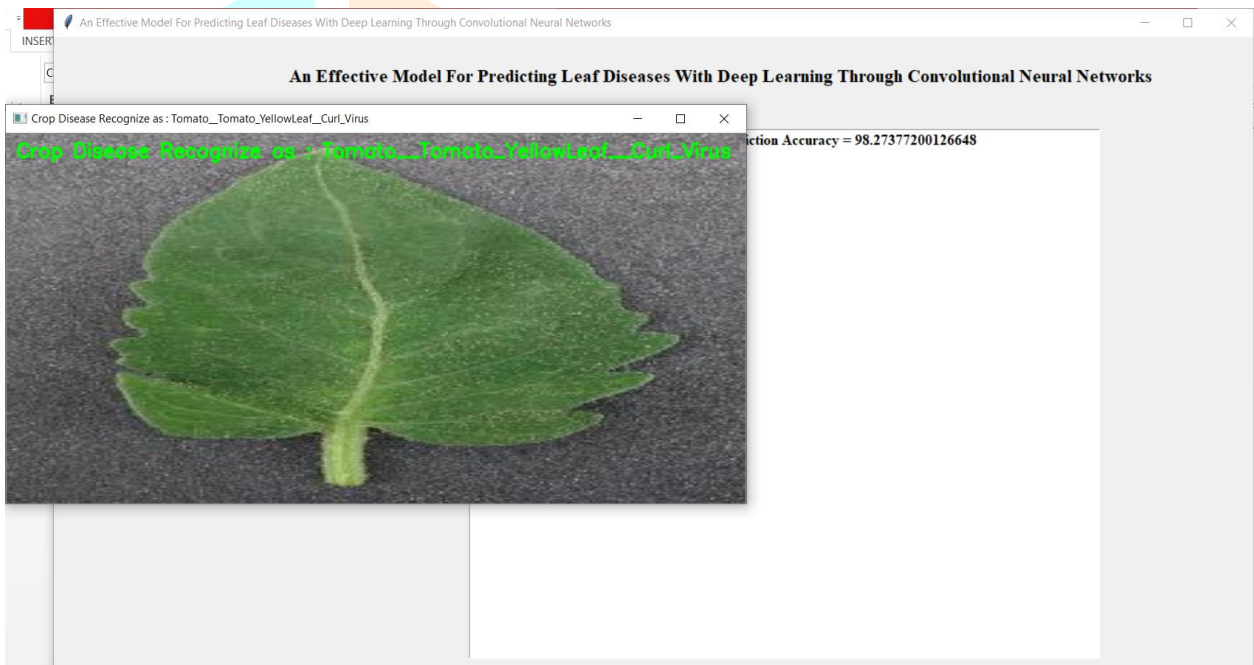


Figure 4: Tomato\_Tomato\_YellowLeaf\_Curl\_Virus disease is detected or recognize

