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Artificial Intelligence Driven Insect Pest and Disease Management: Innovations, Challenges and Future Prospects

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Abstract

This paper reviewed the current applications of AI in insect pest management and critically examined associated challenges such as limited availability of high-quality datasets, variability in field conditions, and restricted model generalization across crops and agro-ecological regions. Insect pests represented a major constraint to global agricultural productivity, food security, and ecosystem stability. Conventional pest management approaches largely depended on manual field surveillance and non-selective chemical control, which were often labour-intensive, environmentally hazardous, and limited in precision. These traditional methods also frequently resulted in delayed detection and excessive pesticide application, further aggravating environmental and economic concerns. Recent advances in Artificial Intelligence (AI) provided innovative opportunities to overcome these limitations by enabling automated pest detection, accurate species identification, outbreak forecasting, and real-time decision support. AI-based technologies, including machine learning, deep learning, computer vision, remote sensing, and Internet of Things (IoT) platforms, have significantly improved the efficiency and reliability of pest monitoring and management systems. These tools facilitated early warning, site-specific interventions, and optimized resource utilization, thereby supporting sustainable pest control strategies. In addition, AI-driven analytics supported data integration from multiple sources, enhancing predictive accuracy and adaptive management approaches. Future prospects, including the integration of explainable AI, autonomous precision robotics, and AI-driven Integrated Pest Management (IPM) frameworks, were also discussed. The effective incorporation of AI into pest management systems had substantial potential to reduce pesticide dependence, enhanced crop health, and improved resilience to climate-induced shifts in pest populations, contributing to the advancement of sustainable and climate-smart agriculture.

Keywords: Insect pest management, artificial intelligence, machine learning, deep learning

1. Introduction

Global agricultural systems are increasingly challenged by climate variability, resource constraints, pest outbreaks. Among these challenges, insect pests and plant diseases represent major threats to crop productivity and ecosystem stability. Moreover, changing climatic variables influence pest phenology, host interactions, and outbreak frequency, necessitating adaptive monitoring systems and proper pest management strategies (Deutsch et al., 2018; Bebber et al., 2019; Bukhari et al., 2025). Advances in digital agriculture and computational sciences have created opportunities to modernize pest monitoring and management through AI-driven systems. Artificial Intelligence (AI) refers to the ability of machines to simulate human intelligence, encompassing tasks such as logical reasoning, learning, problem-solving, and decision-making. AI systems are designed to analyse large volumes of data, identify patterns, and generate predictive or prescriptive outputs with minimal human intervention. In recent years, AI technologies have emerged as transformative tools for improving productivity, precision, and sustainability in agriculture (Liakos et al., 2018; Kamilaris and Prenafeta-Boldú, 2018). Recent advances further highlighted the role of AI in crop protection and digital farming ecosystems (Yang et al., 2025; Chakrabarty et al., 2026). Machine learning (ML) and deep learning (DL) algorithms can analyse large datasets derived from field images, sensor networks, weather records, and remote sensing platforms to detect pest infestations, classify disease symptoms, and forecast outbreak risks with high accuracy (Ferentinos, 2018; Chlingaryan et al., 2018).

