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REVIEW

Transforming Pest Management with Artificial Intelligence Technologies: The Future of Crop Protection

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Abstract
With increasing global population and limited expansion of cultivated land, it is necessary to identify innovative solutions for enhancement of agricultural productivity and meet growing food demand. Despite significant advancements in crop protection methods, substantial annual crop losses persist particularly due to pests. Artificial Intelligence (AI) has emerged as a transformative tool to reform crop protection strategies. With the support of machine learning and deep learning algorithms, AI enables precise pest detection, risk assessment, monitoring, and forecasting thereby minimizing crop losses and maximizing yields. Further, AI integrates expert system and decision support system with crop management aspects for precise and timely decisions for farmers to enhance the crop productivity. In this review article, attempts are taken to explore the applications, implications, and future prospects of AI in field of pest management, emphasizing its pivotal role in agriculture and thus ensuring food security among evolving challenges.

Keywords Pest management · Artificial intelligence · Risk assessment · IoT · Expert system · Pest forecast · Sensors · Pest detection

Introduction

The global population is expected to increase significantly by 2050, with estimates suggesting an addition of approximately 2 billion people. This growth will bring the total population from the current 7.3 billion to around 9.5 billion (Pearson 2016; Borém et al. 2014; Nichols 2019). The United Nations (UN) projections also predicts a population of 9.1 billion by 2050 (Borém et al. 2014). As global population is on constant increase, the pressure on agricultural systems to meet the growing demand for food is escalating. As per the World Health Organization, there is need of 70% increase in food production to meet the food demand of approximately 10 billion people by 2050 (World Health Organization, 2018). Owing to this, there is need for scientific interventions to boost crop yields and link the gap between food production and consumption needs. Despite significant advancements in crop protection approaches, challenges exist, resulting in substantial annual crop losses worldwide. Crop yield losses due to pests are a significant global issue, impacting food security and economic stability. Globally, pests and diseases are responsible for 20–40% of crop yield losses annually (Savary et al. 2019; Beernink et al. 2024; Srinivasan et al. 2022; Vercesi and Cravedi 2011). This in-

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cludes losses from insects, pathogens, and weeds, which collectively pose a major threat to agricultural productivity. The economic losses due to pests and diseases are substantial, with estimates reaching up to $290 billion annually (Beernink et al. 2024; Sahu et al. 2023). For instance, in six African countries, smallholder losses due to five invasive species alone are estimated at $ 0.9–1.1 billion per year (Constantine et al. 2020). In India, where food grain demand is forecasted to exceed 350 million tons by 2030, approximately 15–25% of annual crop yields are lost due to various pests (Dhaliwal et al. 2015). This alarming statistic underscores the critical need for innovative solutions that combines conventional pest control approaches with innovative technological advancements. One such ground breaking innovation to transform agriculture is Artificial Intelligence (AI). As a prominent field of Computer Science Engineering, AI endeavors to redefine human tasks with greater efficiency and accuracy. By enabling machines to comprehend, analyze, and act upon data, AI holds the potential to transform crop protection strategies and enhance agricultural productivity (Srikanth et al. 2020).

Artificial Intelligence technologies offer transformative solutions for pest management in agriculture, addressing challenges such as time-consuming manual methods and increasing pest populations (Kariyanna and Sowjanya 2024; Leybourne et al. 2024). In the field of pest management, AI assists in many different ways, e.g., enables accurate pest identification, early detection and predictive modeling, minimizing indiscriminate pesticide application and optimizing interventions (Kariyanna and Sowjanya 2024). The integration of AI with Integrated Pest Management (IPM) principles can support farmers by providing decision support systems for pest identification and monitoring (Leybourne et al. 2024). AI also facilitates precision agriculture, enhancing resource management and boosting productivity (Dhanta and Mwale 2024). Furthermore, AI-driven systems can fulfil conditions like effectiveness, adaptability, user-friendliness, and mobility to overcome obstacles and integrate with IPM practices (Leybourne et al. 2024). The use of AI in agriculture can improve crop management techniques, disease and pest detection, and monitoring through drones and sensors, leading to increased output and product quality (Naveed et al. 2024).

AI technologies have the potential to transform pest management in agriculture by enabling accurate identification, early detection, and sustainable interventions, ultimately leading to improved crop productivity and reduced environmental impact. This review article highlights the diverse applications of AI in crop protection and its significant potential for enhancement of global food security. It also provides overview and understanding about application of machine learning algorithms for pest detection and also about utilization of deep learning techniques for forecast of pest infestations.

Artificial Intelligence: An Introduction

Artificial Intelligence refers to the ability of computers to perform tasks that typically require human-like intelligence (Sujana and Augustine 2024; Anurag 2024). The concept of AI dates back to the 1940s, with the term "artificial intelligence" first coined in 1955 (Sujana and Augustine 2024; Clermont 2023) (Table 1). AI is a branch of computer science focused on creating systems capable of performing tasks that typically require human intelligence, such as learning, reasoning, problem-solving, and perception (Cappello et al. 2023; Zhang et al. 2021; Bastawrous and Cleland 2022). The field has seen significant growth, with a 205% increase in publications since 2010 (Hemachandran et al. 2024). The primary focus of AI has always been to develop machines that can simulate human behavior by constructing thoughts and responses based on various situations and environments. AI has diverse applications across sectors such as gaming, finance, healthcare, and education (Hemachandran et al. 2024; Sabeer et al. 2023). Notably, AI has gained public attention through achievements like IBM's Deep Blue and Watson, as well as Google's DeepMind (Clermont 2023.)

