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Review Article

Recent advances in insect pest management strategies emphasizing on Artificial intelligence: A overview

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Abstract

Insect pests pose a serious threat to agricultural production and food security, accounting for 30–40% of yearly crop losses worldwide. Conventional pest control techniques are often labour-intensive, ineffective, and unable to adapt to the changing habits of pests. By enhancing pest identification, classification, and management through the application of sophisticated algorithms, sensor technologies, and predictive modelling, Artificial intelligence (AI) provides a game-changing solution. AI-powered methods minimize financial losses and promote sustainable agriculture by enabling early pest detection, reducing pesticide overuse, and facilitating data-driven decision-making. This paper provides a comprehensive examination of AI and smart sensor applications in pest management, highlighting their contributions to crop monitoring, environmental assessment, and resource efficiency. Weather monitoring systems, crop health sensors, automatic irrigation controllers, and soil sensors are some of the key technologies covered. Furthermore, the potential of innovations such as sensor fusion, hyperspectral imaging, and drone-based sensing to enhance real-time agricultural data collection and decision-making is investigated. It also examines how the Internet of Things (IoT) and AI-driven analytics might be integrated into precision agriculture to maximize pest control, fertilization, and irrigation. AI and smart sensors support sustainable pest management and robust agricultural ecosystems by facilitating effective resource use and reducing environmental impact. This review emphasizes how important AI and smart sensor technologies are to improving precision farming and bolstering global food security.

Keywords: Artificial Intelligence (AI), Integrated pest management, Nanopesticide, Weak AI precision farming

INTRODUCTION

Integrated pest management (IPM), is a comprehensive strategy that guarantees efficient, ecologically friendly, and socially conscious pest control. Food production is improved, farmer revenues are increased, and the ecological effect is reduced. Limited farmer involvement and knowledge of IPM principles, however, continue to be problems. The impact of global trade, consumer demands for sustainable food, and technological advancements are all incorporated into a modernized IPM model to address these gaps (Angon *et al*., 2023). Identification of pest control options, utilization of resources and expertise, facilitation of data-driven decision-making, and promotion of broad adoption through outreach are important elements. This strategy promotes a sustainable food system by striking a balance between environmental, social, and economic concerns. Agriculture can become more sustainable, raise farmer incomes, and increase global food security by rearranging IPM (Rossi *et al*., 2023; Deguine *et al*., 2021).

Use of nanopesticides in integrated pest management

In comparison with traditional pesticide formulations, nanopesticides may offer several benefits, including enhanced effectiveness, reduced environmental impact, and targeted delivery to specific pests or plant tissues (Scheff *et al*., 2022). For instance, the stability, solubility, and controlled release of pesticide active components can be enhanced by nanoencapsulation, which reduces the quantity of pesticide required and minimizes off-target effects (Kumar *et al*.,2019) Moreover, pesticides can be more effectively and locally controlled by using nanoformulations to improve their translocation and penetration into plant tissues (Wang *et al*., 2022; Arcot, *et al*., 2024). Innovative pest management options are provided by nanopesticides, which combine nanomaterials such as silica, titanium dioxide, lipid-based carriers, and polymeric nanoparticles. The use of pesticides has decreased significantly, and pest management has improved thanks to Integrated Pest Management (IPM) techniques, which include the use of resistant cultivars, such as Bt cotton. Insect resistance concerns, however, emphasize the necessity of effective resistance control. To guarantee that pest management methods are economical and avoid overusing pesticides while preserving crop health and sustainability, IPM frameworks rely on Action Thresholds (ATs) and Economic Injury Levels (EILs) (Lang *et al*., 2021; Campos *et al*., 2023; Bueno *et al*., 2022).

Monitoring and decision making

Techniques for scouting and sampling are essential components of IPM programs' monitoring and decision-making processes (Hong *et al*., 2021; Wang *et al*., 2023).In addition to these sampling approaches, several instruments and methods are used to track pest populations and the damage they cause to crop plants. These methods include visual inspection, the use of sweep nets, sticky traps, pheromone traps, and remote sensing technologies (Pinto *et al*., 2023; Singh *et al*., 2023).

