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Artificial Intelligence in Integrated Pest Management: A Technological Paradigm Shift

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ABSTRACT

Feeding a world population that is growing exponentially and expected to peak at over nine billion by the year 2050 requires a significant increase in agricultural production. Synthetic pesticides, though still widely used, carry serious risks through bioaccumulation, ecological disruption, and the accelerating emergence of resistant pest populations. Despite decades of progress in crop-protection science, insects and pathogens continue to destroy an estimated 20-40% of crop yields every year. Artificial intelligence (AI) represents a genuine step-change in how these challenges can be addressed. By combining machine learning (ML) and deep learning (DL) with remote sensing and IoT platforms and UAVs, AI enables accurate real-time identification of pests, assessing the risk of infestations, and predicting outbreaks, which goes beyond the scope of traditional scouting methods. This review systematically examines the current landscape of AI-driven Integrated Pest Management (IPM), covering applications in insect systematics, disease surveillance, habitat classification, yield prediction, and decision-support systems. Key sensing modalities, such as acoustic and ultrasonic sensors, electronic noses, UAVs, and hyperspectral imaging, are also evaluated, as they form the data backbone of modern AI-powered pest management. Special attention is given to persistent barriers: data scarcity and heterogeneity, limited field scalability, and model opacity, alongside emerging research directions that may overcome them. This review presents AI not merely as a technological upgrade, but as an essential component of the next generation of sustainable agriculture.

Keywords: Artificial Intelligence; Agriculture; Disease Management; Internet of Things; Pest Management; Remote Sensing

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1. INTRODUCTION

It is predicted that the world population will considerably increase in the middle of the century. Such a constant growth exerts a stress on agricultural systems to compensate the respective growth in food demand (Wen et al., 2019). Scientific interventions are needed to boost the yield of crops and to deal with the collapse between food production and demand. Despite the significant development in the methods to protect crops, the problem still exists, causing significant losses of crops each year all over the world (Junaid & Gokce, 2024; Darode & Kasetwar, 2026). Pests decrease the crop yields, which is a huge issue worldwide with direct impact on the economic stability and food security. It is estimated that every year, pests and diseases result in 20-40% of crop losses in the world (Savary et al., 2019).

Artificial intelligence (AI) offers revolutionary possibilities to manage pests in agriculture by breaking the bottleneck of the traditional approach that relies on labor-intensive methods and increase in pest resistance (Kariyanna & Sowjanya, 2024; Leybourne et al., 2024; Abbas et al., 2026). Within this scope, AI assists in various operations, such as the accurate identification of pests, the early identification, and prediction (Verma & Parganiha, 2026). The field of agricultural pest management has a significant potential of artificial intelligence revolution (Dey & Roy, 2026). These technologies will be able to enhance crop productivity and reduce environmental damages by supporting targeted and sustainable control measures, early-detecting pests, and correct identification of pests (Abbas et al., 2026).

Conventional pest management approaches like the use of chemical pesticides, human observation, and a decision system based on a rule have long been the focal point of curtailing crop losses (Balaska et al., 2023; Vidya et al., 2025). Nevertheless, these methods are being constrained more by environmental hazards, pest resistance, high operation expenses and low scalability. This leads to increased demand of smarter, viable and dynamic pest control solutions (Balaska et al., 2023). The traditional IPM process is a cyclic process: identification of pests, monitoring of their population, making of decisions, implementing actions to control the population and evaluation of the results of the actions (Barzman et al., 2015). This standard IPM process (shown in Figure 1) underlies most contemporary approaches to pest management.

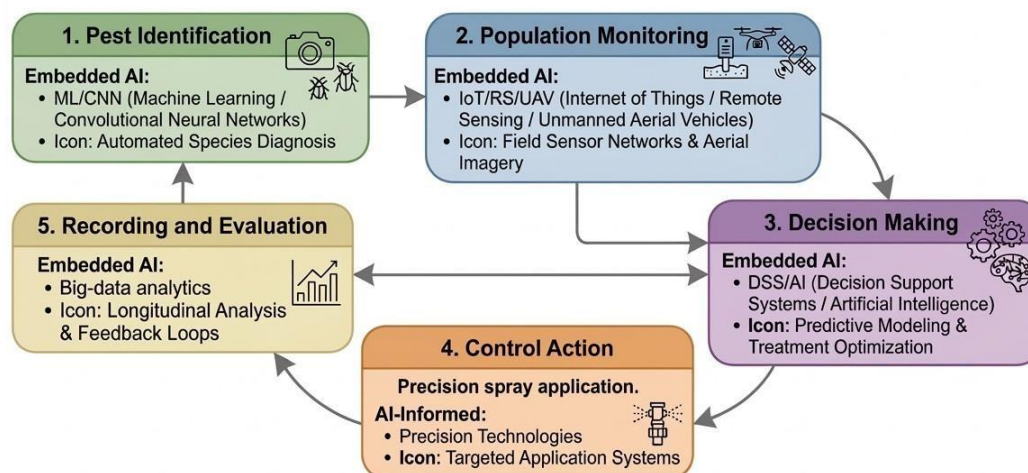


Figure 1. The AI-enhanced IPM cycle. Each of the five stages of pest identification, population monitoring, decision-making, control action, and recording and evaluation is augmented by a distinct AI technology. ML/CNN drives automated species diagnosis; IoT/RS/UAV systems support field sensor networks; DSS/AI tools enable predictive modelling and treatment optimisation; precision technologies deliver targeted applications; and big-data analytics close the feedback loop through longitudinal evaluation.

This systematic review aims to identify and categorize the literature related to AI-based pest management programs with a focus on design methodologies and implementation frameworks. It also compares the different AI technologies, data gathering systems and the control systems used in pest control practices. Using a combination of the recent research results, this review outlines the existing trends, as well as the existing advantages and constraints of the AI-based pest management systems (Wu et al., 2025; Chaudhary & Jabborova, 2026). It further outlines unresolved challenges and research directions that need to be done in future so that effective, scalable and sustainable solutions to pest management can be developed. This review looks at the diverse uses of AI in protecting crops with particular focus on the role it plays in the improvement of world food security.

2. CHARACTERISTICS OF ARTIFICIAL INTELLIGENCE

The term AI refers to the computational systems with the mechanism to fulfill the tasks that would otherwise require human mental abilities (Sujana & Augustine, 2024; Anurag, 2024). Being a subfield of computer science, AI is designed to create machines that can be learned, think logically, solve problems, and process sensory data activities that are at the center of human thought (Cappello et al., 2023; Zhang et al., 2021).

Machine learning (ML) is one of the fundamental applications of artificial intelligence, where improvement of performance is achieved by recognizing patterns in the data and adjusting on experience (Sabrina et al., 2022). Deep learning (DL), a specific branch of machine learning, involves the use of layered computation models, also

known as artificial neural networks, to process information in a way that is similar to biological neural circuits, and allows more complex prediction and classification tasks (Vilar-Andreu et al., 2024).