AI encompasses several key characteristics. Foremost of them include Human-like Intelligence, as AI refers to the ability of machines to mimic human cognitive functions, such as learning from examples, recognizing objects, understanding language, making decisions, and solving problems (Alhafizh et al. 2023; Nazim and Rajewsari 2019). AI involves learning tasks without explicit programming, reasoning to apply intelligence in technology, and self-correction through learning from experience to minimize errors (Alhafizh et al. 2023). Furthermore, AI technologies are designed to imitate human cognitive abilities, enabling them to handle complex and ill-defined problems in an intentional, intelligent, and adaptive manner (Zhang et al. 2021). There exists different fundamental components of Artificial Intelligence, each of which play an specific role like, Artificial Neural Networks (enables machines to learn and recognize patterns (Lewandowski 2008a, b)), Genetic Algorithms (used for optimization and search problems (Lewandowski 2008a, b)), Expert Systems (mimics the human reasoning process and solve specific problems based on acquired knowledge (Ketata et al. 2006; Salem 2019)), Fuzzy Logic Elements (contributes to decision-making processes (Lewandowski 2008a, b)) and Hybrid Systems (combine different AI techniques to solve complex problems (Lewandowski 2008a, b)).

Table 1 Significant milestones in the development of AI (Xu et al. 2021)

Time Period	Key Developments in AI
1940–1956	Birth of AI, with the term “Artificial Intelligence” being coined in the United States
1987–1994	Boom in expert systems aimed at reducing errors in product recommendations
1994–2000	Advent of robotic cars
2000–2010	Emergence of precision agriculture, GPS, GIS, and virtual agents such as Google Now
2010–2018	Rise of cloud computing, the Internet of Things [IoT], big data analytics, networking, data mining, and advanced decision-making technologies

AI involves machine learning (ML), where machines learn from data and experiences to improve their performance (Patel et al. 2024; Atik 2022). A subfield of machine learning, deep learning (DL) processes information similar to the human brain, using computer models to predict and classify information (Pyingkodi et al. 2022). Techniques such as machine learning, deep learning, and big data, are powerful in applications requiring system modeling and future prediction based on past data (Rao et al. 2022). In the current scenario, there is an exponential increase in data leading to role of AI in analysis and management of this vast amount of data. Instead of manually feeding, AI-enabled data is not only gathered but also analyzed with the help of previous experiences. Data ingestion is the transportation of knowledge from assorted sources to a data-storage medium, where it is often accessed, used, and analyzed by a corporation. AI analyses a large amount of such data and provides a logical inference from it (Angelov et al. 2021).

Domains of AI and Their Applications in Crop Protection

AI emerges as a transformative technology reshaping various industries, including agriculture. AI empowers machines to comprehend, analyze, and act upon data to solve complex problems with unprecedented accuracy and efficiency. It offers a wide range of applications in agriculture, including crop and soil health monitoring, pest and disease detection, smart irrigation, weather forecasting, and more. By harnessing vast sets of data and intelligent algorithms, AI systems optimize agricultural practices (Birdwell et al. 1986). In the field of crop protection, different Domains of AI are widely employed. Machine Learning (ML) and Deep Learning (DL) techniques, such as Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNNs), have been extensively applied in agriculture, particularly for precision crop protection (Belattar et al. 2023; Mesías-Ruiz et al. 2023; Naveed et al. 2024). The integration of AI with Internet of Things (IoT) and robotics has shown promise in advancing smart and real-time crop protection systems (Mesías-Ruiz et al. 2023). AI enables predictive modeling for efficient crop monitoring, disease identification, and supply chain optimization (Pandey and Mishra 2024; Rattan et al. 2024). AI shows numerous applications in the field of crop protection for pest and disease management which are mentioned below:

i Precision Crop Protection: AI facilitates precision agriculture techniques, including the detection and control of crop pests (Mesías-Ruiz et al. 2023, Naveed et al. 2024; Peters et al. 2020).

ii Real-time Monitoring: AI-powered systems, including drones and sensors, enable real-time monitoring for early detection of crop lesions and pest infestations (Ajakwe et al. 2024; Khan et al. 2022).

iii Data-driven Decision Making: AI provides accurate data on weather, soils, and plant development, aiding in crop management and disease monitoring (Khan et al. 2022; Wang et al. 2024).

Transforming Pest Management with Artificial Intelligence Technologies

AI techniques enable accurate pest identification, early detection, and predictive modeling, enhancing decision-making for pest control by minimizing indiscriminate pesticide application and optimizing interventions (Kariyanna and Sowjanya 2024; Leybourne et al. 2024). AI provides accurate data on weather, soils, and plant development, aiding in crop management and improving agricultural techniques, including crop rotation, fertilization, and irrigation (Ben-Lhachemi et al. 2024). AI applications have emerged for automatic detection, monitoring, and identification of insects, offering potential in enhancing pest control, decreasing excessive pesticide use, and improving crop output and quality (Teixeira et al. 2023). Different studies have implemented AI approaches for pest management (Table 2). Traditional methods, based on manual checks and expert opinions, tend to be time-consuming and error-prone, while AI, particularly machine learning, has brought innovative shifts in computer vision and predictive analytics, leading to advanced agricultural methods (Wang et al. 2024). AI technologies offer the potential for real-time identification of pests, minimizing the need for human involvement and

Table 2 List of different studies implementing artificial intelligence (AI) in the area of pest management

S. no.	Details	Area of Pest management	Reference
1.	Machine learning techniques for detecting and monitoring specific pests and diseases, including real-time classification of tephritid species using convolutional neural networks	Pest Detection, Monitoring	Tannous et al. (2023)
2.	AI and machine learning models to classify boll-weevil populations using weather data, aiding in pest population management	Pest Monitoring, Forecasting	Toscano-Miranda et al. (2022)
3.	Mobile applications using AI and deep learning for real-time detection and identification of plant pests, supporting crop yield protection and cost reduction	Pest Detection, Monitoring	Christakakis et al. (2024)
4.	Digital insect traps with automated detection and counting of insect pests, enhancing pest management through live monitoring and data-driven decisions	Pest Monitoring	Ludwig-Ohm et al. (2023)
5.	AI and deep learning-based systems for pest management, including multiclass and multi-stadia approaches for counting and identifying different pest species	Pest Detection, Monitoring	Bereciartua-Pérez et al. (2023)
6.	Data mining algorithms for forecasting pest monitoring decisions in kiwifruit crops, using machine learning models to predict insecticide application needs	Pest Monitoring, Forecasting	Hill et al. (2014)

