Education Insights

Article

Practice and Application of a Crop Pest Identification System

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Abstract: Crop pests and diseases are key bottlenecks restricting the improvement of agricultural production efficiency, stability, and product quality. Traditional recognition modes that rely on manual field inspection and expert experience suffer from high misdiagnosis rates, delayed responses, and limited scalability, which are increasingly incompatible with the demands of modern smart agriculture. Using the "Agricultural Security Identification and Prevention" crop disease and pest identification system as the research carrier, this study systematically analyzes the application mechanism of integrating the Internet of Things and artificial intelligence for real-time crop health monitoring. By reviewing the development status of pest and disease identification technologies domestically and internationally, the work clarifies current technical gaps and application challenges. On this basis, a comprehensive system architecture is designed, covering hardware acquisition devices, lightweight image recognition algorithms, data management ecology, and diversified application scenarios for field and mobile use. Experimental and pilot application results demonstrate that the system achieves a detection accuracy of at least 90% and a response time within 3 seconds through dual-mode operation on mobile phone and dedicated hardware terminals, while reducing pesticide use costs by approximately 20%–30%. Furthermore, the paper discusses the industrialization pathway, scalability, and future development trends of intelligent pest identification technology, providing a technical reference and practical paradigm for advancing smart agriculture and supporting rural revitalization.

Keywords: crop pest identification; plant disease recognition; intelligent agriculture; internet of things; artificial intelligence; lightweight deep learning; precision plant protection

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1 Introduction

1.1 Research Background

As a foundational pillar of the national economy, agriculture's stable development is directly linked to food security and socioeconomic sustainability. Grain production losses caused by pests and diseases are estimated to reach 5%-10% annually in China, with economic losses exceeding significant amounts, posing a serious threat to agricultural production [1, 2]. With global climate warming and adjustments in farming systems, major diseases and pests, such as rice pests and wheat stripe rust, are becoming more frequent and recurring. Their rapid transmission and extensive damage necessitate higher standards for timely and technically accurate prevention and control measures.

Agriculture in the country is undergoing a critical transition from traditional methods to modernization. A significant portion of the rural labor force is shifting to secondary and tertiary industries, leading to an aging and increasingly feminized agricultural workforce [1, 3]. Traditional methods of pest and disease identification, which rely on experiential judgment, are no longer sufficient to meet the demands of modern agricultural development [4]. The lack of professional plant protection knowledge among farmers often results in issues such as indiscriminate and excessive pesticide use. This not only leads to excessive pesticide residues in agricultural products but also damages the farmland ecosystem and poses safety risks to applicators [3, 5]. In this context, leveraging modern science and technology to develop an accurate and efficient pest identification and control system has become an urgent necessity to ensure the high-quality development of agriculture.

At the policy level, significant emphasis has been placed on agricultural scientific and technological innovation [6]. National development plans have highlighted the need to accelerate the modernization of agriculture, promote scientific and technological advancements, and encourage the specialization, standardization, scaling, and intensification of agricultural production and operations [7, 8]. Policies have also called for the establishment of professional prevention and control teams to facilitate unified management of major plant diseases and pests, providing robust support for the research, development, and application of intelligent identification technologies for pest and disease control [6, 9].

1.2 Significance of Research

This design constructs a cross-border integration technical framework of "Internet of Things + artificial intelligence + agriculture," which overcomes the limitations of traditional disease and pest identification methods that rely on single data sources and enhances the experimental system for intelligent agricultural detection [1, 10]. By establishing a dynamic database for multi-source data fusion, the transition from static feature extraction to dynamic real-time monitoring in recognition technology is achieved [5, 11]. This provides a novel research perspective for the early warning theory of crop pests and diseases [12]. Additionally, a hierarchical adaptation technical solution is proposed to address the diverse needs of various agricultural production entities, offering practical support for the application theory of smart agricultural technology in specific scenarios.

At the production practice level, the "agricultural safety identification and prevention" system is designed and developed to effectively address challenges such as the low accuracy of traditional pest identification, high operational complexity, and slow prevention and control processes. For individual farmers, the system lowers the barriers to adopting agricultural technology, enabling widespread scientific pest prevention. For large-scale farms, the system enhances the efficiency and coverage of pest monitoring while reducing production losses [13]. For smart farms, the system addresses functional gaps in existing intelligent systems related to disease and pest monitoring, advancing the automation and intelligence of the entire agricultural production process.

