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Artificial intelligence and machine learning in insect pest monitoring and forecasting: A review

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Abstract

Insect pests are major biotic stress resulting in considerable loss of agricultural productivity worldwide, with implications for food security, and they are responsible for considerable yield losses, economic damage, and threats to food security. Conventional pest monitoring and forecasting approaches are usually costly, time-consuming, and restricted in terms of spatial and temporal monitoring contents. Exploiting new technologies such as Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Computer Vision (CV), IoT, Big Data Analytics, etc. contributes to a new revolution in insect pest surveillance and predictive management related systems. AI-based systems can enable automated detection of pests, species identification, population monitoring, prediction of outbreaks, and decision support for integrated pest management (IPM). With the use of machine learning techniques, it is possible to develop better prediction models by processing and analyzing complex data such as climate data, crop data, pest population data, and environmental data. Deep learning methods-based image recognition such systems have found to be very effective in determining the pest species in field images taken with smartphones, drones or smart traps. In addition, AI-based prediction systems provide real-time assessment of risk and early warning, which contributes to the accuracy and sustainability of pest management. Although considerable advances have been made, issues concerning data availability, model generalization, interpretability, infrastructure constraints, and barriers to adoption still exist. In this review paper, recent trends in applications of AI and ML for insect pest monitoring and forecasting with a focus on key technologies and algorithms are discussed, challenges, current achievements and limitations are illustrated, and potential future directions are outlined for smart and sustainable pest management system.

Keywords: Artificial Intelligence, Machine Learning, Deep Learning, Insect Pest Monitoring, Pest Forecasting, Precision Agriculture

1. Introduction

The demands agriculture is under today to feed a burgeoning global population while protecting the environment and conserving resources are greater and more challenging than ever. Of the many biotic limitations on crop production, insect pests are a major biotic stress, leading to considerable loss of yield and financial damage globally. Pests and diseases are estimated by the Food and Agriculture Organization (FAO) to be responsible for 20-40% of annual crop losses worldwide (Aremu *et al.*, 2024). Traditionally, insect pest monitoring has been based on manual field surveying, pheromone traps, sweep net sampling, visual inspection, and expert opinion. These methods, although extensively employed over several decades, are generally laborious, time-consuming, constrained by lag detection, prone to subjective interpretation, limited spatially, and lack adequate forecasting potential. As a result, poor monitoring record has been repeatedly reported to cause delayed control measures and overuse of pesticides, in turn, economic losses and environmental deteriorations (Ma *et al.*, 2025).

The emergence of Artificial Intelligence (AI) and Machine Learning (ML) has further revolutionised insect pest monitoring and forecasting systems (Mittal *et al.*, 2024; Guo *et al.*, 2024). AI driven technologies are now combined with sophisticated sensing devices, remote sensing platforms, UAVs, IoT networks, and cloud computing to provide automated, real-time, and large-scale pest surveillance (Kariyanna and Sowjanya, 2024) [5, 42, 45, 20,30]. In addition, deep learning methods, such as convolutional neural networks (CNNs),

have achieved higher accuracy for detecting, classifying, and estimating pest numbers using digital images (Duhan *et al.*, 2026). AI-based prediction models are capable of processing multidimensional data sets, including weather parameters, crop growth stages, historical pest occurrence, and environmental factors, to forecast pest outbreaks with exceptional accuracy, leading to timely and well-informed decision-making. These innovations facilitate proactive pest management, reduce pesticide application, improve efficacy in crop protection, and ultimately ensure sustainable agriculture production. This review summarizes recent advances in the application of AI and ML in insect pest monitoring and forecasting with emphasis on enabling technologies, real-world applications, existing gaps, and research directions (Hajahmadi and Marfia, 2023; Chakrabarty *et al.*, 2026)^[16, 21, 14].

2. Evolution of Pest Monitoring Systems

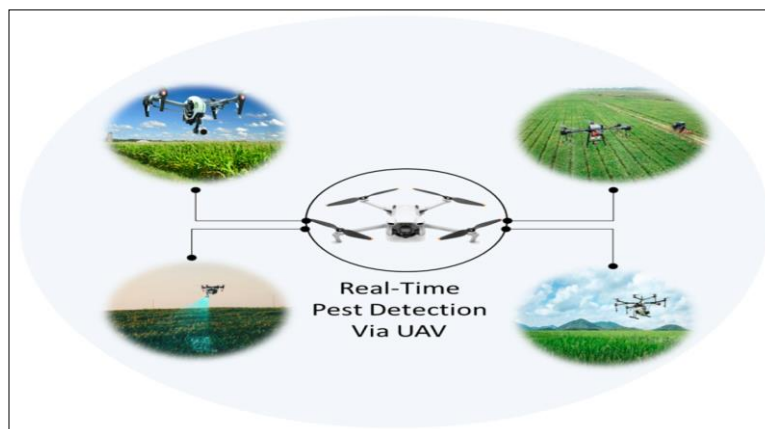
2.1 Traditional Pest Monitoring Approaches

Monitoring insect pest has traditionally been based on field scouting, crop visual observations, sampling with sweep nets, light traps, sticky traps, pheromone traps, and expert observations, which evaluate the insect population status. These have been instrumental in crop protection and pest management decision-making for many years. However, traditional methods of monitoring are usually time-consuming and labor-intensive and may suffer from observational errors due to human involvement (Herrera *et al.*, 2024). In addition, they generally offer limited spatial coverage and delayed response to pest outbreaks and do not have the ability of continuous real-time monitoring. Such limitations may hamper early warning systems and result in

delayed pest control application, increased crop loss and environmental pollution by overused pesticides. As a result, recent advances in traditional surveillance systems have been geared towards digital-based and AI-based monitoring systems which can provide automated, accurate, real-time and large-scale pest detection and forecasting (Bello *et al.*, 2026)^[24, 9].

