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[Review Paper]

Pest and disease management in agricultural production with artificial intelligence: Innovative applications and development trends

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Abstract

This paper reviews the innovative applications and development trends of artificial intelligence (AI) in pest and disease management in agricultural production. As the scale of the agricultural output continues to expand and the complexity of environmental changes increases, the threat of pests and diseases to crops is becoming more prominent. The rapid development of AI technology offers new possibilities for addressing this issue. Firstly, the paper introduces the applications of AI in pest and disease identification and prediction, including the use of image recognition technology, data analysis, and machine learning algorithms, as well as the design and implementation of intelligent early warning systems. Secondly, it discusses the role of intelligent decision support systems in pest and disease management, covering the architecture of data-driven decision support systems, the implementation of intelligent agricultural management platforms, and the establishment of real-time monitoring and response mechanisms. Next, the paper explores the innovative applications of automated control technologies in pest and disease management, such as automated spraying and fertilization systems, intelligent agricultural robots, and the integration of biological control technologies with AI. Through case studies and practical applications, this paper showcases the successful application of AI in agricultural pest and disease management and provides an outlook on future development trends. This paper aims to provide agricultural producers and researchers with a comprehensive understanding, thereby promoting the further application and development of AI in agricultural pest and disease management.

Keywords

AI in agriculture, pest management, disease prediction, intelligent farming, automated control systems

1. Introduction

The challenges of pest and disease management in agricultural production go beyond the direct impact on crop health and yield; they also impose significant pressure on resources and the environment. High control costs not only increase the economic burden on agricultural producers but also limit the sustainability of agricultural production. Traditional monitoring methods rely on manual observation and sampling, which are limited in accuracy and prone to underreporting and false reporting, leading to untimely control of pests and diseases. Additionally, the increasing resistance of pests to pesticides exacerbates the difficulty of pest management, as it necessitates higher pesticide usage and potentially reduces control effectiveness. The

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overuse of pesticides further has an undeniable impact on the environment, with long-term pollution and disruption of ecological balance threatening the stability of ecosystems. Furthermore, the uncertainties brought about by global climate change present greater challenges for pest and disease management; fluctuating climate factors may alter the seasonality, distribution range, and activity patterns of pests, complicating and intensifying management efforts [1-3].

The rapid development of artificial intelligence (AI) technology provides new ideas and solutions for addressing the challenges of agricultural pest and disease management. By leveraging AI technology, precise monitoring and prediction of pests and diseases can be achieved, improving management efficiency and accuracy. The application of image recognition technology, data analysis, and machine learning algorithms enables faster and more accurate identification of pests and diseases, while the design and implementation of intelligent early warning systems further enhance the timeliness and flexibility of management. Moreover, the establishment of data-driven decision support system architectures, the realization of intelligent agricultural management platforms, and the application of automated control technologies offer new approaches and methods for pest and disease management. With continuous development and innovation in AI technology, its application in agricultural pest and disease management is expected to yield more significant results, providing greater possibilities and opportunities for sustainable agricultural production [4-6].

This paper aims to review the innovative applications and development trends of AI in pest and disease management in agricultural production. By systematically summarizing the current applications of AI technology in agriculture, analyzing its advantages and limitations in pest and disease management, and discussing future development directions and challenges, this paper intends to provide references and insights for agricultural producers, researchers, and policymakers.

The structure of this paper is arranged as follows. After the introduction, the latest advancements in AI technology for pest and disease identification and prediction are introduced, including the application of image recognition technology, data analysis, and machine learning algorithms, as well as the design and application cases of intelligent early warning systems. Next, the establishment of data-driven decision support system architectures, the realization of intelligent agricultural management platforms, and the establishment of real-time monitoring and response mechanisms are discussed, along with their application effects and prospects in pest and disease management. Following this, the innovative applications of automated spraying and fertilization systems, intelligent agricultural robots, and the integration of biological control technologies with AI are introduced, exploring their impact on pest control effectiveness and agricultural production. Subsequently, typical case studies are presented to showcase the successful applications of AI in agricultural pest and disease management, summarizing practical application experiences and sharing industry benchmark cases. Finally, the conclusion and outlook section summarizes the main content and research findings of this paper, evaluates the advantages and limitations of AI in

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agricultural pest and disease management, and forecasts future development trends and research directions.

2. Applications of AI in pest and disease identification and prediction

2.1. Development and application of image recognition technology

Image recognition technology is a significant branch of AI, primarily aimed at enabling computers to understand and recognize objects, scenes, and features in images as humans do. In agricultural production, image recognition technology has been widely applied, especially in pest and disease management [7,8].

Traditionally, image recognition technology relied on manually designed feature extraction and classification algorithms. However, the effectiveness of these methods was limited by the selection and extraction of features. With the rise of deep learning, particularly the advent of convolutional neural networks (CNNs), image recognition has seen tremendous breakthroughs. CNNs can automatically learn features from images and achieve accurate recognition of complex images through multi-layer processing, significantly improving recognition accuracy and efficiency. The advantage of CNNs lies in their ability to train on large datasets, automatically extracting and learning features from images, thus overcoming the limitations of manually designed features and achieving more accurate and reliable recognition. The application of deep learning technology has not only achieved significant success in the field of image recognition but has also provided new ideas and methods for pattern recognition and data analysis in other fields.