At the industrial development level, the system employs an ecological closed-loop design of "detection-control-procurement," linking multiple industrial chains such as pesticide production, logistics distribution, and agricultural services to foster the coordinated development of the agricultural industry [14]. Furthermore, the pest and disease data collected by the system can provide decision-making support for plant protection departments, promoting the professional and scientific management of crop pest and disease control [15, 16]. This contributes to improving the agricultural ecological environment, as well as the quality and safety of agricultural products [17].

1.3 Research Content and Technical Route

1.3.1 Research Content

Focusing on the development and application of intelligent identification technology for crop pests and diseases, the primary research areas include analyzing the development status and trends of identification technology for pests and diseases domestically and internationally; designing hardware architecture and developing software algorithms for the "agricultural safety identification and prevention" system; constructing application models of the system for various scenarios, including individual farmers, conventional farms, and smart farms; conducting empirical analysis on the effectiveness of system pilot applications; and exploring industrialization pathways and strategies for risk prevention and control in pest identification technology [1].

1.3.2 Technical Route

The technical route follows a structured approach of "theoretical combing-technology development-scene application-effect verification-trend outlook." Initially, industry pain points and technical requirements were identified through comprehensive literature and market research [10]. Subsequently, leveraging Internet of Things and artificial intelligence technologies, the system's hardware platform and software algorithm model were developed. Pilot applications were then conducted across various agricultural production scenarios to gather user feedback and refine system performance. Finally, based on pilot data and industry trends, recommendations for the path and future direction of technology industrialization were proposed.

2 Development Status of Crop Pests and Diseases Identification Technology at Home and Abroad

2.1 Research Status Abroad

The identification technology for crop pests and diseases has been developed early in foreign countries, leading to the establishment of several representative monitoring systems that are widely applied in agricultural production [3, 7]. One agricultural information system determines optimal schemes for irrigation, fertilization, pesticide application, and defoliant application through a self-developed monitoring and diagnosis system, promoting the informatization and automation of cotton field management and pest control. This system primarily relies on meteorological observation stations, ground survey networks, and field data uploaded by users [6].

A global monitoring system has played a significant role in rust monitoring and control guidance, reducing the usage of rust fungicides by approximately 30%. However, the system lacks integration of multi-source heterogeneous information, such as remote sensing, and has limitations in real-time prevention and control responses. Another disease monitoring system provides timely warnings for the early identification of crop diseases and pests, offering guidance to farmers for field prevention and control measures [17].

A real-time agricultural monitoring system supports farmers in customizing decision-making processes, allowing users to create knowledge bases and model bases tailored to their specific conditions [12]. It is highly practical and flexible, enabling quick and easy secondary and multiple developments [5, 11]. However, the system does not fully address the requirements for real-time pest and disease control. Overall, foreign systems exhibit advantages in technology maturity and data accumulation but face challenges such as high equipment costs, reliance on single data sources, and difficulties in meeting the needs of small-scale farmers.

2.2 Domestic Research Status

In recent years, research on the identification technology of crop pests and diseases in China has achieved significant progress, forming a dual development pattern of scientific research systems and practical applications. The remote sensing monitoring and forecasting system for crop diseases and pests, developed by a leading research institution, integrates high-resolution remote sensing images with multi-source spatial datasets such as meteorological and plant protection data. This system enables continuous monitoring and mapping of wheat, rice, and maize diseases and pests in major grain-producing regions, providing valuable scientific data to support decision-making in plant protection. However, further improvements are required in algorithm integration and practical business applications [12].

The traditional approach to identifying diseases and pests still relies heavily on farmers' experiential judgment and standardized government control measures [9]. This approach suffers from limited technological penetration and inadequate capacity to address emerging diseases and pests. The vast agricultural cultivation areas, regional disparities in development, and varying degrees of local policy implementation further hinder the adoption of modern technologies, indirectly affecting the efficiency of agricultural industry development. Currently, there is a noticeable lack of lightweight and cost-effective intelligent identification tools tailored for individual farmers in the domestic market. Most available products are either designed for scientific research or targeted at large-scale farms, making them unsuitable for the practical needs of small and medium-sized farmers [4].