demonstrating high accuracy in automating pest identification (Ali et al. 2023). Common obstacles in the adoption of AI-driven decision support systems include technology effectiveness, functionality under field conditions, computational expertise and power required, and system mobility (Leybourne et al. 2024). One major hindrance in accurately identifying pests using AI is the complexity of biodiversity and the difficulties involved in differentiating between species. Agricultural pest datasets often contain a wide variety of species, which complicates the detection and identification process. The presence of numerous species with small individuals and high concentration increases the difficulty of accurate identification (Hu et al. 2024; Sun et al. 2024). Further, many pest species exhibit high morphological similarity, making it challenging for AI models to differentiate between them. This is specially concerning for species with subtle differences in appearance (Gan et al. 2022; Xu et al. 2024; Yang et al. 2023). Other challenges in AI-driven pest detection and classification include dataset characteristics, unbalanced classes, incomplete annotation, and limitations of algorithms for small objects (Teixeira et al. 2023). Thus, AI technologies have the potential to revolutionize pest management strategies by enabling accurate pest identification, early detection, and predictive modelling, though, the implementation of AI in pest management is not without its obstacles.

Machine Learning in Pest Risk Assessment and Forecasting

The increasing concern about crop loss due to insect and insect behavioural change has reflected the need for efficient and long-term insect monitoring methods. While passive traps provide valuable data, the time-consuming manual analysis and the required taxonomic expertise create a bottleneck. ML plays a crucial role in modern pest management strategies, offering innovative approaches to detect, monitor, and control pest infestations. ML has revolutionized pest control in agriculture, offering advanced computer vision and predictive analytics (Thorat et al. 2017). ML techniques commonly used for pest outbreak forecasting include Convolutional Neural Networks (CNNs), Light Gradient Boosting Machine (LGBM) classifier, Random Forest algorithm, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and various deep learning models such as Multilayer Perceptron (MLP), Radial Basis Function (RBF), and custom parallel deep convolutional neural networks (Ayed and Hanana 2021; Tarek et al. 2023; Banerjee and Mondal 2023; Huang et al. 2022; Kishi et al. 2023; Anarbekova et al. 2024; Delfani et al. 2024; Corrales et al. 2015; Kumar et al. 2013; Patel and Barot 2024; Balasubramaniam et al. 2024; Tonnang et al. 2022). ML techniques are also used to derive knowledge and relationships from environmental data, allowing for the prediction of diseases and pests in agricultural crops (Ayed and Hanana 2021). Integration of real-time weather data enhances the efficacy of pest outbreak forecasting models, contributing to sustainable and resilient agriculture (Banerjee and Mondal 2023; Huang et al. 2022; Kishi et al. 2023). Machine learning models have been used to protect plants from leaf disease by early detection and classification, aiming to decrease losses incurred by farmers and provide food for the world (Patel and Barot 2024).

Within the realm of pest management, ML techniques are predominantly applied in two main areas: *pest detection and prediction*, and *decision support for pesticide application.* ML algorithms can detect and predict the presence of pests in agricultural fields, enabling timely intervention to prevent widespread infestations. This is particularly crucial for identifying pests such as insects, diseases, and weeds, which can significantly impact crop productivity if remain unnoticed (Ayed and Hanana 2021). In case of supervised learning for pest detection, supervised learning algorithms are trained using labelled datasets containing information about known pest occurrences. By analyzing features extracted from various sources such as remote sensing images or sensor data, these algorithms can accurately detect and classify pests in agricultural landscapes (Corrales et al. 2015). Unsupervised learning for pest prediction is employed for large datasets that lack labelled information. By clustering data points based on similarities, unsupervised algorithms can identify patterns indicative of potential pest outbreaks, allowing farmers to take pre-emptive measures to mitigate pest damage (Rastogi 2024). ML models can identify specific pests based on image inputs, facilitating rapid and accurate pest identification. For example, computer vision algorithms can analyze images captured by drones or surveillance cameras to detect and classify pests present in crops (Kashyap et al. 2024).

Machine learning algorithms also assist in optimizing pesticide application by providing recommendations over the most effective and environmentally sustainable dosage and timing. ML models analyze various factors such as pest population dynamics, weather conditions, and crop health data to determine the optimal dosage of pesticides required to control pest infestations effectively. ML algorithms enable precision agriculture techniques, ensuring targeted pesticide application only in pest affected areas. This reduces pesticide usage, minimizes environmental impact, and preserves beneficial organisms in the ecosystem (Yeshe et al. 2022). ML-powered recommendation systems provide farmers with personalized suggestions over pest management strategies based on real-time data and historical trends. This empowers farmers to make informed decisions regarding pest control measures, optimizing resource utilization and maximizing crop yields.