In terms of application scenarios, image recognition technology has broad prospects. Firstly, it can be used for pest and disease identification. By capturing images of plant leaves or fruits and utilizing trained deep learning models, different types of diseases and pests can be quickly and accurately identified, helping agricultural producers take timely control measures and reduce losses. Secondly, image recognition technology can be used for crop growth monitoring. Capturing growth images of crops, enables monitoring and evaluation of crop growth conditions, including growth status and the impact of pests and diseases, providing agricultural producers with management references and helping them adjust management measures promptly. Additionally, by capturing images of soil surfaces with drones or sensors and combining them with image recognition technology, soil quality can be assessed, including soil moisture, soil type, and vegetation cover. This information supports soil management and agricultural production, helping producers scientifically manage fertilization and irrigation, thus improving agricultural production efficiency and quality.

Despite the achievements of image recognition technology in agriculture, several challenges remain. These include issues related to image quality, lighting conditions, and the diversity of crop growth conditions, all of which can affect the accuracy and stability of image recognition. Further optimization of algorithms and models is needed to address these challenges. For example, varying lighting conditions can alter the color and texture of crop leaves, potentially leading to inconsistent recognition results under different lighting. Moreover, the diversity of crop growth conditions increases the difficulty of image recognition

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since different types of crops may have distinct growth characteristics and morphologies, requiring more flexible algorithms. Nevertheless, with continuous advancements in computer vision technology and improvements in hardware equipment, the application of image recognition technology in agriculture will become more extensive. In the future, with ongoing algorithm and model optimization and enhancements in hardware performance, image recognition technology will provide more intelligent solutions for agricultural production, contributing significantly to the improvement of agricultural productivity and quality, and driving the development of the agricultural industry.

2.2. Applications of data analysis and machine learning in pest and disease prediction

In terms of data collection and processing, the effectiveness of pest and disease prediction relies on the collection and processing of a large amount of relevant data [9,10]. Firstly, it is necessary to gather various types of data, including meteorological data, soil data, crop growth data, and pest and disease occurrence data. These data can be collected in real-time through various means, such as sensors, weather stations, and monitoring devices, or through retrospective analysis of historical data to form a comprehensive data foundation. The collected data then need to be cleaned, processed, and feature-extracted to provide usable inputs for subsequent machine learning algorithms. During the cleaning and processing phase, issues such as inconsistent data quality and non-uniform data formats must be addressed to ensure data accuracy and consistency. Feature extraction involves transforming raw data into representative and distinguishing features so that machine learning algorithms can better understand and utilize the data for effective pest and disease prediction.

In terms of selecting machine learning algorithms, pest and disease prediction involves the application of various algorithms, including decision trees, support vector machines (SVM), random forests, and neural networks. Each of these algorithms has its advantages and applicable scenarios, so multiple factors must be considered when choosing an algorithm. Firstly, the characteristics of the data need to be analyzed, including the data structure, dimensions, and correlations between features, to determine which algorithm is best suited for the current data. Secondly, the prediction goals and application scenarios must be clarified, as different algorithms may differ in terms of interpretability and stability of the prediction results, requiring a balance based on the actual situation. Additionally, factors such as the accuracy, efficiency, and interpretability of the algorithm need to be considered to ensure that the chosen algorithm can achieve good predictive performance in practical applications.

During the model training and optimization phase, once an appropriate algorithm is selected, the next step is to train the model using historical data and evaluate and optimize it through methods such as cross-validation to improve prediction accuracy and stability. During training, feature engineering can be employed to process the raw data and extract more representative and distinguishing features, thereby enhancing the model's expressiveness and generalization ability. Additionally, parameter tuning can be used

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to optimize the model, finding the best parameter combination to further improve the model's performance and effectiveness. Continuous adjustment and optimization of the model are necessary until satisfactory predictive performance is achieved.

In the prediction results evaluation phase, after completing model training, it is essential to validate and evaluate the model using test data to assess its predictive performance and generalization ability. Common evaluation metrics include accuracy, recall, and F1-score, which comprehensively evaluate the model's performance in predicting the occurrence and spread of pests and diseases. Particularly for pest and disease prediction, the accuracy and reliability of the prediction results are crucial. Accurate predictions can help agricultural producers take timely control measures, effectively reducing the damage and loss caused by pests and diseases.

Real-time prediction and application are key steps in applying the trained model to actual pest and disease prediction. Once model training and validation are completed, the model can be deployed in the actual production environment. By integrating real-time collected data, such as meteorological data, soil data, and crop growth data, with the trained model, it is possible to predict future pest and disease occurrences. This real-time prediction capability allows agricultural producers to promptly understand the occurrence and spread trends of pests and diseases, enabling them to take appropriate control measures promptly, thereby reducing losses and improving the efficiency and quality of agricultural production. The application of real-time prediction not only helps agricultural producers effectively cope with pests and diseases but also optimizes the agricultural production process, increases crop yield and quality, and provides important support for sustainable agricultural development.

2.3. Design of intelligent early warning systems

Data collection and monitoring are critical steps in the design of intelligent early warning systems [11,12]. During system operation, it is first necessary to collect relevant data in real-time, including meteorological data, soil data, crop growth data, and pest and disease occurrence data. These data can be collected in real time through a widely distributed network of sensors, weather stations, and monitoring devices and then transmitted to the data center of the early warning system for processing and analysis. The accuracy and timeliness of data are crucial for the effectiveness of the early warning system; therefore, ensuring the stability and efficiency of data collection is a key consideration in system design. Based on data collection, the system can establish a real-time monitoring mechanism to promptly detect the occurrence and spread trends of pests and diseases, providing timely and accurate early warning information to agricultural producers. This helps them take appropriate preventive measures, thereby minimizing losses and ensuring crop growth and yield.

