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Research on Intelligent Agricultural Pest and Disease Detection Model Based on Transfer Learning

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Abstract:In traditional agriculture, the method of identifying pests and diseases that relies on experience and visual observation often fails to respond in time when facing new foreign pests, resulting in delayed prevention and economic losses. To solve this problem, this study proposes an intelligent agricultural pest and disease detection model based on transfer learning, combining modern computer technology, image processing algorithms and big data analysis, and using multispectral imaging technology to monitor crops in real time. The model is first pre-trained using a large data set, and then the features are transferred to the crop pest and disease detection task for fine-tuning to optimize the pest and disease identification accuracy of small samples. The research results show that this method can effectively improve detection efficiency and reduce labor costs in complex environments, providing scientific decision-making support for agricultural production. This innovative technology provides a solution for intelligent pest and disease detection in modern agriculture and promotes the digitalization and intelligent development of agriculture.

Keywords: Transfer learning, disease detection model, intelligent agricultural, vision analysis

1. INTRODUCTION

Traditional agriculture relies on experience passed down from generation to generation and intuitive observation to judge diseases. This method is often effective for common local diseases, but when faced with new foreign pests and diseases, farmers lack sufficient experience to identify and respond in time. The limitations of this lack of knowledge lead to a lag in preventive measures. When the farmers finally realize the seriousness of the problem, they usually miss the best time for prevention and control, especially when the disease develops to the middle and late stages, the difficulty and cost of radical treatment rise sharply, causing serious damage to economic benefits.

In large areas of farmland, it is almost impossible to manually monitor crops in each area. This not only requires a lot of labor, but also consumes time and resources. If a certain area fails to detect the disease in time, the pathogen may spread to neighboring areas, causing large-scale diseases and causing widespread losses. In addition, the limited agricultural resources make it impossible for the human monitoring model to cover all areas in a long-term and comprehensive manner, resulting in some potential risks not being discovered. This traditional method exposes the shortcomings of agricultural production in disease prevention and control, and provides a strong demand for the digital transformation of modern agriculture and the introduction of intelligent pest and disease monitoring technology.

In this context, the intelligent pest and disease monitoring system combining modern computer technology and image processing algorithms came into being. Using multi-spectral images, machine learning models and big data analysis, farmers can quickly and accurately identify pests and diseases in a wide area, achieving real-time monitoring and early warning. This method can not only effectively improve detection efficiency and reduce labor costs, but also detect early signs of diseases in a data-driven way, thereby providing more scientific decision-making support for the farmland management. Intelligent pest monitoring system combined with computer can be studied from the following aspects:

1. Core technologies: In-depth discussion of computer technologies used in pest and disease monitoring, such as image processing, machine learning, and deep learning. Examples can be given of how image processing technology is used to identify the type and quantity of pests and diseases, or how machine learning algorithms can predict the probability of pest and disease occurrence based on historical data.

2. Data analysis and prediction: How the system uses big data technology and intelligent algorithms to analyze historical data to conduct trend prediction and risk assessment. It can further explain how to combine meteorological data and environmental parameters such as soil moisture to more accurately predict the time and location of pest and disease outbreaks.

3. System architecture: Describe the core architecture of the intelligent pest monitoring system. For example, the system can be divided into data acquisition module, data processing module, data transmission module and user interface module. The role and collaborative operation of each module can be described in detail, such as how the data acquisition module uses sensors to monitor environmental changes in real time and collect pest characteristic information.

Under this background, this study proposes the novel intelligent agricultural pest and disease detection model based on transfer learning. In the Figure 1, the example of agricultural pest and disease is demonstrated.

Figure. 1 The Example of Agricultural Pest and Disease (Image source: https://wikifarmer.com/en/category/agricultural-principles/integrated-pest-and-disease-management-in-agriculture/)

2. THE PROPOSED METHODOLOGY

2.1 The Transfer Learning for Image Recognition

In modern agriculture, with climate change and frequent occurrences of pests and diseases, accurate disease identification and prediction have become the key to ensuring the quality and yield of agricultural products. However, traditional crop disease detection methods usually rely on visual observations by experienced agronomists. This method is not only time-consuming and labor-intensive, but also difficult to promote in large-scale agricultural applications. The rise of deep learning technology has provided efficient solutions for agricultural disease identification. Especially when the deep learning model is combined with the agricultural image data, it can automatically and efficiently identify a variety of crop diseases in complex environments.

The application of convolutional neural network (CNN) technology in agricultural image recognition is particularly significant. It can extract minute features of crop diseases in low-contrast, complex backgrounds, thereby achieving higher-precision disease classification. However, the problem of data scarcity in the agricultural field is still prominent, especially in the identification of specific diseases. The problem of small samples makes model training more difficult, and may also cause over-fitting and affect the identification effect. To address this challenge, transfer learning methods become an effective optimization strategy. Transfer learning can not only make use of data features in other fields, but also make fine adjustments according to the characteristics of specific diseases in the target field, significantly improving the accuracy of small sample disease identification.