2.2 Digital Transformation in Pest Surveillance

Digital agriculture has boosted the penetration of novel technologies that are transforming the way insect pest monitoring and management are conducted. The digitalization and convergence of Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Computer Vision (CV), Internet of Things (IoT), Remote Sensing, Cloud Computing, Big Data Analytics and Mobile Applications facilitated in creating smart and data-centric pest surveillance system (Kiobia *et al.*, 2023; Saran *et al.*, 2025). These technologies empower the generation of large-scale real-time field data from a variety of sources (e.g., sensors, drones, satellites, smart traps and mobile devices), which are subsequently collected, processed and analysed. Digital technologies improve the precision, effectiveness and timeliness of pest management interventions by integrating automated detection of pests, identifying species, monitoring populations, forecasting outbreaks and decision-support. As a result, they are vital for the development of precision pest management, minimizing over application of pesticides, enhancing crop protection methodologies and sustainable agricultural production (Pasaribu and Nainggolan, 2025; Lima *et al.*, 2020)^[33, 55, 49, 39].



Source: Khan *et al.*, 2024

Fig 1: Real-Time Pest Detection Using Unmanned Aerial Vehicles (UAVs)

3. Artificial Intelligence in Agriculture

3.1 Concept of Artificial Intelligence

Artificial Intelligence (AI) consists of software and hardware that is designed to mimic human cognition and that can be used to stimulate specific aspects of intelligence, such as problem solving. Such aspects include learning (e.g., acquiring knowledge and skills), reasoning (e.g., drawing inferences from knowledge), pattern detection, decision making, and prediction. Using the power of advanced algorithms and computational models, AI is able to analyze large amounts of structured and unstructured data, discover intricate relationships and hidden patterns, and provide reliable predictions and effective recommendations. In farming, AI promotes data-driven decision making by

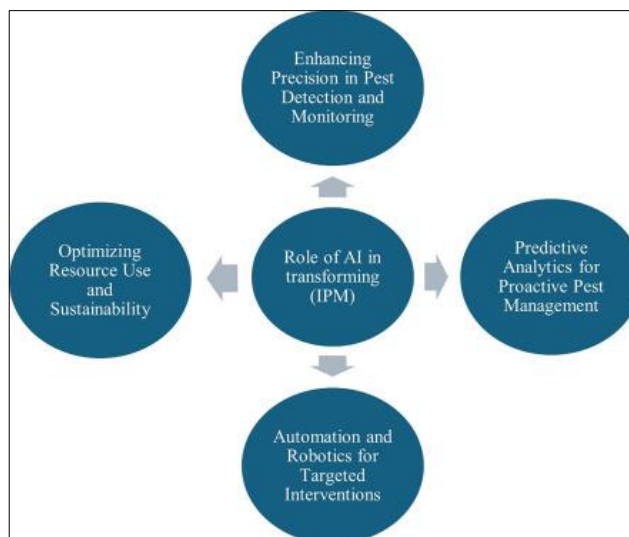
converting multi-source large datasets into meaningful information to enable whole-farm efficient and sustainable management of crops and pests (Jha *et al.*, 2019; Popescu *et al.*, 2023)^[27, 30].

3.2 Major Branches of AI Used in Pest Management

AI has multiple specialized subfields which have been greatly used in monitoring and managing insect pests. Machine Learning (ML) allows computer algorithms to learn patterns and correlations from past data and leverage this knowledge for predictions or classifications. On the other hand, Deep Learning (DL), which is a kind of ML based on multiple-layered neural networks, can automatically learn complicated features from big data and

enhances pest detection and classification accuracy significantly (Teixeira *et al.*, 2023; Li *et al.*, 2021). Computer Vision (CV) supports the image-based pest identification when images or videos taken using smart phones, cameras, drones, or smart traps (Biswas and Tiwari, 2024). Natural Language Processing (NLP) allows for the creation of advisory systems, virtual assistant, and chatbot based systems that facilitate pest diagnosis and management

advice via human language interactions. Also, Expert Systems utilize rule based knowledge representation derived from expert experience and scientific knowledge to provide suggestions for pest surveillance, prediction and control. Together, these AI methods provide the backbone of modern intelligent pest management systems (Zhao *et al.*, 2023)^[37, 10].



Source: Kumar *et al.*, 2026

Fig 2: Role of Artificial Intelligence in Transforming Integrated Pest Management (IPM)

4. Machine Learning Techniques for Pest Monitoring

4.1 Supervised Learning

Supervised learning is the most popular ML method in insect pest detection and prediction, where the algorithms are trained with labeled samples having known inputs and outputs. Supervised learning models could be applied to categorize, predict, and estimate many pest-related parameters, because they learn relationships between predictor and target variables. Some popular supervised learning algorithm are Decision Tree, Random Forest, Support Vector Machine (SVM), Logistic Regression, Naive Bayes and K-Nearest Neighbor (KNN). These are actively used in agriculture for insect pest identification & classification, predicting pest outbreaks, tracking population dynamics, and estimating yield losses. Their capacity to process complex data sets and produce dependable forecasts renders them as excellent candidates for enabling data-driven pest management and decision support (Mittal *et al.*, 2024)^[45].

4.2 Unsupervised Learning

Unsupervised learning is a type of machine learning that is used when there is no labeled data set available, and it enables algorithms to detect concealed structure, patterns, and relationships in data without any knowledge of the results. To begin, unsupervised learning analyses data on its own, and divides observations into groups based on similarity and/or other metrics. Popular algorithms for unsupervised learning K-means clustering, Hierarchical Clustering and Principal Component Analysis (PCA) are amongst the popular algorithms used for unsupervised learning. In monitoring and forecasting of insect pests, these techniques are used for pattern recognition, grouping of pest populations, evaluation of biodiversity, characterization of

habitats, and ecological interpretation. Consistently with its ability to uncover latent patterns and relationships in large and complex data sets, unsupervised learning allows for better understanding of pest dynamics and the derivation of improved pest management strategies.