Data processing and analysis are key steps in an intelligent early warning system. Once data collection is complete, the data must be cleaned, processed, and features extracted to ensure quality and usability. This

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process aims to eliminate noise and outliers from the data, allowing accurate analysis and utilization. Subsequently, machine learning algorithms are used to analyze and model the processed data to uncover patterns and trends in pest and disease occurrences. By learning from and analyzing historical data, the system can identify patterns in pest and disease outbreaks and further predict potential future pest and disease events. These predictions provide valuable reference information for agricultural producers, helping them make timely and effective decisions to minimize the impact of pests and diseases on crops.

Based on data analysis, the intelligent early warning system needs to establish corresponding early warning models to achieve effective prediction and alert of pests and diseases. The establishment of these early warning models involves selecting appropriate algorithms and optimizing parameter settings. Considering the diversity of different types of pests and diseases and their occurrence conditions, the early warning models need to be custom-designed to ensure the accuracy and timeliness of the warnings. By establishing precise and reliable early warning models, the system can issue alerts before pest and disease events occur, providing agricultural producers with ample time for prevention and control, thus minimizing crop losses.

Once the intelligent early warning system detects signs of potential pest and disease events, the next step is to automatically issue warning information to promptly notify agricultural producers and relevant management personnel to take appropriate preventive measures. These warning messages can be disseminated through various channels, including mobile apps, SMS, and emails, to ensure that the information reaches agricultural producers promptly. The warning information not only indicates the current risk level of pests and diseases but also provides specific prevention and response recommendations to help agricultural producers quickly take effective measures to address potential threats and minimize losses.

The functionality of the early warning system extends beyond prediction and information dissemination to include real-time monitoring and response to pest and disease events. Through continuous monitoring, the system can promptly capture the occurrence of pests and diseases and adjust and optimize the early warning models and strategies based on the monitoring results. Once the system confirms the occurrence of actual pest and disease events, it will immediately take emergency response measures. These measures may include sending more detailed warning information, providing specific control recommendations, and organizing and dispatching relevant personnel and resources to address the spread and impact of pest and disease events.

3. The role of intelligent decision support systems in pest and disease management

3.1. Data-driven decision support system architecture

The architecture of a data-driven decision support system (DDSS) aims to utilize data analysis and machine learning technologies to help decision-makers make more informed decisions. Below is a detailed introduction to a typical DDSS architecture [13,14].

One of the critical steps in a DDSS is establishing data sources and creating data collection mechanisms.

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This involves identifying the required data sources for the system, which may include various sensors, monitoring devices, databases, and third-party data providers. Real-time data collection and historical data acquisition are primary tasks at this stage. Real-time data collection ensures that the system can obtain current data to reflect the ongoing agricultural production conditions and environmental factors. Historical data collection aims to build a historical database, providing past data for analysis and model training. Effective implementation of this step provides the necessary foundation for subsequent data analysis and decision-making.

In the construction of a DDSS, data storage and management are crucial. Collected data need to be stored in scalable data storage systems for further processing and analysis. Common data storage systems include relational databases, NoSQL databases, and data warehouses. These storage systems should offer high availability and flexibility to meet the extensive data storage needs and support fast data access and queries. Additionally, data should be stored in structured, semi-structured, and unstructured forms to accommodate various data types' storage and management requirements. Effective data storage and management enable DDSS to provide reliable data support for subsequent data analysis and decision-making.

Data preprocessing and cleaning are essential steps to ensure data quality and accuracy in a DDSS. Key tasks at this stage include data cleaning, data integration, and data transformation. Data cleaning involves removing duplicate data, handling missing values, and addressing outliers to ensure data completeness and consistency. Data integration merges and consolidates data from different sources to establish a comprehensive dataset. Data transformation involves converting data formats, normalization, and standardization to make data suitable for further analysis and modeling. These preprocessing and cleaning operations provide a high-quality, consistent data foundation for DDSS, ensuring reliable support for data analysis and decision-making.

During the data analysis and modeling stage, preprocessed data are utilized through various techniques, including statistical analysis, data mining, machine learning, and deep learning. The main goal of this stage is to discover patterns, trends, and insights within the data and to build predictive models, classification models, and clustering models. Statistical analysis helps understand data distribution and relationships, while data mining aims to uncover hidden knowledge in the data. Machine learning algorithms use historical data for training to build predictive models for future event trends. Deep learning technologies excel in handling large-scale and complex data, using multi-layer network structures to learn advanced features from the data, thereby enhancing model accuracy and generalization capabilities. Data analysis and modeling extract valuable information from vast data, providing scientific evidence and reliable predictive capabilities for DDSS.

In the decision model design stage, based on data analysis results, decision models are designed and established to support various decision tasks. These models can include risk assessment models, optimization models, and decision tree models. Risk assessment models evaluate the risk levels of different decision

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options, helping decision-makers make rational choices under varying risks. Optimization models seek the best decision solutions to achieve predefined goals or maximize benefits. Decision tree models construct decision paths through a series of decision nodes and outcome nodes, assisting decision-makers in understanding decision processes and potential outcomes. These decision models can be customized according to specific decision scenarios and requirements, meeting diverse decision needs across different fields and levels, and providing scientific evidence and guidance for decision-makers.

