Analysis of Crop Pest and Disease Detection Methods Based on Deep Learning

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Abstract. Crop pests and diseases are important factors affecting agricultural production. Traditional manual detection methods are inefficient and inaccurate. With the development of artificial intelligence technology, deep learning methods provide new solutions for pest and disease detection. This paper reviews the detection methods of crop pests and diseases based on deep learning, including a detailed analysis of the application of various advanced models and technologies. The specific research methods of this paper include sorting out and assessing the application of deep learning models such as Faster R-CNN and YOLO, and discussing the performance and improvement schemes of these models in disease and pest detection. The research results show that these deep learning models have significant advantages in feature extraction and detection accuracy, but there are still challenges in dealing with complex environments and high-density pest detection. This paper provides reference and inspiration for the research in this field by analyzing and summarizing the related research on crop pests and diseases based on deep learning, which is conducive to promoting the intelligent and sustainable development of agricultural production.

Keywords: Crops, Pest Detection, Disease Detection, Deep Learning

1 Introduction

Agriculture as the foundation of a country's development, agricultural production is closely related to the country's economy and people's lives. Crop pests and diseases are the main factors affecting agricultural production [1]. Traditional methods rely on manual inspection of pests and diseases, but there are challenges such as diverse types and small differences among them in the detection of pests and diseases. Traditional methods are insufficient to meet the needs of rapid and accurate pest and disease identification, and automated means are needed to further improve the accuracy and applicability of identification [2]. In recent years, the breakthrough progress made by artificial intelligence (AI) technology in the field of recognition has proved the potential and prospects of AI technology. Therefore, AI technology provides a new solution for the detection of crop pests and diseases [3]. As the main representative of AI technology, deep learning can provide more efficient and accurate pest and disease identification solutions for agricultural production, improve the quality and efficiency of agricultural

K. Bellitürk et al. (eds.), *Proceedings of the 2025 2nd International Symposium on Agricultural Engineering and Biology (ISAEB 2025)*, Advances in Biological Sciences Research 50,
https://doi.org/10.2991/978-94-6463-910-0_3

production, and is of great significance for solving the current problems in agricultural production [4]. In conclusion, this paper sorts out and analyzes the methods and applications of AI technology in the field of crop pest and disease identification, providing new ideas and methods for agricultural production, and thereby promoting the intelligent development of agricultural production [5] [6].

2 Disease Detection Methods

2.1 Overview of Diseases

Crop diseases are important in agricultural production. They are diverse and have a serious impact on the growth, development and yield of crops. The diseases mainly include fungal diseases, bacterial diseases and viral diseases [7]. Fungal diseases such as powdery mildew, downy mildew and rust, usually show powdery, mildew-like or rusty spots on the leaves or fruits. They are highly invasive, reproduce rapidly and can spread over a large area in a short time [1]. Bacterial diseases such as bacterial spot disease and bacterial wilt disease can cause black spots, ulcers or rot on the leaves, stems and fruits of plants. They are highly infectious and difficult to control [2]. Viral diseases such as Cucumber Mosaic Virus and Tomato Spotted Wilt Virus are usually transmitted by insects, presenting with leaf deformity, chlorosis or necrosis, which have a serious impact on crop growth. [6] These diseases are characterized by their contagiousness, strong invasiveness and rapid reproduction, etc., and are often difficult to detect and control in time, bringing huge risks and losses to the growth of crops. [8] There is a wide variety of crop diseases, and the symptom manifestations of different diseases also vary, which increases the difficulty of identification and diagnosis. For example, Downy Mildew and Powdery Mildew often show similar symptoms, which can easily lead to misdiagnosis. [6] In addition, many diseases are difficult to detect when the early symptoms are not obvious, and often cause greater losses to the crops by the time the symptoms are obvious. [9]

The traditional disease detection methods rely on manual observation and diagnosis. However, this approach is both time-consuming and laborious, and the detection results are susceptible to subjective factors [3]. To address these problems, researchers have developed various disease detection methods based on automation and intelligent technologies, such as spectral analysis, image processing, and machine learning and so on [10] [11]. Among them, deep learning technology has become a hot topic in disease detection research due to its excellent performance in image recognition [6].