2.1. TIMELINE OF AI ADVANCEMENT IN PEST MANAGEMENT

The incorporation of artificial intelligence into different pest control strategies has gone through some significant stages, starting with simple statistical models and going through large-scale DL systems used nowadays. Figure 2 presents the key milestones in this evolution from 2015 to 2026.

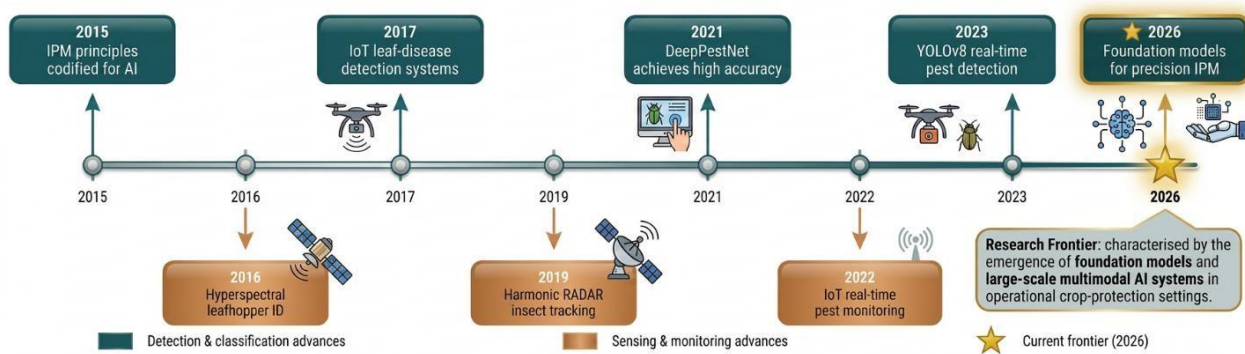


Figure 2. Key milestones in the development of AI for integrated pest management applications. The timeline spans 2015 to 2026 and highlights advances in detection, recognition, and classification tasks (indicated by teal boxes above the timeline). The timeline also shows the codification of IPM processes for AI integration, the demonstration of high accuracy by DeepPestNet, real-time pest detection enabled by YOLOv8, and the appearance of foundational models for precision IPM. Sensing and monitoring advances (orange boxes, below the timeline) include hyperspectral leafhopper identification, harmonic radar insect tracking, and IoT real-time pest monitoring systems.

The trend visible in Figure 2 is clear and consistent: each successive generation of AI tools in pest management has expanded both the range of pest taxa that can be detected and the speed at which detection, monitoring, and decision support can be delivered. The 2026 research frontier characterized by foundation models and large-scale multimodal AI represent the current cutting edge of operational crop-protection systems.

2.2. ARTIFICIAL INTELLIGENCE IN THE CURRENT CROP PROTECTION

AI is a breath-taking paradigmatic technology that has extreme consequences in various fields, including agriculture. This is the technology that gives machines the ability to interpret, process, and react to data, thus solving complex problems with greater accuracy and efficiency in terms of operations (Chen et al., 2020). In the agricultural, AI can be used in a variety of ways: to track the state of crops and soil, to detect pests and diseases, to automate irrigation, and to predict the weather (Batz et al., 2023). With the use of huge datasets and advanced algorithms, AI-based systems enhance and streamline farming practices (Ali et al., 2026).

2.3. AI REVOLUTION IN PEST MANAGEMENT

AI helps to improve pest management through the accurate recognition of pest, early pest detection, and predictive analysis. This can contribute to the more informed decision-making and, as a result, less indiscriminate use of pesticides and the optimization of interventions (Leybourne et al., 2024). AI also helps in tuning up the larger farming methods like crop rotation, manure application, and when to irrigate crops by producing precise data about the weather, soil conditions, and crop development (McDowell, 2017; Shukla et al., 2026). Particularly, the potential of automated insect detection, monitoring, and classification systems is significant, and can be used to reinforce pest control, reduce the use of pesticides that are applied to the fields in excess, and enhance the yield and quality of crops (Aslan et al., 2024). Various AI-based approaches have been used in managing different pests in various studies. The traditional pest surveillance that relies on manual pest scouting plus expert opinion are commonly open to labor and error-based issues. Conversely, AIs, especially machine learning have brought fresh developments in computer vision and predictive analytics to more advanced agricultural procedures (Wang et al., 2025). The technologies enable the identification of pests in real-time and with high accuracy, which eliminates the need to use manual inspection (Ali et al., 2023; Hussein, 2026).

However, there are also several barriers to the use of AI decision support systems. These include doubts about the efficacy and functionality of the technology in the practical conditions, the need for computational competencies

and resources, and limitations in the mobility of the systems (Leybourne et al., 2024). One of the primary technological problems is the correct identification of the pest species in complex agricultural biodiversity. Pest datasets are often highly diverse, and many of them are small species and can be found in high concentrations, making it challenging to detect them and classify them efficiently (Sun et al., 2024). Moreover, the morphological resemblance of most pest species is a major challenge to AI models particularly the ability to discriminate between taxa with slight visual variations (Yang et al., 2023). Other challenges are associated with the quality of the data set, such as the imbalance in the classes, missing annotations, and drawbacks of the current algorithms that identify small objects (Teixeira et al., 2023).

3. INSECT SYSTEMATICS AND TAXONOMY

The threat resulting from the introduction of non-indigenous pest species is growing at an alarming rate and is becoming a biosecurity issue. This is mainly attributed to tourism activities, international trade, and climate change (Hulme, 2009). Three similar species of fruit flies, *Anastrepha sororcula*, *A. fraterculus* and *A. oblique* were discovered with the assistance of reflectance data collected by an RGB camera and the wings and aculeus of the three species compared to each other (Faria et al., 2014). Researchers could distinguish between healthy kernels of wheat and those damaged by insects in the storage using proximal remote sensing (PRS) and hyperspectral reflectance profiles, using a near-infrared spectroscopy (NIR) and a hyperspectral imaging system (Singh et al., 2010). Two species of fruit flies (Dowell & Ballard, 2012), *Chloridea virescens*, and *Helicoverpa zea* (Jia et al., 2007) were also identified using the same technique. Likewise, the imaging spectroscopy was incorporated to distinguish two cryptic species of ants (*Tetramorium impurum* and *T. caespitum*) (Klarica et al., 2011). Wang et al. (2016) applied hyperspectral imaging with spectral bands in the range of 41.1 to 87nm to classify the insects with the help of mitochondrial DNA and morphometry and discovered seven different Evacanthine leafhopper species.

The ML algorithm was developed to examine the images to find out the predominant insect pests that infest coffee fields and proved to be more efficient than the traditional methods to detect and identify pests (Lee & Tardaguila, 2023). One of the areas of ML and DL was utilized to recognize and detect the abundance of whiteflies in tomatoes by identifying whiteflies in different stages (Lutz & Coradi, 2022). Saikumar et al. (2023) experimented on the identification and classification of insect pests in brinjal by means of Python software with Keras and Tensorflow frameworks and used CNN-VGG-16. The input data of this study consisted of 204 images of insect pests captured in course of the research which are employed to identify and classify insect pests such as Brinjal shoot and fruit borers and Epilachna beetle.