Unmanned aerial vehicles (UAVs), satellite imaging, and aerial photography are examples of remote sensing techniques that are being utilized more and more to track crop health and identify insect outbreaks on a wide geographic scale (Hadi *et al*., 2021; Rydhmer *et al*., 2022; Olson *et al*., 2021).

IPM practitioners are empowered to make data-driven decisions about the necessity and timing of pest control actions by integrating various monitoring tools and methodologies with suitable sampling designs. IPM has recently leveraged the development of artificial intelligence (AI) for identification and decision-making. According to Batz *et al*., AI can enhance aphid pest forecasting in several ways. 1) optimal insect identification using image recognition and deep learning, 2) forecasting model based on neural networks and machine learning, and 3) monitoring infrastructure optimization to enhance predictive models (Hunter III *et al*., 2020). In IPM decision-making, action thresholds (ATs) and economic injury levels (EILs) are crucial instruments (Hafeez *et al*., 2023; Batz *et al*., 2023; da Silva *et al*., 2021). When pest control procedures are economically justified, they help farmers and pest management experts make that determination. ATs are set at a lower pest density to keep populations from reaching the EIL, whereas EILs reflect the pest population density at which the cost of crop damage equals the cost of management (Cárcamo *et al*., 2024; Penca *et al*., 2020; da Silva *et al*., 2021).

One of the main causes of agricultural harm worldwide is recognized to be insect pests. Agricultural losses can be reduced by managing and preventing insect pests (Cárcamo *et al*., 2024). This activity requires accurate detection and classification of insect pests to distinguish between species, estimate the quantity of pest management equipment needed, and identify the various host species (Penca *et al*., 2020). Interest in automatic insect pest recognition has grown recently since this activity requires costly, continuous monitoring. The traditional approach to insect pest monitoring relies on subject matter specialists to manually identify, which is labour-intensive, prone to error, and applicable to a wider range of applications (Ahmed *et al*., 2018; Oliveira *et al*., 2014; Ding *et al*., 2016). Additionally, the careless use of pesticides frequently has the unintended consequence of harming ecosystems and beneficial organisms. AI offers a revolutionary solution to these problems, enabling the implementation of targeted treatments that maximize effectiveness while minimizing ecological impacts (Li *et al*., 2021; Sun *et al*., 2018; Sharma *et al*., 2020). A new approach to automatic pest detection and monitoring in contemporary agriculture is provided by implementing AI through computer vision that is integrated with cameras and internet connections. This significantly enhances the effectiveness of insect surveillance in agricultural systems (Preti *et al*., 2021).

Artificial Intelligence (AI) powered pest management: Revolutionizing forestry and agriculture

The field of pest management in forestry and agriculture has become a promising area for the successful application of AI technology, providing innovative solutions that are more accurate, efficient, and environmentally friendly (Streich *et al*., 2020). AI-related theories and technologies, such as Smart Pest Monitoring (SPM), have emerged as a new scientific area within Integrated Pest Management (IPM) due to the rapid advancement of Artificial intelligence in research (Partel *et al*., 2019). By combining artificial crops intelligence (AI), the Internet of Things (IoT), big data, and other modern information technologies and tools, the SPM seeks to improve the ability of pest monitoring and early warning while also advancing the autonomous and intelligent data gathering of important insect pests (Li *et al*., 2021). The decision-making process regarding management actions, such as pesticide spraying and other procedures, is aided by the identification and detection of insects to count and analyze their density using relevant theories (Iqbal *et al*., 2018). Machine learning, computer vision, and data analytics are just a few of the many techniques that comprise artificial intelligence (AI), enabling the analysis of large, complex datasets. By improving precision and forecasting accuracy, this capacity offers a previously unheard-of benefit in addressing pest-related difficulties (Patrício *et al*., 2018). Artificial intelligence and pest management, when combined, have the potential to minimize ecological impact, optimize resource use, and reduce dependency on chemical treatments (Doe *et al*., 2023). Artificial intelligence in pest management has a promising future, but several obstacles remain to be overcome, including concerns about data privacy, legal compliance, and the need for multidisciplinary cooperation among disciplines such as computer science, ecology, and agronomy (Hanif *et al*., 2022).