In a decision support system, user interface and visualization tools are crucial. These interfaces and tools should be user-friendly and intuitively present data analysis results and model outputs, making it easier for decision-makers to understand complex information. Common interface elements include various charts, maps, and dashboards. These visualizations allow decision-makers to observe data trends, changes, and correlations, helping them identify issues, make decisions, and explore potential solutions. Such user interfaces enhance decision-makers efficiency and understanding of data, effectively leveraging the decision support system to guide decision-making processes.

During the operation of a decision support system, its ultimate goal is to provide targeted analysis results to help decision-makers make more accurate and informed decisions. This includes presenting processed and analyzed data to decision-makers, enabling them to make decisions based on this information. Additionally, a well-designed decision support system should have a feedback mechanism to adjust and optimize models and algorithms based on decision outcomes. By continuously collecting and analyzing decision results, the system can identify patterns and trends and update and improve models when necessary, enhancing system performance and accuracy. This feedback loop enables the decision support system to adapt to changing environments and needs, providing reliable and effective support for decision-makers, thus promoting continuous improvement and development within organizations.

In summary, the architecture of a data-driven decision support system includes data collection, storage, preprocessing, analysis, modeling, decision model design, user interface and visualization, and decision support and feedback. Through the coordinated operation of these components, decision-makers are assisted in making more informed decisions.

3.2. Design and implementation of an intelligent agricultural management platform

The intelligent agricultural management platform is a system that comprehensively utilizes information technology and intelligent algorithms to provide comprehensive management and intelligent decision support for agricultural production. Below is a detailed introduction to the design and implementation of the intelligent agricultural management platform [15,16].

1) Requirements analysis and system design. In the construction of an intelligent agricultural management platform, requirements analysis, and system design are crucial steps. First, during the requirements analysis phase, the functions and characteristics of the platform need to be clearly defined.

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This involves identifying the types and sources of required data, including meteorological data, soil data, and crop growth data, and clearly defining user needs and usage scenarios. The key at this stage is to deeply understand the actual needs of agricultural production to ensure that the system design can effectively address agricultural production issues. Second, based on the results of the requirements analysis, system design is carried out, which includes determining the overall architecture of the system and the relationships between various modules. The system design should consider data flow and processing methods, user interface design, system scalability, and maintainability. Through reasonable requirements analysis and system design, a solid foundation can be laid for the subsequent development and implementation of the intelligent agricultural management platform, ensuring that the system can effectively meet the needs of agricultural production and provide a good user experience.

2) Data collection and integration. In the construction of an intelligent agricultural management platform, data collection and integration are crucial. The platform needs to acquire multi-source data to comprehensively understand various aspects of agricultural production. First, meteorological data provides information on weather conditions, temperature, humidity, etc., which significantly impacts crop growth and development. Second, soil data reflects the texture, nutrient content, and other critical information of the soil, which is vital for proper fertilization and soil management. Additionally, crop growth data records the growth status and changes of crops at different stages, helping adjust management strategies in time. Moreover, pest and disease data provide information on the occurrence, distribution, and impact of pests and diseases, offering a basis for monitoring and controlling them. This data can be collected in real-time through various sensors, monitoring devices, and weather stations, and then integrated into the intelligent agricultural management platform's data storage system for unified management and processing. Ensuring timely and accurate data collection and integration is essential for the smooth operation of the intelligent agricultural management platform and provides the necessary foundation for subsequent data analysis and decision-making.

3) Data preprocessing and cleaning. Data preprocessing and cleaning are critical steps in the data processing workflow of an intelligent agricultural management platform. Data may be affected by various factors, such as sensor errors and incomplete data transmission, leading to noise, missing values, and outliers. To ensure the accuracy and reliability of subsequent data analysis and modeling, data preprocessing and cleaning are necessary. First, the data cleaning phase involves removing duplicate data, handling missing values, and addressing outliers to ensure data completeness and consistency. Second, the data transformation phase includes format conversion, normalization, and standardization, making the data comparable and interpretable. Finally, the feature extraction phase extracts useful features from the raw data for analysis and modeling. Through data preprocessing and cleaning, data quality and accuracy can be effectively improved, providing reliable support for data analysis and decision-making in the intelligent agricultural management platform.

4) Data analysis and intelligent algorithms. In an intelligent agricultural management platform, data analysis and intelligent algorithms play critical roles. Once the data is preprocessed, it can be deeply analyzed and modeled using advanced technologies like machine learning and deep learning. Through these intelligent algorithms, the platform can uncover hidden patterns, trends, and relationships in the data, providing deeper insights into agricultural production. For example, by analyzing crop growth data, intelligent algorithms can predict future growth trends, helping agricultural producers plan farming activities rationally. Analyzing pest and disease data can reveal outbreak trends, allowing timely preventive measures to protect crop health and yield. The application of data analysis and intelligent algorithms in the intelligent agricultural management platform provides smarter and more efficient decision support, promoting sustainable development in the agricultural industry.

5) User interface and visualization. The user interface and visualization are vital components of user interaction with the intelligent agricultural management platform. By providing user-friendly interfaces and intuitive visualization tools, the platform makes it easier for users to understand data analysis results and model outputs. These visualization tools include various charts, maps, and dashboards that visually display data trends, correlations, and anomalies. For instance, users can view historical trends in crop growth through visual charts or intuitively display pest distribution on maps. The user interface should be designed to be clear and simple, easy to operate, allowing users to quickly find the needed information and functions. Through intuitive and interactive user interfaces and visualization tools, the intelligent agricultural management platform enhances user experience, strengthens their understanding and confidence in data analysis and decision-making results, and better supports agricultural production management and decision-making.