4.3 Reinforcement Learning

Reinforcement Learning (RL) is a type of machine learning where an agent learns to perform an action optimally after interacting with its environment. This learning is guided by a reward-punishment system, so that, the agent can improve its decision making over time by understanding which actions lead to the greatest long-term rewards. Reinforcement learning is not based on labeled data sets like supervised learning; instead, it makes use of trial-and-error sequences and real-time feedback. In precision agriculture pest control, RL can be applied in intelligent pesticide application systems, robotic pest management systems, and dynamic decision-support systems to adaptively optimize control protocols in varying field conditions. In pest management, reinforcement learning provides a promising approach for continually improving the efficiency, precision and sustainability of pest control methods by adaptively responding to changing environment and pest population dynamics (Wolfert *et al.*, 2017).

5. Deep Learning for Insect Pest Identification

5.1 Convolutional Neural Networks (CNNs)

Convolution Neural Networks (CNNs) constitute a particular class of deep learning models for the analysis of image data. They make images available for object detection, classification, and recognition directly from the pixels without any need for manual feature engineering by automatically learning the hierarchical features from images

using convolutional and pooling operations. In crop pest control, CNNs have been extensively applied for the detection, identification, and classification of insect pests using the images taken by cameras, smartphones, drones, and unmanned aerial vehicles (UAVs). They are capable of differentiating pest species, assessing infestation severity, and enabling real-time pest surveillance with good performance across multiple outdoor scenarios. Fast and dependable pest diagnosis by CNN based systems is a driver of timely pest management decisions, which would reduce reliance on manual scouting and contribute to precise application of pesticides. Thus, CNNs have become one of the most popular deep learning methods for intelligent pest monitoring and sustainable crop protection (Li *et al.*, 2020; Maroto-Gomez *et al.*, 2024) ^[43, 38].

5.2 Object Detection Models

The deep learning based object detection models have been emerged as powerful instruments for the automation of insect pest monitoring due to their high precision in detecting, classifying and quantifying pests. Among those models, YOLO (You Only Look Once) has been the most well-known for real-time detection speed, good accuracy and field applicability, thus, it is most suitable for running on smart traps and mobile devices (Jocher *et al.*, 2023). Faster R-CNN (Region-Based Convolutional Neural Network) has better detection accuracy and precision, so it is more applicable to research where highprecision pest identification is needed. Also, the SSD (Single Shot Detector) processes images quickly and has good performance on devices with limited resources which enable mobile and edge deployments. These algorithms, in combination with the smart traps for real-time pest monitoring (Chaudhary *et al.*, 2023) have been used to automate insect pest counting, population estimation, species identification, and smart trap monitoring system, to achieve continuous, unattended, and real-time monitoring of pest populations for precision pest management (Zahoor *et al.*, 2024) ^[43, 28].

6. Computer Vision-Based Pest Monitoring

Computer vision has become a promising technology in automated insect pest monitoring, where it can be applied to detect, identify, and classify pest species with a high level of accuracy based on digital images. These systems capture images from different platforms, such as smartphones, drones, satellites, smart traps and stationary field cameras, allowing for continuous monitoring over various spatial scales. The standard computer vision process starts with image acquisition, then image processing is carried out to improve quality or remove noise. Next, significant characteristics are extracted from the images and these are then processed using machine learning or deep learning techniques to categorize and identify pests. The emitted results, which are the outputs of data-driven and physically coupled models, are further fed into decision-support systems that offer actionable recommendations for pest control. This integrated process paves the way for fast and accurate real-time pest surveillance, ultimately enhancing the precision agriculture and integrated pest management (IPM) system efficacy (Jelali, 2024; Ebrahimi *et al.*, 2017) ^[26, 17].

Benefits

Insect identification based on computer vision reduces the need for skilled professionals and has great potential for automated pest surveillance. These systems facilitate the real-time observation of pest population, so that decision-makers can be informed quickly and can plan ahead of time for pest control management to prevent crop loss. Automation dramatically reduces labor needs and manual field scouting dependency, thus cutting down operational costs and enhancing efficiency. Advanced image processing and deep learning algorithms can further improve the identification accuracy and consistency consequently reducing human mistakes in visual inspection. Supported by continuous surveillance from smart cameras, drones, and automated traps, persistent monitoring of vast farming lands endows invaluable data for pest forecasting and precision pest management. Taken all together, these benefits make for more effective, sustainable, and data-driven crop protection practices (Cardoso *et al.*, 2022; Mirkin *et al.*, 2025) ^[12, 44].

7. Smart Traps and IoT-Based Pest Monitoring

Smart pest monitoring systems are composed of camera sensors to capture images, wireless communication modules to send the data, cloud storage to handle the data, and AI processing units to automatically identify pests, analyze the population, and provide decision support. These elements collectively allow pest monitoring to be real-time and intelligent (Aloi *et al.*, 2017; Ahmed *et al.*, 2024) ^[3, 2].

Working Mechanism

Smart pest monitoring system works on the steps pest catching, image capture, automated pest identification, cloud data transmission and risk analysis. The captured images are analyzed by the AI algorithm to recognize the pest species and estimate their population, and cloud platform supports data storage and provides real-time decision support. Typical products are the AI-powered pheromone trap, the smart sticky trap and the automated moth counting system, enabling precise pest management through efficient and continuous pest monitoring (Jasim and Fourati, 2023) ^[25].

