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Artificial Intelligence-Based Crop Disease Identification Technology: Applications, Challenges, and Future Prospects

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Abstract: Crop diseases pose a critical threat to global food security. Traditional diagnostic methods are inefficient and fail to meet the demands of modern precision agriculture. In recent years, artificial intelligence (AI) technologies centered on deep learning have revolutionized the rapid and precise identification of crop diseases. This paper systematically outlines key AI techniques for crop disease recognition, including computer vision-based image recognition, multimodal data fusion, and edge computing for field deployment. By analyzing representative domestic and international application cases, this paper highlights the significant advantages of this technology in terms of accuracy and efficiency. Simultaneously, it delves into current technical bottlenecks and deployment barriers, such as the few-shot learning problem, environmental interference, and low farmer trust. The paper concludes by outlining future directions, including self-supervised learning, digital twins, and industry integration, to advance the deep application and implementation of AI technology in smart agriculture.

Keywords: Crop disease identification; Deep learning; Multimodal data; Edge computing

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1. Introduction

In recent years, global crop losses due to plant diseases have reached hundreds of millions of dollars annually. This figure not only highlights the persistent pressures facing agricultural production but also poses a severe challenge to global food security and the stability of the agricultural economy. Traditional disease identification models primarily rely on manual field inspections conducted by agricultural experts or experienced farmers. This method is highly dependent on individual expertise, subject to significant subjectivity, and is both time-consuming and labor-intensive, with limited coverage. Research indicates that traditional pest and disease identification methods typically achieve an average accuracy rate below 60% [1]. An overview of these identification methods is shown in **Figure 1**. This is particularly evident during latent or early stages of disease onset, when subtle symptoms are difficult to discern, often leading to missed or misdiagnosed cases and consequently missed optimal control windows.

With the rapid advancement of information technology, smart agriculture, as a profound industrial transformation, is emerging as a new paradigm to address these challenges. Breakthroughs in deep learning within artificial intelligence technology have provided novel solutions for precise and efficient crop disease identification. Research states that models based on convolutional neural networks (CNNs), such as ResNet and YOLO, achieve stable recognition accuracy exceeding 95% for specific crop diseases after training on large-scale annotated datasets [2]. Simultaneously, response times have been reduced from hours or even days with traditional manual methods to milliseconds. This marks a qualitative shift in disease identification technology from "experience-driven" to "data-driven," demonstrating immense application potential and industrialization prospects. This paper aims to systematically review the research trajectory and current status of AI technology in crop disease identification.

The paper will dissect core technical principles, including mainstream deep learning architectures and training methods. It will then comprehensively evaluate practical application outcomes across scenarios, ranging from leaf image recognition to multimodal information fusion. This study will propose future research directions and development pathways from perspectives including technology integration, platform construction, and industry-academia-research collaboration, aiming to provide valuable references for advancing continuous innovation and practical applications in this field.

Figure 1. Methods for identifying crop diseases.

2. Core technologies for crop disease identification

2.1. Computer vision-based recognition models

CNNs are the undisputed core technology in the field of crop disease image recognition [3]. Through multiple layers of convolution and pooling operations, CNNs can automatically learn hierarchical representations from images, progressing from low-level features like edges and textures to high-level semantic features, thereby enabling end-to-end intelligent recognition of disease characteristics [4]. Regarding specific model architectures, classical networks such as VGG, ResNet, and DenseNet are widely adopted as backbone networks for disease recognition tasks due to their robust feature extraction capabilities [5]. ResNet effectively mitigates the vanishing gradient problem in deep networks by introducing residual connections, enabling the training of deeper networks to capture more abstract and rich features [6]. To enhance model robustness in complex field backgrounds, attention mechanisms have been successfully integrated. Taking the representative Convolutional Block Attention Module (CBAM) as an example, it enables the model to autonomously focus on critical lesion areas on leaves through both channel attention and spatial attention dimensions [7]. Simultaneously, it effectively suppresses interference from irrelevant background information like soil and shadows, significantly improving recognition accuracy and model generalization capabilities [8].