6) Decision support and optimization. The intelligent agricultural management platform plays a key role in decision support and optimization. By analyzing large amounts of data with intelligent algorithms, the platform can provide comprehensive decision support for agricultural production. First, the platform can optimize planting decisions by recommending the most suitable crop varieties and planting times based on historical data, weather conditions, and soil properties to maximize yield and quality. Second, the platform can optimize irrigation decisions by intelligently adjusting irrigation schemes based on crop growth status, soil moisture, and weather forecasts, achieving effective use and conservation of water resources. Additionally, the platform can optimize fertilization decisions by recommending appropriate fertilization plans based on soil nutrient status and crop needs, avoiding over-fertilization or nutrient deficiencies. Most importantly, the platform can optimize pest and disease control decisions by timely monitoring and warning of pest outbreaks, providing targeted prevention and control suggestions and measures to reduce the damage to crops effectively. Through these decision support and optimization functions, the intelligent agricultural management platform can improve the efficiency, quality, and sustainability of agricultural production, bringing real economic and environmental benefits to agricultural producers and practitioners.

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7) Real-time monitoring and response. The intelligent agricultural management platform plays a crucial role in real-time monitoring and response. By continuously monitoring environmental parameters and crop conditions in the field, the platform can promptly detect anomalies and make corresponding adjustments. For example, when low soil moisture is detected, the platform will automatically trigger the intelligent irrigation system to provide adequate irrigation, ensuring the water supply needed for crop growth. When excessive or insufficient nutrients are detected in the soil, the platform will intelligently adjust the fertilization scheme to maintain nutrient balance for crop growth. Additionally, the platform can monitor pest and disease occurrences in real-time, issuing alerts and providing corresponding control suggestions immediately upon detecting anomalies, helping agricultural producers take timely measures to prevent serious impacts on crops. Through these real-time monitoring and intelligent response functions, the intelligent agricultural management platform maximizes the stability, efficiency, and yield of field production, contributing to more sustainable agricultural development.

In summary, the design and implementation of an intelligent agricultural management platform encompass multiple aspects, including requirements analysis, data collection and integration, data preprocessing and cleaning, data analysis and intelligent algorithms, user interface and visualization, decision support and optimization, and real-time monitoring and response. The coordinated operation of these aspects enables comprehensive management and intelligent decision support for agricultural production.

3.3. Establishment of real-time monitoring and response mechanisms

The establishment of real-time monitoring and response mechanisms is crucial in intelligent agricultural management, helping agricultural producers promptly detect and respond to emergencies, and ensuring the healthy growth of crops. Below are the detailed steps and contents for establishing real-time monitoring and response mechanisms [17,18].

1) Deployment of monitoring equipment. Deploying monitoring equipment in the fields is a fundamental step in intelligent agricultural management. Weather stations collect meteorological data, including temperature, humidity, and wind speed, providing climate information for agricultural production. Soil sensors monitor soil moisture, temperature, and nutrient content, helping agricultural producers adjust irrigation and fertilization plans. Crop growth monitoring devices observe indicators such as growth status, growth rate, and leaf color, providing real-time monitoring and assessment of crop growth conditions. Cameras can capture images of the fields, and through image recognition technology, monitor the occurrence of pests and diseases, aiding agricultural producers in taking timely preventive measures. The deployment of these monitoring devices provides essential data for the intelligent agricultural management platform, supporting subsequent data analysis and decision-making.

2) Data transmission and processing. The data collected by monitoring equipment is a vital information

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source for the intelligent agricultural management platform. Before it can be effectively utilized, it must go through a series of transmission and processing steps. First, the data needs to be transmitted in real-time via networks to a data center or cloud server, ensuring its timeliness and completeness. Once the data reaches the data center, it undergoes data cleaning, processing, and feature extraction to ensure quality and accuracy. Data cleaning addresses noise, outliers, and missing values to maintain consistency and completeness. Data processing involves transforming the raw data, making it suitable for subsequent analysis and modeling. Feature extraction identifies representative and distinctive features from the raw data, supporting further data analysis and model building. These data transmission and processing operations provide a high-quality data foundation for the intelligent agricultural management platform, offering reliable support for intelligent agricultural decision-making.

3) Data analysis and modeling. After data processing, the data becomes a usable foundation for the intelligent agricultural management platform. The next step is to analyze and model this data. Using techniques like machine learning and deep learning, data can be deeply mined to uncover patterns and trends, establishing corresponding predictive models. These models can monitor the current field environment and crop growth conditions in real-time and predict future issues such as pest outbreaks, droughts, and flooding. For example, by using historical meteorological and soil data combined with machine learning algorithms, predictive models for crop growth under various conditions can be developed, helping agricultural producers anticipate future crop conditions. Similarly, by analyzing image data of crop growth with deep learning technology, predictive models for pest and disease outbreaks can be established, providing early warnings of potential risks. The results of data analysis and modeling offer scientific basis and technical support for real-time monitoring and response in agricultural production, aiding intelligent agricultural management and decision optimization.