Applications of Deep Learning in Pest Management

The adoption of deep learning in agriculture has the potential to enhance productivity, reduce costs, and improve overall crop management (Mahto et al. 2023). It is already observed that DL can contribute to sustainable agricultural practices by enabling early disease classification and timely action, thereby increasing yield without causing unnecessary environmental damage (Chhetri et al. 2023). Deep learning and computer vision significantly reduce human costs and improve the efficiency and accuracy of pest identification processes (Wu et al. 2022). Traditional pest identification methods are labor-intensive and require significant human resources. Deep learning and computer vision automate these processes, reducing the need for manual labor (Wu et al. 2022; Zhou et al. 2023; Yang and Zhou 2024; Bonilla and Duke 2024). Automated systems using DL are more cost-effective as they minimize the need for extensive human intervention, which is particularly beneficial for large-scale agricultural operations (Gutierrez et al. 2019; Yang and Zhou 2024; Ong and Høye 2024). Deep learning models, including advanced architectures like ResNet, YOLO, and MobileNet, have demonstrated high accuracy in pest detection, often surpassing traditional methods (Yang and Zhou 2024; Qian et al. 2023; Li et al. 2023; Hussain and Balaji 2023; Hassan and Maji 2024). These technologies can handle large datasets and operate continuously, providing consistent and scalable solutions for pest identification across extensive agricultural areas (Wu et al. 2022; Zhou et al. 2023; Vilar-Andreu et al. 2024). The use of deep learning techniques has resulted in improved accuracy rates for disease classification, surpassing traditional methods (Stephen et al. 2024; Omaye et al. 2024; Tekale and Singh 2023). DL models have achieved high accuracy rates in insect categorization and in recognizing and classifying crop pests. For example, one study using the Faster R-CNN Efficient Net B7 model achieved an average classification accuracy of 93.00% for 15 class insect pests (Kundur and Mallikarjuna 2022). Another study using a YOLO V3 classifier reported an accuracy of 99% for pest detection in rice crops (Anitha et al. 2024). In another study, DeepPestNet framework achieved 100% accuracy in recognizing and classifying crop pests into 10 classes (Ullah et al. 2022). Additionally, another study using the EResNet-SVM model reported 100% accuracy for the recognition and classification of six insect pests (Xiong et al. 2024). DL models, particularly Convolutional Neural Networks (CNNs), have shown significant promise in accurately detecting and classifying pests in agriculture (Mahto et al. 2023 Panchbhaiyye and Ogunfunmi 2018; Ullah et al. 2022; Al-Shahari et al. 2024; Banothu et al. 2024; Chithambarathanu and Jeyakumar 2023). DL models, such as CNNs, can process and analyze images much faster than humans, enabling real-time pest detection and monitoring (Cheng et al. 2017; Gutierrez et al. 2019; Bonilla and Duke 2024). These models have been used to recognize various types of pests with high accuracy rates, such as achieving optimal accuracy of 100% in some cases (Ullah et al. 2022). DL algorithms are also utilized for the early detection of plant diseases, which is crucial for timely pesticide application and disease control (Stephen et al. 2024; Omaye et al. 2024; Tekale and Singh 2023). Though deep learning reflects promising approach, there exists issues like lack of explainability of deep learning-based systems and the requirement of large, well-curated datasets (Chhetri et al. 2023; Clark 2020). Further, challenges such as class imbalance, complex backgrounds, multiple pest infestations, and interclass similarity of pests affect the design and efficacy of deep neural networks for crop pest classification (Rafi et al. 2023).

Data Analytics in Pest Management

Data analytics in pest management involves application of advanced data collection, modeling, and analysis techniques to improve decision-making and strategies in pest control and management. In case of pest management, datasets can be from diverse sources, such as, sensor data, satellite and geospatial data, historical records and agronomic data. High-resolution aerial imaging from drones helps in early detection of pest-related stress and continuous monitoring of plant damage (Bhandari et al. 2024). Satellite imagery complements drone data by providing large-scale monitoring capabilities (Bhandari et al. 2024). IoT sensors enable real-time monitoring of environmental conditions and pest activity, facilitating immediate responses (Kumaran et al. 2023). Wireless sensor networks collect dynamic crop-weather-pest data, which is crucial for predictive modelling (Tripathy et al. 2011; Divya et al. 2014). Field scouts and consultants collect data on insect populations, which can be integrated into databases for further analysis (Rosenheim 2021). Automated systems, such as bioacoustics monitoring, use audio recordings to detect pest presence and behavior (Nugroho et al. 2020).

Data analytics in pest management can be grouped in three different categories, Descriptive data analytics, Predictive data analytics and Prescriptive data analytics. Descriptive data analytics is employed for crop monitoring while Predictive data analytics has application in the area of weather data analytics, crop yield prediction, pest and disease forecast among others. Prescriptive data analytics is commonly used in the field of precision agriculture and crop pest management. Further, Multilayer Problem Solving is employed for expert systems development.

Descriptive Data Analytics

In the field of Crop monitoring, data analysis is improving crop management by using satellite and drone images to track plant health, detect diseases, and estimate crop yields. Additionally, soil sensors provide real-time data on soil conditions, aiding in soil management practices (Liu et al. 2019).

Predictive Data Analytics

This kind of data analytics can be applied for weather data or for the purpose of prediction of crop yields or for forecasting pest and diseases. Weather significantly impacts pest outbreaks. By using past weather data and AI, accurate weather forecasts can be generated. These forecasts help farmers plan irrigation, planting, and harvesting effectively, reducing crop damage. Predicting crop yields accurately is crucial for efficient resource management, food security, and market stability (Kumar et al. 2012). ML techniques, combined with historical data and real-time information from satellites and sensors, are used to build models that can forecast crop yields with high precision. Successful examples include predicting wheat and maize yields and the European Space Agency's project that accurately forecasted yield variations across Europe (Filho et al. 2020). Further, Early detection and prediction of pests and diseases are crucial for protecting crops and minimizing losses. By using weather data, location information, and pest behavior, models can forecast potential outbreaks. Modern tools like drones and smartphone apps help farmers identify and monitor threats (Kukar et al. 2019). For example, California's Integrated Pest Management program uses weather models to predict vineyard pests, and apps like Plantix diagnose plant diseases through image analysis. These advancements in data analysis are transforming agriculture by improving crop yields and encouraging sustainable farming methods.

Prescriptive Data Analytics

Precision agriculture employs prescriptive data analytics. Also known as smart farming, it utilizes data analysis to optimize farming practices. By combining information from satellites, weather stations, soil sensors, and crop monitors, farmers can make informed decisions about planting, fertilizing, and pest control (Faiçal et al. 2017). For example, satellite images help identify crop problems, while soil sensors guide irrigation and fertilization. Data analysis tools then convert this data into tailored recommendations to increase yields and reduce waste (Mozny et al. 1988). In the area of crop pest management, data analysis helps farmers optimize resource use by providing insights into the best times and amounts for applying seeds, fertilizers, and pesticides. By analyzing historical data and using tools like soil moisture sensors, farmers can take informed decisions about irrigation, reducing water waste. Additionally, data-driven pest management, including predicting outbreaks and choosing effective treatments, helps protect crops and minimizes the use of harmful chemicals (Bongiovanni and Lowenberg-DeBoer 2004).

Multilayer Problem Solving for Expert Systems

Deep learning facilitates multilayered problem-solving which ultimately assist in developing expert systems for pest management. By integrating deep learning models with expert knowledge and domain-specific rules, these systems can generate optimized pest management strategies tailored to specific agricultural contexts. Deep learning-based expert systems offer enhanced precision and effectiveness in pest control compared to traditional methods. DL techniques, including ANN, CNN, and recurrent neural networking, are instrumental in advancing pest management practices. Through the applications of deep learning algorithms, agricultural stakeholders can enhance pest monitoring, diagnosis, and control efforts, ultimately improving crop yields and agricultural sustainability (Ghosh and Samanta 2023).

