

Artificial Intelligence In Pest And Disease Eradication: A Review Of Automated And Targeted Control Systems

¹Chaitali Anantkumar Darode, ²Dr. Abhay Ramakant Kasetwar

¹Assistant Professor, ²Professor

¹S. B. Jain Institute of Technology, Management and Research,
RTM Nagpur University, Nagpur

²S.B. Jain Institute of Technology, Management and Research, Nagpur, Maharashtra

*Corresponding Mail: Chaitali Anantkumar Darode

Abstract

The rising effect of pest infestations on agricultural productivity and food security has made the demand for intelligent, sustainable pest management solutions more urgent than ever before. Recent advancements in Artificial Intelligence (AI), Internet of Things (IoT), and data analytics have enabled the development of automated systems for pest detection, prediction, and eradication. This systematic review focuses on the design and implementation of AI-based pest eradication systems in terms of detection, decision support, and integrated AI-IoT frameworks. It follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology to ensure transparency and reproducibility in study selection. Relevant studies published between 2020 and 2025 were retrieved from the Scopus database using predefined keywords and subject area filters. After applying inclusion and exclusion criteria, 51 high-quality journal articles were selected for detailed analysis. Results indicate that current research is dominated by Deep Learning (DL)-based computer vision models, IoT-enabled sensing platforms, and predictive analytics with high accuracy and real-time performance capabilities. While integrated AI-IoT systems demonstrate strong potential for reducing pesticide dependency, optimizing resource utilization, and advancing sustainable agriculture, their large-scale deployment is still constrained by issues of scalability, implementation cost, and unequal adoption.

Keywords: Artificial Intelligence, Pest Eradication Systems, Internet of Things (IoT), Precision Agriculture, Sustainable Pest Management.

1. Introduction

The phenomenon of agricultural productivity and food security has been one of the burning topics of the world, especially with the rising rate of population, changes in climatic variations, and poor arable land. Pest infestation has been considered as one of the most unresolved issues in relation to crop yield and quality. The aggregate losses to agricultural productivity occurring annually due to insects, rodents, weeds, and plant pathogens cost both small-scale farmers and large commercial producers a significant amount of money when compared to other causes of losses [1]. Old methods of controlling pests like chemical pesticides, manual surveillance systems and a rule-based decision system have been at the core of reducing these losses [2]. But these methods are becoming increasingly limited by environmental hazards, resistance to pests, high costs of operation and scalability. This leads to the increasing demand of smart, viable, and dynamic pest eradication solutions [3]. The traditional approach to Integrated Pest Management (IPM) is a recyclical process which entails pest identification, population monitoring, decision making, execution of control procedures and assessment of the results [4]. Figure 1 demonstrates the typical IPM process that will be the conceptual basis of most modern-day pest management plans.

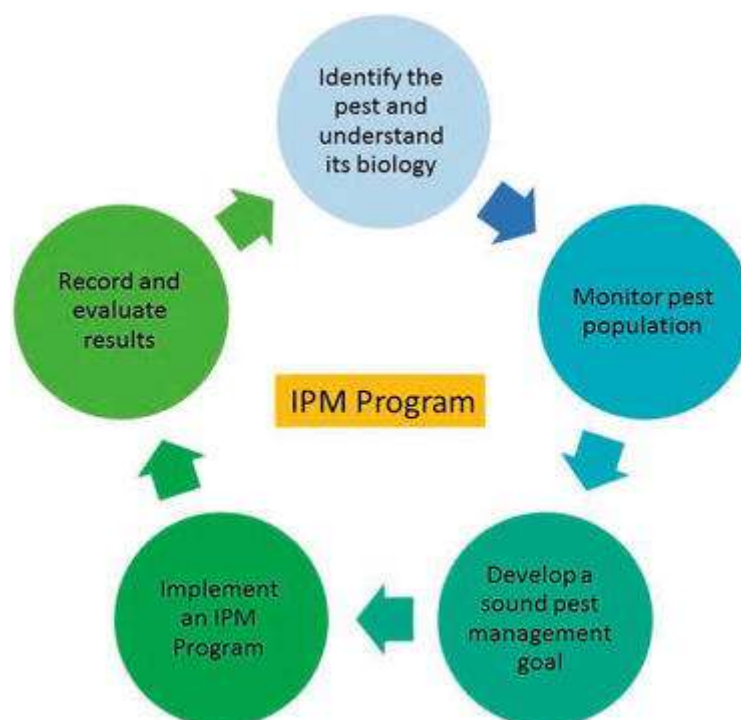


Figure 1: Conventional Integrated Pest Management (IPM) cycle for pest monitoring, decision-making, and control [5].

Recently, significant progress in AI has added revolutionary possibilities to pest management systems. AI technologies such as Machine Learning (ML), DL, computer vision, and intelligent sensor systems are used to automate pest detection, identification, prediction, and control [6,7]. AI-based pest eradication systems are different from traditional systems in the sense that, unlike the latter, AI-based systems are capable of learning from past experiences, adapting to changing environments, and providing timely decision support tools [8]. These characteristics of AI-based systems are accelerating the urgency of research in developing intelligent pest management systems in agricultural, horticultural, and stored products systems [9].

AI-based pest eradication systems are usually designed in such a way that several elements are incorporated, including data collection devices, feature extraction, predictor models, and control devices [10]. The data is gathered via a wide range of sources, among them being field cameras, Unmanned Aerial Vehicles (UAVs), IoT sensors, satellite images, and environmental monitoring devices [11]. The multimodal data is processed through AI algorithms to determine the pest species, estimate the severity of infestation and prescribe specific control measures. Unlike blanket pesticide application, the systems enable precision agriculture because of reduced usage of chemicals at the expense of maximum effectiveness. As a result, AI-based pest management will not just lead to higher yield of crops, but also environmental sustainability and protection of human health [12].

One of the most researched fields in the AI pest eradication studies is computer vision-based methods [13]. The Convolutional Neural Networks (CNNs) and vision transformers have shown a high level of accuracy in the detection and classification of pests based on image of leaves, trap images, and aerial images. The approach allows promptly identifying pest outbreaks, which is important to avoid massive damage to crops. Correspondingly, time-series forecasting systems, e.g., recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, are used to forecast pest

population behavior using past data on infestations and climatic factors [14,15]. These prediction abilities can be applied in proactive pest control measures as opposed to in reactionary measures.