Convolutional Neural Networks (CNNs) have demonstrated superior performance in automated pest and disease detection compared to traditional feature-engineering approaches (Mohanty et al., 2016; Fuentes et al., 2017). Recent studies have reported improved classification accuracy and field applicability using deep learning architectures for pest monitoring (Venkateswara and Padmanabhan, 2025). Similarly, machine learning-based insect classification and detection systems have been successfully implemented under real-field conditions (Kasinathan and Uyyala, 2021). The integration of AI with Internet of Things (IoT) devices, unmanned aerial vehicles (UAVs), remote sensing platforms, and automated imaging systems has further strengthened precision agriculture frameworks. AI-enabled remote sensing approaches have been recognized as promising tools for large-scale pest surveillance and disease monitoring (Abd El-Ghany et al., 2020). Sensor-based predictive models have also enhanced early warning systems by integrating environmental and biological datasets. Such systems facilitate real-time monitoring, spatially explicit risk assessment, and targeted interventions, reducing uncertainty in decision-making and optimizing resource use (Wolfert et al., 2017). AI-based decision support systems (DSS) are increasingly embedded into digital platforms and mobile advisory tools to assist farmers in selecting appropriate control strategies within Integrated Pest Management (IPM) frameworks (Yang et al., 2025). Despite these advancements, several methodological and operational challenges persist. Despite these advancements, several methodological and operational challenges persist. Limited annotated datasets, environmental variability, scalability issues, and limitations in model generalisation often constrain AI model deployment in agricultural pest-monitoring systems. Interpretability and explainability remain critical concerns for farmer adoption and regulatory acceptance. Socio-economic barriers, including infrastructure limitations, digital literacy gaps, and uncertainty regarding economic returns, further influence adoption rates (Rose et al., 2021). Emerging research emphasizes the need for explainable AI, adaptive learning models, and collaborative frameworks integrating entomology, agronomy, and data science to improve real-world applicability (Chakrabarty et al., 2026). Although numerous studies have explored AI applications in agriculture, comprehensive synthesis specifically focusing on AI-driven insect pest and disease management remains relatively limited. Therefore, this paper reviewed the current applications of AI in insect pest detection, forecasting, and critically examined associated challenges such as limited availability of high-quality datasets, variability in field conditions, restricted model generalization across crops and agro-ecological regions. This paper also explored future prospects for integrating intelligent technologies within sustainable and climate-resilient pest management frameworks.

2. Machine Learning (ML)

Machine learning is a branch of artificial intelligence that allows computer systems to learn from data and generate predictions or decisions without explicit programming. It identifies patterns from labelled or unlabelled datasets, improves with increasing data availability, and often relies on feature engineering, where relevant input features are manually selected. The most commonly used ML Algorithms are Decision Trees, Support Vector Machines (SVM), Random Forests, k-Nearest Neighbors (k-NN), Linear/Logistic Regression, and Naive Bayes

3. Deep Learning (DL)

Deep learning is a subfield of machine learning that utilizes artificial neural networks with multiple hidden layers to automatically learn hierarchical and complex representations from data. It is particularly well suited for analysing unstructured data, including images, audio, and text. In contrast to conventional machine learning methods, deep learning requires minimal manual feature engineering, as feature extraction is performed intrinsically by the model. However, its effective application generally requires large, well-annotated datasets and substantial computational resources.

Common deep learning architectures include Convolutional Neural Networks (CNNs), which are extensively employed for image recognition and visual analysis; Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, which are designed for sequential and time-dependent data; Transformer-based models, which have demonstrated strong performance in natural language processing and complex sequence modelling tasks; and autoencoders and Generative Adversarial Networks (GANs), which are primarily applied in unsupervised learning and synthetic data generation.

4. AI in Pest and Disease Identification

The timely and accurate detection of pests and diseases is a fundamental component of effective pest monitoring systems. Conventional approaches relying on manual field scouting and expert-based identification are often labour-intensive, time-consuming, and susceptible to human error. Artificial intelligence (AI) provides robust alternatives to these limitations by enabling automated identification through image analysis, sensor-derived data, and predictive modelling techniques (Paul et al., 2024; Upadhyay et al., 2025).

Machine learning algorithms, particularly classification-based methods such as Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (k-NN), have been widely applied to differentiate between healthy and diseased plant tissues. These approaches typically rely on manually engineered features extracted from pest or plant images, including colour, shape, and texture descriptors. While such models have demonstrated satisfactory performance under controlled conditions, their accuracy and robustness may decline when applied to large-scale field datasets due to variations in illumination, background complexity, and pest morphology (Subburaj et al., 2025).