4) Design and implementation of the early warning system. Based on data analysis results, the design and implementation of an early warning system become a crucial part of the intelligent agricultural management platform. First, the early warning system needs to integrate the outputs of predictive models, monitoring field conditions in real-time, including meteorological conditions, soil moisture, crop growth status, and other indicators. By comparing monitored data with predictive models, the system can promptly detect potential anomalies, such as pest outbreaks, droughts, or flooding risks. Once an anomaly is detected, the early warning system automatically triggers the warning mechanism, sending alerts to agricultural producers or managers through various channels, including SMS, app notifications, and emails, enabling them to take timely preventive or emergency measures. The design and implementation of the early warning system can enhance the resilience and risk resistance of agricultural production, reducing losses and ensuring the safety of fields and crops, thereby promoting intelligent and efficient agricultural production.

5) Establishment of emergency response mechanisms. Establishing emergency response mechanisms is a critical step to ensure the effective operation of the intelligent agricultural management platform. Upon

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receiving warning information, agricultural producers or managers need to quickly take response measures to address potential disasters or anomalies. Emergency responses may include adjusting irrigation amounts based on soil moisture and meteorological conditions, arranging fertilization plans to meet crop needs, and taking pest and disease control measures, such as pesticide spraying or biological control methods. Additionally, emergency responses may involve taking measures to prevent flooding and protect crops from natural disasters. By establishing emergency response mechanisms, agricultural producers and managers can respond more timely and effectively to emergencies, minimizing losses and ensuring stable and sustainable agricultural production.

6) Establishment of monitoring and feedback mechanisms. Establishing monitoring and feedback mechanisms is essential for the effective operation of the intelligent agricultural management platform. Through real-time monitoring systems, agricultural producers or managers can continuously understand field conditions, including meteorological conditions, soil moisture, crop growth status, and potential pest occurrences. This real-time monitoring capability allows agricultural producers to promptly sense any potential problems or risks and take swift action to address them. Additionally, the feedback mechanism is crucial as it provides timely feedback of monitored data and information to agricultural producers or managers, enabling them to make adjustments and decisions based on actual conditions. The establishment of monitoring and feedback mechanisms can improve agricultural production efficiency and quality, helping agricultural producers better protect crops, reduce losses, and achieve sustainable agricultural development.

7) Technical support and maintenance. In addition to establishing real-time monitoring and response mechanisms, technical support and maintenance are indispensable parts of the intelligent agricultural management platform. Monitoring equipment, as the system's foundation, needs regular maintenance and inspection to ensure proper operation and accurate data collection. Similarly, data processing and analysis systems require periodic updates and optimization to adapt to changing environments and needs, enhancing system stability and reliability. The technical support team can provide timely technical assistance and training, helping users resolve issues encountered during use and guiding them to better utilize platform functions. Through technical support and maintenance, the intelligent agricultural management platform can continuously operate effectively, providing sustained and stable services and support to agricultural producers and managers.

Implementing the above steps can establish a comprehensive real-time monitoring and response mechanism, improving the efficiency and quality of agricultural production, reducing losses, and promoting sustainable agricultural development.

4. Innovative applications of automation technologies in pest management

4.1. Application cases of automated spraying and fertilization systems

1) Application of intelligent agricultural drones. The use of intelligent agricultural drones has brought

significant technological innovations to agricultural management. Equipped with high-resolution cameras and sensors, these drones can monitor various critical parameters of the farmland in real-time, such as crop growth conditions, pest occurrences, and soil moisture levels. This monitoring data provides valuable decision support, helping agricultural producers and managers better understand the state of their fields. Based on the monitoring results, intelligent agricultural drones can automatically adjust the spraying amount and range of sprayers, achieving precise application of pesticides, spraying, and fertilization. This intelligent management approach not only enhances the efficiency of spraying and fertilization but also reduces the waste of pesticides and fertilizers, lowering agricultural production costs and promoting sustainable agriculture [19].

2) Application of intelligent irrigation systems. Intelligent irrigation systems play an important role in modern agriculture. These systems are equipped with soil moisture sensors and weather stations to monitor soil moisture and meteorological conditions in real-time. By collecting and analyzing this data, intelligent irrigation systems can smartly adjust irrigation amounts and frequencies to ensure crops receive the right amount of water. When soil moisture is too low or weather conditions indicate a need, the system automatically initiates irrigation, ensuring crop growth is not limited by water availability. This automated adjustment of irrigation not only improves irrigation efficiency but also helps reduce water waste, thereby promoting sustainable agriculture [20].

3) Application of intelligent fertilization systems. Intelligent fertilization systems are a crucial agricultural technology that uses data on soil quality, and crop growth conditions and needs to automatically calculate and adjust fertilization amounts and timings. Using sprayers or drip irrigation systems, the system can evenly distribute fertilizers across the fields, ensuring crops receive appropriate nutritional support at different growth stages. This precise fertilization approach not only improves fertilization efficiency but also reduces fertilizer waste, lowering agricultural production costs and helping minimize negative environmental impacts [21].

4) Application of intelligent weeding systems. Intelligent weeding systems are innovative agricultural tools that use machine vision and deep learning technologies to identify weeds in the fields and take corresponding weeding measures. Through high-resolution cameras and advanced image recognition algorithms, the system can accurately identify different types of weeds and automatically spray herbicides or operate mechanical devices to perform weeding tasks based on preset parameters. This automated weeding system significantly reduces the labor costs of manual weeding and improves weeding efficiency, helping to ensure the healthy growth of crops while reducing human-induced environmental disturbances [22].