To ensure broad benefits across various agricultural landscapes, it is also crucial to verify fair access to Artificial intelligence technology for small-scale farmers and areas with limited resources (Uzhinskiy *et al.,* 2023). The application of Artificial intelligence has great promise for transforming the control of insect pests in horticulture, forestry, and agriculture. Stakeholders can successfully mitigate pest risks, enhance productivity, and promote environmental sustainability in food and fibre production systems by leveraging AI-driven insights and solutions (Pandey *et al*., 2024). The security of global food systems can be ensured while reducing their ecological footprint by utilizing AI to transform pest control from a reactive to a proactive and intelligent approach (Kanwal *et al*., 2022).This review examines the various facets of AI's role in pest management. Through an analysis of technical developments, this investigation examines the benefits and limitations of AI, as well as how AI-driven systems support sustainable agricultural practices, early pest identification, and informed decision-making.

Artificial intelligence in modern agriculture: Enhancing sustainability and productivity

The foundation of human civilization, agriculture has provided food, raw materials, and employment. However, it faces numerous challenges today, including resource management, pest infestations, climate change, and soil degradation. Artificial Intelligence (AI) has emerged as a transformative force in agriculture, helping farmers increase sustainability, reduce costs, and optimize productivity. Artificial Intelligence is categorized using various methods, including functionality, learning methodology, and application domain. First, the Artificial intelligence was separated into two main divisions according to its functionality: narrow AI (weak AI), which handles one or a small number of tasks. It lacks overall intelligence, despite being quite good at what it does. Virtual assistants, picture recognition systems, and recommendation algorithms are a few examples. Weak AI is frequently utilized in modern farming to perform specialized tasks, including yield prediction, insect control, and crop monitoring. Sensors, big data analytics, and machine learning algorithms are the foundation of its operation (Zhang *et al*., 2018).

Weak Artificial intelligence (Weak AI or Narrow AI) in agriculture

Agriculture is one of the most critical sectors for ensuring food security and economic stability worldwide. Farmers, however, face various challenges, including climate change, soil erosion, water shortages, and unstable market demands (Wolfert *et al*., 2017). AI, specifically Weak AI, has become a revolutionary force, streamlining farming operations through data-driven insights and automation. The use of Artificial Intelligence (AI) in contemporary agriculture has led to significant improvements in efficiency, precision, and sustainability. Weak AI (Narrow AI), created for a single purpose, has been instrumental in automation, predictive analysis, and real-time decision-making in agriculture. This report examines the applications, benefits, and drawbacks of Weak AI in agriculture, supported by empirical examples and scholarly research.

Weak AI systems are tailored to particular tasks, including:

Precision farming (soil health and crop monitoring)

To enhance maximum soil health and crop observation for increased agricultural performance, precision farming makes use of advanced technologies such as remote sensing, GPS mapping, Internet of Things (IoT) sensors, and artificial intelligence (Patel *et al*., 2025). Using soil sensors to gauge critical properties such as moisture levels, pH levels, and nutrient levels in real-time, farmers can effectively control fertilizer and irrigation (Bandgar & Biradar, 2024). Drone and satellite imagery high-resolution data deliver crop health information that can detect stressors like pest attack, nutrient deficiencies, and water stress before they intensify (Gupta *et al*., 2025). Based on the analysis of such data, machine learning models deliver forecasted information that supports targeted interventions that have reduced environmental footprints, higher yields, and less waste (Bassine *et al*., 2023). Aside from boosting productivity, this data-driven approach encourages sustainable agriculture through resource conservation and reducing excessive chemical use, ensuring long-term ecosystem and soil fertility stability in the end.