In recent years, deep learning techniques, especially Convolutional Neural Networks (CNNs), have increasingly outperformed traditional machine learning models in pest and disease identification tasks by automatically learning hierarchical feature representations directly from raw image data. Comparative evaluations have shown that CNN-based models generally achieve higher classification accuracy, improved generalisation capability, and reduced dependence on manual feature engineering (Upadhyay et al., 2025; Khan et al., 2025). CNNs have been successfully employed for the detection and classification of leaf diseases (e.g., blight, rust, and mildew), pest infestations (e.g., aphids, whiteflies, and caterpillars), and fungal and bacterial infections across a wide range of crops (Jain et al., 2025; Zhao et al., 2022). Widely used architectures such as ResNet, VGGNet, and Inception are commonly adapted through transfer learning approaches, allowing effective utilisation of pre-trained networks for agricultural datasets with limited labelled samples (Upadhyay et al., 2025).

Beyond individual image classification, CNN-based approaches are increasingly being incorporated into integrated pest monitoring and decision-support systems. When combined with data acquired from smartphones, unmanned aerial vehicles (UAVs), field-based sensors, and remote sensing platforms, these models enable continuous surveillance, early detection, and spatial assessment of pest and disease outbreaks (Khan et al., 2025; Zhang et al., 2025). Such AI-driven decision-support systems support timely intervention, targeted pest control measures, and optimized resource use, thereby contributing to sustainable and precision-oriented pest management practices (Zhang et al., 2025).

Multilayer perceptrons, a class of artificial neural network models, have demonstrated effectiveness for the semi-automated identification and monitoring of thrips. In such approaches, quantitative morphometric traits, including measurements of the head, clavus, wings, and ovipositor length and width, are used as input variables within a neural network framework, such as the Trajan simulator. These features are processed through multiple hidden layers to produce accurate species-level identification (Fedor et al., 2009). Although the analytical and classification stages are computationally efficient, the processes of sampling and constructing a comprehensive and representative morphometric database are comparatively more labour-intensive. Notably, the inclusion of a broad range of morphological characters enables reliable identification even in damaged specimens, for which conventional dichotomous keys are often ineffective. For optimal performance and broader applicability, artificial neural network–based methods should be integrated with multi-access identification keys, thereby enhancing flexibility and accuracy in taxonomic decision (Moritz et al., 2001). Despite their potential, the practical application of artificial neural networks (ANNs) for pest identification is subject to several limitations (Gaston and O'Neill, 2004). Intraspecific variation in thrips, particularly wing polymorphism and sexual dimorphism, can complicate accurate identification and subsequent management decisions.

Nevertheless, substantial evidence suggests that precise and reliable pest monitoring systems can deliver significant benefits for farmers and agricultural policy while minimizing negative impacts on biodiversity, reducing dependence on costly inputs, and avoiding adverse implications for human well-being (Paul et al., 2024; Khan et al., 2025). The adoption of ANN-based approaches is therefore associated with improved targeting and control of economically important pests, contributing to the prevention of severe crop losses. AI technologies are also increasingly integrated into decision support systems for Integrated Pest Management (IPM). These AI-driven systems analyse multiple datasets, including weather parameters, pest population dynamics, and crop growth stages, to provide optimized recommendations for managing pests and diseases such as aphids, rust, blotch, and powdery mildew in cereal crops (Tratwal et al., 2025; Zhang et al., 2025). Overall, these diverse applications highlight the significant potential of AI in transforming pest and disease surveillance, enabling timely interventions, and promoting sustainable crop protection practices.

5. Computer Vision Technology

Computer vision is a field that includes methods for acquiring, processing, analysing, and understanding images, known as Image analysis and image understanding. It duplicates the ability of human vision by electronically perceiving and understanding an image. Image data can take many forms, such as a video sequence, depth images, views from multiple cameras, medical scanners, satellite sensors, etc. AI-based computer vision systems use high-resolution imagery (from smartphones, drones, or fixed cameras) to detect and classify symptoms such as lesions, discolouration and pest damage (Upadhyay et al., 2025). These systems are deployed in Precision agriculture for continuous monitoring, Mobile apps for farmer-level diagnosis and Autonomous robots for in-field scouting (Zhang et al., 2025; Khan et al., 2025).