3.1. MOVEMENT AND MIGRATION OF INSECTS

The entomological RADAR can be utilized to track the target species of migrant insects. The remote sensing (RS) technology allows the automatic recording of the altitude, horizontal speed, direction, orientation, plus the body mass and shape of the insects. The recent advancements in the field of RS have enabled the development of innovative harmonic RADAR systems that can effectively monitor specific insect species at an altitude of 500 meters (*Vespa vellutina*) (Maggiora et al., 2019).

3.2. BIOTIC STRESS DETECTION

Crop productivity can be greatly influenced by biotic stresses, diseases and insect pests. RS can be applied to identify crop stress due to pests and diseases, and it is founded on the idea that biotic stress leads to changes in pigmentation and physical appearance of plants, as well as photosynthesis, that directly change the rate of energy absorption and reflectance pattern of plants (Prabhakar et al., 2012).

3.3. PEST MONITORING AND FORECASTING

A larval age distribution within a field is an important factor determining primary and secondary outbreaks of pests and the timing of effective application of an insecticide in a pest management strategy. RS is vital in availing data about stage of insect pest in the field depending on the growth rate (Yones et al., 2012; Chaudhary & Jabborova, 2026). The result of a study carried out by Nansen et al. (2015) on two insect species, *Sitophilus zeamais* and *Cynaues angustus*, showed that the variation in time in terms of body reflectance patterns was associated with the reaction of two killing agents entomopathogenic nematodes (EPNs) and insecticidal plant extract. The author has analyzed the infestation of black fly and brown spot scale in citrus orchards and whitefly infestation in cotton by means of color infrared photography. Similarly, the presence of mites in cotton fields was monitored with multispectral RS at an early stage by observing the changes in the appearance, color, and canopy of the cotton over time (Fitzgerald, 2000). The ML models can be used to predict the outbreak of pests, such as the major pests of tomato crops were predicted with far higher precision than classical statistical models (Holzinger et al., 2023);

Thayalan et al., 2026). AI can be used to fulfill agricultural interventions by aiding in precise identification and regulating agricultural pests (Naveed et al., 2024; Rajabpour & Yarahmadi, 2026).

The table highlights the identification, detection, and evaluation of the key crop insect pests in various agricultural systems. The field of artificial intelligence is applied to detect image and sound insect species automatically. They facilitate the forecasting of pest outbreak and population patterns using big data. The methods aid in accurate pest management through maximization of control measures. AIs are also useful in researching the insect behavior, distribution, and reaction to environmental changes (Table 1).

Table 1: *AI and machine learning applications in entomology*

Insects	Crop	Research Focus	Reference
Thrips	Tomato	Pest management decision support	(González et al., 2022)
Whitefly	Tomato	Life-stage assessment and identification	(Lutz & Coradi, 2022)
Major insect pests	Tomato	Pest outbreak prediction	(Holzinger et al., 2023)
Whitefly	Cotton	Detection of pest traits	(Toscano-Miranda et al., 2022)
<i>Riptortus pedestris</i>	Soybean	Detection and forecasting	(Park et al., 2023)
Major insect pests	Coffee	Detection and identification	(Lee & Tardaguila, 2023)
Locust	—	Monitoring and management	(Klein et al., 2021)
Aphid	—	Pest population forecasting	(Batz et al., 2023)
Fruit fly & Aphid	—	Species identification and population dynamics analysis	(Murmu et al., 2022)
Insect pests (multiple species)	—	Pest classification	(Xia et al., 2023)
Insect pests (multiple species)	—	Insect activity monitoring	(Rydhmer et al., 2022)

3.4. AI IN DISEASE SURVEILLANCE

AI-augmented systems, including drones, sensor networks will allow surveillance around the clock to detect the initial signs of lesions in plants (Ajakwe et al., 2024). The table also highlights some of the main ways of using RS technologies in identifying, detecting, and evaluating major crop diseases in various agricultural systems. It also states that hyperspectral and multispectral remote sensing have been widely used to detect disease symptoms, monitor the disease at early stages of infection, study disease-alteration, and estimate the severity of diseases in crops such as wheat, rice, apple, sugarcane, peanut, broccoli and oil palm. Hyperspectral methods are favored early detection and disease discrimination because of their sensitivity to minor physiological and biochemical variations, whereas multispectral satellite data are generally used to map disease in large regions and to analyze its severity. Overall, the table shows that remote sensing is an effective, non-destructive, and scalable instrument of monitoring crop diseases and it is the main factor in precision agriculture and the management of plant health (Table 2).

Table 2: *The role of artificial Intelligence in managing diseases*

Disease	Crop	Research Objective	AIs Technique	References
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Powdery mildew	Wheat	Identification of diseases caused by <i>Erysiphe graminis</i> and <i>Gaeumannomyces graminis</i>	Hyperspectral RS	(Graeff et al., 2006)
Yellow rust (<i>Puccinia striiformis</i>)	Wheat	Early-stage disease detection	Hyperspectral RS	(Bravo et al., 2003)
Leaf rust	Wheat	Disease detection and classification	Hyperspectral RS (HyMap)	(Franke & Menz, 2007)
Orange rust	Sugarcane	Disease detection and discrimination	Hyperspectral RS (Hyperion)	(Apan et al., 2004)
Bacterial leaf blight	Rice	Disease severity estimation	MLR Hyperspectral RS	(Yang, 2010)
Stem rot (<i>Ganoderma</i> spp.)	Oil palm	Disease mapping and identification	Multispectral RS (QuickBird)	(Santoso et al., 2011)

4. INSECT HABITAT CLASSIFICATION AND IDENTIFICATION

RS imagery is also available by using multispectral scanners, which are installed on Earth-orbiting satellites, Landsat, which can be useful in determining the habitat of a certain insect. The Lewis and Clark Lake in the states of Nebraska and South Dakota in the USA were determined as the habitat of mosquito larvae by using a multispectral scanner. Seven mosquito species were observed to be living in this lake; *Aedes dorsalis*, *A. vexans*, *Culex tarsalis*, *C. restuans*, *C. silinarius*, *Culiseta annulate*, and *Anopheles walkeri* (Hayes et al., 1985). Likewise, RS and GIS methods have also been applied in locating locust habitat monitoring and breeding areas in Africa, South Europe and Southwest Asia (Latchininsky & Sivanpillai, 2010).