8. AI-Based Pest Forecasting Models

Weather Parameters

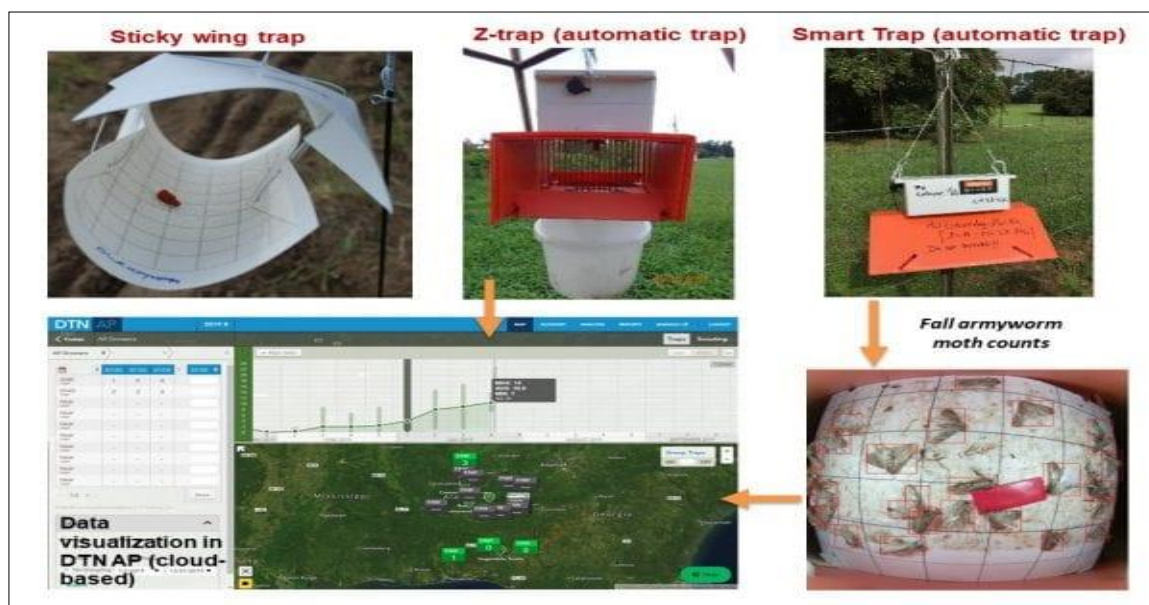
Temperature, humidity, precipitation, wind, and solar radiation are important inputs in pest prediction models based on AI. These factors have a high impact on insect growth, survival, reproduction, dispersion and population size, hence they are the optimal parameters to forecast outbreak of pest and infestation risk evaluation (Saiyam and Meena, 2026; Bukhari *et al.*, 2025) ^[54, 11].

Crop Factors

Growth stage, cultivar and plant density are the key determinants of crop water demand and yield. Water requirements vary according to crop growth stage being low at germination and early growth, maximum at flowering and reproduction stages and minimum at maturity. Different crop varieties have different lengths of growth period, rooting pattern, canopy size and drought resistance, so they need different amounts of water and have different water-

use-efficiency. In the same way, plant density has an impact on water use through its effects on canopy cover, transpiration and the level of competition for soil moisture, with a greater number of plants being required for high

water use and maximum crop yield (Hatfield and Dold, 2019) and with optimum plant density ensuring efficient use of water and such maximum crop yield [22].



Source- <https://www.aces.edu/blog/topics/farming/modern-insect-pest-monitoring-using-automatic-traps>

Fig 3: Automated Smart Traps and Cloud-Based Monitoring for Insect Pest Surveillance

Pest Factors

Historical prevalence, population density and migration patterns play a significant role in shaping outbreaks of insect pests and their control. The historical incidence describes past occurrences of pest infestations (population size and severity) in a given area, which is useful to anticipate future outbreaks. Population density represents the currently pest population size in a field, which is useful for making the right decision in a timely manner for pest control. Migration trends refer to the flow of pest movement between regions, influenced by environmental factors, presence of host crops, or changes in seasons and provides an anticipation-based approach to pest management (Mungee, 2026) [47].

Forecasting Techniques

Random Forest, Artificial Neural Network, Gradient Boosting, Deep Neural Network and Hybrid Models are among the most popular AI techniques for prediction and decision-making in agriculture. Random forest models are accurate and interpretable, and artificial neural networks can model complex nonlinear interaction among variables. The Gradient Boosting model provides good predictive performance as an ensemble of weak learners, and the Deep Neural Network is well suited to large complex data sets. Hybrid models combine two or more prediction algorithms to improve the accuracy, robustness and performance of the overall system (Kapetas *et al.*, 2025; Castillo-Girones *et al.*, 2026) [29].

9. Remote Sensing and UAV Applications

Monitoring based on UAVs (unmanned aerial vehicles) employs drones with high-end sensors (e.g. RGB cameras, multispectral sensors, thermal sensors) to track crop health, identify insect pest outbreaks, and evaluate field conditions. They provide high-resolution visual images through RGB

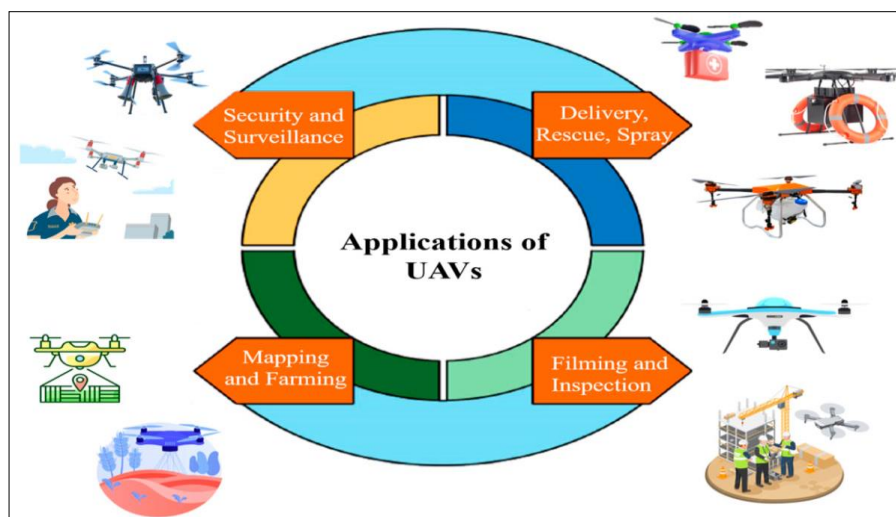
cameras, multispectral sensors preliminarily assess plant reflectance signatures for stress and pest damage, and thermal sensors identify temperature changes related to crop stress and pest activity leading to early and accurate pest management decisions (Padua *et al.*, 2017; Aziz *et al.*, 2025) [48, 7].

