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REVIEW ARTICLE

AI-Driven Strategies for Predicting and Managing Insect Pest Dynamics under Climate Change

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ABSTRACT

Insect pest dynamics are significantly influenced by climate change and the threats thus pose severe threats to the global agricultural systems. Pest increased survival, redistribution and resistance as consequence of rising temperatures, pattern alteration of precipitation, and altered seasonal cycle, needing adaptive management. In this paper, artificial intelligence (AI) is used for the integration of machine learning (ML), deep learning (DL) and remote sensing technologies in order to increase precision pest prediction and control. Pest can be monitored and identified in real time using the artificial Intelligence driven models like convolutional and recurrent neural networks to predict risk, predicting when something is going to happen so that one can act anytime the risk seems high. Despite these limitations in accessing data, generalization of the model, and computational constraints, AI has great potential in controlling the climate induced pest outbreaks. This study highlights critical necessity of durable and resilient agriculture to which is needed interdisciplinary collaboration, better data quality and incorporation of AI in ecological modeling.

Key words: AI in Pest Management, Climate Change and Insect Dynamics, Machine Learning in Agriculture, Precision Forecasting for Pest Control, Sustainable Pest Management Strategies

INTRODUCTION

Climate change significantly impacts insect pest populations and agricultural ecosystems through various mechanisms, including temperature shifts, altered precipitation patterns, and changing seasonal cycles. Warmer temperatures can lead to increased survival rates of pests during overwintering, allowing for more generations per year and facilitating geographic range expansion. For instance, the corn flea beetle, a vector for Stewart's Wilt, is projected to expand its range northward in the United States due to milder winters, increasing the risk of severe crop damage (Schattman, Merrill et al. 2024). Similarly, the fall armyworm, an invasive pest, benefits from climate change as it enhances its reproductive and distribution capabilities, posing a threat to maize crops globally (Zanzana, Dannon et al. 2024). In India, climate change accelerates insect development and reproduction, affecting pest populations in vegetable crops such as whiteflies, which may adapt to warmer climates by altering their distribution and behavior (Skendžić, Zovko et al. 2021). Additionally, climate change disrupts the balance between pests and their natural enemies, as seen in vineyards where rising temperatures and chemical stresses affect both the pest Lobesia botrana and its biological control agent, Trichogramma oleae, potentially undermining pest management efforts (Nusillard, Garinie et al. 2024). These changes necessitate adaptive management strategies, such as integrated pest management (IPM), which combines agro-ecological practices and biological control to mitigate pest pressures while minimizing environmental harm (Radwan, Abdel-Hameed et al. 2024). The complex interplay of climate variables also affects insect behavior, including feeding and migration patterns, which can lead to mismatches in plant-pollinator relationships, further impacting biodiversity and ecosystem stability (John, Kaur et al. 2024).

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Therefore, to maintain agricultural productivity and health of ecosystem, it is necessary to understand the multifaceted impacts of climate change on insect pest.

The technology combination of machine learning (ML) and deep learning (DL) within AI platforms provides beneficial solutions for pest management mainly during climate change times. Wind farms collect extensive data through satellite imagery with climate variables to improve precision forecasting of agricultural pest activity and their corresponding effects through these modern technologies. The pest population dynamics under altering climatic conditions become easily understandable through AI models like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) because these models capture complex spatial and temporal patterns effectively (Bist, Rawat et al. 2024). The automated processing of AI-based methods outperforms conventional methods through their quick speed and extended scalability which enables immediate observation together with adaptable management systems (Maideen, Basha et al. 2024). The capability proves crucial for managing pests because climate change affects their distribution patterns and requires organizations to implement quick and adaptable methods (Fischer, Beswick et al. 2021). AI predictive models enable organizations to perform focused intervention planning which directs resources and cuts down crop damage to boost farming resistance levels (Arya 2024). AI gathers multiple datasets such as atmospheric and oceanic information to create more precise climate forecasting that enables pest risk assessment and strategic mitigation development (Amiri, Heidari et al. 2024). AI pest management implementations face two critical barriers that consist of securing sufficient high-quality data and overfitting risks which limit model applicability (Maideen, Basha et al. 2024). AI technologies present opportunities to revolutionize pest management practices by establishing a forward-looking protocol that fights against climate change effects in agriculture (Raghav, Singh et al. 2024).