Single-source visual information inherently faces limitations when addressing early-stage, latent, or complex symptomatic composite diseases. Multimodal data fusion technology offers a more comprehensive diagnostic perspective to address this challenge [9]. This approach integrates data from diverse sources and formats to construct a complementary, holistic assessment system. Spectral-image fusion represents a key direction. Hyperspectral imaging captures crop canopy reflectance data across hundreds of narrow spectral bands, which encode rich information related to internal physiological and biochemical parameters (e.g., chlorophyll content, moisture status) [10,11]. Fusing this with conventional RGB imagery enables detection of early stress responses invisible to the naked eye or standard cameras, facilitating early diagnosis of “asymptomatic” or “latent-stage” diseases. On the other hand, spatio-temporal sequence modeling is crucial for diseases with propagation characteristics. By introducing recurrent neural networks (RNNs) or Transformer models to analyze multi-day sequences of field images, precise modeling of disease propagation patterns across spatial and temporal dimensions becomes possible [12]. This enables prediction of disease spread trends, providing critical decision support for regionalized precision control.

To achieve real-time field diagnosis, deploying AI models from cloud servers to lightweight edge computing devices at the field level has become an imperative [13]. This requires models to maintain high accuracy while reducing size and computational overhead. Consequently, a series of model compression and lightweighting techniques have been widely adopted, primarily including knowledge distillation, network pruning, and quantization. Knowledge distillation enables a lightweight model to inherit high performance by learning from a large, accurate model [14]. Quantization converts model weights from 32-bit floating-point numbers to 8-bit integers, significantly reducing model size and memory consumption [15]. Lightweight network architectures specifically designed for mobile and embedded devices, such as MobileNet, ShuffleNet, and SqueezeNet, achieve an excellent balance between model accuracy and computational efficiency through innovative techniques like separable convolutions and channel shuffling [16]. This enables real-time operation of complex disease recognition models on embedded devices with limited computational resources (below 1 TOPS).

3. Application cases and performance analysis

In practical implementation, AI-based disease identification technology has yielded multiple representative success stories both domestically and internationally, fully validating its technical feasibility and significant socioeconomic value. In China, DJI Agriculture's P-series crop protection drones demonstrate an integrated "sky-ground" precision operation model. While surveying farmland, these drones simultaneously collect visible and multispectral data. Through integrated AI algorithms, they accurately identify and grade the severity of diseases such as rice sheath blight and rice blast. This process automatically generates variable-rate application maps, guiding drones to perform precise spraying. Practical application demonstrates that this solution enhances the accuracy of rice sheath blight detection.

By enabling targeted pesticide application, it reduces overall pesticide usage, significantly lowering environmental impact. Internationally, India's agtech company CropIn offers an inclusive solution through its "SmartFarm" mobile app. This application enables farmers to directly photograph diseased crops using smartphones, leveraging built-in lightweight AI models for offline diagnosis. It instantly returns disease classifications and control recommendations, effectively addressing core challenges in remote areas such as poor network coverage and scarce expert resources. Currently serving over 5 million smallholder farmers globally, the platform reduces diagnostic processes, previously taking days, to under 10 minutes. This dramatically enhances timely disease response, effectively curbing the spread of pathogens and demonstrating AI's immense potential to empower smallholder farmers and promote equitable development.

4. Challenges

4.1. Technical limitations

The transition of intelligent plant disease recognition technology from laboratory settings to practical field applications is constrained by two major technical bottlenecks. Small sample sizes and data scarcity constitute a major obstacle to improving model performance [17]. For newly emerging or regionally rare diseases, it is often difficult to obtain sufficient, accurately annotated image data within a short timeframe to support adequate model training [18]. This severe imbalance in data distribution leads to significantly poor recognition performance for rare categories when models process real-world data exhibiting "long-tail distribution" characteristics. Environmental complexity poses a severe challenge to model generalization. Unlike controlled laboratory settings, real-world farmland scenarios are rife with variable factors, including but not limited to dramatic dynamic changes in lighting, complex mutual occlusion between plants, high diversity in leaf morphology and posture, and significant phenotypic differences across crop growth stages [19]. The combined effect of these factors causes high-accuracy models trained under ideal conditions to encounter severe "domain gap" issues when directly transferred to open field environments. Key performance metrics such as accuracy and recall may experience significant degradation, severely limiting the practical application value and deployment potential of these technological achievements.