Applications

Early pest detection, hotspot detection, and spatial distribution analysis are the precision pest management techniques widely used which provide the information for timely and site specific pest control. Early pest detection allows detection of infestations in early stages and consequently reduces the damage on crops and the loss of yield. Hotspot mapping identifies clusters of pest activity within a field, allowing you to treat these areas specifically instead of blank spraying. Spatial distribution analysis allows for a more precise study of pest dispersion patterns within the field, thus enabling information-based predictions and better-guided pest management strategies (Amarasingam *et al.*, 2025) [4].

Satellite-Based Monitoring

Remote sensing enables monitoring of crops across vast agricultural landscapes, offering early detection of vegetation stress and pest outbreaks, and allowing monitoring of crop health in an early and efficient manner. It is useful for the detection of stressed vegetation based on changes in spectral reflectance and also for prediction of possible pest outbreaks by using environmental and crop condition information. Typical sources of remote sensing data include Sentinel, Landsat, and MODIS, which provide multispectral and temporal satellite data that may be used to develop strategies for precision agriculture and pest management.



Source: Mohsan *et al.*, 2023

Fig 4: Applications of Unmanned Aerial Vehicles (UAVs)

10. Integration of AI with Integrated Pest Management (IPM)

Early Detection

Early detection is the detection of pests in the crop field at the initial stage of the pest attack or in its very early days for the invasion often before any symptoms or significant damage observed. It is important in integrated pest management, as it provides farmers with the opportunity to immediately implement control measures such as monitoring, trapping or selective pesticide application. Early detection of pests also inhibits them from multiplying and dispersing to other parts of the same field or to neighboring fields. This, in turn, not only mitigates the severity of infestation, but also reduces the loss of crop yield and the cost for pest management. Early detection also contributes to more sustainable farming with less excessive chemical use and more precise, needs-based application interventions (Abdullah *et al.*, 2023; Vidya Madhuri *et al.*, 2025) ^[1].

Economic Threshold Estimation

Estimation of the economic threshold is the estimation of the pest density at which control should be taken to keep the pest population from reaching the economic injury level. It serves to inform the decisions of integrated pest management practice in terms of the trade-off between pest control and potential yield loss from pest damage. In layman's terms, the pest population at which it is profitable to implement control measures rather than to wait or do nothing. Such strategies contribute to minimize their negative environmental and economic impacts by reducing needless pest control treatments and guaranteeing that control is warranted in an economic and environmental sense (Legwaila, 2023; Keasar *et al.*, 2023) ^[36, 31].

Precision Pesticide Application

Application of pesticides should be more precise and needs-based according to the location, density and the severity of the infestation within a field. Rather than spraying the whole area evenly, pesticides are sprayed in patches where pest populations exceed economic threshold level, sometimes using high tech-tools such as GPS, drones and sensor-based technologies (Llorens *et al.*, 2010; Esau *et al.*, 2014). This reduces the overuse and waste of chemicals, and farmers' input costs as well. It also reduces soil and

water contamination, protects beneficial organisms, and lessens pesticide residues in soil, water and crops. In summary, precision application enhances efficiency and sustainability of pest management practices (Tao *et al.*, 2022) ^[31, 41, 60, 18].

Resistance Monitoring

Resistance monitoring is a long-term surveillance of alterations in susceptibility of the pest to pesticides. It enables the detection of the first appearance of resistant individuals in the pest population, which may be induced by the recurrent or unselective usage of the same active ingredients. Early detection of reduced sensitivity allows for timely interventions by farmers and researchers, such as pesticide rotation by mode of action, modification of dosage, or implementation of non-chemical control strategies. This procedure is vital for pesticide efficacy preservation and sustainable pest control (Wu *et al.*, 2023; Vanlalhmuliana *et al.*, 2026; Rauf, 2024) ^[52].

Biological Control Optimization

Biocontrol management is the efficient use and conservation of natural enemies (predators, parasitoids and microbial pathogens) to manipulate pest populations. Enhancing survival, activity and efficacy of these beneficial organisms via specific habitat manipulation and conservation practices and augmentative release of biological agents. The strategy includes ecologically sound and sustainable pest management practice that utilizes the natural control of pest populations to maintain the population below economic injury levels and retard the outbreak of pests. It also reduces reliance on chemical insecticides, thus decreasing the cost of production, environmental pollution and loss of beneficial insect biodiversity in the agro-ecosystem (Galli *et al.*, 2024; Shao *et al.*, 2026) ^[19].

Benefits

Reduced Pesticide Use

Use of pesticides is reduced in amount and frequency by employing integrated pest management, precision agriculture and biological control methods. The use of pesticides is limited to situations when pest populations are above the economic threshold, avoiding unnecessary applications. This increases the efficiency of pest control

and decreases chemical residues in the crops and the potential of pest resistance to be developed (Deere *et al.*, 2024) ^[15].

Environmental Protection

Environmental control in agriculture is aimed at reducing the impacts of pesticides on soil, water, air and non-target species. Using fewer chemicals helps maintain populations of beneficial insects, pollinators and natural predators, and prevents contamination of soil and water. It contributes to the ecological balance and the sustainable agricultural production system (Babendreier *et al.*, 2022) ^[8].

Improved Profitability

Profitability can be increased by minimizing input expenditures and by improving crop productivity through effective pest management. Reduced pesticide use leads to less spending on chemicals, labor and application and healthier crops result in better yield and quality. Collectively, these elements improve farm net income and the economic viability of agriculture (Klinnert *et al.*, 2024) ^[34].