Despite these promising results, several challenges remain in the effective deployment of AI-based pest and disease management systems. One of the primary constraints is the scarcity and imbalance of high-quality datasets, particularly for rare pests and emerging diseases, which limit model training and reduce predictive robustness (Kamilaris and Prenafeta-Boldú, 2018; Li et al., 2023). Additionally, significant variability in real-field conditions, including differences in lighting intensity, background noise, occlusion, and overlapping symptoms among pests and diseases, often affects detection accuracy and model reliability (Zhao et al., 2022; Upadhyay et al., 2025).

Another major limitation is the restricted generalisation capability of AI models across diverse crop varieties, growth stages, and geographical regions, as models trained under specific conditions often fail to perform consistently in new environments (Khan et al., 2025). Furthermore, the limited explainability of complex AI algorithms poses challenges in building trust among farmers, extension personnel, and other non-technical stakeholders, thereby influencing adoption and practical implementation (Zhang et al., 2025). Machine vision with artificial intelligence can identify key visual attributes of citrus groves associated with pests, diseases, physiological events and disorders (Schumann et al., 2018).

6. Drone Technology

In aviation and in space, a drone refers to an unpiloted aircraft or spacecraft. Companies such as Skymet are using drones to provide agricultural survey services in India. Drone imagery is very useful in giving an accurate estimate of loss. Drones with infrared, multispectral and hyperspectral sensors can analyse the crop health (Tsouros et al., 2019; Zhang et al., 2025).

Drones for monitoring pests and diseases: Drone-based imaging enables the detection and spatial mapping of disease incidence, such as mildew infections in vineyards, allowing for the assessment of severity and the development of targeted phytosanitary interventions (Bouroubi et al., 2018). The integration of deep learning techniques with drone imagery has facilitated the development of advanced image-based applications that are difficult to achieve using conventional image processing methods (Khan et al., 2025). Moreover, GPU-based processing enables near real-time analysis, making these systems suitable for operational use in precision agriculture (Zhang et al., 2025).

Drones for spraying: In 2015, the Federal Aviation Administration approved the Yamaha RMAX as the first drone weighing more than 55 pounds to carry tanks of fertilizers and pesticides in order to spray crops. This helps reduce costs and potential pesticide exposure to workers who would have needed to spray those crops manually. The DJI Agras MG-1 (DJI, 2017) was developed to support precision farming through accurate, variable-rate application of liquid pesticides, fertilizers and herbicides (Tsouros et al., 2019; Zhang et al., 2025).

7. Electronic Nose (E-NOSE)

An electronic nose operates by simulating the human olfactory mechanism, employing an array of chemical sensors and computational pattern-recognition methods to detect and discriminate between odours or flavours. Different insects emit unique chemical signatures. E-noses can distinguish between species or developmental stages of insects based on these odour profiles (Fuentes et al., 2021). It detects insect pheromones used in communication (e.g., mating) and also helps in population monitoring and mating disruption strategies in IPM (Integrated Pest Management). E-noses can identify hidden infestations in imported/exported agricultural goods by sensing pest-related volatiles and are useful in phytosanitary inspections. Plants emit specific VOCs in response to insect feeding. E-noses can detect these signals even before visible symptoms appear (Fuentes et al., 2021).

E-noses can detect Volatile Organic Compounds (VOCs) emitted by plants under pest attack. It is used for early detection of pest infestations, including aphids, whiteflies, and beetles. E-noses have been used for extensive investigations of VOCs profiles emitted by tomato plants infested with spider mites, under different growth conditions (Zhang et al., 2011). This technology has been successfully applied in detecting aphid infestations in wheat by analysing plant-emitted volatiles (Fuentes et al., 2021). AI is also being used in autonomous pest control systems, in which drones and robotic platforms equipped with AI algorithms perform targeted pesticide spraying or deploy traps, particularly in vegetable crops and orchards, thereby reducing chemical use and improving precision in pest management (Sankaran et al., 2015 ; Khan et al., 2025).

