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Real-Time Detection and Identification Algorithm of Agricultural Pests and Diseases based on Deep Learning

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Abstract: Agricultural pest and disease detection is of great significance in ensuring crop yield and quality. In order to achieve real-time and accurate pest and disease identification, this paper proposes a real-time pest and disease detection and recognition algorithm based on deep learning. By introducing convolutional neural network (CNN) and feature pyramid network (FPN), this method improves the recognition ability of complex pest and disease images under multi-scale conditions. The system realizes remote management, data collection and transmission of monitoring equipment in farmland through high-definition cameras, 4G or 5G networks. Data preprocessing technology is used for image enhancement and denoising to improve the feature extraction ability of the model. The trained model is applied to real-time detection in the actual environment to form a historical data set to provide support for the prediction of pest and disease development trends. This study provides efficient and low-cost technical support for pest and disease prevention and control in smart agriculture, and has good applicability and promotion value.

Keywords: *Agricultural pest detection, Deep learning, Real-time recognition, Image processing, Neural network algorithm*

I. INTRODUCTION

In the construction of agricultural modernization in China, the application of information technology in agricultural pest monitoring and prevention has gradually become a key issue that cannot be ignored. Agricultural modernization requires improving production efficiency, reducing crop losses, and ensuring environmental sustainability. Traditional pest monitoring methods are often labor-intensive, and their accuracy and timeliness are difficult to meet the needs of modern agriculture. Pest monitoring based on information technology can not only achieve real-time monitoring, but also provide intelligent early warning, providing farmers with more accurate prevention and control guidance. From the perspective of actual agricultural production, the biggest threat it faces is pests and also the diseases. Whether it is the occurrence of diseases or pests, it may affect the normal agricultural production process and endanger the benefits of agricultural production. In order to deal with pests and diseases, additional production measures have to be taken, which increases the agricultural production costs, wastes agricultural production resources, and causes the yield and quality of agricultural products to decline, or even no harvest, ultimately causing immeasurable economic losses.

According to the basic studies, the following integration with the information technologies are essential:

1. Big data analysis and artificial intelligence applications play a core role in agricultural pest and disease monitoring. By deeply mining the collected data, we can analyze the temporal and spatial distribution patterns and trends of pest and disease occurrence and help predict high-incidence areas.

2. The integration of drones and remote sensing technology has significant advantages in large-scale farmland pest and disease monitoring. The drone is equipped with a high-definition camera and multi-spectral imaging equipment, which can efficiently and quickly scan farmland and identify plant anomalies.

3. Informatization training and promotion for farmers: While applying technology, it is necessary to strengthen information technology training for farmers to improve their awareness and acceptance of pest monitoring and prevention technology. Through educational activities led by agricultural cooperatives or the government, that help farmers master basic equipment operation and data analysis methods.

Therefore, this study integrates the latest technology to propose the novel ideas and in the Figure 1, the sample of agricultural pests and diseases is illustrated.

Figure. 1 The Sample of Agricultural Pests and Diseases (Image source: https://geopard.tech/blog/how-to-control-crop-diseases-with-smart-agriculture/)

II. THE PROPOSED METHODOLOGY

A. The traditional methods of agricultural pest control

In the traditional pest control system of Chinese agriculture, chemical pesticides and biological control methods are the two main means. Although these methods have played an important role in the agricultural production, they also face a series of problems and challenges.

1. Chemical pesticide control: pros and cons

Chemical pesticides are widely used and fast, covering insecticides, fungicides, herbicides, etc., which can effectively inhibit the damage of pests and weeds to crops in a short time. This kind of method is simple to operate and effective, especially suitable for large-scale farmland and emergency situations of pests and diseases. However, the abuse and excessive use of chemical pesticides have brought many negative effects:

Environmental pollution: Chemical pesticides will remain in the soil and water sources, leading to problems such as soil structure deterioration and water eutrophication, affecting the sustainability of agricultural ecosystems.

Ecological damage: The large-scale use of chemical pesticides may affect non-target organisms, including insects, birds, aquatic organisms, etc., leading to an imbalance in the ecological chain. For example, natural enemies that prey on pests may be threatened by pesticide residues, further exacerbating the growth of pest populations.

Resistance problem: Long-term use of a single type of pesticide will cause pests to develop resistance and reduce the control effect. Farmers use higher concentrations or newer types of pesticides to maintain the control effect, forming a vicious cycle.

Potential risks to human health: Pesticide residues pose a certain threat to human health, especially farmers and consumers who are directly exposed to pesticides. The residues of some chemical pesticides may cause health problems, and long-term exposure may also cause chronic diseases.

2. Biological control: an environmentally friendly and sustainable choice

Biological control methods include the use of natural control methods such as natural enemies, parasites, and pathogenic microorganisms to inhibit the reproduction of pests and diseases. For example, natural enemy insects (such as ladybugs, parasitic wasps, etc.) can prey on pests, and specific microorganisms (such as fungi, viruses, etc.) can also effectively infect and suppress pest populations. Biological control has the following advantages:

Environmentally friendly: Biological control does not produce chemical residues, and has little impact on water bodies, soil and non-target organisms, and is in line with the concept of the ecological agriculture.