The process of measuring the activity of flying insects can be carried out with the help of infrared sensors using near-infrared LED lights and high-speed photodetectors (Rydhmer et al., 2022). The process of measuring the various parameters such as the frequency of wing beats, melanization and the ratio of the wings to the body is possible in the field and uploading the information in a cloud database automatically and then analyzed by ML and AI. Xia et al. (2023) evaluated the usefulness of the Vision Transformer (ViT) model in the classification of pests. The researchers have used, DNVt, MMAInet, ResNet50 and an ensemble learner to combine the results of these three models with a final classification vote. MMAInet included an attention process to determine discriminative image regions. The classification models that were trained on the identified regions and at different resolutions were then classified to classify fine-grained objects. The locusts' outbreaks in various regions across the globe are common every year. This is because locust habitats are difficult to map and track down, which are primarily, found in inaccessible conflict zones of various nations. Nevertheless, RS applications have been applied in recent years (1980s) to monitor and control locust swarms. Today, UAVs have introduced a new prospect of managing locusts in a more proficient way. AVHRR, SPOT-VGT, and MODIS and Landsat have been used in the studies to monitor locust outbreaks (Klein et al., 2021).

5. PEST INFESTATION AND YIELD PREDICTION

The damage of crops caused by pests can be analyzed knowing the reflectance pattern with the assistance of unmanned aircraft systems and the percentage of crops that should be harvested under certain conditions such as pest damage (Hunt & Rondon, 2017; Vinatier & Perez-Lopez, 2026). Remote sensors have been used in the crop yield forecast based on the correlation between the VIs and the yield (Casa & Jones, 2005). The sensitivity to various factors and specially pests and diseases make it challenging parameter to determine but with the help of sensors the identification of this pattern has enabled predicting the yield. To estimate the yield of wheat crops, Sharma et al. (2020) used a combination of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models on the raw images data (Figure 3). The suggested model had an impressive 74% accuracy increase over the traditional methods of predicting crop yield and was 50% more accurate than other deep learning models. The comparative analysis of three methods namely Artificial Neural Network (ANN), CNN, and Recurrent

Neural Network (RNN) with LSTM was performed by Dharani et al. (2021) and Bal et al. 2026 to determine the efficiency of the methods in predicting crop yield (Figure 3). These findings showed that CNN was more accurate than ANN, whereas RNN with LSTM was best with 89% accuracy (Dharani et al., 2021; Bal et al., 2026). Model CNN-RNN was suggested to predict soybean and corn yield in the United States (Khaki et al., 2020; Gupta et al., 2025).

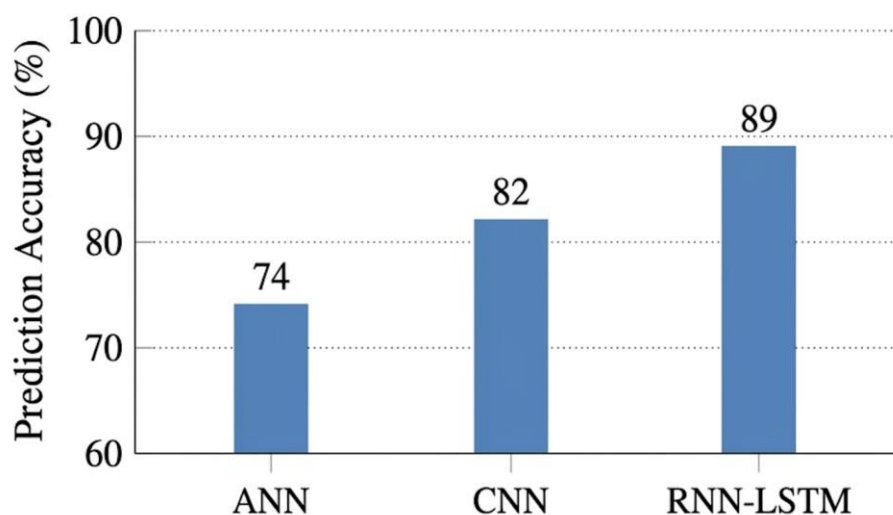


Figure 3. Comparison of the predictive accuracy of three deep learning architectures ANN (74%), CNN (82%) and RNN-LSTM (89%) for crop yield estimation tasks. The RNN-LSTM architecture has the highest accuracy because its recurrent structure is able to capture temporal growth patterns not captured by purely spatial networks such as the CNN. These values are taken from Dharani et al. (2021) and Sharma et al. (2020).

Jae-Hyun (2021) has implemented artificial intelligence, particularly artificial bee colony optimization, ANN, and extreme learning machine algorithms, for the detection of sunn pest damage in wheat grains. In the study of cotton crops, Toscano-Miranda et al. (2022) have applied AI feature extraction, image segmentation, and classification processes, using such algorithms as support vector machines, CNN, back-propagation neural networks, and fuzzy inference. The experiment was conducted to identify the most frequent pests, namely, whiteflies, and pathogens, including the root rot.

6. MACHINE LEARNING IN PEST MANAGEMENT

The issues of crop loss that could be due to insects and the changes in the behavior of insects highlight the need to find methods of monitoring that would be more effective and sustainable. ML has yet become an inseparable part of the modern pest management and it offers new ways of detecting, monitoring and controlling infestations. The introduction of ML has revolutionized the agricultural pest control due to the development of computer vision and predictive analytics (Thorat et al., 2017). The use of ML methods is now an accepted practice in predicting pest outbreaks. These comprise (CNNs), the Light Gradient Boosting Machine (LGBM) classifier, random forest algorithms, Support Vector Machines (SVM), k nearest neighbor (KNN) classifier and other DL models, including Multilayer Perceptrons (MLP), Radial Basis Function (RBF) network, and parallel deep convolutional neural networks of their own (Huang et al., 2022; Kishi et al., 2023). One of the major applications of these methods is to identify useful tendencies and associations with datasets of environmental data, thus making it possible to predict the presence of crop diseases and pests (Bravo et al., 2003). Real-time meteorological data can significantly enhance the accuracy of these forecasting models and help to create more sustainable and resilient agricultural systems (Huang et al., 2022). Moreover, the application of ML models is used to improve plant health by performing early detection and classification of foliar diseases, a technique that helps minimize losses to farmers and promote food security in the world (Kishi et al., 2023).

The applications of ML in agricultural pest management fall into two primary categories, namely, the identification and prediction of pests and the smart use of pesticide spraying. ML algorithms can be used to identify and predict the presence of pests in crop fields to take early action before the infestations grow out of control. This feature is considered to be particularly important in detecting insects, diseases and weeds, the uncontrolled growth of which may significantly decrease the yield. Artificial intelligence also facilitates optimization of pesticide application by giving recommendations of environment friendly dose and time of application. The combination of ML models

including pest population vectors, local weather and crop health can estimate the exact amount of pesticide that should be used to control the infestations.