Apart from detection and prediction, the field of AI has witnessed applications in implementing autonomous mechanisms for the eradication of pests in the agricultural domain [16]. Robotic equipment and spraying drones powered with AI tools have the capability to detect affected areas with the presence of pests and apply the required spray in localized proportions. Reinforcement learning tools have also been used in optimizing the number of pesticides used in the spraying process [17]. The decision support tools developed with the aid of AI have further helped farmers in selecting efficient techniques for the eradication of agricultural pests [18].

Although AI-based systems of pest eradication have made considerable strides in their design and implementation, a number of challenges are encountered. Information access and quality, in turn, are also a major constraint, since most AI models use massive, labeled data, which is hard to have in a real farming environment [19]. Model generalization can be negatively influenced by the differences in lighting, crop development stages, the morphology of the pests, and environmental factors. Moreover, the implementation of AI in rural settings with resource limitations attracts issues that are associated with cost, infrastructure, energy use, and accessibility to the user [20]. Ethical and regulatory concerns, such as data privacy, algorithmic transparency, and environmental safety, should be taken into consideration as well [21]. Due to the active growth of studies in this field, it is necessary to conduct a systematic review that will allow consolidating the current knowledge, pointing out design patterns, assessing implementation strategies, and determining gaps in research. Other past analyses have tended to concentrate on particular methods or single applications, e.g., image-based detection of pests or UAV spraying. Nevertheless, there is an overall lack of review studies that look into the end-to-end architecture and the deployment of AI-based pest eradication systems. This review may offer a good detail of system architectures, algorithmic decisions, metrics of performance, and experience in deploying systems in the real world.

This systematic review attempts to explore and classify existing literature on AI-based pest removal systems with emphasis on design methodologies and implementation frameworks. The review also assesses various AI techniques, data acquisition approaches, and control mechanisms employed in pest management applications. By bringing together results from recent studies, this work describes trends as well as current strengths and weaknesses of AI-driven pest eradication systems [22]. It further specifies open challenges plus future research directions needed for robust, scalable, and sustainable solutions to pest management.

Thus, the role of AI as a future pest eradication tool has come to be realized as an enabler of the next generation of such eradication techniques. This being the case, a critical analysis of the existing literature on the subject becomes integral to the understanding of the various ways in which AI, as a concept, is being developed and implemented in the real world. Therefore, the insights obtained can be of immense value in the development of such intelligent pest eradication techniques for the betterment of the environment.

1.1 Emerging Methods of Pest Control

• Biorational Products

Biologically based pesticides and biorational products are nontoxic and have minimal environmental impact because they contain pheromones or living microorganisms. Pheromones are released into the environment by animals, especially insects and

mammals, and they affect the physiology or behavior of other species. The most efficient biorational pesticides are microbial insecticides based on *Bacillus thuringiensis*-based (Bt). Biorational pesticides like this can replace chemical alternatives that are outright forbidden in export markets and other places where people are worried about pesticide residue in food [23].

"Pheromone-assisted technique" makes pesticides work better against ant infestations. Ants can be successfully lured away from their nests and trails by combining pesticide with pheromones [24]. So, it increases ant exposure to the pesticide for eradication while decreasing pesticide interaction with the environment.

- ***Insect growth regulators (IGRs)***

To control populations of dangerous pest insects, scientists have developed synthetic hormones called insect growth regulators (IGRs) [25]. By disrupting the molting process, IGRs stop insects from maturing. Insect growth regulators (IGRs) are often used with other pesticides that target adult insects. In general, IGRs pose less of a threat to human health [26].

- ***Nontoxic heat treatments***

As an example, using heat to kill insects is one of the newer, less harmful ways of pest management that has the potential to be more sustainable and successful than poisonous pesticides [27]. Rentokil's Entotherm is an innovative product that effectively gets rid of cockroaches and bedbugs. Unlike sprays, which are frequently unable to penetrate the insect's tough exterior, the Entotherm system uses heat to kill the insect from the inside out by causing dehydration and disrupting vital physiological processes. Insects in all their phases of development may be quickly and easily killed by heat, including eggs, larvae, pupae, and adults, all without reaching temperatures higher than 56-60°C.

- ***CRISPR technology to control pests***

The CRISPR gene editing technique allows scientists to change important genes that control insect reproduction and sexual dimorphism [28]. Researchers have developed a novel effective control method for a certain species' genetic population using CRISPR technology. This method is safe, self-limiting, and scalable. Many different kinds of insect pests and disease vectors might benefit from its development and use. It is possible to employ this technology in a safe manner to control or eliminate certain species in the wild [29].

- ***Second-generation green products***

From a public health standpoint, environmentally friendly products have been the center of attention in recent years. Environmental preservation is driving a change in consumer demand for eco-friendly goods. These days, new eco-friendly items are coming out. The ingredients, effectiveness, and side effects of these green goods of the second generation will be superior. An off-putting odor could be released by a first-generation pesticide that uses essential oils from plants. On the other hand, second-generation insecticides are less odorous and just as effective because they use different proportions of the original chemicals or other compounds [30].

- ***Digital Communication tools***

Implementing mobile data-capture devices into pest control operations allows for the real-time collection of data on the location and kind of pest problems. This data is then stored in a central database online, where facility managers and pest control experts have access. This also made it easy to monitor several locations, which facilitated faster problem-solving and more precise pest-control measures [31].

- ***Rodent birth control***

In order to decrease the numbers of problem birds, such as pigeons, pest management has recently turned to birth control. An efficient method of controlling prolific breeders

like rats and mice may soon be available through rodent birth control, which does not harm many nontarget species [32]. In the future, there could be a method to prevent the birth of rodents.

- ***Fly baits***

Stick the fly bait stickers in high-traffic areas, including around food storage or elsewhere where flies tend to gather. An pesticide and insect food coating the tiny sticker makes it effective against flies in as little as one minute of contact [33].

1.2 Artificial Intelligence in Modern Pest Management

- ***Early Pest Detection***

In order to detect early indications of pest infestations, AI systems may assess data from several sources, such as satellite photography, drones, and ground sensors. Using ML, these models detect minute patterns and irregularities in the state of the plant, notifying users of the existence of pests or diseases before any symptoms show up [34]. When it comes to detecting pests and protecting crops, farmers often turn to ML tools like Decision Tree (DT), Support Vector Machine (SVM), Naive Bayes (NB), and Random Forest (RF) as well as DL approaches like Convolutional Neural Networks (CNNs), Deep Belief Networks (DBNs), and Long Short-Term Memory (LSTM) [35].

