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RECOGNITION OF CROP DISEASE AND INSECT PESTS BASED ON DEEP LEARNING IN HARSH ENVIRONMENT

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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. The data set comes from the public data set of the AI Challenger Competition in 2018, with 27 disease images of 10 crops. In this paper, the Inception-ResNet-v2 model is used for training. The cross-layer direct edge and multi-layer convolution in the residual network unit to the model. 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. After the training of this model, we designed and implemented the Wechat applet of crop diseases and insect pests recognition. Then we carried out the actual test. The results show that the system can accurately identify crop diseases, and give the corresponding guidance.

I.INTRODUCTION

Agriculture serves as the backbone of many economies worldwide, providing sustenance and livelihoods for billions of people. However, crop diseases and insect pests pose significant threats to agricultural productivity, food security, and farmer incomes. Early detection and management of these threats are essential for mitigating losses and ensuring sustainable agricultural practices.

Traditional methods of disease and pest detection often rely on visual inspection by farmers, which can be time-consuming, subjective, and prone to human error.

Furthermore, in harsh environments characterized by adverse weather conditions, limited resources, and remote locations, such as rural areas or developing countries, these challenges are exacerbated.

The "Recognition of Crop Disease and Insect Pests Based on Deep Learning in Harsh Environments" project aims to address these challenges by leveraging the power of deep learning techniques to automate and improve the detection of crop diseases and insect pests. Deep learning, a subset of machine learning, has demonstrated remarkable capabilities in image recognition and pattern detection, making it well-suited for this task.

II.EXSISTING SYSTEM

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, misjudgments 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.

III.PROPOSED SYSTEM

The central sever provide forecast service of weather condition and disease. Another kind of solution related of monitoring traps which are used to capture pest is with the help of image sensors [6]. In [6], he authors designed and implemented a low power consumed system which is based on wireless image sensors and powered by battery. The frequency of capturing and transferring trap images of sensors can be set and remote adjusted by trapping application. Acoustic sensors are also used in monitoring system. In [7], the authors give a solution to detect red palm weevil (abbr. RPW) with them. With the help of acoustic device sensor, the pest's

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noise can be captured automatically. When the noise level of pest increases to some threshold, the system will notify the client that the infestation is occurring in the specific area. It helped farmers to be economical of time and energy to check every part of cropland by themselves and increase the labor efficiency. All acoustic sensors will be connected to base stations and each one will report the noise level if the predefined threshold value is surpassed [7]. Machine learning also had been applied in the agricultural field, such as investigation of plant disease and pests and so on. Plenty of techniques of machine learning had been widely used to solve the problem of plant disease diagnosis. In [8], a Neural Network based method of estimating the health of potato with leaf image datasets is proposed. Additionally, the experimental research in [9] was carried out, which aimed to implement a system of recognizing plant disease with images.