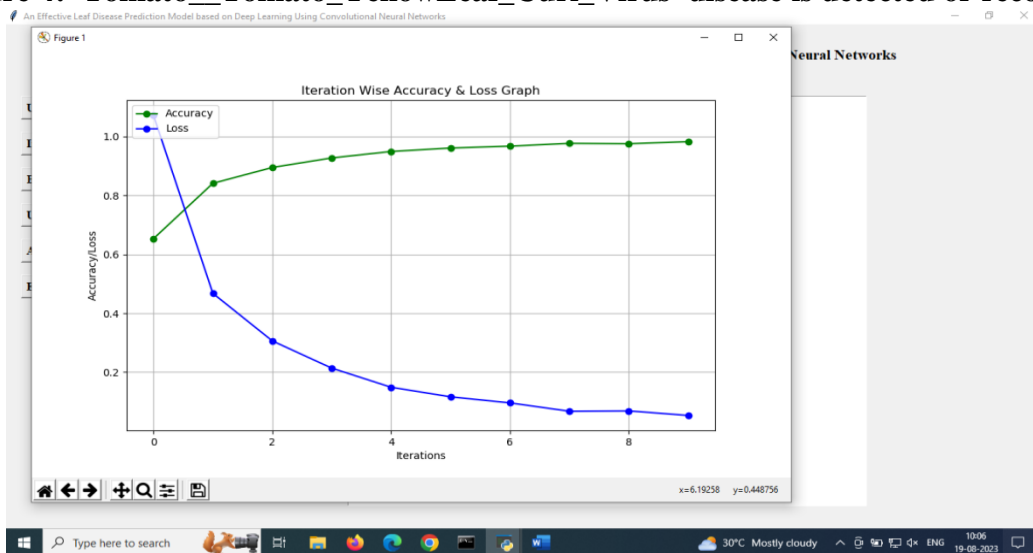
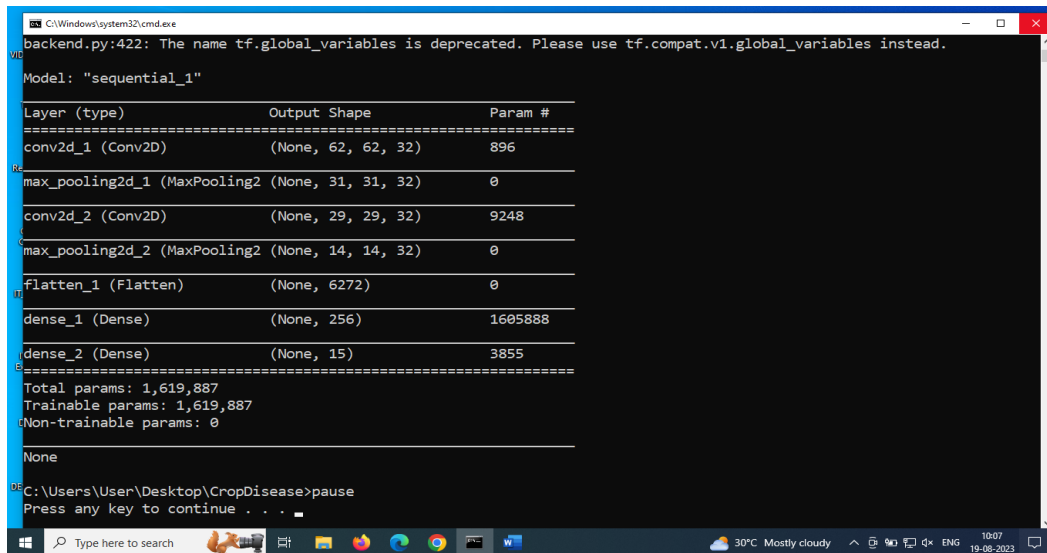


Figure 5: Accuracy graph



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C:\Windows\system32\cmd.exe
backend.py:422: The name tf.global_variables is deprecated. Please use tf.compat.v1.global_variables instead.
Model: "sequential_1"
Layer (type)                Output Shape                Param #
-----
conv2d_1 (Conv2D)           (None, 62, 62, 32)         896
max_pooling2d_1 (MaxPooling2 (None, 31, 31, 32)         0
conv2d_2 (Conv2D)           (None, 29, 29, 32)         9248
max_pooling2d_2 (MaxPooling2 (None, 14, 14, 32)         0
Flatten_1 (Flatten)         (None, 6272)               0
dense_1 (Dense)             (None, 256)                1605888
dense_2 (Dense)             (None, 15)                 3855
-----
Total params: 1,619,887
Trainable params: 1,619,887
Non-trainable params: 0
None
C:\Users\User\Desktop\CropDisease>pause
Press any key to continue . . .
  
```

**Figure 6: Layers and Params**

## V. CONCLUSION

This project focuses on the recognition of 11 different diseases affecting 3 distinct crop types. Leveraging deep learning principles and convolutional neural network techniques, the study employs the Inception-ResNet-v2 model. Empirical evaluations underscore the model's proficiency in accurately identifying the dataset, achieving an impressive 98% overall recognition accuracy. The findings indicate that this amalgamated network model outperforms conventional methods, proving its applicability in detecting and identifying plant diseases and insect infestations.

Looking ahead, there are two key areas that warrant refinement:

1. **Expansion of the Dataset:** The current study delves into 11 diseases across 3 specific crop species. However, the scope can be broadened to encompass additional species and diseases. Incorporating images of crops like rice and wheat, along with their associated diseases, will enrich the dataset, enabling more comprehensive research.
2. **Model Optimization:** The experimentation reveals the prowess of the Inception-ResNet-v2 hybrid model, harnessing the strengths of its constituent architectures. This model's impressive recognition accuracy underscores its potential for further enhancement and exploration. Concurrently, it's crucial to devise a network model capable of achieving even higher accuracy in classifying crop images.

By pursuing these directions, the research can achieve a more encompassing understanding of crop disease recognition, incorporating a broader range of species and diseases, while also refining the model to achieve even greater precision in classification tasks.

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