- ***Precision Monitoring of Pest Activity***

Drones equipped with high-definition cameras and sensors and powered by AI can keep a close eye on agricultural or woodland regions. Computer vision algorithms examine the data to find problem regions, assess crop health, and pinpoint pests in images; this information allows for targeted actions and the allocation of resources [36]. In order to lessen the use of pesticides and their negative effects on the environment, AI studies data on crop health, insect dispersal, and environmental variables [37]. Using pheromone traps for pest management and monitoring, grape moths pose a hazard to wine production in vineyards. More and more, people are seeing the benefits of smart pest monitoring systems that use AI, sensors, and cameras.

- ***Data Integration and Analytics***

AI integrates a number of factors, including weather patterns, agricultural phenology, and insect life cycles, to build prediction models for pest forecasting. These models utilize both historical data and real-time inputs to forecast the occurrence of insect outbreaks. This provides the way for quick reactions and proactive management strategies [38]. Accurate and quick pest detection and monitoring is made possible with data on insect population, movement, and behavior collected using IoT-enabled cameras and sensors [39]. Overuse of pesticides, environmental factors, and insect dynamics all interact in complex ways, making life difficult for farmers. Researchers have developed an IPM platform that uses AI, data analytics, and many data sources to tackle these difficulties. By reducing environmental harm and the development of chemical resistance, this novel solution seeks to optimize agricultural pest management operations, providing farmers with more efficient and sustainable methods of crop protection [40].

- ***Automation in Pest Monitoring Systems***

AI-enabled systems streamline pest surveillance and detection by automating monitoring tasks, thereby lowering dependence on manual labor and improving overall agricultural productivity. Autonomous platforms equipped with sensors and intelligent algorithms can navigate agricultural fields or forested areas, gather environmental and visual data, and detect pest concentration zones, facilitating precise interventions and real-time decision support [41]. Moreover, AI enhances Integrated Pest Management (IPM) frameworks by integrating multiple control approaches, including biological and cultural methods. By processing heterogeneous data from sensors, imagery, and

historical records, AI-driven systems can recommend optimal and environmentally sustainable pest management strategies [42].

- **Decision Making Activities**

Unmanned Aerial Vehicles (UAVs) have emerged as transformative tools in modern agriculture, enabling a wide range of aerial operations. Their navigation, stability, and control mechanisms are increasingly optimized through AI and ML techniques [43]. Equipped with AI-driven computer vision systems, UAVs are extensively used for field mapping, crop monitoring, data acquisition, and analytical assessment, as well as for emergency and disaster-related applications. In pest management, drones support multiple spraying mechanisms, including gaseous, centrifugal, kinetic, and hydraulic approaches, allowing precise application of control agents [44]. Furthermore, ML algorithms enable UAVs to assess sunlight distribution across fields and identify pest-affected zones, supporting site-specific and targeted pesticide deployment [45].

2. Research Methodology

This paper features a vibrant analysis of the significant technological innovations that are coming along with AI-based pest detection, monitoring, and management systems based on IoT-enabled sensors, imaging devices, and data-driven analytics in the period between 2020 and 2025. As a result, it is concerned with the development of AI-based pest detection algorithms, precision monitoring strategies, decision-support systems, and smart pest management systems used in agricultural and environmental settings. The research indicates that implementation of AI application is critical in enhancing early pest detection, accurate monitoring, minimized use of pesticides, and green pest management activities. The review has been performed according to the PRISMA framework in order to assure transparency and reproducibility of the identification, screening, and evaluation of studies.

The various stages that have been considered for the review process include planning, searching, and analysis. These stages have been employed to conduct this review systematically. The existing literature has been categorized using these stages to identify some thematic areas in the field of intelligent pest management, which include AI-based pest detection methods, various IoT-based pest management systems, data integration and analytics solutions, and decision-making solutions for intelligent pest management. This framework helps to identify the existing gaps in the literature and highlight new directions for more effective research to be conducted in the field of intelligent pest management.

2.1 Planning Stages

In the modern systems of pest management, it is important to create powerful and flexible systems, which are equipped to process vast quantities of diverse data obtained through IoT devices, UAVs, satellite images, and environmental devices. The patterns of pest infestations are subject to change and are determined by diverse influences, including the growth stages of the crops, environmental conditions, lifespan of the pests, characteristics of the soil, and farming techniques.

To address these challenges, recent studies have increasingly explored hybrid AI approaches, combining ML, DL, computer vision, and edge-based IoT processing to enable timely pest detection, accurate forecasting, and real-time decision-making. Optimization techniques such as evolutionary algorithms, swarm intelligence, and reinforcement learning are also integrated to enhance system scalability, reduce computational latency, and improve the effectiveness of pest control strategies.

This review follows recent trends in AI-enabled pest detection and management research and examines how the integration of AI, IoT, and data analytics has evolved over time. The research questions guiding this systematic review are as follows:

- I. Which AI and IoT techniques have emerged between 2020 and 2025 for pest detection, monitoring, and management?
- II. Which hybrid AI models, such as DL combined with IoT sensing and computer vision, are most effective for early pest detection and precision monitoring?
- III. What are the major technical, operational, and infrastructural challenges associated with deploying AI-based pest management systems in real-world agricultural environments?
- IV. How can emerging technologies such as edge-cloud computing, UAVs, advanced analytics, and intelligent decision-support systems enhance the scalability, reliability, and sustainability of pest eradication systems?

The primary sources of the literature corpus were SCOPUS, IEEE Xplore, and Springer databases. Literature retrieval was conducted using keyword combinations such as “AI-based pest detection,” “intelligent pest management,” “IoT-enabled pest monitoring,” “precision agriculture,” and “automated pest control.” The selected studies span domains including agricultural engineering, AI, computer science, environmental monitoring, and precision farming. Through systematic synthesis, the review identifies innovative approaches related to early pest detection, precision monitoring, reduced pesticide dependence, and sustainable agricultural practices.

2.2 Review Stages

The review process follows well-defined inclusion and exclusion criteria to ensure the selection of high-quality and relevant research articles. The criteria are outlined as follows:

- (i) Publications indexed in the SCOPUS database from January 2020 to December 2025 are included.
- (ii) Documents other than research articles are excluded.
- (iii) Only journal articles are considered; conference papers, books, and other document types are excluded.
- (iv) Only articles related to India are included to ensure a focused and context-specific analysis.