5) Application of intelligent control platforms. The intelligent control platform, as a comprehensive intelligent agricultural management system, integrates multiple intelligent agricultural devices to achieve intelligent management of the entire farmland. By monitoring environmental parameters and crop growth conditions in real-time, the intelligent control platform can use intelligent algorithms for data analysis and

optimization, thereby automatically adjusting the working parameters of agricultural equipment. This means that irrigation, fertilization, weeding, and pest management can all be coordinated and optimized within one system, achieving comprehensive management and intelligent decision support for farmland. The use of such an integrated platform not only improves the efficiency and quality of agricultural production but also reduces management costs and resource consumption, bringing more possibilities for intelligent and sustainable agricultural production [23].

The implementation of the above application cases can not only improve the efficiency and quality of agricultural production but also effectively reduce resource waste, lower labor costs, and promote sustainable agricultural development. Through intelligent agricultural management systems, agricultural producers can more accurately understand the environmental conditions of their fields and the growth status of their crops, allowing them to timely adjust planting strategies and management measures.

4.2. The role of intelligent agricultural robots in pest and disease control

1) Real-time monitoring. Intelligent agricultural robots are equipped with various sensors and cameras, enabling them to monitor crop growth conditions and pest occurrences in real-time. Sensors can measure environmental parameters such as soil moisture, temperature, and light, while cameras can capture images of crops and even detect signs of pests and diseases. By patrolling and inspecting the fields, intelligent agricultural robots can promptly identify early symptoms and occurrences of pests and diseases, providing crucial information to agricultural producers. This helps them take timely and effective control measures to protect crop health. Such timely monitoring and feedback mechanisms help reduce damage caused by pests and diseases, enhancing the stability and efficiency of agricultural production [24].

2) Automatic identification and classification. Intelligent agricultural robots, equipped with machine vision and deep learning technologies, can automatically identify and classify pests and diseases in the fields. Using machine learning algorithms, these robots can analyze collected image data to identify different types of diseases and pests on crop leaves or fruits. By extracting and comparing features from the images, the robots can determine the types of pests and diseases and accurately locate their positions and distribution in the fields. This intelligent pest and disease identification technology not only helps agricultural producers detect and diagnose plant diseases and pests promptly but also provides effective control suggestions, helping them take targeted control measures to protect crop health and improve agricultural production quality and yield [25].

3) Preventive role in early stages. In the early stages of pest and disease outbreaks, intelligent agricultural robots play a crucial preventive role. Using advanced techniques such as spraying biological pesticides, releasing predatory insects, and improving soil conditions, robots can effectively prevent the further spread and diffusion of pests and diseases. The use of biological pesticides reduces environmental and human health impacts and avoids residue issues on agricultural products. Releasing predatory insects can effectively

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control pest populations, reducing damage to crops. Additionally, improving soil conditions, such as adjusting soil pH and enhancing soil nutrient content, can boost plant resistance to pests and diseases, reducing their occurrence. These comprehensive preventive measures help minimize pest and disease damage to crops, ensuring the stability and sustainability of agricultural production [26].

4) Key role in control during outbreaks. When pests and diseases have already occurred and reached a certain level, intelligent agricultural robots play a key control role. Using advanced technologies like targeted pesticide spraying and carrying optical devices, robots can achieve precise pest and disease control. Targeted pesticide spraying allows precise application of pesticides to the affected plant parts, reducing pesticide usage and minimizing environmental and ecosystem impacts. Robots equipped with optical devices can accurately identify and locate pests and diseases using optical means, achieving more precise control. This intelligent pest and disease control method not only effectively curbs the spread and diffusion of pests and diseases but also maximizes the protection of crop health and growth, supporting sustainable agricultural production [27].

5) Data analysis and decision support. Intelligent agricultural robots play a crucial role in data analysis and decision support. Equipped with various sensors and cameras, these robots can collect large amounts of real-time field data, covering crop growth conditions, soil moisture, and weather conditions. Using machine learning and data analysis technologies, this data can be effectively processed and analyzed, providing comprehensive decision support for agricultural producers. For example, based on data analysis results, agricultural producers can understand the growth status of different crops, the occurrence of pests and diseases, and potential development trends, enabling them to develop more scientific pest and disease control strategies. This intelligent data analysis and decision support system not only helps agricultural producers respond to various field issues promptly but also improves agricultural production efficiency and quality, promoting sustainable agricultural development [28].

6) Efficiency improvement and cost reduction. The use of intelligent agricultural robots can significantly improve work efficiency and reduce labor costs. Through automated operations, these robots can reduce dependence on human labor, achieving autonomous execution of field tasks. Compared to traditional manual operations, robots perform tasks more precisely and consistently, without fatigue or time constraints, allowing them to complete large amounts of work in a shorter time. Additionally, intelligent agricultural robots can operate at night or under adverse environmental conditions, increasing the flexibility and continuity of agricultural production. These advantages not only effectively enhance agricultural production efficiency and yield but also reduce labor costs, bringing considerable economic benefits to agricultural producers [29].

Through these roles, intelligent agricultural robots play an essential part in pest and disease control, effectively improving the quality and efficiency of agricultural production, reducing pest and disease damage to crops, and promoting sustainable agricultural development.