Pest and disease identification (image recognition and predictive analytics)

A novel technique for detecting pests and diseases using machine learning, computer vision, and artificial intelligence (AI) to detect and manage agricultural threats is image recognition and predictive analytics (Zhao *et al*., 2024). Through deep learning models, including convolutional neural networks (CNNs), image recognition technology examines crop images and employs morphological characteristics, color variations, and visual patterns to detect pests or diseases (Brahimi *et al*., 2023). For improved accuracy and adaptability across numerous plant species and weather conditions, such systems are often taught big datasets that have thousands of labeled images (Ferentinos, 2018). Predictive analytics, by contrast, applies real-time sensor readings, past data, and weather patterns to predict the probability of disease occurrence or insect infestations (Kamilaris & Prenafeta-Boldú, 2018). When combined, both technologies enable early warnings to farmers and agricultural experts, allowing them to adopt preventive measures like crop rotation, precision pesticide application, or biological pest control. This combination conserves loss of crops, decreases the use of chemicals, and promotes sustainable agriculture practices, in addition to enhancing precision in pest and disease control. To smallholder farmers and large agribusinesses, this technology is accessible and scalable because of real-time monitoring facilitated by mobile apps and drone surveillance systems with AI-based recognition platforms. Accuracy, efficiency, and integration of the identification of pests and diseases with intelligent farming ecosystems will all grow in the future as the study of AI models and data collection continues.

Intelligent irrigation (Efficiency in using water)

By merging intelligent technology such as artificial intelligence (AI), data analysis, and the Internet of Things (IoT), smart irrigation is an innovative approach that optimizes water utilization in agriculture (Niu *et al*., 2023). Because of overuse, inefficient dispensation, and insufficient real-time tracking, conventional irrigation methods are prone to wastage of water. These problems are fixed by smart irrigation systems, which employ remote sensing, weather forecasting, and soil moisture sensors to accurately calculate the right quantity of water crops need at any time (Adeyemi *et al*., 2024). In order to automate watering schedules and have water supplied efficiently and only when required, AI-based algorithms interpret real-time data about the soil, water needs of plants, and climatic conditions (Raza *et al*., 2023). Additionally, monitoring through drones and satellite images are able to analyze plant health by determining the levels of stress that point towards excessive moisture or deficiency of water (Patel *et al*., 2025). Smart irrigation optimizes crop yields in agriculture, minimizes erosion of the soil, and saves energy for pumping and distribution, while also saving a precious resource by reducing water wastage and optimizing distribution. Applying intelligent irrigation systems is increasingly vital for sustainable and resilient agriculture as worries about water shortage and climate change grow.

Market forecasting (examining market trends for more informed pricing)

Producers, suppliers, and farmers can make informed production and price decisions using market forecasting, an important agriculture tool that uses data analytics, machine learning, and economic models to forecast market trends (Zhang *et al*., 2024). Market forecasting assists in anticipating future price movements by studying historic price information, supply and demand fluctuations, shopper behavior, and extrinsic conditions like weather conditions, trade policies, and international commodity trends (Nair & Jain, 2023). In order to analyze enormous amounts of real-time data and find patterns and relationships not discernible using traditional analysis, sophisticated prediction models use artificial intelligence (AI) and big data analytics (Li *et al*., 2024). In addition, satellite imagery and remote sensing have the capability to offer current data regarding crop health globally, helping in predicting supply shortages or surpluses that affect market prices (Karthikeyan *et al*., 2023). Through facilitation of strategic thinking for trade regulations and food safety, market forecasting also benefits policymakers. Farmers and agribusinesses can assist in developing a more stable and efficient agricultural market, reduce financial risks, and boost profitability by leveraging technology-based forecasting methods.

Although General AI (Strong AI) is still in its theoretical phases, Weak AI is already extensively used in actual agricultural practices (Kamilaris & Prenafeta-Boldu, 2018).

Artificial intelligence's revolutionary effect on modern agriculture

Artificial intelligence (AI) is transforming contemporary agriculture (Liakos *et al*., 2018; Sharma, 2023). Narrow AI already enhances agriculture using predictive modeling, automation, and real-time analysis (Kamilaris & Prenafeta-Boldú, 2018). AI-driven hardware that maximizes irrigation, planting, and crop tracking technologies includes drones, satellites, IoT sensors, and smart tractors from John Deere (Patel *et al*., 2025). Whereas intelligent irrigation systems such as NetBeat enhance water efficiency through integrating soil and weather information, AI-based pest and disease management

Table 1. Artificial intelligence (AI) based strategies for insect pest management