Data Processing and Integration for Pest Management

Major steps in data processing for pest management are data cleaning and preprocessing, data integration, data validation and data visualization (Fig. 1). Various data processing techniques are available for this purpose (Ayed and Hanana 2021). During data preprocessing, data quality and consistency is ensured. This involves identifying and removing outliers, addressing missing values, and standardizing data formats to facilitate accurate analysis and modelling. Data integration is a critical process that involves consolidating information from diverse sources into a unified dataset. This comprehensive dataset serves as basis for in-depth analysis, allowing researchers to identify patterns, trends, and relationships that can remain unnoticed while examining individual data sources in isolation. By combining data from multiple perspectives, like ground-based measurements, satellite imagery, and historical records, researchers can develop a more holistic understanding of complex phenomena and can take informed decisions. Successful data integration requires careful consideration of data compatibility, format consistency, and potential biases. It often involves data cleaning, transformation, and standardization to ensure data quality and consistency. Ultimately, a well-integrated dataset enhances the reliability and validity of research findings. Data validation is crucial for maintaining data integrity. This involves implementing rigorous cross-verification checks to identify inconsistencies between different data sources and applying statistical methods to detect anomalies, outliers, and patterns that deviate from expected values. These quality control measures help to ensure the accuracy and reliability of the dataset,

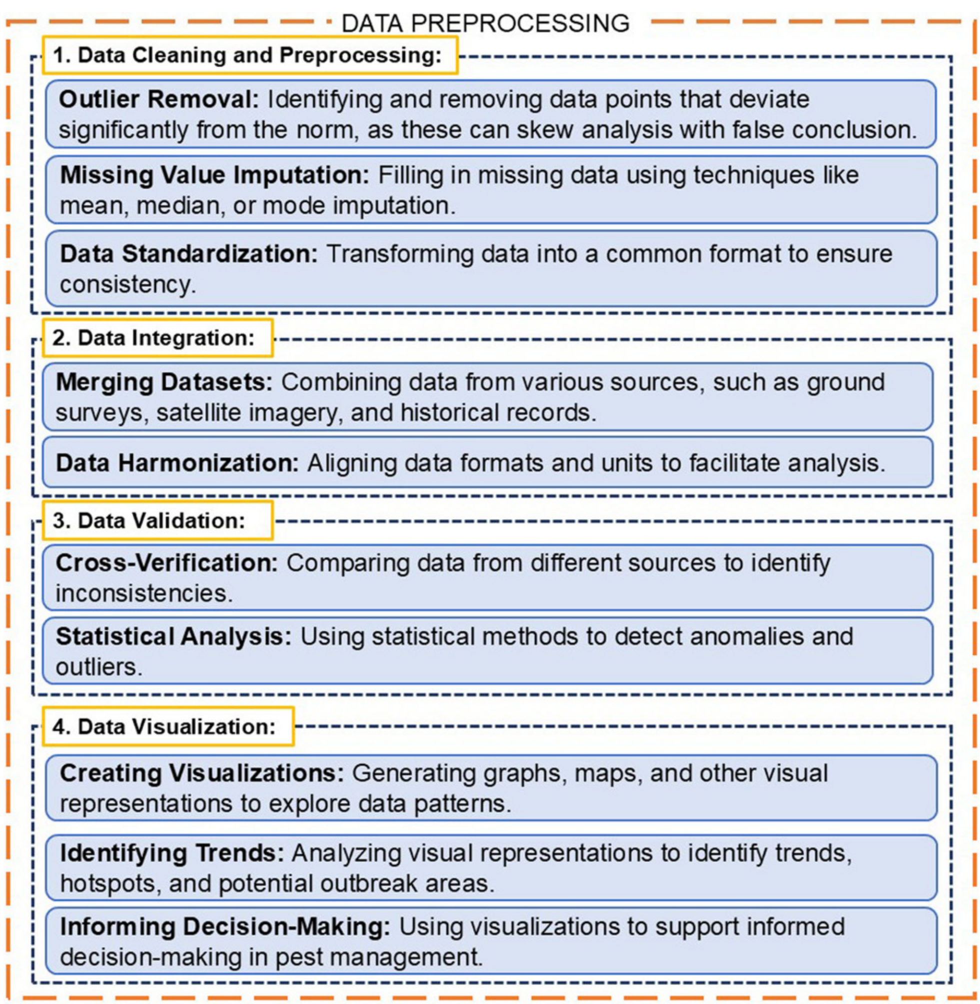


Fig. 1 Major steps in Data processing in the field of pest management

thereby enhancing the credibility of subsequent analyses and conclusions.

Finally, Data Visualization is implied for the analysis and interpretation of pest management data. Visualization is crucial in translating data into ecological understanding and knowledge, guiding quantitative analyses, and effectively translating findings in ecological decision-making. It is a powerful tool for understanding complex pest population dynamics. By creating informative graphs and maps, researchers can efficiently identify patterns, trends, and spatial distributions of pest populations over time. These visual representations can reveal hotspots, outbreak areas, and potential migration corridors, providing valuable insights for targeted pest management strategies. Furthermore, comparing pest population data with environmental factors, such as weather conditions or land use changes, can help uncover underlying causes and inform early warning systems.