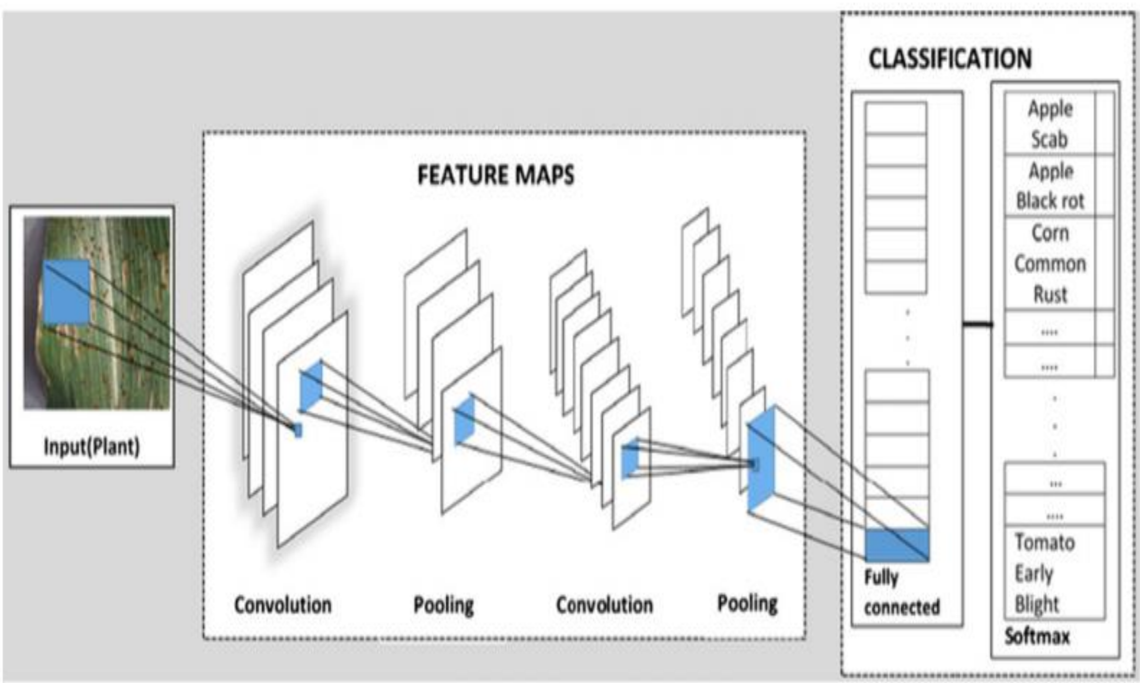

Fig : System Design

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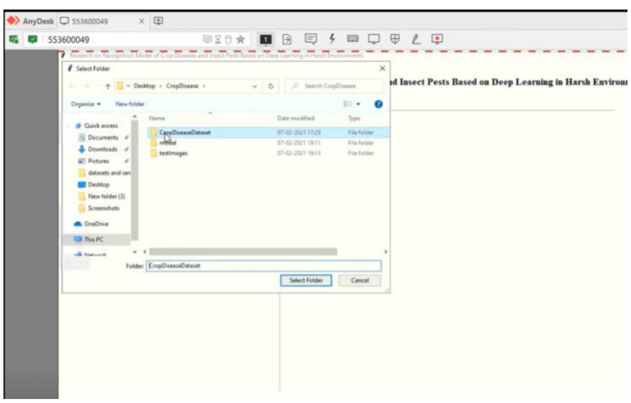
IV.IMPLEMENTATION

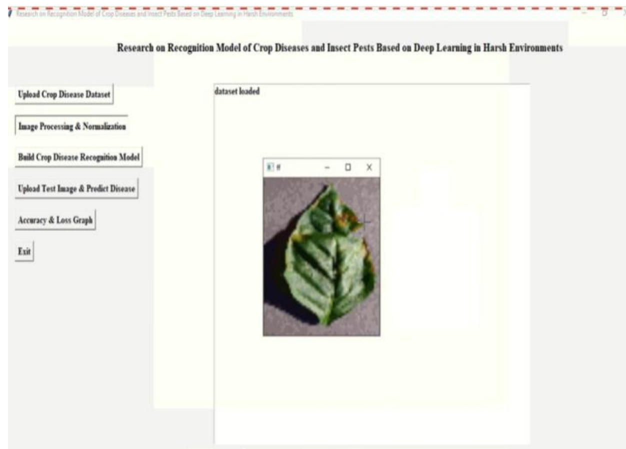
➢ **Dataset Acquisition and Preprocessing Module:**

This module is responsible for acquiring a dataset of images containing crop samples affected by diseases and insect pests. It involves collecting images from various sources, annotating them with labels indicating the presence of diseases or pests, and preprocessing the images to ensure uniformity and quality.



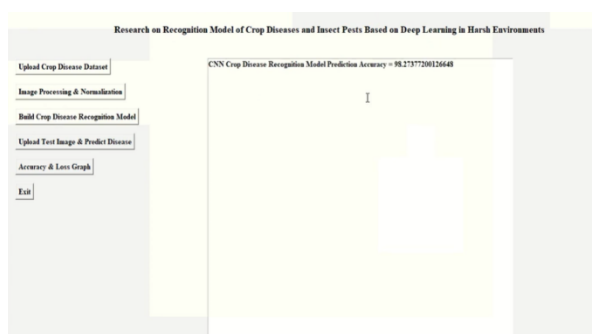
➢ **Image Processing and Normalization Module:**

This module focuses on standardizing and enhancing the quality of the acquired images. It includes tasks such as resizing images to a consistent resolution, adjusting brightness and contrast, removing noise, and applying transformations like rotation or cropping to improve model performance.



➢ **Model Building and Training Module:**

In this module, deep learning models are developed and trained using the preprocessed image dataset. Various deep learning architectures, such as convolutional neural networks (CNNs),



may be explored and optimized to achieve high accuracy in detecting crop diseases and insect pests.

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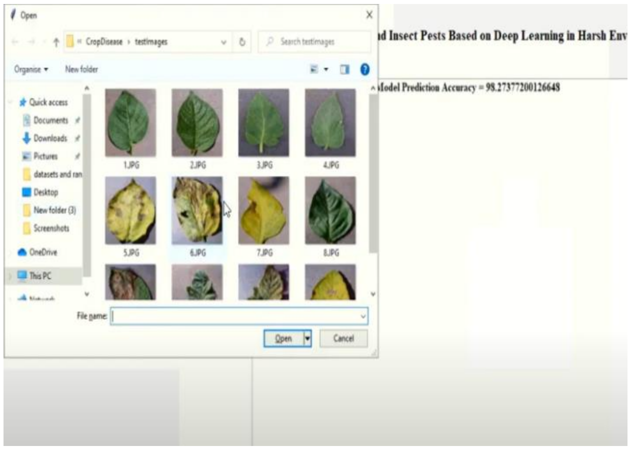

➢ **Model Evaluation and Validation Module:**

Once trained, the models need to be evaluated and validated to assess their performance and generalization ability. This module includes tasks such as splitting the dataset into training and testing sets, measuring metrics like accuracy and precision, and analyzing the model's behavior on unseen data.

➢ **Deployment and Integration Module:**

After successful evaluation, the trained models are deployed for practical use. This module involves integrating the models into a user-friendly application or platform accessible to farmers or agricultural extension workers. It includes tasks such as developing APIs for model inference, creating a user interface for uploading images and viewing predictions, and ensuring scalability and reliability of the deployed system.

➢ **Image Upload and Prediction Module:**

This module provides functionality for users to upload images of crop samples potentially affected by diseases or pests and receive predictions from the trained models. It includes components for image upload, preprocessing, model inference, and displaying prediction results to the user.

V.CONCLUSION

In this paper, 27 kinds of disease recognition of 10 kinds of crops were studied. The Inception-ResNet-v2 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: 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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