2.2 Disease Detection Methods Based on Deep Learning

Traditional disease detection methods have some problems, such as time-consuming and labor-intensive manual detection, low accuracy rate, and being affected by subjective factors. Deep learning is a machine learning method, the core of which is to learn the representation of data through a multi-level neural network structure to achieve the learning and understanding of complex patterns and relationships. Compared with traditional machine learning methods, deep learning has the following several advantages:

Firstly, it can automatically learn the abstract features of the data without the need for manual feature design, and therefore is more suitable for handling complex data types and tasks [11]; Secondly, deep learning models can handle large-scale data and complex tasks, and have good generalization ability; Furthermore, deep learning algorithms can usually improve their performance through training with large-scale data and therefore often demonstrate better results in practice. Due to the aforementioned advantages of deep learning, this method has been widely applied in the field of disease detection. Utilizing the ability of deep learning to automatically learn features, the feature representations of diseases can be learned from a large amount of disease image data [11]. Additionally, deep learning models have strong expressive capabilities, can handle complex disease image data, and can achieve good performance when there is sufficient training data, thereby enhancing the accuracy and efficiency of disease detection, reducing the labor burden of farmers, and thus better ensuring the growth and yield of crops.

At present, a large number of studies have applied deep learning technology to crop disease detection. Among them, many studies have effectively improved the performance of crop disease detection by using the Faster R-CNN deep learning model, including Researchers used Faster R-CNN combined with deep feature extractors such as VGG-Net and ResNet to achieve the location and detection of tomato diseases and achieved a high detection accuracy, indicating that this method is highly effective in accurately detecting and locating diseases [12][13]. Later, Wang et al. employed the enhanced Faster R-CNN algorithm in the detection of grape leaf diseases, integrating the Inception module and the SE module, and put forward a model based on the self-constructed grape leaf disease dataset (GLDD) and the Faster R-CNN detection algorithm. Experiments indicated that the improved model performed outstandingly in feature extraction capability and detection speed [14]. Additionally, another research proposed a Faster R-CNN structure for the automatic detection of beet leaf spot disease. By adjusting the parameters of the CNN model and enhancing the Faster R-CNN for the detection of beet leaf spot disease, the classification accuracy was significantly elevated, verifying the role of parameter optimization in enhancing the performance of the model [15].

However, the above methods respectively implemented the corresponding crop disease detection task based on the Faster R-CNN model.They all only conducted research on either a single crop or a single disease type and were unable to achieve universal detection of multiple crops or diseases. To achieve detection applicable to multiple crops and diseases simultaneously [13], researchers proposed using Convolutional Neural Networks (CNN) technology to process image data of various plant diseases such as rice, tomatoes, grapes, and cotton, explored the application of machine learning technology in plant disease detection, and experimentally demonstrated that CNN effectively enhanced the accuracy of disease recognition. Then, Kumar et al. developed a deep learning-based plant disease detection model and achieved real-time detection via mobile devices. They studied the PlantDoc dataset, conducted the detection and classification of various diseases such as leaf spot, powdery mildew, and downy mildew in multiple plants such as tomatoes, grapes, apples, etc. through deep learning models, and achieved efficient real-time detection on mobile devices [15][12].

3 Pest Detection Methods

3.1 Overview of Pests

Pests are common and serious problems in agricultural production, mainly including insects, mites, mollusks, etc. These pests harm crops in various ways, such as sucking plant sap, damaging plant tissues, and spreading pathogens, etc. [3]. According to living habits and damage characteristics, pests can be divided into borers, biting pests and sucking pests. Borers mainly feed on the interior of plants, such as the corn borer and cotton bollworm, etc. They drill into the interior of plants for food, causing severe damage to plant stems and fruits [1]. Biting pests feed on the leaves and stems of plants, such as the sugarcane borer and aphids, etc. These pests gnaw on the above-ground parts of plants, resulting in a reduced leaf area and a decreased photosynthetic efficiency of the plants [16]. Sucking pests such as aphids and stink bugs, etc., cause the loss of plant nutrients and growth stagnation by piercing and sucking the sap of plants [7].

The manifestations of damage caused by different types of pests on crops vary, but all have a serious impact on the growth and yield of crops. For example, aphids not only suck plant sap directly but also spread various viral diseases, further aggravating the health problems of crops [6]. Moreover, many pests cause damage to crops at different stages of their life cycle, which increases the difficulty of prevention and control [15]. Traditional pest detection methods mainly rely on manual observation and identification. This approach is time-consuming, labor-intensive and prone to human errors, etc. [17]. Therefore, the latest research introduces deep learning methods into the pest detection of crops to achieve automated pest detection and improve the efficiency and accuracy of detection [18][19].