The screening process focuses on research conducted in the Indian context to observe publication trends, institutional contributions, and domain-specific advancements during the selected timeframe. Table 1 presents the inclusion and exclusion criteria applied for selecting relevant studies.

Table 1: Criteria for inclusion and exclusion

Criterion	Inclusion	Exclusion
Keywords	AI-Based Pest Management, IoT-Enabled Pest Monitoring, Precision Agriculture, Automated Pest Control	Records with unrelated variables
Document Type	Article	Conference paper, Review, Erratum
Source Type	Journals	Book series, book, book chapters

Timeframe	2020-2025	<2020
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The inclusion and exclusion criteria were predefined and efficiently used to filter relevant studies and the distribution of the selected papers is presented as Figure 2. The PRISMA flow chart shows the successive screening of the research articles through various screening processes. The first search in SCOPUS conducted in 2020-2025 revealed 699 records, which represented a wide range of publications in the field of AI, pest management, and other related fields. After having used keyword and subject area filters, i.e., AI, Pest Management, Computer Science, and Engineering, the records were narrowed down to 225 and the scope was narrowed down to the works that are directly related to the research area. Further screening was done on the basis of the relevance of the document and title abstract screening which narrowed down the dataset to 84 records which could be assessed in detail. Further exclusion criteria were subsequently used to maintain quality and relevancy of the identified studies. The sources which did not include the final screening phase were sifted out (141 records), and language restriction was used to filter out non-English publications (4 records). Moreover, it was filtered out documents that were not published in peer-reviewed journals (29 records), which retained only high-quality journal articles. The outcome of this process of rigorous and systematic screening was a final set of 51 studies that were to be included in the systematic review. These researches were established to be very useful regarding the aims of this study and altogether create a holistic background to analyse the design and implementation of AI based pest management systems. The PRISMA model gives a very clear picture of how searches are gradual and that studies are narrowed down to a high quality and narrow collection of articles that are important to review and examine.

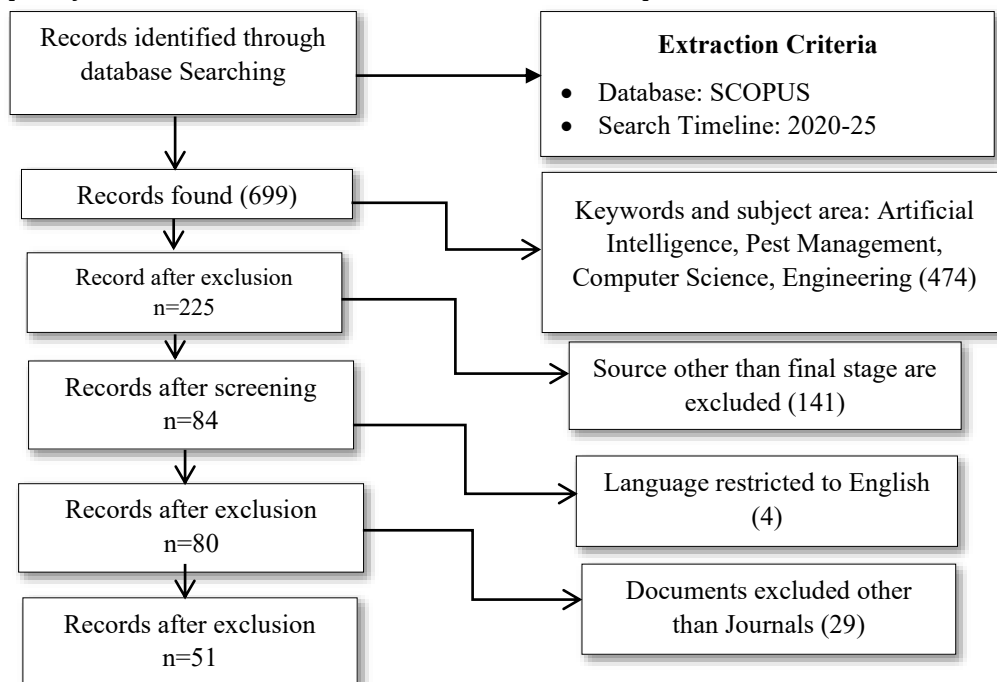


Figure 2: PRISMA Model for literature analysis

3. AI-Based Pest Detection and Monitoring Systems

AI has proven to be a groundbreaking means of carrying out pest detection and monitoring as AI helps to ensure the accurate and efficient identification of pests. Earlier studies by Bestelmeyer et al. (2020) [46] and Guimapi et al. (2020) [47] particularly

underscored the functions of AI data analytics and spatial models as applied to the provision of early warning mechanisms for the outbreak of pests. Following the earlier trends, Zhang et al. (2020) [48] and Lopez et al. (2020) [49] particularly underscored the functions of IoT and AI as applied to the enhancement of the accuracy and efficiency of real-time pest management. From the figure 3, it is observed that CNN and YOLO models are the dominant AI-driven research on the efficient identification of pests.

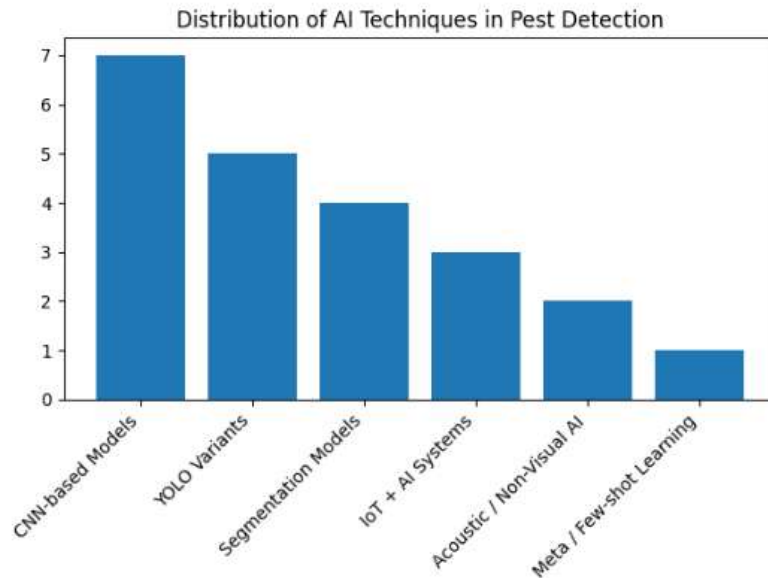


Figure 3: Distribution of AI techniques used in pest detection studies.