Infected rice plants attacked by the striped rice stem borer (*Chilo suppressalis*) and the brown planthopper (*Nilaparvata lugens*) can be easily distinguished from healthy plants using an E-nose (Lu et al., 2006). The age and number of brown planthoppers were estimated using an E-nose with classification accuracies of 100% and 48.93%, respectively (Xu et al., 2014). The gender and species of stink bugs have been precisely predicted using a portable E-nose (Lan et al., 2008).

The electronic nose (e-nose) technology offers several important advantages in pest and disease monitoring systems. It is non-destructive and rapid, enabling early detection of infestations without causing damage to plant tissues or agricultural produce. The technology is also cost-effective for large-scale monitoring, as it allows continuous and automated assessment of volatile organic compounds associated with pest activity. Furthermore, portable versions of e-nose devices are available for field use, facilitating on-site detection, real-time analysis, and timely decision-making within Integrated Pest Management (IPM) programmes (Fuentes et al., 2021; Li et al., 2023) (Table 1).

8. Chatbot

A chatter robot (chatbot) is a type of conversational agent, a computer program designed to simulate an intelligent conversation with one or more human users in natural language via audio or text. In short, chatbots are virtual assistants programmed to answer user requests automatically. In agriculture, several AI-based chatbot systems have been

Table 1: Applications of AI in insect and disease detection and management

Application area	AI technique used	Purpose	Crop	References
Insect pest identification	Convolutional neural networks (CNNs)	Automated visual identification of insect pests from images	Multiple (e.g., cotton, rice)	Fuentes et al., 2017
Disease detection	Deep learning (CNN, ResNet)	Detect and classify plant diseases from leaf images	Tomato, maize, wheat	Mohanty et al., 2016
Pest forecasting	Machine learning (random forest, SVM)	Predict pest outbreaks using weather and historical data	Brown planthopper in rice	Chlingaryan et al., 2018
Early warning systems	AI-integrated IoT and remote sensing	Real-time pest/disease alerts using sensor and satellite data	Field-scale crops	Kamilaris and Prenafeta-Boldu, 2018
Pest monitoring	AI+Electronic nose (e-nose)	Detect volatile compounds from pest-infected plants	Aphid-infested wheat	Fuentes et al., 2021
Disease diagnosis App	AI-based mobile apps (e.g., Plantix)	On-field diagnosis using image recognition	Multiple crops	Ferentinos, 2018
Autonomous pest control	AI-guided drones and robots	Spot spraying and trap deployment for pest control	Vegetables, orchards	Sankaran et al., 2015
Integrated pest management (IPM)	AI-driven decision support systems	Optimize aphid, rust, blotch and powdery mildew control decisions based on ai predictions	Cereals	Tratwal et al., 2025

developed to support farmers. These systems enable farmers to obtain real-time information on pest identification, diagnosis, and control measures through mobile applications or voice-based interfaces. For example, the Plantix chat assistant developed by PEAT GmbH provides pest and disease diagnosis using image recognition and NLP technologies across multiple crops (Ferentinos, 2018; Anonymous, 2023a). Similarly, RML AgTech Bot offers personalized pest alerts and agricultural advisory services for crops such as cotton and soybean in India (Anonymous, 2024). Digital Green's farmer chatbot provides pest and disease guidance using NLP and IVR-based communication tools (Anonymous, 2023b). The FarmRise Assistant developed by Bayer Crop Science integrates AI-based decision support with chatbot systems to provide pest advisory and weather-based risk predictions (Anonymous, 2026a).