Advanced disease and pest management approaches in protected cultivations involve the use of modern technologies such as computer vision, image processing (including thermal imaging and hyperspectral imaging), and IoT. Spatial data for agricultural and invasive pest management includes satellite images, aerial photos, soil types, elevation, and crop type and yield, which are essential for understanding pest infestation location, type, and severity (O'Neill and Dalsted 2011). ML techniques have revolutionized the detection, identification, and prediction of pests and diseases in agricultural crops, by deriving knowledge and relationships from the data (Domingues et al. 2022) and offering proactive solutions that benefit food security, environment, and economic sustainability (Rajendiran and Rethnaraj 2023). Data analysis techniques are advancing with the use of object detection models and IoT technologies. IoT is being integrated into agricultural pest and disease monitoring technologies to collect data from various sensors, cameras, and drones, addressing challenges such as energy supply and communication limitations in remote outdoor farms (Shi et al. 2019). IoT devices are designated to be used for data collection and pest identification and classification, demonstrating improved performance and technical indications for population estimation and pest monitoring (Kathole et al. 2023). Integration of IoT in pest management data collection is a promising approach to improve agricultural production efficiency while reducing the use of chemical agents. Furthermore, Ecoinformatics-based data sets from farmers and private consultants can provide enhanced statistical power, revealing early-season windows of crop sensitivity and informing pest management decisions (Rosenheim and Meisner 2013; Rosenheim et al. 2011). An object detection-based decision support system, PestDSS, integrates agricultural decision support systems and state-of-the-art object detection models to semi-automatically make pest management decisions for farmers, demonstrating its usability in wheat pest management (Yuan et al. 2023).

Challenges Associated with Data Analysis in Pest Management

A lot of challenges are associated with data analysis in pest management. First and foremost is data collection for pest management. Farmers and private consultants collect vast amounts of decentralized data on pest density during cropping cycles, which can be harnessed for pest-crop interaction studies (Thorat et al. 2017). The quality of data collected from commercial field scouting can be quantified using repeatability analysis, providing a measure of the underlying reliability of observations (Jayageetha et al. 2020). Though, worth mention point is data heterogeneity as data for agricultural applications originates from diverse sources. Traditional weather stations provide valuable meteorological information, while increasingly dense sensor networks offer granular insights into local conditions. Remote sensing technologies, particularly satellite imagery capture vast geographical areas, providing valuable data on crop health, soil moisture, and land cover. Ground-truth data, collected through field observations and manual measurements, is essential for calibrating and validating models. Integrating these diverse datasets into an interrelated framework presents significant challenges owing to different spatial and temporal resolutions, data formats, and potential inconsistencies (Jayageetha et al. 2020). Second major issue is data inconsistency. Diverse data sources often considers different formats, units, and time stamps, complicating the process of unifying and analyzing information. Inconsistencies in data representation can hinder effective integration, making it difficult to compare and contrast datasets accurately. To ensure seamless analysis, substantial preprocessing efforts are typically required to harmonize data formats, standardize units, and align time stamps across different sources. This preprocessing step is crucial for generating reliable and comparable insights from the integrated dataset (Benos et al. 2021). Data sparsity also represents significant challenge in developing accurate predictive models for pest management lies in the often-limited availability of comprehensive and reliable data for specific pests or geographical regions. Inadequate data on pest populations, their distribution, and historical patterns can obstruct the development of effective predictive models. This data scarcity can be particularly evident in areas with limited research infrastructure or for emerging pests with insufficient historical records, thus limiting the accuracy and applicability of predictive tools in those areas (Tewari et al. 2020). In last, data accuracy requires significant attention owing to the fact that inaccurate pest population estimates and sub-

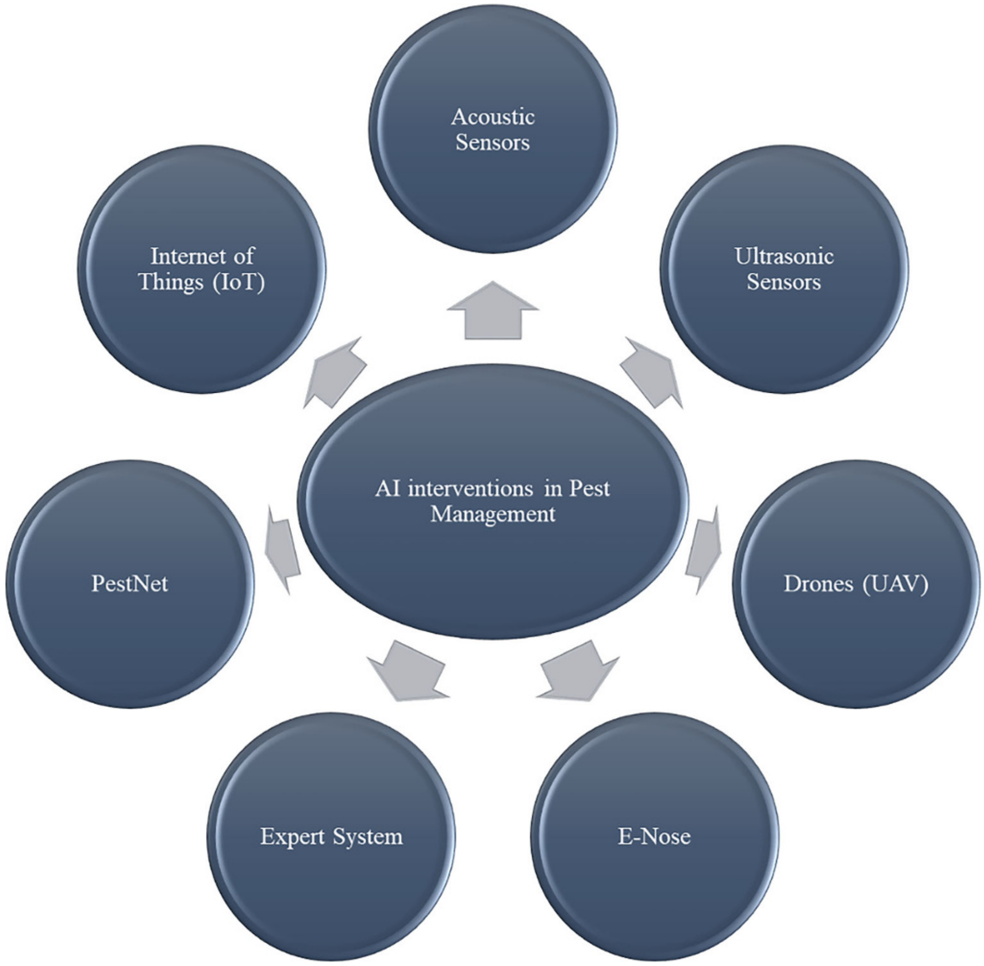


Fig. 2 Different interventions of Artificial Intelligence in the field of pest management

optimal control strategies can result from errors introduced during data collection or processing. These errors can come from various sources, such as human mistakes in data entry, equipment malfunctions affecting sensor readings, or flaws in data cleaning and analysis procedures. Subsequently, decisions taken on the basis of erroneous data may lead to misallocation of resources, delayed or inappropriate pest management actions, and eventually, increased economic losses and environmental risks.