7. DEEP LEARNING IN PEST CONTROL

The development of DL in the agricultural sector offers a great opportunity to boost its productivity, reduce operational costs, and improve the comprehensive management of crops (Mahto et al., 2023). It has been shown that deep learning can be used in sustainable agriculture to assist in early detection and classification of crop diseases and allow immediate action, which can increase yields and reduce negative environmental consequences (Rafi et al., 2023). Moreover, DL and AI increase the effectiveness of pest detection and reduce the labor needs by a significant margin (Zhang et al., 2021). The traditional approaches to the pest detection are hinder by nature and require a lot of manual work. DL and AI, automate these processes, which reduces the need of human labor (Zhou et al., 2023). Such DL-based automated systems are more cost-effective since they reduce the number of people involved in large-scale procedures (Gutiérrez et al., 2019). Figure 4 compares the performance of major DL architectures across both pest and disease detection tasks, confirming that YOLO and EfficientNet lead across both categories. Hybrid DL frameworks that combine multiple model types within secure, integrated architectures have extended these performance gains further in operational settings (Verma & Parganiha, 2026).

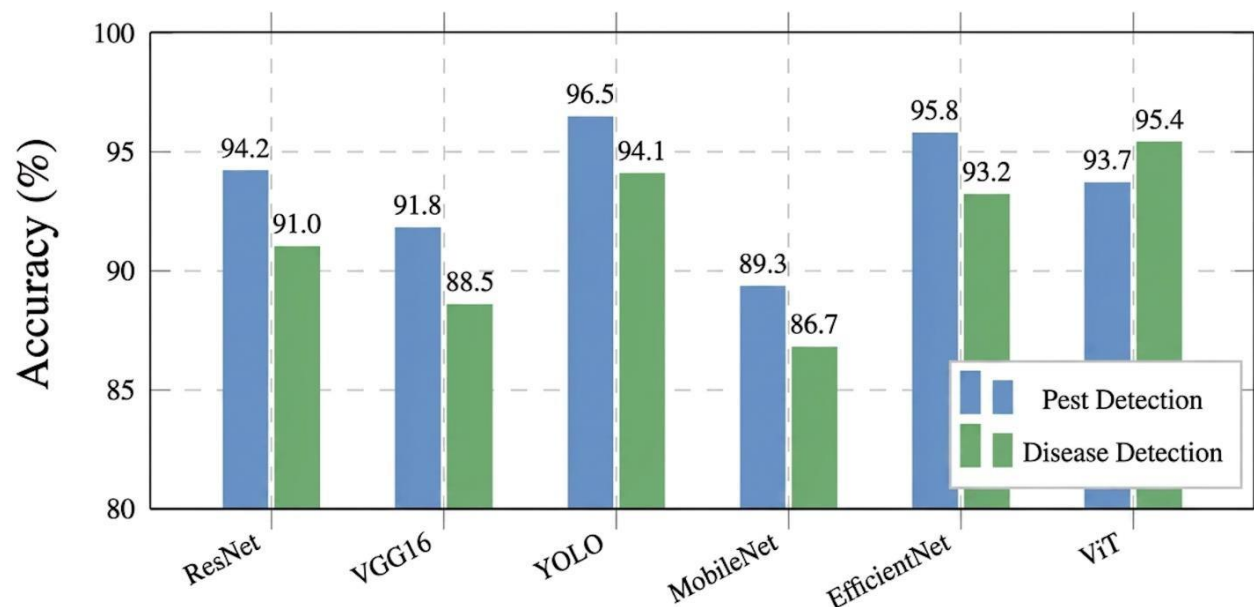


Figure 4. The bar chart below compares the accuracy of six deep learning models for pest detection (blue bars) and disease detection (green bars). The accuracy of YOLO is the highest among all models for pest detection and is equal to 96.5%. The second one is EfficientNet with 95.8%. For disease detection, ViT leads at 95.4%, followed by YOLO at 94.1%. MobileNet performs the lowest in both categories due to its compressed architecture. These results confirm that no single architecture dominates both tasks, motivating the use of ensemble approaches in practice.

The ResNet, YOLO, and MobileNet deep learning models have been shown to be more accurate in detecting pests than traditional ones (Qian et al., 2023). These technologies are capable of processing large amounts of data and working around the clock, providing sustainable and scalable pest detection at large agricultural scales (Vilar-Andreu et al., 2024). DL application has therefore contributed to increased precision in disease diagnosis, surpassing the conventional methods of diagnosis (Omaye et al., 2024).

One of the most important benefits of these models is their speed of processing, CNNs can analyze imagery much faster than human inspectors which means that they can regularly observe pests in real-time (Gutiérrez et al., 2019). The capability is crucial in early detection of diseases on the plant as this facilitates early action to address the disease and achieve its proper management (Omaye et al., 2024).

8. LIMITATIONS OF DEEP LEARNING

There are several key factors that limit the broader application of deep learning: the nature of explainability in many DL-based systems and the large and carefully tuned training sets that are needed (Clark, 2020). Other technical challenges are variations between classes in the data set, complicated backgrounds of the image, co-occurring pests, and extreme morphological similarity between pest species that can impair the design and performance of deep neural network to classify pests (Rafi et al., 2023).

8.1. DATA ANALYTICS IN PEST MANAGEMENT ESSAY

The data analytics in a pest management entails the application of enhanced data collection, modelling and data analysis methods to improve decision making and planning in relation to pest management. The relevant datasets are acquired through various sources, e.g. sensor networks, satellites and geospatial platforms, past agricultural records, and agronomic databases. Unmanned aerial vehicles (UAVs, or drones) provide high-resolution aerial images that help in detection of stress caused by pests on plants and regularly monitor the damage to crops (Bhandari et al., 2024). Satellite remote sensing also provides synoptic, large-scale observation of areas like farmlands (Bhandari et al., 2024).

The sensors based on Internet of Things (IoT) make it possible to monitor environmental parameters and the activity of pests in real time (Kumaran & Saravanan 2023) (Figure 5). The wireless sensor networks are used to collect the dynamic data on status of crops, weather, and pest density, which constitutes an essential premise in predictive modeling (Tripathy et al., 2011; Divya et al., 2014). Field data collection involves scouts and agricultural consultants that offer first-hand information regarding the population of insects; this data can be integrated into centralized databases where they can be further analyzed (Rosenheim, 2021). Moreover, there are automated surveillance systems, e.g., based on bioacoustics, which examine audio recordings to identify the movement and presence of pests (Nugroho et al., 2020).

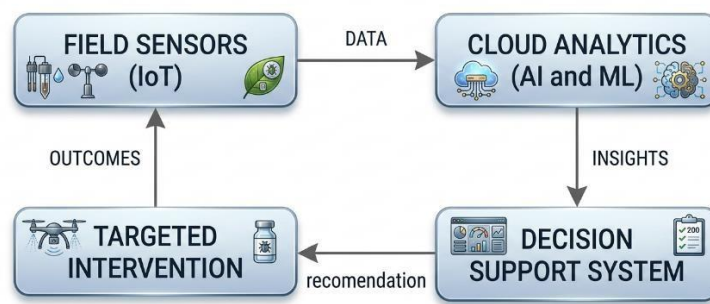


Figure 5. Closed-loop architecture of an AI-driven IoT pest management platform. Field sensors (IoT) transmit environmental and biotic data to cloud analytics (AI and ML), which generate actionable insights for the Decision Support System (DSS). The DSS issues targeted intervention recommendations that are executed in the field; outcomes are fed back to the sensor network, completing the adaptive monitoring loop.