In addition, platforms such as KrishiGuru, AgriBot, and the AgroStar virtual assistant assist farmers with pest-related queries and management recommendations through AI-driven conversational interfaces (Anonymous, 2026b; Anonymous, 2026c; Anonymous, 2023c). Collaborative initiatives such as the Microsoft–ICRISAT AI chatbot further support farmers by predicting pest infestations and suggesting appropriate control measures (Anonymous, 2018). These chatbot-based systems highlight the growing role of AI in delivering timely pest management advisory services to farmers. Similarly, FarmChat (Jain et al., 2018) and AgronomoBot (Mostaco et al., 2018) were developed to address farmers' queries and to integrate agricultural sensor networks. In addition, multipurpose robotic systems such as Agribot and Hortibot are increasingly used in agriculture for automated assistance and decision support (Table 2).

9. Challenges and Limitations of AI in Insect Pest and Disease Management

Although AI has demonstrated considerable promise in improving insect pest and disease management, its practical application is constrained by a range of methodological, technical, and socio-economic limitations (Kamilaris and Prenafeta-Boldú, 2018; Liakos et al., 2018). One of the foremost challenges is the scarcity of reliable and well-annotated datasets for many pest species, particularly those involving field images and sensor-derived information, which limits effective model training and validation (Thenmozhi and Reddy, 2019). Variations in real-world conditions, including inconsistent lighting, heterogeneous backgrounds, insect crowding, and partial visibility, further reduce detection accuracy under field settings (Waldchen and Mader, 2018).

In addition, pest populations are highly dynamic, with behavioural shifts, seasonal movement, and evolutionary changes that can quickly render static AI models outdated (Bebber et al., 2019). Accurate identification of pest species continues to be challenging because many species exhibit similar visual characteristics, and symptom expression may vary across growth stages or environmental conditions,

Table 2: Chatbots in insect pest and disease management

Chatbot	Developer / organization	Primary function	Target crop / Region	Technology used	References
Plantix chat assistant	PEAT GmbH (Germany)	Pest/disease diagnosis, treatment advice, farmer support	Multiple crops (India, Africa)	AI, Image recognition, NLP chatbot	Ferentinos (2018) Anonymous, 2023a
RML AgTech bot	RML AgTech (India)	Personalised pest alerts, agri-advisory via chatbot	Cotton, soybean, etc. (India)	Machine Learning, NLP	Anonymous, 2024
Digital Green's Farmer Chatbot	Digital green NGO	Audio+text chatbot for pest and disease guidance	Various crops (India)	NLP, IVR chatbot	Anonymous, 2023b
FarmRise assistant	Bayer crop science	Pest advisory, weather-based risk predictions	Maize, soybean (India)	AI-based DSS, chatbot	Anonymous, 2026a
KrishiGuru	Tata consultancy services (TCS)	Voice-enabled chatbot for pest/disease help and agri queries	General crops (India)	Voice AI, NLP	Anonymous, 2026b
AgriBot	ICAR-IARI (India)	Information on pest management, crop health FAQs	Field crops (India)	Rule-based AI	Anonymous, 2026c
AgroStar virtual assistant	AgroStar	Chatbot in app for pest alerts, control methods, and input suggestions	Cotton, wheat, chilli, etc.	NLP, recommendation engine	Anonymous, 2023c
Microsoft AI chatbot for farmers	Microsoft India +ICRISAT	Predict pest infestation, offer control advice via chatbot	Groundnut, pigeonpea	AI, ML, Bot Framework	Anonymous, 2018

thereby complicating reliable recognition using conventional approaches (Liu and Wang, 2021). Furthermore, AI models often show limited robustness across different agro-ecological zones, as systems developed for specific crops or regions may not perform consistently elsewhere, necessitating repeated recalibration and localised retraining (Ferentinos, 2018). he operational deployment of AI-enabled sensing and monitoring systems in agriculture is often constrained by the high cost of advanced hardware and infrastructure, the need for stable connectivity and skilled users, and the susceptibility of sensors and IoT devices to field conditions such as variable light, harsh weather, and environmental noise, which together limit real-world adoption and scalability (Elijah et al., 2018).