12. Challenges and Limitations

Technical Challenges

Small datasets, variation in image quality, model overfitting, poor transferability are amongst the main challenges in the use of AI and machine learning in agriculture. A small sample of data limits the accuracy of learning and the trustworthiness of the models, and variations in image quality caused by lighting, resolution, weather, and camera angles cause inconsistencies in the data. Overfitting of the model results in bad prediction when faced to previously unseen data as the model also learns noise as patterns. Poor transferability also constrains model performance when applied to different regional or crop conditions limiting its potential practice in diverse agricultural environments (Talaviya *et al.*, 2020) ^[58].

Infrastructure Challenges

Connectivity to the internet, sensor costs, and cloud computing requirements pose the biggest constraints in the promotion of digital and precision agriculture technologies. Because data are transferred in real-time, reliable internet connectivity is crucial for remote monitoring and decision-making, but it is usually insufficient or non-existent in many rural areas. Another barrier to adoption is the costs of high sensors, as sophisticated instruments such as soil, weather, and pest monitoring sensors are expensive to purchase and maintain. Furthermore, cloud-computing requirements pose yet another challenge because of the need for continuous data storage, computational power, and subscription based services, which can potentially increase the overall cost of operations and limit the accessibility of the technology for small scale and marginal farmers (Ayaz *et al.*, 2019) ^[6].

Socioeconomic Challenges

Farmer awareness, capacity and barriers to adoption are the pressing challenges to up-scaling modern agricultural technologies. Awareness of farmers is low and so farmers don't understand new tools, techniques and its benefits which hinders adopting innovations. Technical capacity is also insufficient, and this prevents correct usage, maintenance and analysis of digital and precision

agriculture tools. And several constraints for adoption like high upfront costs, lack of infrastructure, and resistance to change hinder the dissemination of development based high-technology farming methods particularly among small and marginal farmers (Rose *et al.*, 2021) ^[53].

Ethical Concerns

Data privacy, algorithm transparency, and the ownership of agricultural data have been identified as key ethical and policy issues in the application of digital agriculture technologies. Data privacy is the security of sensitive information about farms and farmers that is collected by sensors, drones, and other digital tools, and that is at risk of being misused or accessed without permission. Algorithmic transparency is the degree to which AI and machine learning models are made comprehensible and explainable to farmers and stakeholders so that they trust in how decisions or predictions are made. Agricultural data ownership includes the matter of who owns and who profits on farm generated data with farmers holding rights to their own data and not being unfairly exploited by agribusiness or service providers (He *et al.*, 2022) ^[23].

13. Future Research Directions

Advances in agricultural AI are anticipated to revolutionize pest management with the implementation of more capable intelligent systems. Explainable AI will enhance transparency and enable farmers and researchers to better understand and trust AI decisions. Federated learning will enable the training of models on data distributed across farms, without the need to share raw data, while improving the privacy of the data and the collaboration. Edge AI is set to enable real-time data analysis on devices such as drones and sensors themselves, reducing reliance on cloud connectivity. Digital twins will be used to generate virtual models of farms or crops to predict pest dynamics and control options ahead of field use. Swarm robotics will employ a team of collective robots/drones to perform high efficient monitoring and pest control of farms (Liu *et al.*, 2023) ^[40].

Moreover, generative AI will enable predictive modeling and scenario building for pest outbreaks, while networks of autonomous pest surveillance will be continuously monitoring fields through a web of interconnected smart devices. Climate-smart forecasting tools will combine weather and climate information to provide more accurate predictions of pest occurrence in a changing environment. Collectively, these novel technologies will enable the construction of fully automated, intelligent pest management ecosystems with improved precision, sustainability, and productivity (Satapathy, 2024) ^[56].

14. Conclusion: Artificial Intelligence (AI) and Machine Learning (ML) are on the verge of revolutionizing insect pest surveillance and prediction from reactive management strategies to anticipatory and prescient constructs. The application of AI, DL, computer vision, IoT, R/S and cloud computing have enhanced the accuracy of pest detection, prediction of pest outbreaks and efficiency of decision making. Precision pest management is being brought closer to real-time surveillance by tools such as smart traps, unmanned aerial vehicles (UAVs), mobile applications, and AI-based forecasting platforms. Notwithstanding barriers in data quality, infrastructure, scalability and uptake, ongoing

innovation in AI tools and approaches holds promise to disrupt pest management around the world. Studies in this direction should be targeted to develop explainable, scalable and farmer centric AI-systems to promote sustainable agriculture and food security at a global scale.