2.3 Technology Development Trend

2.3.1 Multi-Source Data Fusion

The monitoring technology of pests and diseases is advancing from single spectral feature extraction to multi-temporal remote sensing, UAV data, and comprehensive monitoring of field environmental factors, including weather and soil [8]. By integrating multi-dimensional data, the patterns of occurrence and development of pests and diseases can be captured more comprehensively, enhancing recognition accuracy and improving early warning efficiency [13].

2.3.2 Intelligent and Portable Equipment

The continuous optimization of artificial intelligence algorithms will further enhance recognition accuracy, while hardware equipment will evolve toward lower costs and greater ease of operation [17]. Mobile applications eliminate the need for additional equipment, reducing the barrier to entry and serving as a vital technological tool for small and medium-sized farmers [6, 15]. Concurrently, portable hardware devices designed for large-scale planting will undergo continuous upgrades to enable offline detection and batch data processing [8].

2.3.3 Monitoring Globalization and Realtime

The development of a global-scale pest monitoring system has become increasingly prevalent [12]. By integrating satellites and ground networks with high spectral, spatial, and temporal resolution satellite data, precise monitoring and real-time early warning of pests and diseases are achieved [6]. This approach provides essential technical support for cross-regional pest prevention and control efforts [1, 14].

3 System Technical Architecture and Research and Development Practice

3.1 System Design Concept

The "Agricultural Security Identification and Prevention" system adopts the core design concept of civilianizing technology, integrating service scenarios, and promoting ecological industrialization [10]. It prioritizes the practical requirements of agricultural production and aims to develop low-cost, high-precision, and user-friendly intelligent identification solutions for crop pests and diseases. Adhering to the plant protection policy of prioritizing prevention and implementing comprehensive control, the system addresses the challenges of traditional agricultural disease and pest identification through technological innovation [6, 7]. It strives to achieve the objective of enabling farmers to effectively utilize intelligent plant protection technology [17].

3.2 Hardware Architecture Design

3.2.1 Core Hardware Composition

The system hardware is constructed around a control center that integrates a camera module, display, and other essential components to enable contactless data acquisition. This platform offers advantages such as affordability, low energy consumption, and robust scalability, making it suitable for extensive applications in agricultural contexts [3]. The camera module facilitates high-definition image capture, with adjustable acquisition distances to ensure clear crop imagery across diverse field conditions. The display screen is designed for outdoor visibility, allowing users to directly observe identification results and operational recommendations in real-time field scenarios (As shown in Figure 1).

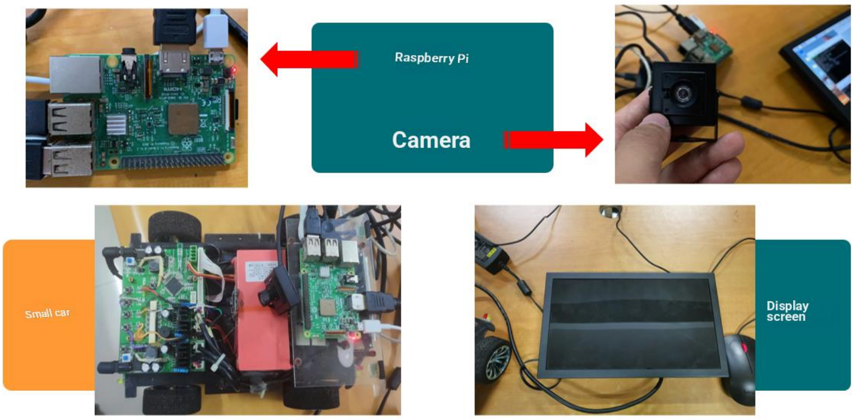

Figure 1 Hardware system

3.2.2 Dual-Mode Hardware Configuration

The system incorporates a dual-mode hardware configuration tailored for different user groups. The mobile terminal mode eliminates the need for additional hardware purchases, allowing farmers to collect data by capturing crop images using standard smartphone cameras [3]. This approach is particularly suitable for addressing the fragmented detection needs of individual farmers. The hardware mode, on the other hand, offers customized portable equipment designed for farm users, enabling batch detection and offline operation across multiple plots. This configuration is well-suited for large-scale planting scenarios. Once data is collected, it can be transmitted to the cloud server using Socket network communication technology (As shown in Figure 2).