The focus of the literature is on computer vision-based pest detection, and most of the systems use convolutional neural networks (CNNs). The research by Caldeira et al. (2021) [50], Zhao et al. (2022) [51], Khalid et al. (2023) [52], and Ray et al. (2025) [53] revealed that DL models including ResNet, EfficientNet, and YOLO versions and custom CNN backbones can be highly accurate in pest and disease symptoms detection in the field environment. The results provided by Oyege et al. (2025) [54] also attested to the excellence of YOLO-based architectures at small pests' detection and deployed in real-time, especially in the context of a mobile application. In addition to the detection based on fixed images, there were some works on more sophisticated segmentation methods and multi-task learning. The semantic segmentation and Mask R-CNN frameworks utilized by Martins et al. (2023) [55] and Júnior et al. (2022) [56] in the studies detect pests on sticky traps and leaf images and enable them to count and estimate the severity of a pest effectively. In the same vein, Salamai et al. (2023) [57] proposed a few-shot meta-learning model to enhance generalization in pest and disease diagnosis in a restricted data situation, which is a significant drawback of conventional DL models. The figure 4 reveals that image-based data is the dominant source of input in pest detection with little usage of sensor data, acoustic data, and multimodal data but increasing.

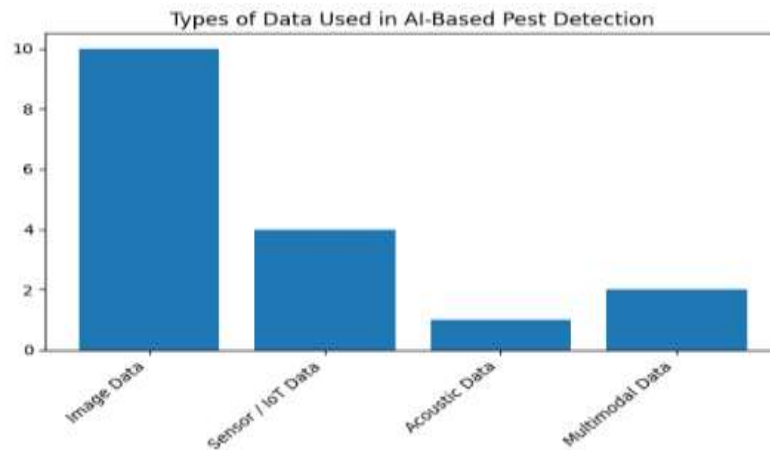


Figure 4: Types of input data utilized for AI-based pest detection systems.

Recent scientists have broadened the pest surveillance to non-visual information. The experimental study by Esmail Karar et al. (2022) [58] suggested an acoustic detection system based on DL and IoT to identify the red palm weevil larvae at the earliest stage and stages of infestation, reaching an accuracy of more than 97 percent. The system described by Mohamad Sa'ad et al. (2025) [59] is a paddy field bird detection system that is accelerated on an FPGA chip and allows real-time notifications, which decreases the number of hands-on controls to perform by humans. The study by Zhou et al. (2024) [60] and Rocha et al. (2020) [61] showcased the work with smartphone-based pest detection and counting, which explains the feasibility of inexpensive and user-friendly AI tools that are accessible to farmers. The biological and interdisciplinary approaches have also become prominent. Manduca et al. (2025) [62] explored the behavior of termites in relation to their caste interactions with computer vision and transfer entropy, and found patterns on which bio-inspired pest management can be implemented. As well, Manduca et al. (2025) [63] utilized AI and microfluidics to examine entomopathic nematodes to develop sustainable biological control of pests. This figure 5 shows that the majority of pest detection systems are implemented on the field cameras and on-hand platforms, which is now shifting to real-time and on-hand AI applications.

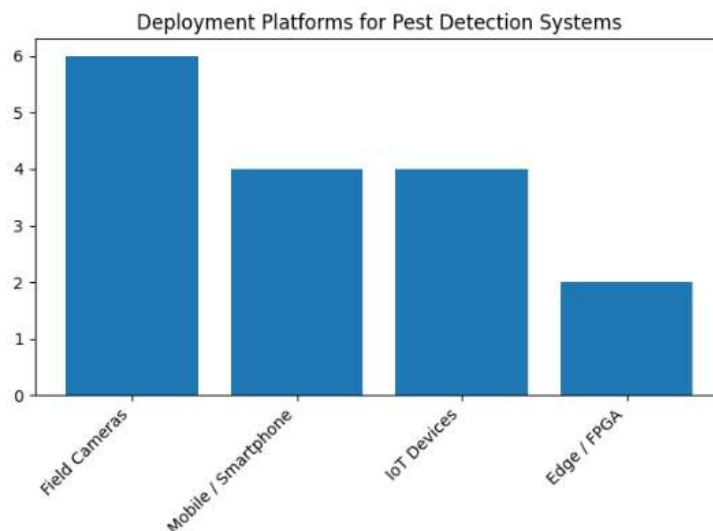


Figure 5: Deployment platforms adopted for AI-based pest detection systems.

Overall, the reviewed studies validate that AI-based pest detection systems are no longer in the developmental stage, being tested, but are instead practical systems that are applicable in the real world. The use of DL, IoT devices, mobile devices, and explainable AI is instrumental in achieving precise, timely, and scalable pest detection, which is the foundation of intelligent pest management systems. This table 2 provides a comparison of AI models, data, and results used for precise and scalable pest detection.

Table 2: AI-based pest detection and monitoring systems.