AI-Based Strategy	Mechanism Of Action	Applications	Core Benefits	Examples of AI-Powered Tools	Target Insect Pest(s)	Supporting References
Smart Sensor networks	In addition to monitoring temperature and humidity, IoT-enabled sensors use motion, sound, and pheromone-based traps to identify insect activity.	Pest population tracking, ongoing field surveillance, and automated alerts for early pest identification	Reduced pesticide use, real-time monitoring, early identification, and cheaper expenses.	Semios (pheromone sensors powered by AI)	Corn borers, fruit flies, and codling moths.	Eze et al., 2025
Automated Drones using AI and Computer Vision	Drones and cameras using artificial intelligence (AI) take pictures of crops, then use image recognition to determine the extent of damage and detect the presence of pests.	Early-stage detection, mapping of affected areas, and extensive pest identification	Minimal crop damage, precision pest management, and decreased reliance on manpower	Precision Hawk (pest monitoring via drone)	Grasshoppers , armyworms, and locusts.	Bai et al., 2023
AI-Powered Automated Pest Traps	Smart traps using cameras, sensors, and artificial intelligence (AI) algorithms automatically provide data while identifying and classifying pests they have trapped	Analysis of population density, intelligent pest management, and non-chemical pest control.	Eco-friendly approach, reduced reliance on pesticides, real-time pest population monitoring.	Trapview (AI-powered automated pest trap)	Stink bugs, beetles, and fruit flies.	Hinojosa-Dávalos et al., 2025
Big Data & Cloud Computing	AI provides insights into pest management by integrating data from several sources, including field sensors, satellite	AI-assisted pest management suggestions and remote pest monitoring.	Enhanced resource efficiency, data-driven decision-making, and real-time risk assessment	Climate Corporation (AI-powered disease and pest prediction)	Cutworms, Weevils, and Thrips.	Dawn et al., 2025
Decision Support Systems with AI Integration (DSS)	AI-powered systems examine pest patterns and recommend the best use of pesticides, biological control techniques, and other forms of intervention.	Action plans, pest alarms, and smart agricultural dashboards via mobile apps.	Lower environmental impact, more economical farming, better decision-making, and higher agricultural output.	Plantix (a pest detecting mobile app)	Leaf miners, spider mites, and caterpillars	Marinko et al., 2024
Pest-Resistant Genetic AI Models	AI analyzes plant DNA responses to pest invasions, which helps with genetic engineering research to create crop varieties resistant to pests.	Creation of crops resistant to pests and environmental friendly pest management techniques.	Long-term insect resistance, decreased reliance on chemicals, and improved crop resilience.	The genetically modified pest-resistant crop known as BASF's InVigor Canola	Bollworms, Stem borers, and root maggots	(Ma et al., 2025