Effective incorporation of AI tools into existing Integrated Pest Management programmes remains uneven, as farmer adoption is influenced by limited technical familiarity, uncertainty regarding economic returns, and variability in regional IPM practices (Rose et al., 2021). Moreover, the limited transparency of complex AI models often makes it difficult for users to understand the rationale behind predictions, which can reduce confidence and slow practical implementation. Strengthening interpretability through explainable AI techniques is therefore crucial to ensure reliability, informed decision-making, and broader acceptance of AI systems in agriculture (Pai et al., 2025).

Concerns related to data ownership, privacy, and governance further challenge adoption, particularly in the context of evolving and fragmented regulatory policies across countries (Wolfert et al., 2017). High initial investment costs, coupled with the need for stable internet connectivity, cloud-based infrastructure, and skilled human resources, present additional barriers, especially in remote agricultural regions (Liakos et al., 2018). Finally, the rapid adaptation of insect pests and the growing influence of climate change and global trade can outpace AI systems that rely heavily on historical datasets, limiting their capacity to anticipate emerging pest threats and resistance patterns (Deutsch et al., 2018; Bebber et al., 2019).

10. Future Prospects

The future of artificial intelligence in insect pest and disease management is expected to advance toward more integrated, intelligent, and sustainable solutions. A key development will be the integration of multimodal sensing systems, wherein data from drones, satellite imagery, Internet of Things (IoT) sensors, electronic noses, and acoustic sensors are fused to enable comprehensive, real-time surveillance of insect activity, crop health, and surrounding environmental conditions (Zhang et al., 2025; Khan et al., 2025). Increasing emphasis will also be placed on explainable and interpretable

AI (XAI), allowing models to provide transparent reasoning behind predictions and recommendations, thereby enhancing trust among farmers, researchers, and policymakers and supporting regulatory acceptance (Ibrahim et al., 2025: Arrieta et al., 2020). AI-driven decision support systems (DSS) are likely to be embedded within user-friendly digital platforms and mobile applications to assist farmers with pest identification, real-time risk assessment, and selection of appropriate control strategies, including biological, chemical, and mechanical interventions (Upadhyay et al., 2025).

Advances in predictive analytics will enable AI models to forecast pest outbreaks by integrating historical infestation records with weather variables and climate projections, facilitating proactive management and reducing reliance on excessive pesticide use (Khan et al., 2025; Yang et al., 2025). Precision pest control represents a highly promising frontier in AI-assisted agriculture, where intelligent drones and autonomous robotic platforms are expected to perform targeted interventions, such as precision pesticide application, spatially controlled release of biological control agents, or automated deployment of pheromone traps thereby reducing off-target chemical exposure, lowering environmental contamination, and mitigating the acceleration of pest resistance development (Aziz et al., 2025; Zhang et al., 2025). Future systems are also expected to move toward personalised pest management by developing location and crop-specific models tailored to local pest complexes and farming practices, which is particularly beneficial for smallholder agriculture.

Integration of AI with genomic and metagenomic data will further enhance understanding of insect behaviour, resistance mechanisms, and microbial interactions, supporting the development of advanced biocontrol strategies and novel approaches such as gene editing (Yang et al., 2025). In addition, collaborative platforms and open-data initiatives will promote the creation of global pest surveillance networks, enable real-time data sharing and coordinate responses to emerging and invasive pest threats (Zhang et al., 2025). AI is also expected to play a critical role in pest risk analysis associated with international trade by supporting automated phytosanitary inspections and early detection of invasive species.

Collectively, these developments will contribute to the evolution of sustainable and climate-smart Integrated Pest Management (IPM) systems that are resilient to climate change and aligned with environmentally responsible agricultural practices.

11. Conclusion

Artificial Intelligence, revolutionizing insect pest management by enabling faster, more accurate and data-driven decision-making in agricultural ecosystems. Through advanced technologies such as computer vision, machine learning, remote sensing and decision support systems, AI offered powerful tools for early pest detection, species identification, outbreak forecasting and targeted control measures. These innovations reduced reliance on broad-spectrum pesticides, lower crop losses and promote sustainable pest control practices, supporting next-generation sustainable agriculture.

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