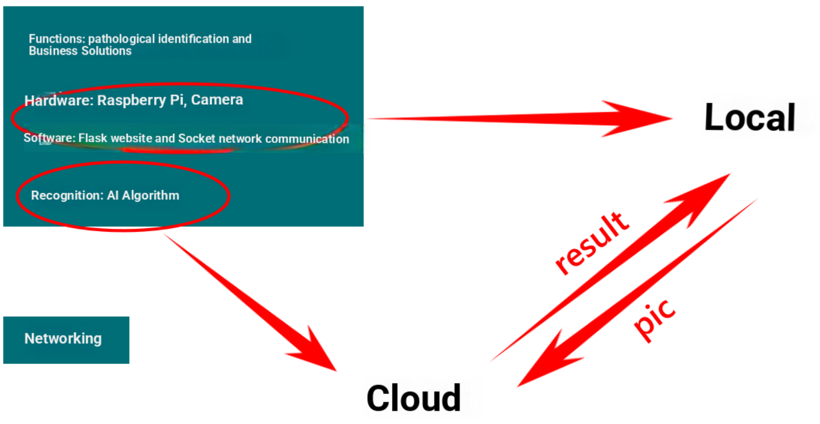

Figure 2 System composition structure

3.3 Software Algorithm Development

3.3.1 Software System Architecture

The system software utilizes an architecture design based on "local collection, cloud analysis, and terminal feedback," comprising three core modules: a Flask cloud platform, a Socket network communication protocol, and an AI image recognition algorithm [1]. The Flask cloud platform manages data storage, algorithm execution, and result feedback while supporting high concurrent access [16]. The Socket network communication protocol facilitates efficient data transmission between the local device and the cloud server [4]. The AI image recognition algorithm, developed using a Convolutional Neural Network (CNN), enables precise extraction and classification of pest features (As shown in Figure 3).

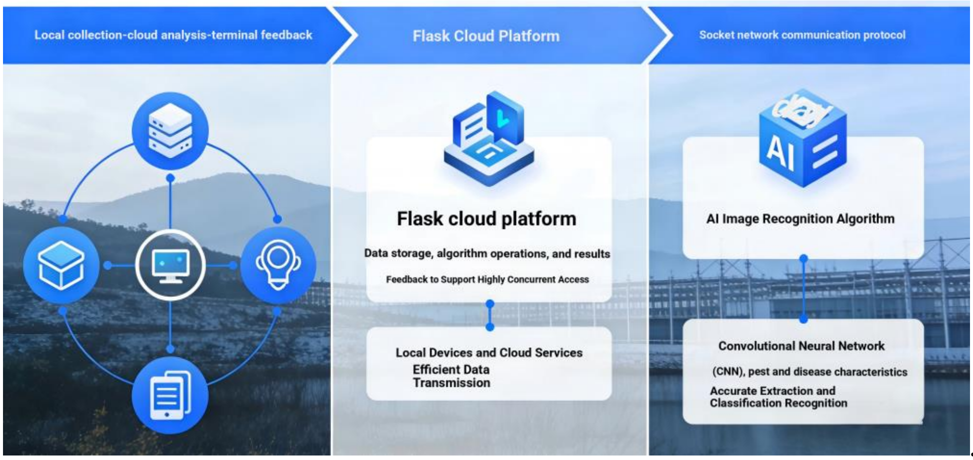

Figure 3 Software system architecture

3.3.2 Intelligent Recognition Algorithm

During the development of the algorithm, image data for over 100 common crop diseases and pests were collected and organized in collaboration with agricultural research institutions, leading to the establishment of a dynamically updated database of crop diseases and pests [12]. The image data underwent preprocessing steps, including image enhancement, denoising, and segmentation, to improve the accuracy of feature extraction [12]. A recognition model was then constructed using a CNN algorithm, with model parameters optimized through extensive sample training to ensure a system recognition accuracy of 90% or higher [3].

Considering the complexity of agricultural environments, the algorithm incorporates an environmental factor correction mechanism, integrating field meteorological, soil, and other data to dynamically adjust recognition results and further enhance accuracy [4]. The system demonstrates rapid response times, with the mobile terminal mode requiring approximately 2-3 seconds and the hardware terminal mode requiring about 1-2 seconds, effectively meeting the demands of real-time field detection [11] (As shown in Figure 4).