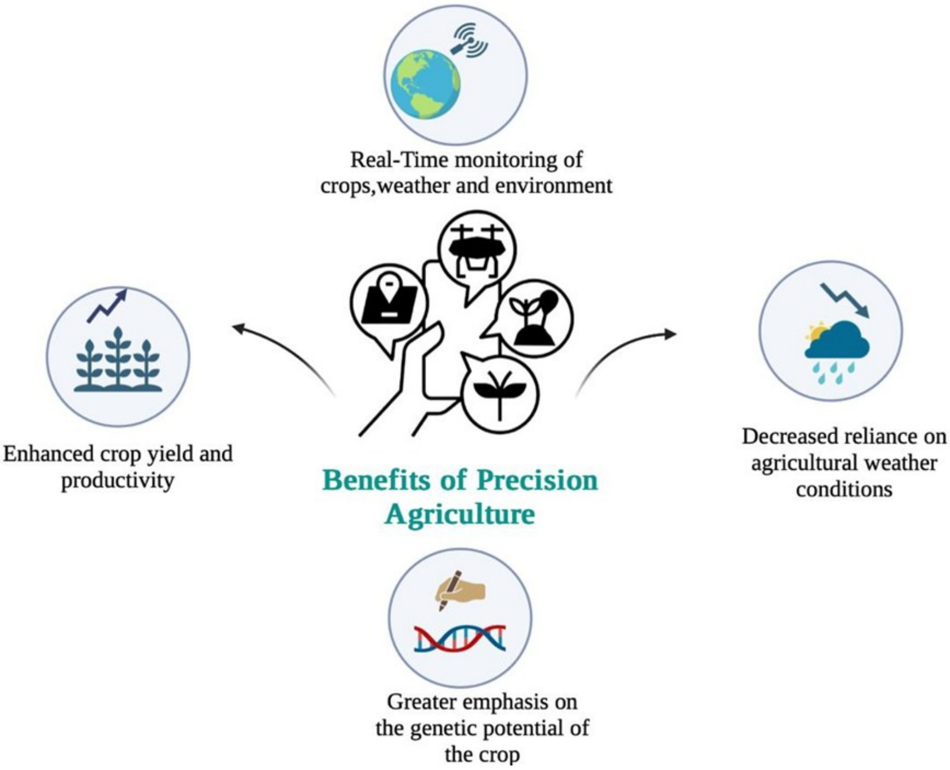

Fig. 1. *Precision agriculture enhancing efficiency*

technologies such as Plantix facilitate early diagnosis of problems. AI-based market forecasting strengthens price forecasts and supply chain management (Zhang *et al*., 2024). General AI can potentially develop improved climate adaption strategies, enhance autonomous farming, and aid decision-makers in ensuring the sustainability and security of food in the future. AI can also result in virtual agronomists for on-the-spot farming guidance and genetic engineering advancements such as CRISPR-based crop modification. AI in agriculture also has tremendous potential for enhancing resilience, sustainability, and efficiency in the future but ensuring its benefits widely reach will need to address cost, accessibility, and ethics concerns.

Using Precision technology to address global agricultural challenges: Smart farming for a growing world

A revolutionary approach to contemporary agriculture, precision ag. riculture—also referred to as smart farming or precision farming—has arisen to solve the urgent global issues of resource efficiency, environmental sustainability, and food security. Precision agriculture allows farmers to precisely customize inputs and interventions to meet the demands of individual plants or fields by integrating smart sensors to monitor and evaluate particular characteristics of crops, soil, and environmental conditions. Precision farming has several potential advantages. Initially, it promises to drastically boost crop yields and overall production while cutting down on resource waste (Akaka *et al*., 2023). In addition, precision agriculture promotes sustainable and ethical agricultural methods by reducing environmental effects and maximizing resource utilization (Zaman and Q. U., 2023). Moreover, resilience to climatic variability is improved by anticipating and adapting to changing environmental conditions, which increases the sector's capacity to endure the difficulties brought on by global climate change.

Role of Smart sensor technologies in advancing modern agriculture

In a bid to change the way food is produced and cope with numerous challenges in the agricultural sector today, smart sensor technologies need to be embraced in modern agriculture (Shanmugasundaram *et al*., 2023). These advanced sensors, with their modern capabilities and connectivity with cutting-edge technology, offer many benefits that underpin stronger, more efficient, and sustainable farming practices (Shanmugasundaram *et al*., 2023). Smart sensors provide precision, real-time information on key areas like crop well-being, nutrient status, soil water, and environmental factors (Malik *et al*., 2020). It state that the presence of such precise and timely information allows farmers to design their practices exactly according to crop needs and make efficient decisions. Through precision agriculture practices — where each area of the field is managed based on its own requirements — farmers can optimize the use of resources, minimize waste, and boost total output (Malik *et al*., 2020).

Enhancing Agricultural sustainability and climate resilience through Smart sensor technologies

This minimizes wastage and ensures that inputs are used where and when they are most required by facilitating targeted use of water, fertilizers, and pesticides (Suman *et al*., 2023). With the world's growing population and limited natural resources, efficiency in using resources is paramount. Through the provision of precise scheduling of irrigation, better application of nutrients, and tracking of environment conditions to prevent wasteful practices, smart sensors play a crucial role in improving resource efficiency (Aarif *et al*., 2025). Enabling environmentally sound and sustainable agriculture by conserving energy, water, and fertilizer, smart sensor technologies are promoted (Aarif *et al*., 2025). Early indication of diseases, pests, and stressors can be identified with the help of smart sensors in crop health monitoring, allowing prompt action. Rapid detection and response to potential threats minimize yield losses and prevent disease spread, reducing dependence on chemical application while promoting overall crop health (Mukherjee *et al*., 2024). Smart sensors also enable the development of climate resilience as climate change keeps impacting agricultural productivity. Farmers are able to adjust their practice in accordance with changing climatic patterns by tracking weather, soil water holding capacity, and other climatic conditions (Aarif *et al*., 2025).