2. AI-Based Prediction Models for Insect Pest Dynamics

Advanced AI techniques lead the prediction of insect pest behavior under different climate conditions since machine learning algorithms effectively unite climate data with pest forecasting models. Research studies depend on machine learning models that use regression, classification and clustering for climate pattern analysis to understand pest dynamics (Bist, Rawat et al. 2024). Deep learning models particularly CNNs and RNNs prove beneficial for analysing time-series data in addition to making forecasts by extracting complex temporal patterns from climate data (Goyal, Singh et al. 2024). Both ecological and traditional models get used together through hybrid modeling approaches to keep predictions relevant to ecological systems (Desai and Sharma 2024). AI applications in climate forecasting have demonstrated effective results to enhance the precision of weather prognoses and emergency systems designed to foresee pest invasions (Kumar, Goel et al. 2024). AI deep learning and neural networks processes extensive climate data to recognize intricate patterns that help explain pest behavior because these are essential components of understanding behavioral causes. Deep learning models from AI face two significant obstacles which include complex model interpretation alongside their high computational requirements (Redhu, Thakur et al. 2022). The complete potential of Artificial Intelligence to improve climate observation and forecasting functions will strongly influence pest management tactics. The potential value of AI systems greatly increases when their optimization focuses on climate science activities because such models deliver swift and detailed pest data regarding environmental changes (Kumar, Goel et al. 2024). AI techniques in climate-pest models establish an essential instrument which helps control climate change effects on agriculture through advanced pest management approaches (Goyal, Singh et al. 2024).

AI models use climate information for pest prediction outcomes by applying advanced machine learning systems which process different meteorological variables including air temperature and relative moisture levels and precipitation amounts. The combination of historical information along with pest-weather correlation data produces accurate and prompt analytical outcomes that enable proper pest control measures to prevent agricultural losses from pest attacks (Goyal, Singh et al. 2024). Weather-based pest and disease forecasting depends on data collection from temperature along with rainfall measurement alongside humidity observation and wind speed tracking with pattern analysis to determine optimal pesticide usage for lower environmental consequences (Vänninen 2022). The adoption of deep learning ensemble algorithms along with AI models has succeeded in increasing both the accuracy and operational speed of pest outbreak estimates because they understand sophisticated pest-environment connections (Goyal, Singh et al. 2024). There are multiple issues that appear when trying to combine climate data with AI models. The successful use of real-time data for climate prediction faces barriers from restricted infrastructure in developing countries making it challenging to acquire quality information (Boatemaa, Asare et al. 2024). AI models used in weather forecasting become less accurate when integrated with traditional data assimilation methods because this combination leads to increased computational requirements (Xu, Duan et al. 2024). Scientists must incorporate stochastic processes into climate prediction because unpredictable climate behavior demands better prediction reliability yet such methods tend to create complexities in model development as well as interpretation (YesuJyothi, Shaik et al. 2024). AI-driven systems keep evolving