The analysis of data has enhanced crop monitoring, which combines satellite and drone imagery to estimate the state of crops and the occurrence of disease symptoms and yield predictions. Meanwhile, in the field, soil sensors provide data about the parameters of soils, which are useful in making more informed decisions about soil stewardship (Liu et al., 2019).

8.2. DESCRIPTIVE DATA ANALYTICS AND PREDICTIVE DATA ANALYTICS

Descriptive analytics focuses on analyzing historical and current information to understand how to monitor the condition of crops and pests. Predictive analytics is a statistical model in machine learning used for prediction purposes, such as weather forecasts or crop yield, pest, and disease predictions. Predictive analytics goes beyond these predictions by prescribing intervention measures. Therefore, this is a foundational pillar of precision agriculture and optimization in pest management. Secondly, to make the development of agricultural expert systems, a structured and multilayer problem-solving framework is frequently utilized to combine these methods of analysis and offer the entire range of decision support (Ali et al., 2025).

Precision agriculture, also known as smart farming, combines predictive data analytics to optimize agricultural processes. The methodology combines the data of various sources (satellite image, weather stations, soil sensors,

and crop monitoring systems) in order to make a decision based on the timing to plant, nutrient application method, and the pest management strategy (Faical et al., 2017). In the crop pest management context, data analytics is valuable in terms of resource allocation efficiency because it provides information about the most suitable time and dose on applying seed, fertilizer, and pesticides.

8.3. DIFFICULTIES IN PEST MANAGEMENT DATA ANALYSIS

There are a number of difficulties associated with the process of data analysis.

1. Firstly, there is the problem of collection of data. Although farmers and private consultants have recorded vast amounts of pest density across all cropping cycles with high potential to characterize the relations between pests and crops (Thorat et al., 2017) to analyze its quality is imperative. Repeatability analysis can be used to determine the viability of commercial field scouting data (Jayageetha et al., 2020).
2. Data heterogeneity is also an issue that is closely related to agriculture. Agricultural data will be sourced differently: traditional weather stations, high-density sensor networks, remote sensing platforms (e.g., satellites), and field observations of the truth. The combination of these datasets into a single analytical system is complicated because of differences in spatial and temporal resolution, data formats, and the possible discrepancies (Jayageetha et al., 2020).
3. Inconsistency of data also makes integration difficult. Various sources usually use different formats, unit of measure and time, making it difficult to standardize and effectively compare incoming information.
4. Another serious obstacle is the sparsity of data. It is common with the development of accurate predictive models due to lack of comprehensive and reliable data that can be used in development of accurate models of different pests and areas.
5. Lastly, there is the issue of accuracy of the data that should be taken seriously. The miscalculation of the population of pests and inefficient control measures may occur due to errors added by the collection (e.g., human error, sensor malfunction) and processing (e.g., troublesome cleaning procedures).

9. ADVANCED AI TECHNOLOGIES FOR PEST MANAGEMENT

Use of AI applications in the field of pest management is transforming the agricultural practices in terms of detection and surveillance of pests. (Figure 6). With the emergence of new trends in the population of pests and the demand to introduce more sustainable farming mechanisms, the use of AI methods has increased (Kariyanna & Sowjanya, 2024). The use of AI is a game changer as it implements advanced algorithms to exert the patterns of complex data in various sources like sensors and digital imagery to help in proper pest recognition, early detection, and predictive modeling (Kariyanna & Sowjanya, 2024).

ADVANCED AI SENSING TECHNOLOGIES IN INTEGRATED PEST MANAGEMENT (IPM)

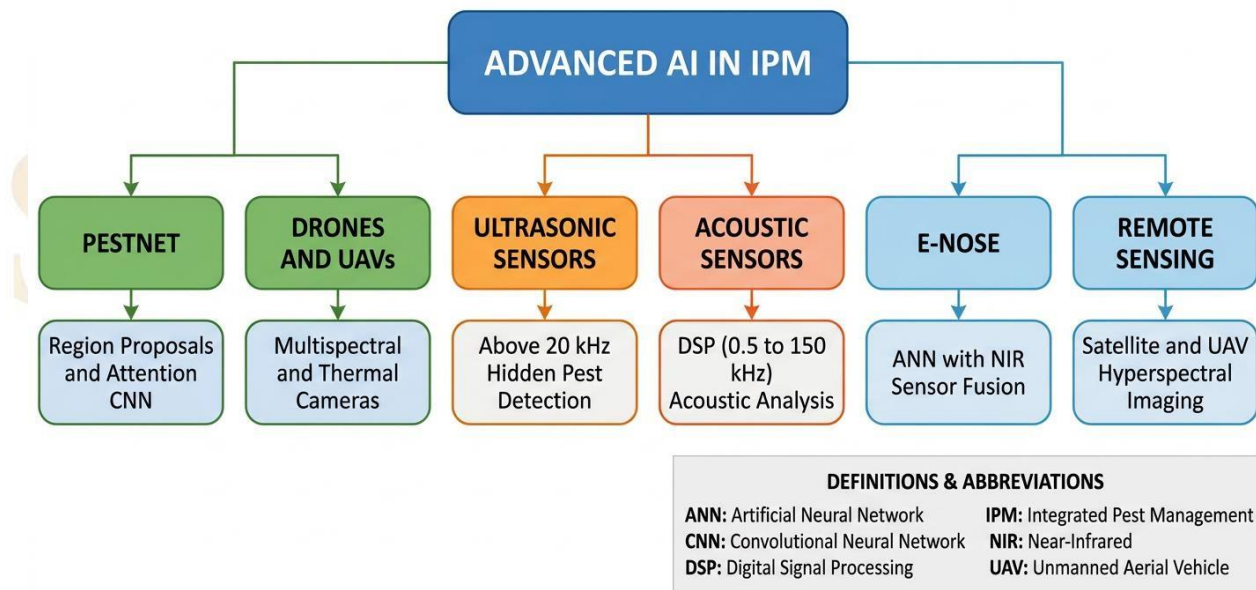


Figure 6. *Advanced AI sensing technologies integrated in modern IPM. PestNet and drone/UAV systems form the detection and aerial imaging branch; ultrasonic and acoustic sensors serve the hidden-pest detection branch; E-nose and remote sensing technologies form the chemical and spectral sensing branch. Key abbreviations: ANN = Artificial Neural Network; CNN = Convolutional Neural Network; DSP = Digital Signal Processing; NIR = Near-Infrared; UAV = Unmanned Aerial Vehicle.*

The main AI technologies used are ML, DL, and computer vision, which are applied to the automated detection, monitoring, and classification of insects in farms (Teixeira et al., 2023; Kalfas et al., 2023). This content is presented here because it was rewritten from scratch in simple English language

AI supports the pest management processes by enhancing the precision of the pest detection, early warning, and forecast models. This leads to improved decision-making and reduced use of pesticides, as well as targeted interventions can be promised (Kariyanna & Sowjanya, 2024). Multiple AI-interventions have been implemented in the pest management area already. In particular, there is a combination of image processing and optical sensor technology with pheromone traps that directly detect the pests. Proper pest identification is one of the basic requirements of successful application of Integrated Pest Management (IPM) practices.