4.2. Deployment and scalability challenges

Transitioning plant disease detection models from algorithmic prototypes to large-scale field deployment and adoption presents dual challenges stemming from hardware constraints and societal factors. Severe hardware resource constraints represent the primary physical bottleneck. Despite significant advances in model lightweighting techniques (network pruning, quantization, knowledge distillation), the computational power, storage capacity, and battery life of most field-deployed edge computing devices (handheld terminals, drones, IoT nodes) remain extremely limited [20]. Under these constraints, compressing complex models with practical accuracy to sizes suitable for terminal deployment (under 5MB) without significant performance degradation remains an unresolved technical challenge.

Furthermore, insufficient user trust and acceptance constitute deeper societal barriers. Agricultural practitioners, particularly traditional farmers long reliant on practical experience, generally harbor doubts about the decision-making logic of "black-box" technologies like AI. They tend to trust intuitive feelings and generations-old farming knowledge, while approaching model diagnostic results lacking intuitive explanations with caution or even rejection. This underscores that breaking down trust barriers and enhancing technological transparency and explainability are crucial for successful technology implementation.

5. Future development directions

To overcome current bottlenecks and drive widespread technological adoption, future research and practice must advance synergistically across two dimensions: technological innovation and industrial ecosystem development. At the frontier technology exploration level, research will shift focus toward new paradigms that fundamentally alleviate data dependency, such as few-shot learning, zero-shot learning, and self-supervised learning. These methods can leverage large volumes of readily available unlabeled field images for pre-training or enable models to rapidly identify novel diseases with minimal samples, effectively addressing the "long-tail distribution" challenge.

Simultaneously, digital twins and simulation systems will construct virtual crop-environment-disease models. Simulation engines will generate vast, diverse synthetic datasets with precise annotations, providing abundant training and testing resources. This approach will compensate for real-world data scarcity and significantly accelerate algorithm iteration cycles. At the industrial collaboration and ecosystem development level, the first step is to deepen integration with financial tools like agricultural insurance.

Objective AI disease detection results should serve as key evidence for loss assessment and claims settlement. This will drive insurance models to shift from traditional "post-event compensation" to more valuable "pre-event warning and proactive intervention," creating significant socioeconomic value. Additionally, establishing a global collaborative network is crucial. By creating cross-border, open-source databases of crop disease images and knowledge graphs, we can foster worldwide knowledge sharing and technological cooperation to collectively address the growing challenges posed by emerging diseases in the context of climate change.

6. Conclusion

Intelligent crop disease recognition is a pivotal component of smart agriculture development, holding significant strategic importance for ensuring global food security and promoting sustainable agricultural development. This paper systematically reviews the current state of AI research in this field, focusing on deep learning-based technologies, core methodologies, application outcomes, and challenges. Image recognition models, particularly CNNs, combined with advanced techniques like attention mechanisms, have achieved high-precision, efficient identification of multiple crop diseases under specific conditions, significantly outperforming traditional manual diagnosis methods. Multimodal data fusion techniques, by integrating spectral, temporal, and spatial information, have opened new pathways for diagnosing early-stage and complex diseases. Meanwhile, edge computing and model lightweighting technologies designed for field deployment provide critical technical support for bringing AI from laboratories to farm fields, enabling real-time online diagnosis. Successful application cases worldwide demonstrate that AI-based disease identification not only significantly enhances diagnostic efficiency and accuracy but also delivers substantial economic and ecological benefits through precision pesticide application. However, large-scale deployment and adoption face significant challenges.

Technologically, the "small sample size" problem and insufficient model generalization due to environmental complexity remain core bottlenecks limiting robustness. In deployment, hardware resource constraints of edge devices and low trust in "black-box" models among agricultural practitioners create practical barriers to implementation. Moving forward, the development of intelligent crop disease recognition technology should follow a dual-track approach driven by "technological breakthroughs" and "industrial collaboration." On the technical front, efforts should focus on exploring novel paradigms like few-shot learning and self-supervised learning, while leveraging digital twin technology to build virtual simulation environments. This approach aims to overcome data scarcity and domain gaps. At the industrial level, deep integration of AI with sectors like agricultural insurance and agrotechnical services is essential. Building an open-source, globally collaborative network will ultimately yield smart agriculture solutions that are technically viable, economically sound, and user-trusted. Through continuous technological innovation and cross-sector collaboration, artificial intelligence will undoubtedly play an increasingly pivotal role in combating crop diseases and building resilient agricultural systems.

Disclosure statement

The author declares no conflict of interest.

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