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4.3. Integration of biological control technologies and AI

1) Data-driven methods. Data-driven methods play a crucial role in biological control technologies. Biological control relies on biological agents, such as biopesticides and predatory insects, to suppress pests and diseases in the fields. Compared to traditional chemical pesticides, biological control is more environmentally friendly and sustainable. However, it faces challenges like application difficulty and inconsistent effectiveness. Data-driven methods leverage AI algorithms to optimize and manage the biological control process, enhancing its effectiveness and reliability. By analyzing vast amounts of field data and key factors in biological control, these methods provide more accurate decision support for agricultural producers, optimizing application plans and management strategies. This leads to more effective pest control, higher crop yields, and improved quality, contributing to sustainable agriculture [30].

2) Machine learning for pest monitoring. Machine learning is crucial in pest and disease monitoring. Using machine learning algorithms, we can analyze image data from fields to accurately identify pest occurrences and their severity. By deeply analyzing and modeling these monitoring data, we can predict pest outbreak trends and take timely control measures. For instance, using deep learning algorithms, we can automatically identify and classify pest and disease images in fields, helping agricultural producers promptly detect and address potential threats. This data-driven approach enhances monitoring accuracy and efficiency, providing real-time, reliable decision support for agricultural production, reducing pest damage, and improving crop yield and quality [31].

3) Application of intelligent agricultural robots. Intelligent agricultural robots have enormous potential in biological control. Equipped with various sensors and actuators, these robots can autonomously patrol fields and execute biological control measures, such as spraying biopesticides and releasing predatory insects. Utilizing machine learning algorithms and adaptive control technologies, these robots can adjust spraying amounts and application methods in real-time based on actual field conditions, enhancing the effectiveness and precision of biological control. By continuously collecting and analyzing data, intelligent agricultural robots can optimize their decisions and operations, playing a more accurate and effective role in the fields. This intelligent biological control approach not only effectively manages pests but also reduces environmental impact, promoting sustainable agricultural development [32].

4) Data analysis and optimization. Data analysis and optimization play a vital role in biological control. Analyzing large amounts of data generated during the biological control process can reveal patterns and trends, helping to optimize biological control technologies and improve their efficiency and reliability. For example, machine learning algorithms can optimize biopesticide application amounts and spraying frequencies, adjusting them based on real-time monitored field conditions and pest severity to achieve optimal control effects. This data-driven optimization continually improves biological control technologies, making them more intelligent and precise, providing more effective support for agricultural production [33].

5) Establishment of decision support systems. Establishing decision support systems is an important

practice combining biological control technologies and AI algorithms. These systems provide decision support and technical guidance to agricultural producers, helping them better manage fields and combat pests and diseases. By analyzing and predicting field data, decision support systems can identify potential pest risks, forecast pest outbreak trends, and offer targeted control plans and response strategies. This system not only reduces pest damage to crops but also improves agricultural production quality and yield, offering more reliable support for agricultural producers' decisions and operations [34].

In summary, the integration of biological control technologies and AI has enormous potential in agricultural production. This fusion not only improves production efficiency but also promotes sustainability and enhances product quality. Through intelligent biological control technologies, agricultural producers can more precisely address pest threats, reduce pesticide use, lower environmental impacts, and increase crop yield and quality. This new solution and development direction bring more possibilities and opportunities to agricultural production, potentially advancing and developing the agricultural sector.

5. Conclusions and future prospects

1) Advantages of AI in pest management. AI has significant advantages in pest management. Firstly, its precision and efficiency enable accurate monitoring, identification, and control of pests and diseases in fields, thus improving agricultural production efficiency and quality. Secondly, AI technology is both real-time and predictive, allowing it to monitor and forecast pest and disease trends, helping agricultural producers take timely control measures to effectively reduce the damage caused by pests. Furthermore, AI technology is sustainable and environmentally friendly. Reducing the use of chemical pesticides, lowers pesticide residues and helps protect the ecological environment, promoting sustainable agricultural development. These advantages make AI an essential tool in pest management, providing comprehensive, efficient, and sustainable support for agricultural production.

2) Challenges of AI in agricultural pest management. AI faces several challenges in agricultural pest management. Firstly, the application difficulty is a notable challenge since implementing AI technology in this field requires agricultural producers to possess certain technical skills and professional knowledge, which may be a barrier for those lacking relevant backgrounds. Secondly, data acquisition and processing pose challenges because AI technology relies heavily on data, but acquiring and processing field data can be restricted by factors such as data collection, transmission, storage, and analysis. Additionally, system cost and return on investment are considerations. Although AI technology offers many benefits in pest management, its application entails system costs and investments, and the return on investment is not always ideal.

3) Future trends and research directions in agriculture. AI technology will continue to evolve in agriculture, showcasing several future trends and research directions. Firstly, intelligent agricultural production will become the primary development direction, with AI being further applied in all aspects of

agricultural production, including planting, management, and harvesting, to achieve intelligent agricultural production and improve efficiency and quality. Secondly, multimodal data fusion will become an important research direction, emphasizing the integration and application of various data types (such as images, sounds, and videos) to enhance the accuracy and reliability of pest monitoring in fields. Thirdly, the development of intelligent decision support systems will further advance, providing more comprehensive and precise decision support for agricultural producers, and helping them formulate scientific and reasonable agricultural production strategies to improve efficiency and quality. Lastly, the research and application of intelligent agricultural robots will be strengthened to achieve intelligent field management and operations, further enhancing agricultural production automation and promoting sustainable agricultural development. These trends will bring new technological innovations and development opportunities to agriculture, driving agricultural production toward intelligent, digital, and efficient advancements.

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