Leveraging Smart sensor technologies for sustainable agriculture and global food security

This flexibility ensures consistency in agricultural production and enhances the sector's resistance to extreme weather conditions (Chen *et al*., 2023). Intelligent sensors produce voluminous amounts of data which, when combined with data analytics and artificial intelligence, offer actionable insights into farm management and crop yields optimization (Chaudhary & Singh, 2025). The analytics allow for trend analysis, predictive modeling, and customized recommendations to boost agriculture practice and profitability (Ali et al., 2025) The development of sensor technology has brought about cost-effective and accessible solutions that are within the reach of smallholder farmers, giving them access to innovative farming methods. Encouraging efficient resource use, smart sensors aid in supporting sustainability by minimizing chemical use, conserving water, and healthier soils (Liu *et al*., 2025). In addition, smart sensors provide for the early detection of pests and diseases by providing real-time crop health information, allowing instant intervention and minimized use of chemical controls (Mansoor *et al*., 2025). In a world with food security and environmental threats, integrating smart sensor technology in contemporary agriculture is critical to improving productivity, sustainability, and resilience.

Future perspectives

AI-based pest control is shifting towards edge AI systems integrated within traps, UAVs, and farm gateways to facilitate real-time decision-making without full dependence on cloud computing. Initial tests pairing IoT sensors with embedded AI chips have shown fast pest detection and intervention functions (Al-Haddad *et al*., 2025). At the same time, intelligent pheromone traps and UAV-assisted monitoring pipelines are enhancing the accuracy of small-insect recognition, making timely and targeted pest management possible with minimal pesticide application (Zhang *et al*., 2025; Li *et al*., 2025).

A further developing field is the application of digital twins to crop–pest ecosystems—virtual representations that combine real-time sensor streams and predictive models to model management options prior to application in the field (Gutiérrez *et al*., 2024; Zhai *et al*., 2023). Such systems will allow for optimization of intervention timing, resource deployment, and cost–benefit planning (Rahman *et al*., 2024).

Scaling these technologies, however, involves overcoming challenges like dataset imbalance, regional variability, data governance, and farmer adoption (Kour *et al*., 2025). Solutions lie in federated learning to enable updates on AI models without raw data transfer, explainable AI to foster trust, and human-in-the-loop systems that integrate AI analytics with human expertise (Kour *et al*., 2025; Khan *et al*., 2025). Combined, these advances in edge AI, intelligent monitoring devices, and digital twin technology hold the potential for more sustainable, efficient, and responsive pest management in the future.

Conclusion

By limiting crop damage, decreasing the environmental impact, and optimizing pesticide usage, AI-driven pest management enhances efficiency. Precision farming, which increases production and sustainability, is made possible by smart sensors and predictive analytics. Food security and resource optimization rely on AI advancements, despite ongoing issues such as cost and accessibility. AI will propel global agriculture toward a more sustainable and effective future as technology develops. This review highlights the importance of smart sensors in enhancing agricultural sustainability, improving production, and optimising resources. Their combination of IoT, AI, and data analytics provides creative answers to problems related to environmental preservation and food security. The key to guaranteeing broad adoption will be removing implementation obstacles via cooperation and information sharing. Smart sensors will continue to revolutionise contemporary farming as technology advances, facilitating precision farming and enabling the development of robust, sustainable food production systems. The combination of smart sensor technologies, IoT, AI, and data analytics has tremendous potential to improve food security and environmental sustainability. Widespread acceptance depends on overcoming implementation obstacles via cooperation and knowledge exchange. Through the use of real-time data and sophisticated analytics, farmers can enhance yields, optimise resource management, and implement more sustainable farming practices. Future prospects for precision farming are enormous, as it promotes increased production, enhanced efficiency, and improved resilience. As technology advances, smart sensors will be crucial in developing farming systems that are both flexible and sustainable, thereby meeting the demands of a changing environment and an expanding global population.

Conflict of interests

The authors declare that they have no conflict of interest.

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