References

1. Abdullah HM, Mohana NT, Khan BM, Ahmed SM, Hossain M, Islam KS, *et al.* Present and future scopes and challenges of plant pest and disease (P&D) monitoring: Remote sensing, image processing, and artificial intelligence perspectives. *Remote Sens Appl Soc Environ.* 2023;32:100996.
2. Ahmed S, Marwat SNK, Brahim GB, Khan WU, Khan S, Al-Fuqaha A, *et al.* IoT-based intelligent pest management system for precision agriculture. *Sci Rep.* 2024;14(1):31917.
3. Aloï G, Caliciuri G, Fortino G, Gravina R, Pace P, Russo W, *et al.* Enabling IoT interoperability through opportunistic smartphone-based mobile gateways. *J Netw Comput Appl.* 2017;81:74-84.
4. Amarasingam N, Powell K, Sandino J, Bratanov D, Salgado ASA, Gonzalez F. Mapping of insect pest infestation for precision agriculture: A UAV-based multispectral imaging and deep learning techniques. *Int J Appl Earth Obs Geoinf.* 2025;137:104413.
5. Aremu AO, Omogbene TO, Fadiji T, Lawal IO, Opara UL, Fawole OA. Plants as an alternative to the use of chemicals for crop protection against biotic threats: Trends and future perspectives. *Eur J Plant Pathol.* 2024;170(4):711-766.
6. Ayaz M, Ammad-Uddin M, Sharif Z, Mansour A, Aggoune EHM. Internet of Things (IoT)-based smart agriculture: Toward making the fields talk. *IEEE Access.* 2019;7:129551-129583.
7. Aziz D, Rafiq S, Saini P, Ahad I, Gonal B, Rehman SA, *et al.* Remote sensing and artificial intelligence: Revolutionizing pest management in agriculture. *Front Sustain Food Syst.* 2025;9:1551460.
8. Babendreier D, Tang R, Horgan FG. Prospects for integrating augmentative and conservation biological control of leafhoppers and stem borers in rice. *Agronomy.* 2022;12(12):2958.
9. Bello SK, Alayafi AH, Sadiq FK, Ozlu E. Artificial intelligence in soil salinity monitoring and management: Current practices and future directions. *Agron J.* 2026;118(3):e70441.
10. Biswas D, Tiwari A. Utilizing computer vision and deep learning to detect and monitor insects in real time by analyzing camera trap images. *Nat Eng Sci.* 2024;9(2):280-292.
11. Bukhari SAS, Mushtaq AR, Butt MH, Shahid M. AI-driven strategies for predicting and managing insect pest dynamics under climate change. *Trends Anim Plant Sci.* 2025;5:46-53.
12. Cardoso B, Silva C, Costa J, Ribeiro B. Internet of things meets computer vision to make an intelligent pest monitoring network. *Appl Sci.* 2022;12(18):9397.
13. Castillo-Girones S, Munera S, Martinez-Sober M, Blasco J, Cubero S, Gómez-Sanchis J. Artificial neural networks in agriculture, the core of artificial intelligence: What, when, and why. *Comput Electron Agric.* 2025;230:109938.
14. Chakrabarty S, Deb CK, Marwaha S, Haque MA, Kamil D, Bheemanahalli R, *et al.* Application of artificial intelligence in insect pest identification: A review. *Artif Intell Agric.* 2026;16(1):44-61.
15. Deere JA, Beretta GM, van Rijn PC, Messelink GJ, Leman A, Janssen A. Does alternative food for predatory arthropods improve biological pest control? A meta-analysis. *Biol Control.* 2024;198:105605.
16. Duhan S, Gulia P, Gill NS, Gupta C. A comprehensive review of image segmentation techniques for plant disease detection in precision agriculture: Models, trends, and challenges. *Arch Comput Methods Eng.* 2026;1-36.
17. Ebrahimi MA, Khoshtaghaza MH, Minaei S, Jamshidi B. Vision-based pest detection based on SVM classification method. *Comput Electron Agric.* 2017;137:52-58.
18. Esau TJ, Zaman QU, Chang YK, Schumann AW, Percival DC, Farooque AA. Spot-application of fungicide for wild blueberry using an automated prototype variable rate sprayer. *Precis Agric.* 2014;15(2):147-161.
19. Galli M, Feldmann F, Vogler UK, Kogel KH. Can biocontrol be the game-changer in integrated pest management? A review of definitions, methods and strategies. *J Plant Dis Prot.* 2024;131(2):265-291.
20. Guo B, Wang J, Guo M, Chen M, Chen Y, Miao Y. Overview of pest detection and recognition algorithms. *Electronics.* 2024;13(15):3008.
21. Hajahmadi S, Marfia G. Effects of the uncertainty of interpersonal communications on behavioral responses of the participants in an immersive virtual reality experience: A usability study. *Sensors.* 2023;23(4):2148.
22. Hatfield JL, Dold C. Water-use efficiency: Advances and challenges in a changing climate. *Front Plant Sci.* 2019;10:103.
23. He Q, Li Liu D, Wang B, Li L, Cowie A, Simmons A, *et al.* Identifying effective agricultural management practices for climate change adaptation and mitigation: A win-win strategy in South-Eastern Australia. *Agric Syst.* 2022;203:103527.
24. Herrera MS, Forero D, Calor AR, Romero GQ, Riyaz M, Callisto M, *et al.* Systematic challenges and opportunities in insect monitoring: A Global South perspective. *Philos Trans R Soc B Biol Sci.* 2024;379(1904):20230102.
25. Jasim AN, Fourati LC. Agriculture 4.0 from IoT, artificial intelligence, drone, and blockchain perspectives. In: 2023 15th International Conference on Developments in eSystems Engineering (DeSE). Piscataway (NJ): IEEE; 2023. p. 262-267.
26. Jelali M. Deep learning networks-based tomato disease and pest detection: A first review of research studies using real field datasets. *Front Plant Sci.* 2024;15:1493322.
27. Jha K, Doshi A, Patel P, Shah M. A comprehensive review on automation in agriculture using artificial intelligence. *Artif Intell Agric.* 2019;2:1-12.
28. Jocher G, Chaurasia A, Qiu J. YOLO by Ultralytics. 2023.
29. Kapetas D, Christakakis P, Faliagka S, Katsoulas N, Pechlivani EM. AI-driven insect detection, real-time