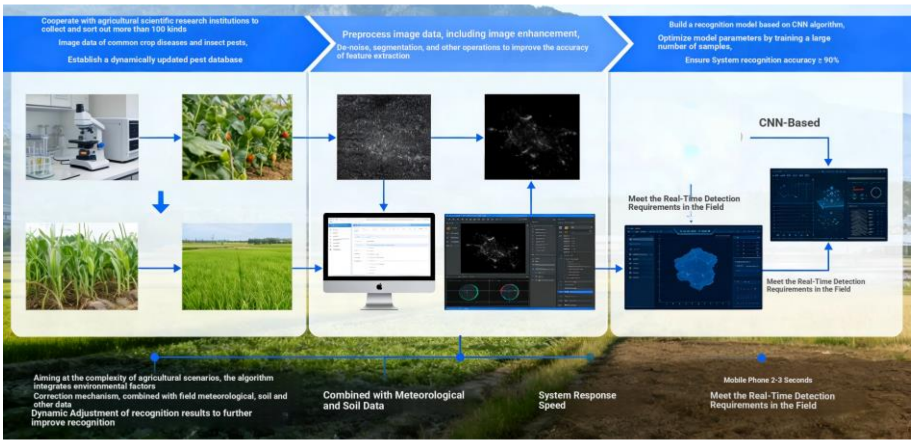

Figure 4 Intelligent recognition algorithm operation process

3.4 System Function Design

3.4.1 Core Features

The core functions of the system include three modules: pest identification, prevention and control scheme recommendation, and pesticide procurement link push. After the user captures and uploads a crop image, the system utilizes an AI algorithm to identify the types of pests and diseases and provides an assessment of the damage level. Based on the identification results, targeted control programs are delivered, including detailed information such as recommended pesticide types, dilution ratios, and application times [14]. Additionally, relevant pesticide purchase links on e-commerce platforms are provided simultaneously, enabling a streamlined service process encompassing testing, control, and procurement.

3.4.2 Auxiliary Functions

The system incorporates auxiliary functions such as data statistical analysis, historical record queries, and early warnings with reminders. Farm users can utilize the platform to view trend charts of pests and diseases across different plots, providing valuable data support for production decision-making [4]. Individual users can access historical identification records to monitor crop health status over time. Additionally, the system delivers early warning information to users based on patterns of pest and disease occurrences and meteorological data, enabling proactive prevention and control measures [17].

4 System Application Scenarios and Practical Effects

4.1 Adaptation of Application Scenarios

4.1.1 Scenario of Individual Farmers

In rural areas, the permanent population is approximately 500 million, with each farmer managing an average of more than 5 mu of land. Over 200 million migrant workers are expected to gradually return to agricultural activities as they age. This user group primarily requires systems that are simple to operate and deliver accurate results. The mobile phone functionality of the system effectively addresses these needs, enabling farmers to complete identification tasks without requiring specialized knowledge [2, 9]. By simply taking a photo with their mobile phone, the system significantly lowers the barrier to usage.

To address the challenge of limited experience among individual farmers, the system provides not only precise identification of pests and diseases but also detailed explanations of control principles and operational steps [5, 17]. This approach helps farmers gradually build knowledge in plant protection [17]. Additionally, by recommending precise pesticide solutions, the system prevents indiscriminate use of chemicals, reduces production costs, and minimizes environmental pollution.

4.1.2 Common Farm Scene

With the implementation of land transfer policies, a significant number of professional farmers have begun managing extensive areas of farmland in China. The primary requirements of these users include batch testing, efficient prevention and control measures, and cost management [7]. The system offers tailored hardware solutions for standard farms, enabling simultaneous monitoring of multiple plots, generating visual reports on pests and diseases, and assisting farm managers in comprehensively understanding field conditions.

The system's hardware can integrate seamlessly with the existing farm management framework to facilitate centralized pest and disease control, enhance operational efficiency, and reduce labor demands. By utilizing the system, farms can extend pest detection coverage from 5 acres per person per day to 20 acres, lower control costs by 25%, and achieve a 10% increase in grain production [4, 13].

4.1.3 Smart Farm Scenario

Currently, smart farms typically include features such as automatic light supplementation and irrigation but often lack real-time monitoring modules for diseases and pests. Losses in production due to these issues account for approximately 15% to 20%. The "Agricultural Safety Identification and Prevention" system can be seamlessly integrated into existing intelligent systems to enable the coordinated functions of monitoring, early warning, and regulation [16]. When pests or diseases are detected, corresponding prevention and control measures are automatically initiated, such as precise pesticide application and adjustments to environmental growth parameters [1].