3.2 Pest Detection Method Based on Deep Learning

Pest detection is critical in agriculture, but traditional methods struggle to cope with complex environments and variable pest characteristics. The introduction of deep learning provides new solutions for pest detection. Among these, Li et al. proposed using the improved YOLOv5 model for pest detection. By collecting pest images in a greenhouse environment, they significantly improved the accuracy of multi-class pest recognition. Concrete experimental results from Dai et al. (2023) [21] showed that their enhanced YOLOv5m model achieved a precision of 93.2% and a recall of 91.8% on a multi-class pest dataset, with an F1-score reaching 92.5%. This represents a substantial improvement over the baseline YOLOv5m model (F1-score: 89.1%) and is particularly effective for small target detection. In comparison to two-stage detectors like Faster R-CNN, while Faster R-CNN might achieve a slightly higher precision (e.g., 94.5% as reported in [20]), the YOLO series models, with their single-stage architecture, offer a significant advantage in detection speed, often processing images over 50 FPS (Frames Per Second), which is crucial for real-time field applications. However, the data used in this method was collected in a relatively simple greenhouse environment, and there is still room for improvement in small target detection for this method [20, 21]. To solve the problem of small target pest detection and improve the adaptability and robustness of the method in the field environment, Yao et al. significantly improved the accuracy of small target pest detection in the field environment by improving the deep learning model and data enhancement technology, but this method still needs optimization in high-density pest detection [21, 22]. To address the challenges brought by different lighting and backgrounds to pest detection, Zhang et al. studied the application of the YOLOv5 model under different lighting and background conditions. The model's detection accuracy was as high as 98.3%, but it still faced challenges when dealing with complex backgrounds [23, 24]. Moreover, Zhao et al. focused on data under different backgrounds and lighting conditions and adopted a multimodal deep learning framework, combining TinyBERT and ResNet-18. By integrating text and image data, they improved the accuracy of pest detection and classification [20]. Other studies include the PestLite model proposed by Wang et al. which combines multilevel spatial pyramid pooling and an efficient attention mechanism to improve the performance of real-time target detection while reducing the number of parameters [24]. Additionally, to further enhance the application of knowledge in pest detection, Liu et al. constructed a pest detection system based on knowledge graphs and deep learning. Through semi-automatic extraction and storage of knowledge, they improved the comprehensiveness and accuracy of the system [23, 22].

4 Conclusions and Prospects

Agriculture, as the foundation of a country's development, the detection of pests and diseases in its production process is vitally important. This paper analyzes and summarizes relevant research on crop pest and disease detection based on deep learning. This paper systematically sorts out the detection methods of diseases and pests based on deep learning techniques. Furthermore, the research on disease detection mainly focuses on image recognition using deep learning models such as Faster R-CNN and YOLO. By automatically learning the features in a large number of disease image data, the accuracy and efficiency of disease recognition have been significantly improved. The research on pest detection focuses on the improvement and optimization of different deep learning models, enhancing the detection accuracy and robustness under different environmental conditions. By analyzing and collating the existing research on pest and disease detection based on deep learning, it was found that most studies have shown significant advantages of deep learning technology in improving detection accuracy and efficiency. However, most of these studies are targeted at a single crop or a single disease, lacking universality. In addition, there are still challenges in aspects such as complex environments and high-density pest detection, and the robustness and adaptability of the models in practical applications need to be further enhanced. Through systematic analysis and collation of the existing literature, this paper provided references and inspirations for future research on pest and disease detection, promoting the intelligent development of agricultural production.

Future research should focus on developing a universal detection model capable of simultaneously identifying multiple pests and diseases to address the issues of lack of diversity and universality in current research. This requires larger-scale and more diverse datasets, as well as further optimization of the model structure. Enhancing robustness in complex environments is also an important research direction. Research should focus on improving the adaptability and robustness of the model under different environmental conditions such as different lighting and backgrounds. This may involve multi-modal data fusion, data augmentation techniques, and improvements in the model structure. In addition, applying deep learning models to mobile devices to achieve real-time pest and disease detection is of great significance to agricultural production. Future research should explore the development and optimization of lightweight models to meet the demands of practical applications. Integrating knowledge graph technology, a more intelligent and comprehensive pest and disease detection system can be constructed, which is capable of providing pest and disease identification, diagnosis and prevention and control suggestions, and improving the practicability and decision support ability of the system. In conclusion, deep learning technology has demonstrated broad application prospects in the field of crop pest and disease detection. Future research should further expand its application scope, and enhance the generalization ability and practical application effect of the models, thereby promoting the intelligent and sustainable development of agricultural production. The integration of these advanced technical solutions, multimodal data fusion and robust model architectures, is expected to be a key driver in developing next-generation detection systems that are not only accurate but also practical and reliable for real-world agricultural applications.

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