9.1. PESTNET

PestNet, a deep learning-based model, was developed to deal with this challenging aspect of pest control since precisely locating and recognizing different insect species in photos is a difficult task (Liu et al. 2019). It uses a new channel-spatial attention merge to optimize the feature extraction, a region proposal network to find the pest positions, and position-sensitive score map to perform classification and bounding box refinement. Also, the contextual information is used to enhance the detection accuracy (Liu et al. 2019). Similarly, DeepPestNet model demonstrated 100 percent accuracy on different pest categories (Ullah et al., 2022). The PestNet can be regarded as the next big step in the field of pest detection and classification since it can be taken as a powerful and correct solution to the problem of managing several pest species on mass-scale. Its novel features and high performance rates give it some prospects of being implemented in the real world of agriculture.

9.2. DRONES AND UAVS (UNMANNED AERIAL VEHICLES)

Unmanned aerial vehicles (UAVs) or drones allow farmers to maximize the use of input applications (seeds, fertilizers, water etc.) to treat biotic stressors such as weeds, pests, and fungal infections so they can also respond quickly to these stresses (Semwal et al., 2026). Some of these AI-based agricultural instruments have been developed by different companies, including Trace Genomics, AGEYE Technologies, Blue Reiver Technology, aWhere, FarmShots, Hortau Inc., Harvest CROO Robotics, Fasal, HelioPas AI, Root AI, Ibex Automation, VineView and PEAT are used to fulfill a variety of tasks, like weather prediction and correlation with pest population dynamics, weed management, picking and packing fruits and vegetables, and irrigation and fertilization (Dutta et al., 2014).

Drones are equipped with multispectral sensors that capture images within the visible and near-infrared regions of the electromagnetic spectrum. Thermal cameras may also be installed to measure the stress levels of crops and identify the presence of pests using image processing methods (Shiva et al., 2020). The process of data acquisition is started by the geospatial planning as the target area is defined, analyzed, and its GPS coordinates are uploaded into the navigation system of a drone. UAVs are autonomous platforms, and therefore, perform preset flight patterns to collect sensor data with multispectral or RGB cameras. After the collection, the raw data are processed using a special program to extract meaning and analyze it. The outputs are presented in easily usable forms-3D maps or photogrammetric models that present the farmer with actionable and understandable information.

9.3. ULTRASONIC SENSORS

The ultrasonic signals generated by insects while feeding can be intercepted to identify which insects are hiding in the seeds, wood, and other fibrous plant materials. Ultrasonic sensors are one of the appropriate instruments to use in detecting wood-boring pests because, at frequencies over 20kHz, background noise is typically minimized (Mankin et al., 2011). One typical pest detecting system consists of an ultrasonic transducer, low-noise narrow-band amplifier, signal conditioner, and an output display. When used, sensor emitted waves bounce off insects in the material; returning signals are digitally processed in order to approximate direction of movement and rough real-time position of the pests. Nonetheless, this type of systems has not been able to maintain consistent performance under diverse environment conditions. Additional research and development projects are needed to make a smart handheld ultrasonic instrument useful in monitoring the pests in the field (Ahouandjinou et al., 2017).

9.4. ACOUSTIC SENSORS

The application of acoustic technology in the detection of insect infestations that are concealed goes way back to the early twentieth century. Acoustic sensors offer a non-destructive, remote way of detecting and tracking hidden

insect presence in substrates of soil, stored grain and wood (Balingbing et al., 2024). Such systems can detect the hidden insects, estimate their density and map their spatial distribution (Mankin et al., 2011).

The advances in the computer technologies enabled more sophisticated digital signal processing schemes that could filter the insect generated sounds from the sounds of the environment. This advancement has triggered the invention of new acoustic systems that can be used to detect and track the invasions of underground and other concealed pests. Modifications of this technology in the modern world enable the detection of insects during feeding. Target species are usually determined by the low-frequency sound (0.5150 kHz) produced by an activity like flight, feeding, and plate calls (Bhairavi et al., 2020).

9.5. E-NOSE

Fuentes et al. (2021) offer a low-cost and efficient tool, which is based on e-nose sensors, combined with machine learning algorithms and NIR. The researchers have designed ANN models in order to determine the extent of insect infestation, predict the pest's life cycle and assess the vitality of the plants with the help of the data obtained from sensors. The authors also suggest the application of such models on a drone-carrying e-nose system to deploy it in the field in real-time, which would provide farmers with a convenient instrument to assist them in making pest management decisions.

9.6. REMOTE SENSING (RS)

Remote sensing is the science of compiling information about an object, area, or phenomenon through the analysis of data collected by a non-contact technology (Lillesand et al., 2015). AI devices used in conjunction with remote sensors, including drones and sensor networks, can enable constant monitoring of the disease site in order to detect the outbreak of the pests at an early stage (Ajakwe et al., 2024). Insect pest populations on large scale are monitored using remote sensing techniques (Table 3).

Table 3: The role of remote sensing in entomological research.

Insect species	Crop	Research objective	RS and AI technique	References
Aphid (<i>Diuraphis noxia</i>)	Wheat	Crop stress quantification	Multispectral RS	(Backoulou et al., 2011)
Tobacco budworm; corn earworm	Cotton	Species identification	Proximal RS	(Jia et al., 2007)
Cotton leafworm	Cotton	Management timing optimization	Satellite RS	(Yones et al., 2012)
Mite	Cotton	Early infestation detection	Multispectral RS	(Fitzgerald, 2000)
Leaf miner	Tomato	Damage assessment and incidence mapping	Leaf reflectance spectroscopy	(Xu et al., 2007)
Cyst nematode	Sugar beet	Symptom mapping	RS and GIS technique	(Hillnhütter et al., 2011)
Brown planthopper (<i>Nilaparvata lugens</i>)	Rice	Spectral response analysis to infestation	Hyperspectral RS	(Yang et al., 2007)
Mountain pine beetle	Pine	Infestation dynamics analysis	Multispectral RS	(Goodwin et al., 2008)
Evacanthine leafhopper	Jujube	Species classification	Hyperspectral imaging	(Wang et al., 2016)
Desert locust	—	Habitat detection and breeding-zone mapping	RS and GIS technique	(Latchininsky & Sivanpillai, 2010)