Innovative Ways of AI Intervention in Pest Management

In pest management, innovative AI intervention are revolutionizing agricultural practices, offering transformative approaches to pest identification, monitoring, and control. AI techniques have been increasingly adopted in pest identification and management owing to the challenges developed as consequence of evolving pest populations and also for developing sustainable agricultural practices (Kariyanna and Sowjanya 2024). AI offers a transformative approach by utilizing advanced algorithms to analyze intricate data patterns from numerous sources like sensors and imagery, enabling accurate pest identification, early detection, and predictive modeling (Kariyanna and Sowjanya 2024). AI techniques include ML, DL, and computer vision technologies, which are applied for automatic detection, monitoring, and identification of insects in agricultural scenarios (Teixeira et al. 2023; Venkatasaichandrakanth and Iyapparaja 2024; Kalfas et al. 2023; Toscano-Miranda et al. 2022). AI improves the efficiency of pest management processes by enabling accurate pest identification, early detection, and predictive modeling, which enhances decision-making for pest control, minimizes indiscriminate pesticide application, and optimizes interventions (Kariyanna and Sowjanya 2024). Different AI interventions are currently available which works in the area of pest management (Fig. 2). Image processing and optical sensor technologies combined with pheromone traps are also available for direct identification of pests. Accurate detection of pests is crucial for implementation of Integrated Pest Management (IPM) strategy.

Acoustic Sensors

Sensitive acoustic technology has been used since the early 20th century to detect hidden insect infestation. Acoustic sensors are effective for nondestructive, remote detection and monitoring of hidden insect infestations in soil, grain, and wood etc (Mankin et al. 2011; Mankin 2012; Balingbing et al. 2024). They can detect cryptic insects, estimate population density, and map distributions (Mankin et al. 2011). The development of modern computer technology has made possible the digital signal processing techniques that facilitate the separation of insect sounds from background noise and provide the driving force for research on new acoustic vehicles to detect and monitor the invasion of underground insect pests. Recently acoustic technology has been adapted to detect insects in feeding areas. Insect species can be usually detected through low sounds [0.5–150 kHz] that they produce when they are flying, feeding, or calling their opposite sex (Bhairavi et al. 2020).

Ultrasonic Sensors

Insects that are hidden in seed, wood and some other fibrous plant materials can be detected by ultrasonic signals emitted during feeding activities. Ultrasonic sensors are effective in detecting wood-boring pests due to minimal background noise at frequencies above 20 kHz (Mankin et al. 2011). A pest detection system with ultrasonic sensors contains components such as an ultrasonic transducer, a low-noise narrow-band amplifier, a signal conditioner, and an output display device. In a system containing these components, the wave sent from the ultrasonic sensor bounces back after it hits the insects, and it sends them to the machine capable of processing digital signals. Thus, the movement direction and actual position of the insects in the area can be estimated in real-time. But so far, this system has not been able to run consistently in different environments. In order to develop an intelligent, portable ultrasonic device for monitoring pests in the field, more research and development projects are needed (Ahouandjinou et al. 2017).

Drones (Unmanned Aerial Vehicles (UAVs))

Drones can help farmers to optimize the use of inputs (seed, fertilizers, water), to react more quickly to threats (weeds, pests, fungi), to save time crop scouting (validate treatment/actions taken), to improve variable-rate prescriptions in real time and estimate yield from a field. The aerial view provided by a drone can assists in the information of crop growth stages, crop health and soil variations in real time helping in any mitigation if required. Multispectral sensors can collect image in near infrared as well as in visible spectrum of the electromagnetic spectrum. Drones can be fitted with thermal cameras to monitor crop health and detect pests using image processing techniques (Shiva et al. 2020). Capturing data from agriculture drone initially involves analyzing the area, where the territory being tested is identified. Therefore, the first step includes establishing a boundary, analyses of the area, and then finally, uploading the technical GPS information into the drone's navigation system. Since Unmanned aerial vehicles (UAVs) are independent, they enter flight patterns into their already established system to collect required data. After capturing all the required data through sensors such as the multispectral sensor/RGB sensor, it is processed through numerous software for further analysis and interpretation. After data collection, they format it so that farmers can understand the data with no hassle, bringing them a step closer to precision farming. 3D mapping or photogrammetry are popular methods to display extensive data collected.

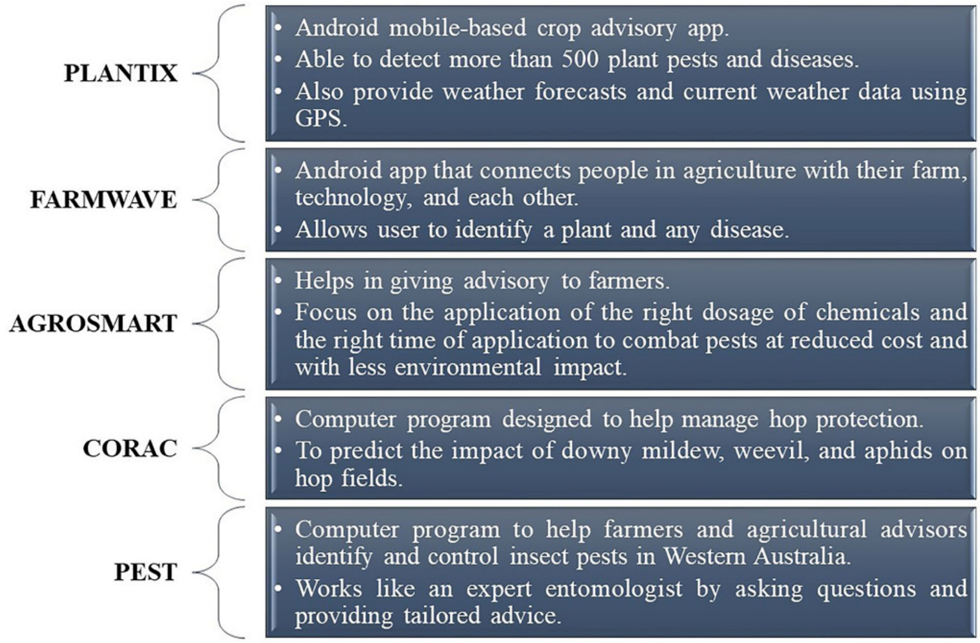
E-Nose

The study by Fuentes introduces a low-cost approach using near-infrared spectroscopy (NIR) and electronic nose (e-nose) sensors coupled with machine learning. Artificial neural networks were developed to estimate insect infestation levels, predict insect populations, and assess plant health based on sensor data. The authors propose a drone-based system equipped with an e-nose to deploy these models in real-world agricultural settings, assisting farmers in pest management (Fuentes et al. 2021).