Author (Year)	Pest / Application Domain	Methods Used	Data Type	Key Outcome
Bestelmeyer et al. (2020)	General agricultural pest monitoring	AI-based data analytics	Environmental & spatial data	Provided early warning mechanisms for pest outbreaks using AI-driven spatial analytics
Guimapi et al. (2020)	Biological pest management	Mathematical modeling + DSS	Experimental & temperature data	Developed a decision-support system for pest dynamics modeling and spatial prediction
Zhang et al. (2020)	Smart agriculture pest monitoring	AI + IoT + Edge computing	Sensor data	Enabled low-latency, real-time pest monitoring using edge-based IoT architecture
López et al. (2020)	Integrated pest management (IPM)	AI + Blockchain + IoT	Sensor & expert data	Proposed a traceable and secure IPM framework ensuring data reliability
Rocha et al. (2020)	Mango pest identification	CNN	RGB images	Achieved accurate pest identification using smartphone-based image analysis
Caldeira et al. (2021)	Cotton leaf disease detection	CNN (GoogleNet, ResNet50)	Field images	Demonstrated superior lesion detection compared to traditional ML methods
Júnior et al. (2022)	Insect detection from traps	Mask R-CNN	Trap images	Automated insect detection and counting with strong correlation to manual methods
Zhao et al.	Automatic	Custom CNN	Image data	Improved detection

(2022)	pest monitoring	(DPeNet)		accuracy for pests of varying sizes under field conditions
Esmail Karar et al. (2022)	Red palm weevil detection	MixConvNet (DL)	Acoustic (sound) data	Enabled early-stage pest detection with over 97% accuracy
Martins et al. (2023)	Leafminer fly severity estimation	U-Net, FPN (DL segmentation)	Leaf images	Automated pest severity estimation under complex field conditions
Salamai et al. (2023)	Crop disease & pest diagnosis	Meta-learning + Vision Transformers	Leaf images	Improved generalization for pest diagnosis under limited training data
Khalid et al. (2023)	Small pest detection	YOLO variants	Field images	Achieved high mAP for early and small pest detection in crops
Zhou et al. (2024)	Site-specific pest management	YOLOv7 + Spatial interpolation	Smartphone images + GPS	Developed low-cost mobile app for pest counting and spatial mapping
Hernández et al. (2024)	Grapevine disease detection	Explainable DL (EfficientNetV2)	Canopy images	Enabled interpretable detection and localization of disease symptoms
Mohamad Sa'ad et al. (2025)	Bird pest detection in paddy fields	DETR + FPGA acceleration	Video/image data	Achieved real-time bird detection with 200% FPS improvement
Ray et al. (2025)	Multi-class pest identification	EfficientNet B4, Inception V3	Image dataset (IP102)	Demonstrated high accuracy for large-scale pest classification
Oyege et al. (2025)	Armyworm & stem borer detection	YOLOv8	Image data	Confirmed YOLOv8 as the most robust model for real-time pest detection
Manduca et al. (2025)	Termite behavior analysis	Computer vision + Transfer Entropy	Movement & speed data	Revealed caste-specific interaction dynamics for bio-inspired pest control
Manduca et al. (2025)	Biological pest control (EPNs)	CNN + Microfluidics	Video & optical flow	Advanced AI-driven understanding of entomopathogenic nematode behavior

4. Intelligent Pest Management, Prediction, and Decision Support

The essential need for detection methods exists but pest management needs both accurate predictive systems and decision-support tools which provide assistance during critical moments of pest control operations. The AI-driven pest prediction models use historical pest data together with climatic variables and crop conditions to predict the likelihood of pest infestations. The early decision-support frameworks which Tahri et al. (2022) [64] and Katsoulas et al. (2021) [65] developed succeeded in spatially explicit pest risk assessment through their use of fuzzy logic and Bayesian belief networks together with climate models. ML approaches for pest prediction have become popular because they can represent how environmental factors affect pest behaviors through complex mathematical patterns. Hessane et al. (2025) [66] created an AI-based pest prediction system for date palm cultivation which combines ensemble learning with SHAP-based explainability to establish trust and enhance understanding. The research by Shafique et al. (2025) [67] and Kim et al. (2023) [68] used ensemble ML models to forecast pest outbreaks based on weather data which resulted in accurate predictions that supported effective integrated pest management practices. This figure 6 indicates that ensemble ML and DL models are most frequently used for pest prediction, with growing adoption of explainable AI techniques.

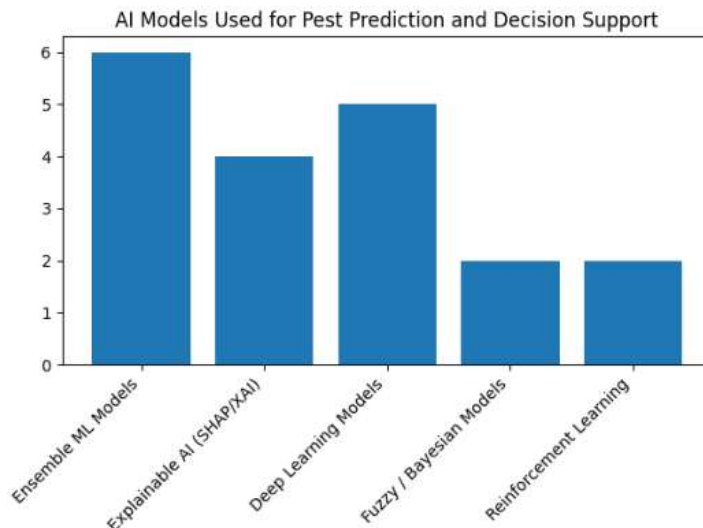


Figure 6: AI models applied for pest prediction and decision-support systems.

A number of research associates pest prediction with the crop development and environmental surveillance. Prapanitisatian et al. (2025) [69] and Farbo et al. (2024) [70] used satellite imagery and NDVI, NDWI, and ML models to make better crop stage identification and stress predictions, which indirectly aids in pest management decisions. Tkatek et al. (2023) [71] and Abrol et al. (2025) [72] applied AI to fertilizer and crop recommendations and provided examples of how losses in the yield caused by pests can be avoided by using holistic decision-support systems. The figure 7 indicates that weather and climatic data constitute the main input of the pest prediction models, and this is followed by the pest records and vegetation indices.