The system offers an API interface for smart farms, facilitating data exchange with automatic irrigation systems, water and fertilizer integration equipment, and more, thereby constructing an intelligent agricultural production system covering the entire process [8]. Practical applications in smart farms demonstrate that after system integration, the response time for pest prevention and control is reduced from 24 hours to 2 hours, pesticide usage decreases by 30%, and the qualification rate of agricultural products improves by 15%.

4.2 Effect of Pilot Application

4.2.1 Application Effect Data

The pilot data indicate that the average recognition accuracy of the system is 92.3%. Specifically, the recognition accuracy for bulk crops such as rice and wheat exceeds 95%, while the accuracy for complex crops surpasses 88%. These results are markedly higher compared to the 65% accuracy achieved through traditional manual recognition methods [9]. By implementing systematic guidance and precise prevention and control measures, pesticide usage in the pilot areas was reduced by an average of 26.7%, and the rate of excessive pesticide residues in agricultural products decreased to 1.2%, significantly below the national average.

From an economic perspective, the average income per mu for individual farmers is 120 yuan, for ordinary farms is 150 yuan, and for smart farms is 200 yuan [5]. Regarding ecological benefits, pesticide residues in farmland soil within the pilot area decreased by 32%, and field biodiversity showed improvement. In terms of social benefits, the system alleviates the intensity of agricultural labor, encourages some young workers to return to farming, and enhances farmers' knowledge of plant protection practices [12].

4.2.2 User Feedback

Through a questionnaire survey and field interviews, 92% of users expressed satisfaction with the system's recognition accuracy, 88% found the system simple and easy to use, and 85% indicated a willingness to continue using the system and recommend it to others [15]. Users generally reported that the system effectively addresses three major challenges: lack of understanding of pests and diseases, uncertainty about treatment methods, and difficulties in purchasing pesticides. This provides practical and effective technical support for agricultural production. Additionally, users suggested improvements such as expanding recognition to include more crop types and optimizing offline functionality, offering valuable guidance for future system upgrades.

5 Summary and Prospect

5.1 Development Summary

This study successfully developed an intelligent identification system for crop diseases and pests, leveraging Internet of Things and artificial intelligence technologies. The system integrates "hardware + software + service" into a comprehensive solution. Utilizing a cost-effective hardware architecture based on Raspberry Pi and cameras, combined with a high-precision recognition model using CNN algorithms, the system supports dual-mode operation through both mobile phone and hardware terminals. It addresses the needs of diverse scenarios, including individual farmers, conventional farms, and smart farms.

The pilot application results demonstrate that the system achieves a recognition accuracy of 90% or higher, with a response time of three seconds or less. Additionally, it reduces pesticide usage costs by 20% to 30% and increases grain yields by 10% to 15%, delivering significant economic, social, and ecological benefits. The system overcomes the limitations of traditional pest and disease identification technologies, fills the gap in lightweight intelligent tools for small and medium-sized farmers, and offers a practical technical solution for advancing intelligent agriculture.

5.2 Future Perspectives

5.2.1 Direction of Technology Upgrading

Future enhancements to the system will focus on optimizing performance and expanding its capabilities to identify over 200 types of crop diseases and pests. To improve recognition in complex environments, the system will integrate UAV remote sensing data for large-scale, high-precision pest monitoring. An offline recognition feature for the mobile application will be developed to support usage in non-network environments. Additionally, blockchain technology will be incorporated to ensure the authenticity and reliability of agricultural product quality traceability.

5.2.2 Application Scenario Expansion

The system's application will be extended to specialized crop cultivation, facility agriculture, and ecological agriculture, with tailored identification and control programs. Collaboration with platforms such as agricultural insurance and e-commerce will be explored to establish a broader industrial ecosystem. By utilizing big data analysis, a regional pest early warning model will be developed to provide proactive prevention and control recommendations for both policymakers and farmers.

The advancement of crop disease and pest identification technology is a critical enabler for the transformation and modernization of intelligent agriculture. The practical implementation of the system demonstrates that by pursuing a development path focused on technology accessibility, service adaptability, and ecological industrialization, it effectively addresses challenges in agricultural production. Looking ahead, as technology continues to evolve and the industrial ecosystem matures, intelligent identification technologies for crop diseases and pests will play an increasingly pivotal role in agricultural production, contributing significantly to food security, ecological sustainability, and the quality and safety of agricultural products.

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