In the application of transfer learning, the model is first pre-trained from a large amount of crop data or data sets in similar fields to obtain a universal feature representation. Subsequently, these features are transferred to the target crop disease identification task and fine-tuned with limited target field data to improve the generalization ability of the model. This method is particularly suitable for situations where it is difficult to obtain sufficient disease samples. It not only reduces the cost of data collection, but also avoids the dilemma of relying too much on expert annotated data. In addition, transfer learning can also be combined with data enhancement techniques, such as image rotation, scaling, flipping, etc., to further enrich training samples and improve the model's adaptability to diverse disease characteristics.

Therefore, combining deep learning, convolutional neural networks and transfer learning strategies can effectively improve the accuracy and stability of crop disease identification. This innovative technology combination provides a new intelligent disease detection solution for modern agriculture, which not only reduces the labor cost of disease identification, but also improves the sustainability of agricultural production and lays a solid technical foundation for future smart agriculture.

Transfer learning can successfully apply the image classification skills learned from ImageNet to target classification tasks in new problems. Based on the existing optimal network architecture, you can use fine-tuning the network layer structure in the new target classification task to build a model suitable for the research problem, which is much faster and easier than retraining a completely new network.

2.2 The Suggestions for Smart Agricultural Pest Detection

In the last section, the approaches for the transfer learning based image recognition basis is introduced, and in this section, some new suggestions for the smart agricultural pest detection will be provided.

In the identification of pests and diseases in the agricultural field, the monitoring scenes are mainly distributed in outdoor fields and indoor greenhouses. The monitoring equipment usually uses close-range cameras to shoot crops in real time. Compared with pedestrian recognition, vehicle recognition and animal recognition, agricultural pest recognition has some unique challenges, which are derived from the complexity of agricultural scenes and the characteristics of pest targets.

First, pests on crops are usually small in size and irregular in shape, and are easily confused with backgrounds such as leaves and branches in the natural environment. Compared with the recognition of the larger targets, the recognition granularity of pests is smaller, which requires the deep learning model to have extremely high resolution and be able to accurately locate and classify tiny targets in the image. At the same time, pests move quickly between crops, so the recognition system needs to be able to perform real-time detection at a high frame rate to capture the slight changes of pests. This puts strict requirements on the real-time recognition, especially in the scene of open-air monitoring, and it is also necessary to deal with the interference of environmental factors such as natural light changes and wind.

Secondly, the outdoor environment and the greenhouse environment have their own characteristics, resulting in differences in brightness, contrast and clarity of the collected image data. Outdoor monitoring is often faced with strong light, shadows, and weather changes, and it is difficult to maintain consistent image quality, which makes the model's ability to generalize in different environments particularly important. In greenhouses, environmental conditions are relatively controllable, but due to space limitations, pest density is high and target overlap is more serious. The model not only needs to be highly accurate, but also has to have strong separation capabilities to accurately distinguish the multiple pests in complex backgrounds.

Therefore, the agricultural plant protection drone should be considered. As the application scope of agricultural plant protection drones expands, their functions are gradually diversified and are no longer limited to traditional plant protection spraying operations, but are also widely used in all aspects of precision agriculture. In modern agricultural production, plant protection drones play an important role in farmland monitoring, crop growth management, soil fertility assessment and other fields. With the help of multiple types of sensors and high-definition camera equipment, drones can conduct high-resolution monitoring of farmland and collect multi-dimensional agricultural data. These data can not only provide farmers with real-time information on crop health and growth status, but also provide more accurate data support for agricultural production decisions, thereby helping to improve the level of intelligent and refined management of agricultural production.

Thanks to the continuous advancement of aerospace and sensor technology, modern plant protection drones have achieved significant improvements in flight stability, flight endurance, and load-carrying capacity. For example, thanks to new batteries and lightweight structural designs, the endurance of drones has been greatly improved, and they can cover a wider range of farmland and provide more efficient operating services. At the same time, UAV systems equipped with deep learning algorithms can identify crops more accurately, gradually improving the versatility and accuracy on different crops and types of pests and diseases. Many pests and diseases will produce specific sound signals when they attack crops. Highly sensitive sound sensors, combined with machine learning technology, can analyze and identify these characteristic sounds, thereby detecting pests and diseases at an early stage and helping farmers to take control of pests and diseases in their early stages. measures to reduce losses.

In addition, the application of Lidar and spectral analysis technology provides drones with more means of detecting pests and diseases. The Lidar technology can obtain three-dimensional information on crop growth status and analyze structural characteristics such as height and density of crops, while spectral analysis can detect color and spectral changes in crops under attack by diseases and insect pests. By combining these two technologies, drones can identify the impact of pests and diseases on crops with high precision, thereby achieving precise monitoring of farmland and providing more advanced solutions for the development of precision agriculture. The application of these new technologies not only improves the applicability of the agricultural plant protection drones, but also opens up new possibilities for intelligent agriculture.

3. CONCLUSION

The intelligent agricultural pest and disease detection model based on transfer learning developed in this study achieves accurate identification and real-time monitoring of pests and diseases through in-depth mining of image data, solving the limitations of traditional manual monitoring methods in large-scale agricultural applications. Experimental results prove that the model shows significant advantages in recognition accuracy and adaptability, and can operate stably in changing field environments. In the future, with the further development of drones and multi-sensor technology, the method proposed in this study is expected to be applied in more diversified agricultural scenarios, providing comprehensive data support for crop management, thereby improving the efficiency of pest and disease prevention and control and ensuring sustainable development of agricultural production.

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