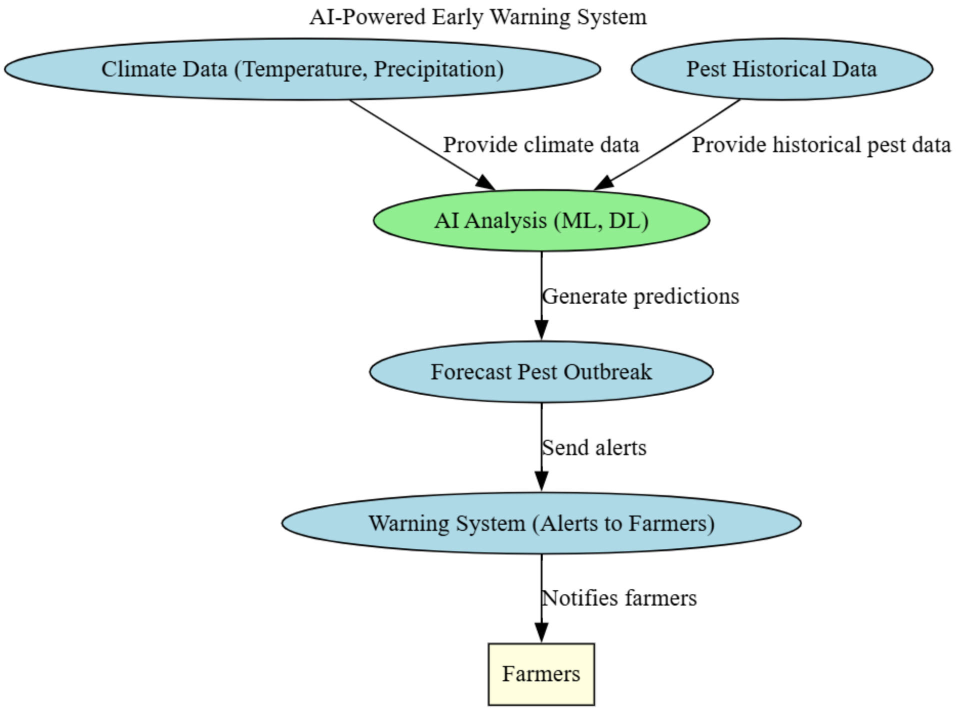

Fig. 1.1: Predictive Modeling and Early Warning Mechanism

although they face multiple hurdles that enable them to create substantial changes in climate management and environmental resilience through knowledge-based strategic decisions (Jaber, Ali et al. 2022). The ongoing efforts must focus on improvement of data integration models refining, and overcome ethical and governance challenges associated with AI to realize the potential of AI in predicting the pest outbreaks (Rees, Ng et al. 2019).

3. AI-Enhanced Pest Monitoring and Detection Systems

The combination of remote sensing devices with IoT and artificial intelligence for real-time pest identification becomes possible through an extensive arrangement of drone technology along with satellite observation systems and soil-based sensors that perform time-sensitive assessment and decision-making. The multiple-sensors contained on drones described by Fuentes-Peñailillo et al. 2024 enable the drones to fly over fields and collect environmental data that connects to IoT clouds for real-time evaluation (Fuentes-Peñailillo, Gutter et al. 2024). Remote sensing image processing utilizing UAVs together with CNNs achieves efficient pest identification through aerial imagery (Wang and Zhang 2024). The paper by (Gade, Yadav et al. 2023)., discusses ground sensors that measure soil moisture and environment conditions because these data help understand pest outbreak triggers (Antropov, Molinier et al. 2024). Real-time processes of environmental data become feasible through AI algorithms that were detailed by Alotaibi and Nassif (Alotaibi and Nassif 2024). Under the leadership of Hassan, Kowalska and their team external learning models with deep reinforcement learning and ensemble learning capabilities optimize data handling and resource consumption to improve pest monitoring system accuracy (Hassan, Kowalska et al. 2023). The YOLO architecture used for computer vision identifies insect species in real-time according to Venverloo and Duarte as it provides essential pest management information (Venverloo and Duarte 2024). The complete fusion of technological systems creates an efficient pest identification network which enables swift responses as well as helping farmers sustain their agricultural operations through superior timing of interventions.

Mathematical systems operated by AI have proven effective for pest outbreak detection which leads to higher sustainability and better agricultural stability. The systems base their operation on sophisticated machine learning models that collect many data types to deliver quick notifications allowing farmers to protect their land from impending pest outbreaks. The ALIC model represents an outstanding demonstration of pest outbreak prediction by merging historical pest information with meteorological data through an Attention-based Long Short-Term Memory Interaction Convolutional Neural Network structure. The processing pipeline of this model conducts three sequential stages for identifying key forecasting elements before understanding time-related patterns and revealing feature relationships that produce exact predictions of pest outbreaks. Research conducted with Chinese data proved that the ALIC model minimized forecasting mistakes along with establishing temperature and rainfall as crucial pest prediction variables (Wang and Zhang 2024). The combination of satellite imagery with IoT sensor feeds, meteorological data and satellite imagery allows predictions of crop-disease outbreaks. Recurrent neural networks and convolutional neural networks take part in this system because they process time-series data and satellite imagery which leads to

Table 1.1: AI Technologies, Applications, Benefits, and Challenges in Pest Management