Fruit fly	—	Species identification	RGB camera	(Faria et al., 2014)
Fruit fly	—	Species identification	Proximal RS	(Dowell & Ballard, 2012)
Ants	—	Cryptic species identification	Imaging spectroscopy	(Klarica et al., 2011)
Biological control (EPNs)	—	The high-tech AI-based knowledge of entomopathogenic nematode behavior	CNN + Microfluidics	(Manduca et al., 2025)
Termite behavior	—	Uncovered caste-specific interaction dynamics to bio-inspired pest control	Computer vision + Transfer Entropy	(Manduca et al., 2025)
Multi-class pest	—	Multi class pest identification	EfficientNet B4, Inception V3	(Ray et al., 2025)
Bird pest	—	Real-time bird detection with 200% FPS improvement	DETR + FPGA acceleration	(Mohamad Sa'ad et al., 2025)
Armyworm & stem borer	—	Real-time pest detection	YOLOv8	(Oyege et al., 2025)

9.7. INTERNET OF THINGS (IoT)

Internet of Things (IoT) Internet of Things (IoT) refers to a system of interconnected physical objects that are equipped with sensors, software, and other technologies that enable them to connect to the internet and exchange data with other systems and devices. IoT can be used in agriculture to provide fast and easy-to-use systems on the field of application. It complements existing knowledge through contributing to the identification of better management choices and processing capacity of big data. IoT has a very strong ability to revolutionize the farming processes, hence enhancing agricultural productivity and sustainability (Abu et al., 2022).

Moreover, IoT technologies can improve the sensing and monitoring of diverse aspects of the production factors, such as use of farm resources, livestock behavior, crop development and food processing stages (Abu et al., 2022). IoT makes possible precision farming where sensors are deployed to ensure continuous monitoring and automation of farming activities, optimizing their resources and improving their harvests (Sharma et al., 2023). These systems provide real-time information on the environment, which enables farmers to make effective decisions to improve the quality and productivity of crops (Sarkar et al., 2023).

Being one of the most promising technologies with the far-reaching economic implications, sensors and actuators, data transmission networks, and cloud computing are integrated into successful agricultural IoT. Being one of the most promising technologies with the far-reaching economic implications, sensors and actuators, data transmission networks, and cloud computing are integrated into successful agricultural IoT. Such integration enables it to achieve precision farming, which leads to increased crop yield, quality, economic benefits through better labor use and resource utilization.

10. CHALLENGES IN USE OF AI IN PEST MANAGEMENT

1. Data issues: It is challenging to access high-quality and labeled data to apply AI in managing pests because of imbalance, visual distortion, and expensiveness of expert labelling. Measured data and inconsistent standards are also a further complication to model development. Some solutions to this would be the adoption of standardized

protocols for data sharing and the use of semi-supervised or synthetic data. Presently available data sets such as IP102 work well but are scanty for species in terms of data (Figure 7).

2. Barriers to adoption: AI is not widely adopted by farmers because of lack of infrastructure (devices and connectivity), the cost of the devices is prohibitive, and farmers lack awareness or training. Access and trust should be enhanced by affordable IoT technologies, convenient interfaces, multilingual services, and educating farmers (Figure 7).

3. Weak AI coverage: The applications of AI are mostly focused on detecting pests, and there has been little progress in predicting the outbreak and control strategy or the ability to make decisions in real-time according to field conditions (Figure 7).

4. Scalability concerns: Most AI models are tested on a small scale and are not easily scalable because of the differences in the environment, connections, and cost. The accuracy of these systems relies on external factors such as lighting and weather conditions plus technical limitations like battery and sensor positioning. Future systems should be equipped with adaptive learning, multimodal input, and site-flexible architectures. (Figure 7).

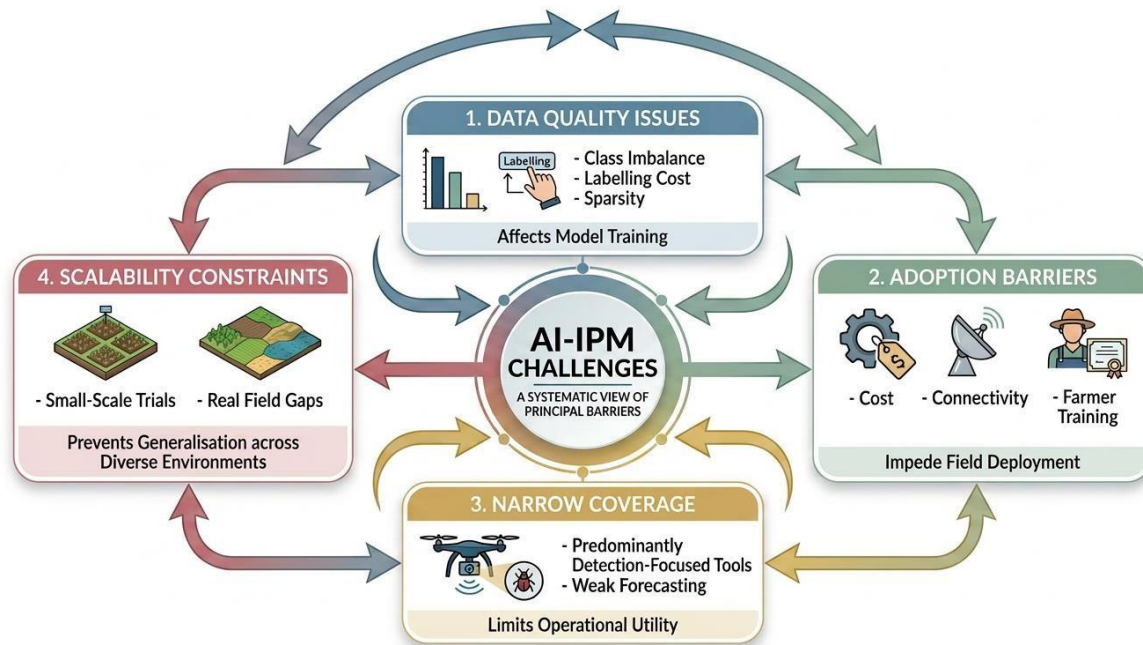


Figure 7. The four principal challenges facing AI-based integrated pest management. Data quality issues (class imbalance, labelling cost, sparsity) affect model training; adoption barriers (cost, connectivity, farmer training) impede field deployment; narrow coverage (predominantly detection-focused tools with weak forecasting) limits operational utility; and scalability constraints (small-scale trials, real field gaps) prevent generalisation across diverse environments

11. CONCLUSION

Artificial Intelligence (AI) is transforming the agricultural industry by enabling it to be automated and accurate, thus improving crop production and yield while also being efficient in terms of resources. Food production sustainability is one of the issues that AI promises to solve in agriculture, being at the forefront of addressing food production challenges that have plagued agriculture in the past years. By employing machine learning and deep learning techniques, AI can help the industry in the identification, monitoring, and control of pests and diseases, as well as make decisions about interventions to take to address these problems. This will result in the optimization of pesticides, higher productivity and more sustainable practices. The incorporation of AI-sensors, robotization, image recognition, and large data analytics can offer real-time information and custom interventions, which can be added to the agriculture resilience and food security. Irrespective of its potential, AI use in crop protection has challenges, such as affordability, technical skills, and ethical aspects. However, the future is bright, and new studies are conducted to develop technologies of protecting plants and to help to sustain the agricultural system.

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