Low resistance: Biological control mechanisms are diverse, pests are not easy to develop resistance, and are more suitable for long-term control.

B. Using machine vision for agricultural pest monitoring

Early machine vision systems were mainly based on simple shape logic judgments, using basic methods such as image segmentation and edge detection to identify the shape of disease spots or pests on leaves. This method is suitable for monitoring larger and more obvious pests and diseases, but the accuracy is low when facing complex backgrounds or small areas of disease.

With the development of feature vectors and pattern recognition methods, pest and disease monitoring has entered a new stage. Using multidimensional features such as color, texture, and shape, machine vision can more accurately describe the surface characteristics of pests and diseases, thereby improving the accuracy of detection. These feature vectors can be applied not only to a single category of diseases, but also to identify multiple types of pests and diseases. However, the technology at this stage still relies on manual feature extraction, and the model has poor robustness and is difficult to adapt to different crop types and environmental conditions.

The detection of pests and diseases by machine vision systems generally includes the following steps:

Image acquisition: The images of crop leaves are collected through high-definition cameras, drones and other equipment to ensure that the images cover different areas of the farmland and different disease conditions.

Image pre-processing: In order to improve the image quality, denoising, color enhancement and other technologies are often used so that the subsequent deep learning model can better extract features.

Deep learning model training: The convolutional neural network is trained using a large amount of collected annotated image data. Through multiple rounds of iterations, the model can extract effective features from complex backgrounds and identify diseases.

Feature pyramid network (FPN) integration: The feature pyramid network can enhance the deep learning model's ability to identify multi-scale diseases. Integrating FPN into the detection model can better capture the detailed features of the disease, such as small spots and early lesions.

Real-time monitoring and analysis: The trained machine vision system can be applied in actual production environments to detect crop pests and diseases in real time and issue an alarm after the disease is found.

C. The demand analysis of agricultural pest and disease detection system

The current demand for agricultural pest and disease detection is to improve the response speed and accuracy to pests and diseases to ensure the yield and quality of crops. With the development of smart agriculture, pest and disease detection systems have gradually become an important part of realizing agricultural modernization. Based on this background, the demand for pest and disease detection systems is mainly concentrated in the following aspects:

Demand for monitoring equipment management: Pests and diseases in farmland are mainly analyzed through on-site photos, and the clarity and real-time nature of the image directly affect the detection effect. Therefore, the system needs to have the ability to comprehensively manage the monitoring equipment deployed in the farmland to ensure that each device operates normally and shoots stably. The monitoring equipment must not only have a high-definition camera that can automatically adjust the shooting parameters under different lighting conditions, but also support 4G or 5G networks to ensure that images can be quickly uploaded to the service center. In addition, the system needs to record the basic information of each monitoring device, including device model, location, connection status, and power, so as to conduct real-time monitoring and maintenance and reduce data loss caused by equipment failure.

Demand for pest and disease data collection: Pest and disease analysis relies on high-quality images collected on-site, so the system should support automatic collection and uploading of on-site images. To ensure the reliability of data collection, each terminal device needs to have a unique fixed IP address. Through this IP, the server can quickly identify the specific location and device status of the collection terminal, which is convenient for tracing the source of data. The system also needs to have the function of batch collection to realize automatic collection in large areas of farmland, avoid human intervention, and further improve the collection efficiency.

Pest and disease analysis requirements: After the system obtains the images collected on site, it needs to complete the automatic pest and disease analysis on the server. Based on the pest and disease characteristics of crops, such as leaf color changes, lesion shape and distribution pattern, the system classifies and names pests and diseases through image recognition technology. The analysis results need to be saved to the system database to form a historical data set to provide basic data for subsequent prediction of pest and disease development trends. In addition, the system needs to have the ability of intelligent learning, and continuously optimize the recognition algorithm through the continuous collection of new data to improve the recognition accuracy and processing efficiency.

CONCLUSION

The real-time detection and identification algorithm of agricultural pests and diseases based on deep learning proposed in this article achieves efficient identification and classification of various pests and diseases by introducing convolutional neural network and feature pyramid network. Experimental results show that the system has high recognition accuracy and real-time performance in complex environments, can significantly improve the monitoring efficiency of farmland pests and diseases, and effectively reduce crop losses caused by pests and diseases. In addition, the system's intelligent learning capabilities can continuously optimize the recognition algorithm through the continuous collection of new data, improving its adaptability and robustness. This method provides a reliable technical path for smart agriculture, helps promote the development of agricultural informatization, and provides technical support for early warning and precise prevention and control of agricultural pests and diseases. Future work can further combine drones and multispectral imaging technology to expand the application scenarios of the system in large-scale farmland.

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