AI Technology	Application in Pest Management	Key Benefits	Challenges/Limitations
Machine Learning (ML)	Pest forecasting using climate and environmental data	Improved prediction accuracy, real-time analysis, scalability	Dependency on high-quality, large datasets, limited generalization across regions
Deep Learning (DL)	Pest detection via satellite imagery, IoT sensor data	Enhanced detection, higher accuracy in classification, ability to process large-scale data	High computational demand, risk of overfitting without sufficient data
Convolutional Neural Networks (CNNs)	Image-based pest species identification	Real-time detection, higher accuracy in detecting pest species from images	Requires large labeled datasets for training, high computational cost
Recurrent Neural Networks (RNNs)	Forecasting pest behavior over time with climate data	Ability to process time-series data, captures temporal dynamics	Sensitive to data quality, requires continuous data streams for effective prediction
IoT Devices (Sensors)	Real-time monitoring of soil, temperature, humidity, and pest activity	Continuous data collection, environmental and pest behavior monitoring	Infrastructure costs, sensor calibration, data transmission limitations
Robotics and Autonomous Systems	Autonomous pesticide application and pest removal	Optimizes pesticide use, reduces labor cost, precise application	High implementation cost, technical expertise required for setup and maintenance
Decision Support Systems (AI)	Personalized pest management recommendations and alerts	Improves decision-making efficiency, enhances resource allocation	Data quality concerns, scalability issues in large-scale applications
Hybrid AI Models	Combining ecological models with ML/DL for better climate-pest predictions	Improved ecological relevance and prediction accuracy	Complex integration, data heterogeneity, limited scalability in diverse conditions
Ensemble Learning Models	Pest outbreak prediction by combining multiple AI models	Improved prediction accuracy by leveraging diverse algorithms	Computationally expensive, requires diverse and high-quality datasets
Remote Sensing with AI	Satellite and drone imagery analysis for pest infestation detection	Provides large-scale monitoring, enhances early detection	Limited by resolution of satellite imagery, requires advanced image processing
Edge AI (Real-time Processing)	In-field pest detection using edge computing devices	Faster data processing, immediate pest control response	Limited computing power at edge devices, network connectivity requirements
Genetic Algorithms	Optimizing pest control strategies and biological control agent deployment	Adaptive optimization, better resource allocation for pest management	Complex computational models, requires iterative adjustments to refine solutions
Swarm Intelligence	Coordinating multiple autonomous devices (e.g., drones or robots) for pest control	Coordinated response to large infestations, flexible and scalable systems	Complex system integration, potential communication issues among devices
Natural Language Processing (NLP)	AI-powered chatbots or virtual assistants to advise farmers on pest management	Personalized advice, quick access to expert knowledge	Limited understanding of local context or dialects, dependency on user input quality
Predictive Analytics	Anticipating pest outbreaks and climate events that affect pest dynamics	Supports proactive pest management, reduces crop damage	Data quality and availability, risk of inaccurate predictions in rapidly changing environments

superior predictions than traditional approaches. The model delivers advance notifications which enables farmers to stop biotic threats and enables agronomists to enhance their pest management approaches (Palani, Ilangovan et al. 2023). Transfer learning methods enabled the creation of new models which excel at detecting field crop pests early on. The EfficientNetV2 serves as one example of pest species detection models which effectively identify targets that enable farmers to conduct prompt preventive actions which minimize crop destruction and maintain sustainable agricultural operations (Haider, Khan et al. 2024). Pest management systems are improving by AI-powered early warning systems by collecting useful data advance.

4. AI in Pest Management Strategies

Precision agriculture receives substantial benefits from AI because it uses different advanced technologies and methodologies to achieve better targeted and effective pest control. AI,application of remote sensing and machine learning and IoT devices enable crop evaluation and disease/pest identification for proper preventive measures (Jeyalakshmi, Vijay et al. 2024). Real-time analytics from AI models on extensive agricultural data enables farmers to plan ahead against pest invasions which eliminates generic pesticide spraying while protecting the environment (Polwaththa, Amarasinghe et al. 2024). The marriage of AI to robots resulted in the creation of autonomous pesticide spray bots equipped with deep learning algorithms to detect specific pests so they could apply pest control only to the targeted areas thereby achieving maximum efficiency and minimizing environmental harm (Meshram, Vanalkar et al. 2024). The deployment models of precision agriculture use satellite imaging along with field mapping techniques to segment fields which enables site-specific pest management practices for maximizing resource efficiency as well as boosting agricultural output (Jeyalakshmi, Vijay et al. 2024). The AI solutions enhance pest control operations and promote sustainable farming through minimized chemical applications and ecological balance retention (Prabha, Subramanian et al. 2024). AI platforms offered by industry leaders IBM and Microsoft deliver farm management software which uses data to improve the performance of pest control strategies (Jeyalakshmi, Sowmia et al. 2024). Precision agriculture becomes more efficient through AI integration because it shows promise as a pest management method which promises better production outcomes and sustainable farming practices (Polwaththa, Amarasinghe et al. 2024).