Expert Systems

An Expert System (ES), also called a Knowledge Based System (KBS), is a computer program designed to simulate the problem-solving behavior of an expert in a narrow domain or discipline. The expert system could be developed for decision-making and location specific technology dissemination process. An expert system is software that attempts to reproduce the performance of one or more human experts, most commonly in a specific problem domain, and is a traditional application and/or subfield of artificial intelligence. Expert systems help in selection of crop or variety, diagnosis or identification of pests, diseases and disorders and taking valuable decisions on its management. Expert System are recognized as an appropriate technology because they address the problem of transferring knowledge and expertise from highly qualified specialists to less knowledgeable personnel. In agriculture, this transfer is always taking place from research to extension, from extension to farmers, and even from farmers to farmers. Expert system present excellent tools for relieving the increasing pressure on the limited expertise available in developing nations. One example is TEAPEST, an expert system de-

Fig. 3 Different Successful IoTs in field of Pest Monitoring, i.e. Plantix (Rafea and Shaalan 1996) FARMWAVE (https://digitalscientists.com/case-studies/farmwave/), AGROSMART (Pasqual and Mansfield 1988), CORAC (Martins et al. 2019), PEST (Mulla 2013)



signed to identify insect pests in tea plantations and recommend appropriate control measures, such as chemical miticides and pesticides. TEAPEST is an object-oriented, rule-based system that derives its knowledge from human experts, published literature, and field observations. It supports decision-making by utilizing AI to compensate for the lack of human expertise and assist existing experts (Ghosh and Samanta 2023). Performance evaluations show TEAPEST effectively identifies pests and recommends appropriate controls.

PestNet

Accurately identifying and locating multiple pest species within images is a challenging aspect of pest management, PestNet, a deep learning-based model was proposed for this purpose (Liu et al. 2019). The model incorporates a novel channel-spatial attention module to enhance feature extraction, a region proposal network to identify potential pest locations, and a position-sensitive score map for classification and bounding box refinement. Additionally, contextual information is utilized to improve detection accuracy (Liu et al. 2019). PestNet achieved a mean average precision (mAP) of 75.46%, outperforming state-of-the-art methods in multi-class pest detection. PestNet represents a significant advancement in the field of pest detection and classification, offering a robust and accurate solution for managing multiple pest species on a large scale. Its innovative components and impressive performance metrics highlight its potential for real-world agricultural applications.

Internet of Things (IoT)

IoT describes the Network of physical objects—things—that are embedded with sensors, software, and other technologies for the purpose of connecting and exchanging data with other devices and systems over the internet. IoT provides Fast and user-friendly systems for on-ground utilization. It also assists to existing expertise in the selection of better management options and allows large data accessibility and processing ability to farmers. IoT has the potential to revolutionize farming practices and improve agricultural productivity and sustainability (Abu et al. 2022). Additionally, IoT technologies have been shown to improve sensing and monitoring of production, including farm resource usage, animal behavior, crop growth, and food processing (Abu et al. 2022). IoT enables precision farming through the use of sensors for monitoring and automation, leading to optimized resource utilization and improved crop yields (Daga and Aruna 2024; Prabha and Nath 2024; Sharma et al. 2023). IoT systems provide real-time data on environmental conditions, allowing farmers to make informed decisions to enhance crop quality and productivity (Siva and Ponnusamy 2024; Rathor and Kumari 2021; Sarkar et al. 2023).

IoT is one of the key technologies that can profoundly change the economy of the country and the world at the current stage. Successful agricultural IoT systems exploits sensors, actuators, data transmission, and cloud computing to enable precision agriculture, leading to improved crop yield and quality, economic benefits through labor efficiency and resource optimization, and positive environmental impacts through sustainable resource management and eco-friendly practices (Fig. 3).

Conclusion

Artificial Intelligence (AI) is revolutionizing agriculture by enabling farmers to automate their practices and adopt precision cultivation techniques that enhance crop yield and quality while conserving resources. The field of crop protection, crucial for sustainable food production, faces numerous challenges that demand innovative solutions. AI emerges as a significant technology in addressing these challenges, particularly through its applications in pest and disease management. Through the applications of machine learning and deep learning, AI enhances pest detection, disease monitoring, and management strategies, empowering farmers to make informed decisions and prevent crop damage proactively. This leads to optimized pesticide use, higher productivity, and sustainable agricultural practices. AI's integration into crop protection not only boosts agricultural resilience but also ensures food security for a growing global population. The ombination of AI-powered tools, sensors, robotics, image recognition, and big data analysis offers real-time insights and personalized pest control measures, making agriculture more robust, productive, and sustainable. Owing to these facts AI stands as a transformative force in modern agriculture, reflecting efficiency, sustainability, and resilience in field of crop protection. AI found applications in precision crop protection, real-time monitoring, and data-driven decision making. However, challenges such as cost-effectiveness, lack of expertise, and ethical considerations need to be addressed. The future prospects of AI in crop protection research and development are promising, with a focus on sustainable agriculture and advancements in plant protection technologies.

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Conflict of interest E. Vidya Madhuri, J.S. Rupali, S.P. Sharan, N. Sai Pooja, G.S. Sujatha, D.P. Singh, K. Ahmad, A. Kumar and R. Prabha declare that they have no competing interests.

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