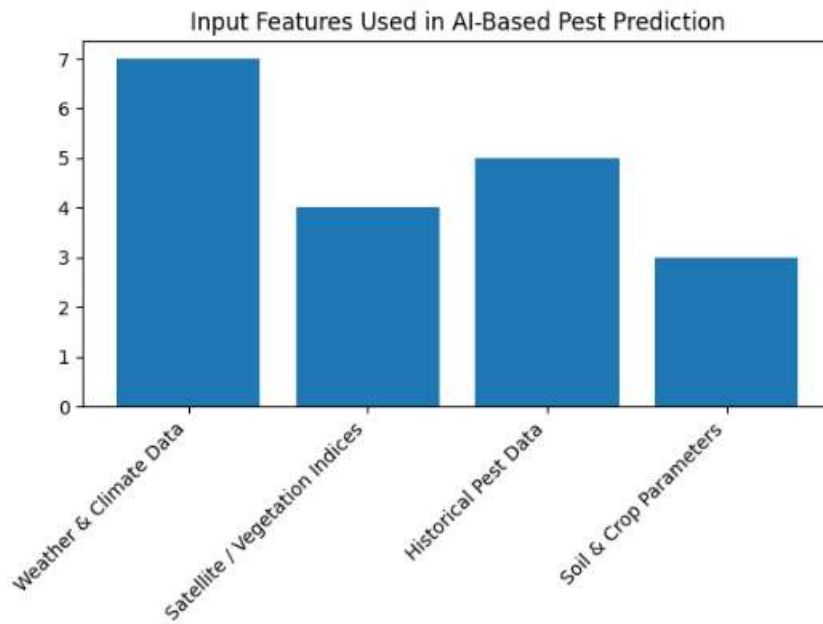


Figure 7: Input features employed in AI-driven pest prediction models.

The AI-driven management is meant to develop further by the concept of precision pest control. The proposed autonomous cycle of data analysis tasks by Toscano-Miranda et al. (2024) [73] also implemented classification, prediction, and prescription to manage cotton pests, and it was found to be highly accurate and adaptable. The article by Hussain et al. (2025) [74] has shown how AI-based Variable-Rate Spraying (VRS) can be connected to autonomous vehicles and that, in this case, the use of pesticides is minimized without losing the control effect. The hybrid DL and reinforcement learning framework by Mohan et al. (2025) [75] was introduced, which is not only able to identify pests, but also provide the best strategy of pesticide usage, with accuracy of 99.6%. The figure 8 shows that there is a great movement to integrate AI-IoT systems which means that one has to abandon individual models and adopt integrated and intelligent decision spaces.

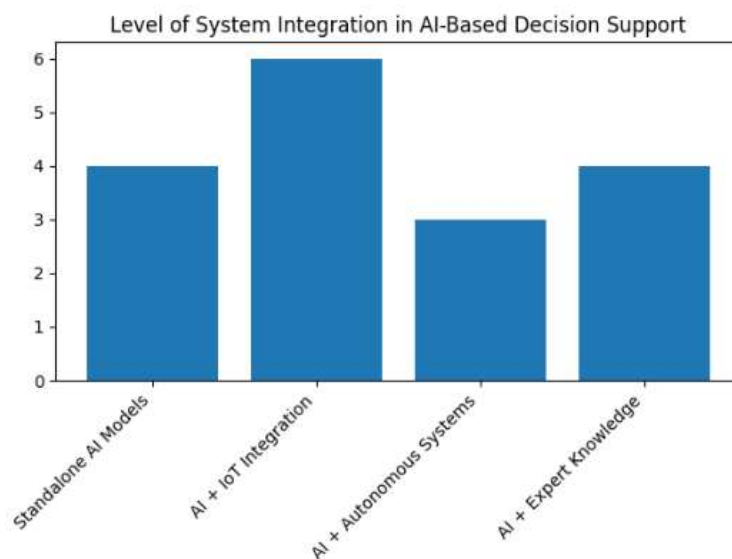


Figure 8: System integration levels in AI-based pest decision-support frameworks.

The use of explainable AI and human-in-the-loop systems creates new decision-support frameworks for their development. Hernández et al. (2024) [76] used explainable AI methods in their disease and pest detection systems which resulted in better understanding and usage of their technology. Parr et al. (2021) [77] showed how multimodal AI systems use expert knowledge and sensor data and historical records to create adaptive pest management solutions. The studies demonstrate that AI systems which make predictions and support decisions help pest management organizations to move from reactive methods to proactive approaches which result in accurate pest control and resource efficiency and environmentally friendly pest management. The table 3 displays ML models together with their input data sources and decision-support systems which enable pest control treatments to start at appropriate times.

Table 3: AI-driven pest management, prediction, and decision-support systems.

Author (Year)	Application Domain	Methods Used	Input Data	Key Outcome
Katsoulas et al. (2021)	Greenhouse disease & pest risk	Climate-based DSS + disease models	Weather forecasts & microclimate data	Developed a web-based decision-support system for predictive disease and pest risk assessment
Tahri et al. (2022)	Forest pest risk (bark beetle)	Fuzzy-AHP + Bayesian Belief Networks	GIS & environmental data	Enabled spatially explicit pest predisposition mapping for proactive forest management
Kim et al. (2023)	Greenhouse pest and disease control	Faster R-CNN + environmental augmentation	Image & environmental sensor data	Improved pest detection accuracy under real greenhouse conditions
Tkatek et al. (2023)	Crop yield & pest-related nutrient management	ML (RF, SVM, XGBoost)	Soil, weather & crop data	Optimized fertilizer recommendations to mitigate pest-induced yield loss
Farbo et al. (2024)	Crop stress & pest risk forecasting	ANN + Bi-LSTM	NDVI, NDWI, climate time series	Enabled proactive pest and crop management via short-term vegetation forecasting
Prapanitisatinn et al. (2025)	Rice crop growth & pest decision support	ML (Random Forest)	Satellite & street-level images	Improved growth-stage classification supporting pest management timing

Abrol et al. (2025)	Smart farming decision systems	ML (RF, SVM, Gradient Boosting)	Crop & soil parameters	Integrated crop, fertilizer, and pest-related decision support with high prediction accuracy
Hessane et al. (2025)	Date palm pest prediction	Ensemble ML + SHAP (XAI)	Climatic & temporal data	Achieved explainable pest forecasting with strong predictive performance
Shafique et al. (2025)	Cotton pest prediction (Jassid, Thrips)	Ensemble ML + SHAP	Meteorological data	Delivered accurate, interpretable pest incidence predictions for IPM
Toscano-Miranda et al. (2024)	Cotton pest management	XGBoost + Fuzzy systems + Genetic Algorithms	Pest population & crop variables	Proposed an autonomous AI cycle integrating detection, prediction, and prescription
Hussain et al. (2025)	Precision pest control	AI + VRS + Autonomous vehicles	Sensor & spatial field data	Reduced pesticide usage while maintaining effective pest control
Mohan et al. (2025)	Pest detection & pesticide recommendation	DL + Reinforcement Learning (PPO)	Image datasets	Achieved 99.6% accuracy with optimal pesticide recommendation
Hernández et al. (2024)	Explainable disease & pest management	XAI-enabled CNN & ViT	Field images	Improved transparency and trust in AI-based pest management decisions
Parr et al. (2021)	Multimodal agricultural decision support	AI + NLP + Computer Vision	Text, images & numeric data	Integrated expert knowledge with AI for adaptive pest management strategies