- monitoring, and population forecasting in greenhouses. *AgriEngineering*. 2025;7(2):29.
30. Kariyanna B, Sowjanya M. Unravelling the use of artificial intelligence in management of insect pests. *Smart Agric Technol*. 2024;8:100517.
 31. Keasar T, Wajnberg E, Heimpel G, Hardy ICW, Harpaz LS, Gottlieb D, *et al*. Dynamic economic thresholds for insecticide applications against agricultural pests: Importance of pest and natural enemy migration. *J Econ Entomol*. 2023;116(2):321-330.
 32. Khan A, Malebary SJ, Dang LM, Binzagr F, Song HK, Moon H. AI-enabled crop management framework for pest detection using visual sensor data. *Plants*. 2024;13(5):653.
 33. Kiobia DO, Mwitwa CJ, Fue KG, Schmidt JM, Riley DG, Rains GC. A review of successes and impeding challenges of IoT-based insect pest detection systems for estimating agroecosystem health and productivity of cotton. *Sensors*. 2023;23(8):4127.
 34. Klinnert A, Barbosa AL, Catarino R, Fellmann T, Baldoni E, Beber C, *et al*. Landscape features support natural pest control and farm income when pesticide application is reduced. *Nat Commun*. 2024;15(1):5384.
 35. Kumar R, Bagul VD, Kumar M. AI in precision pest management and agricultural inputs. In: *Artificial Intelligence Interventions in Agriculture, Food and Health Sectors*. Cambridge (MA): Academic Press; 2026. p. 65-90.
 36. Legwaila MM. Farmers' knowledge of the carmine spider mite, *Tetranychus cinnabarinus* Boisduval (Acari: Tetranychidae), its susceptibility to acaricides and activities of detoxifying enzymes in Botswana [doctoral dissertation]. Gaborone: Botswana University of Agriculture and Natural Resources; 2023.
 37. Li W, Zheng T, Yang Z, Li M, Sun C, Yang X. Classification and detection of insects from field images using deep learning for smart pest management: A systematic review. *Ecol Inform*. 2021;66:101460.
 38. Li Y, Wang H, Dang LM, Sadeghi-Niaraki A, Moon H. Crop pest recognition in natural scenes using convolutional neural networks. *Comput Electron Agric*. 2020;169:105174.
 39. Lima MCF, de Almeida Leandro MED, Valero C, Coronel LCP, Bazzo COG. Automatic detection and monitoring of insect pests: A review. *Agriculture*. 2020;10(5):161.
 40. Liu L, Du Y, Li X, Sun T, Zhang W, Li G, *et al*. An automatic forage unloading method based on machine vision and material accumulation model. *Comput Electron Agric*. 2023;208:107770.
 41. Llorens J, Gil E, Llop J, Escolà A. Variable rate dosing in precision viticulture: Use of electronic devices to improve application efficiency. *Crop Prot*. 2010;29(3):239-248.
 42. Ma CS, Wang BX, Wang XJ, Lin QC, Zhang W, Yang XF, *et al*. Crop pest responses to global changes in climate and land management. *Nat Rev Earth Environ*. 2025;6(4):264-283.
 43. Maroto-Gómez M, Bueno-Adrada M, Malfaz M, Castro-González Á, Salichs MÁ. Human-robot pair-bonding from a neuroendocrine perspective: Modeling the effect of oxytocin, arginine vasopressin, and dopamine on the social behavior of an autonomous robot. *Robot Auton Syst*. 2024;176:104687.
 44. Mirkin CA, Petrosko SH, Artzi N, Aydin K, Biagione A, Brinker CJ, *et al*. 33 unresolved questions in nanoscience and nanotechnology. 2025.
 45. Mittal M, Gupta V, Aamash M, Upadhyay T. Machine learning for pest detection and infestation prediction: A comprehensive review. *Wiley Interdiscip Rev Data Min Knowl Discov*. 2024;14(5):e1551.
 46. Mohsan SAH, Khan MA, Ghadi YY. Editorial on the advances, innovations and applications of UAV technology for remote sensing. *Remote Sens*. 2023;15(21):5087.
 47. Mungee M. Monsoon meteorology and agricultural phenology structure atmospheric transport of aerial biomass across the Indian subcontinent. 2026.
 48. Padua L, Vanko J, Hruska J, Adão T, Sousa JJ, Peres E, *et al*. UAS, sensors, and data processing in agroforestry: A review towards practical applications. *Int J Remote Sens*. 2017;38(8-10):2349-2391.
 49. Pasaribu SAP, Nainggolan BD. Feature-based pistachio classification: A 28-dimensional dataset with KNN. *JADEN J Algorithmic Digit Eng Netw*. 2025;1(1):1-8.
 50. Popescu D, Dinca A, Ichim L, Angelescu N. New trends in detection of harmful insects and pests in modern agriculture using artificial neural networks: A review. *Front Plant Sci*. 2023;14:1268167.
 51. Prabhakar M, Thirupathi M, Mani M. Principles and application of remote sensing in crop pest management. *Trends Hortic Entomol*. 2022:157-183.
 52. Rauf S. Insecticide resistance in agricultural pests: Challenges and solutions. *Trends Biotech Plant Sci*. 2024;2(1):36-41.
 53. Rose DC, Wheeler R, Winter M, Lobley M, Chivers CA. Agriculture 4.0: Making it work for people, production, and the planet. *Land Use Policy*. 2021;100:104933.
 54. Saiyam D, Meena MK. Chickpea immunity enhancement and direct pest-targeting strategies for managing *Helicoverpa armigera*. *Plant Physiol Rep*. 2026:1-13.
 55. Saran S, Hiremath SS, Kumar A, Ashoka P, Singh H, Chakraborty S, *et al*. Remote sensing and automated monitoring systems for insect pest detection and surveillance. *Uttar Pradesh J Zool*. 2025;46:155-171.
 56. Satapathy S. Adoption challenges of Industry 4.0 in agrisector and designing. In: *Advanced Computational Methods for Agri-Business Sustainability*. Singapore: Springer; 2024. p. 305-320.
 57. Shao X, Zhang Q, Zhang B, Xie Z, Xu K. Biological control of insect pests in agroecosystems: Current challenges, innovative strategies, and future directions. *Agriculture*. 2026;16(5):597.
 58. Talaviya T, Shah D, Patel N, Yagnik H, Shah M. Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. *Artif Intell Agric*. 2020;4:58-73.
 59. Tan PN, Steinbach M, Karpatne A, Kumar V. Classification: Basic concepts and techniques. In: *Introduction to Data Mining*. 2nd ed. Boston: Pearson; 2019. p. 113-192.
 60. Tao W, Wang X, Xue JH, Su W, Zhang M, Yin D, *et al*. Monitoring the damage of armyworm as a pest in summer corn by unmanned aerial vehicle imaging. *Pest Manag Sci*. 2022;78(6):2265-2276.