Artificial intelligence (AI) delivers a vital function to find and optimize biological control agents through data analytics and predictive modeling and machine learning systems. AI models perform predictions about biological control agent effectiveness by processing vast datasets through which they detect connections that traditional methods cannot detect simply. AI platforms used in precision agriculture combine remote sensing with data analytics to detect crop conditions which leads to prompt pest interferences and puts a stop to pesticide utilization (Jeyalakshmi, Vijay et al. 2024). Biological control agents particularly parasitoids and predators gain efficiency through AI predictions of their performance under different environmental conditions throughout the process of managing pests in sericulture (Sujatha, Kumar et al. 2024). The Insecticide Activity Prediction (IAPred) model represents AI-based possibilities for evaluating compounds' insecticidal activity while starting a more extensive evaluation of biological control agent potential (Cui, Li et al. 2024). The YOLOv8 deep-learning model demonstrates success in accurate pest species identification for deploying correct biological control agents per recommendations from (Butera, Ferrante et al. 2021). The detection and management of insect predators and parasitoids caused by human activities require AI to maintain positive pest control functions without harming native ecosystems (Fenn-Moltu, Liebhold et al. 2024). AI enhances biological control agent deployment process by enabling specific identification and placement while making predictions about agent-pest-environment influences which leads to better sustainable agricultural methods.

5. Challenges and Limitations of AI in Pest Management

The successful development of AI pest management models requires high-quality accurate data along with sufficient availability because these factors determine both model reliability and performance results. The formation of solid AI models is hindered by the insufficient quantity and incomplete nature of pest-related and climate data. Diverse agricultural conditions make it difficult for such models to provide reliable and generalized results (Yang, Ma et al. 2024). Data quality emerges as a fundamental factor because inappropriate data quality leads to wrong pest detection by describing the requirement for high-quality image data in electronic traps and deep learning models for precise pest identification (León García, Palomares Muñoz et al. 2024). Sensor-based electronic traps linked with deep learning technologies require adaptive algorithms to process various pest species because dataset availability often represents a restriction (Passias, Tsakalos et al. 2024). AI models using YOLO and Detectron2 for pest detection achieve their best results when trained with high-quality datasets since smaller datasets typically lead to inferior performance according to (de Almeida, dos Santos et al. 2024). Data management challenges in AI application development with their impacts on data scarcity and quality issues are established in research (Li, Zhang et al. 2024). Thus better data collection and management strategies need to be developed to enhance model results. (Chaouche, Randon et al. 2024). The implementation of DQM library standard metrics enables assessment and enhancement of AI model datasets to ensure adequate quality standards for pest management applications. The improvement of AI model reliability in pest management depends on proper resolution of these data-related difficulties which leads to better sustainable agricultural outcomes. (Mittal, Gupta et al. 2024).

AI models in agriculture encounter major obstacles while managing diverse conditions between regions and pest varieties and climates because the systems cannot deal with generalization or data diversity problems. The power of these agricultural optimization models diminishes because they fail to apply knowledge across diverse pest species and different geographical areas because sufficient high-quality data is difficult to attain. The precision agriculture systems implemented by Artificial Intelligence have limited effectiveness in unfamiliar regions because they rely on remote sensing and weather forecasting data but experience performance degradation when specific local data is difficult to obtain (Tanna, Jatakia et al. 2024). artış in AI weather model processing speed and accuracy has not eliminated their inability to adjust to natural environmental changes and changing climate patterns. The platform demonstrates global-mean cold bias during future weather state predictions because it fails to correctly extrapolate past training scenarios (Rackow, Koldunov et al. 2024). The capability of AI models in pest management for predicting unusual pest behaviors becomes diminished because of scarce commercial pesticide information which limits both effectiveness and ability to generalize (Yang, Ma et al. 2024). The inclusion of information about insect toxicity proves beneficial but model generality

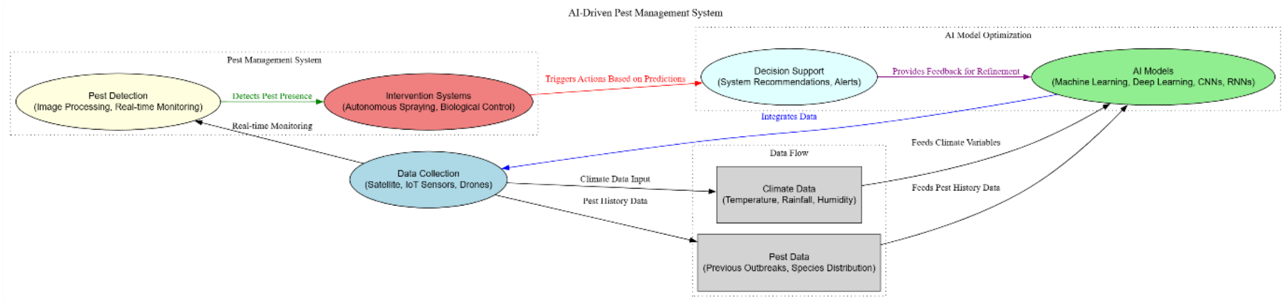

Fig. 1.2: Integrated AI Model for Pest Control and Decision Support

continues to present difficulties. The secure partnership between AI and precision agriculture methods like drone systems and remote sensing technologies resulted in major progress yet financial cost along with lack of qualified staff and limited infrastructure prevents global deployment especially in rural territories. (Sethuramalingam and Perumal 2022). The present shortcomings of Artificial Intelligence do not hinder its ability to advance sustainable agriculture since it aids farmers in precise resource allocation and environmental protection. (Yalamati 2024). AI needs to solve the problems related to different data types and universal model applicability to achieve its maximum effectiveness in agricultural systems across varied conditions.

6. Future Directions and Research Opportunities

Using climate and pest data and socio-economic information together with AI models for pest prediction creates tremendous prospects to raise model accuracy and agricultural decision-making results. The joint operation of cloud computing with IoT and AI lets organizations collect big data that leads to real-time analytical capabilities needed for useful pest monitoring. Automated systems that include remotely configurable electronic traps produce superior pest population data that merges well with additional datasets to strengthen pest prediction models. For complete pest dynamics comprehension researchers must incorporate numerous datasets which include climate information. Predictive AI systems that operate using environmental and economic data enable them to forecast climate systems which lead to changes in pest numbers and farm production levels. The IAPred model represents AI applications in agriculture that boost insecticide development efficiency because it predicts insecticidal activity to support environmentally friendly pest control methods. AI-based integration with traditional methods of data assimilation for weather forecasting led to higher prediction accuracy which confirms that similar accuracy improvements are possible when AI connects with traditional pest monitoring procedures. The predictive power of agropreneurship through data-driven approaches gets strengthened when farmers use multiple sources of data for better decision support while managing resources efficiently. Using AI models with multi-source information creates a complete method to predict pest behavior patterns which results in enhanced and evidence-based pest management solutions.

Artificial intelligence through decision support systems enables farmers to control pests in real time which boosts their situational decision-making abilities in pest management. There are two key aspects to these systems because they utilize AI technologies including computer vision together with machine learning and predictive analytics to do automated pest identification and control recommendations and risk forecasting. AI predictive models for pest control operating at 85–90% accuracy success rates have managed to diminish pest damage between 20–25%. The pest detection system Plantix from PEAT combines accurate professional diagnostic services with satellite-based Farm Shots services that monitor crops and predict weather to optimize operational resources and decrease operational risks. The mutual connection between AI systems and IoT networks with autonomous equipment results in real-time observation and exact intervention solutions that increase production output and cut operational expenses. Small-scale farmers throughout developing regions face difficulties due to poor data quality and expensive hardware implementation and insufficient infrastructure. AI systems require three essential features to break through current barriers including effectiveness and adaptation capabilities and user-friendliness as well as mobility for handling real-world data across different conditions. AI systems make existing precision irrigation systems together with fertilization technology yield up to 5–15% higher crops with much smaller water and fertilizer usage. The future agricultural sector can achieve better efficiency along with sustainability through improved pest management with AI systems development that would help sustainable food security and environmental sustainability efforts.

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