5. Integrated AI-IoT Frameworks and Sustainable Pest Eradication Approaches

AI technology has merged with IoT systems to create complete pest management solutions which deliver sustainable results that can grow and respond to situations as they occur. The study conducted by Iyanda et al. (2025) [78] showed that using IoT sensors together with AI models enables better crop resilience and higher yields and

improved resource usage in areas which experience environmental stress. The field of sustainability-centric pest management research has become a focus of academic investigation. Benhoussa et al. (2025) [79] developed a bird detection system which uses federated learning to operate smart cameras that perform at the same level as centralized systems while using much less power. The research by Manduca et al. (2025) [80] achieved progress in biological pest control through an AI and microfluidics and behavioral analysis framework which enables better deployment of entomopathogenic nematodes. Li et al. (2025) [81] constructed an AIoT-based comprehensive pest control solution which uses lightweight YOLO models to provide budget-friendly and environmentally sustainable pest management solutions. The figure 9 shows how various AI-IoT system types distribute between smart monitoring systems and digital decision platforms which primarily lead sustainable research on pest elimination.

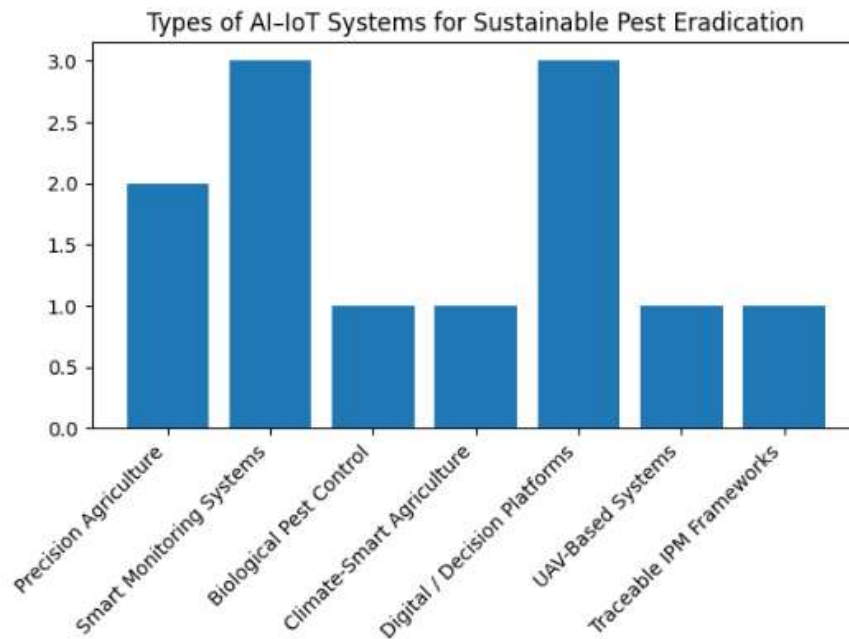


Figure 9: Types of AI-IoT Systems for Sustainable Pest Eradication

Maraveas et al. (2023) [82] and Chavula et al. (2024) [83] conducted extensive research which demonstrated that integrated AI-IoT systems decrease pesticide usage while increasing climate resilience and enabling sustainable agricultural practices. The research identified ongoing challenges which included expensive implementation processes and insufficient infrastructure resources and uneven technology usage across different areas specifically in developing countries. The research conducted by Kitole et al. (2024) [84] and Azizi et al. (2024) [85] demonstrated that organizations must develop digital proficiency and financial accessibility and governance support systems to implement AI technologies. The figure 10 demonstrates that the most common technological combination used by organizations to develop effective pest control systems combines AI with IoTs technology and computer vision systems.

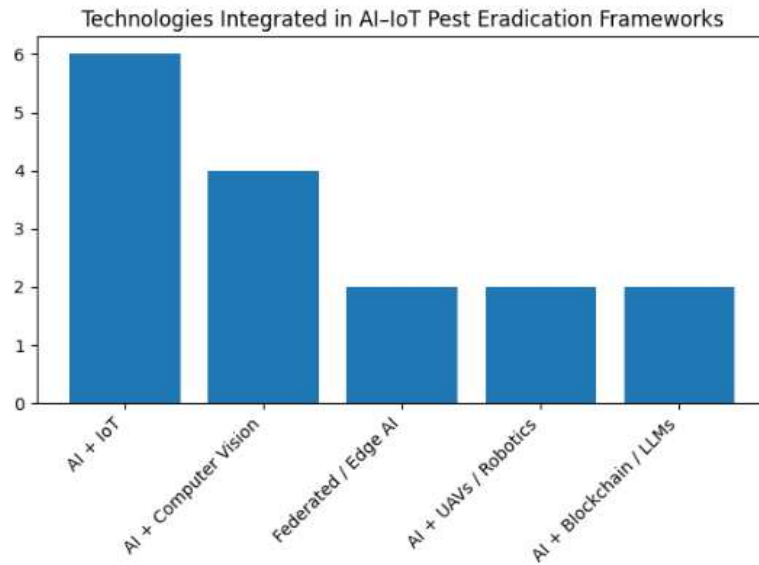


Figure 10: Technologies Integrated in AI-IoT Pest Eradication Frameworks

The development of large language models (LLMs) and blockchain technology together with UAVs creates new possibilities for AI-IoT ecosystems. Yuan et al. (2025) [86] demonstrated how IoT-LLM integration can automate pest management recommendations which reduces the need for expert knowledge. Toscano et al. (2024) [87] and Rosado et al. (2022) [88] highlighted the growing role of UAVs and mobile AI platforms in large-scale pest monitoring and decision support. Amrani et al. (2024) [89] stressed the importance of blockchain-enabled traceability to ensure trust and data integrity in IPM systems. The figure 11 demonstrates that integrated AI-IoT pest management frameworks achieve efficient pest detection and sustainable pest control as their primary reported outcomes.

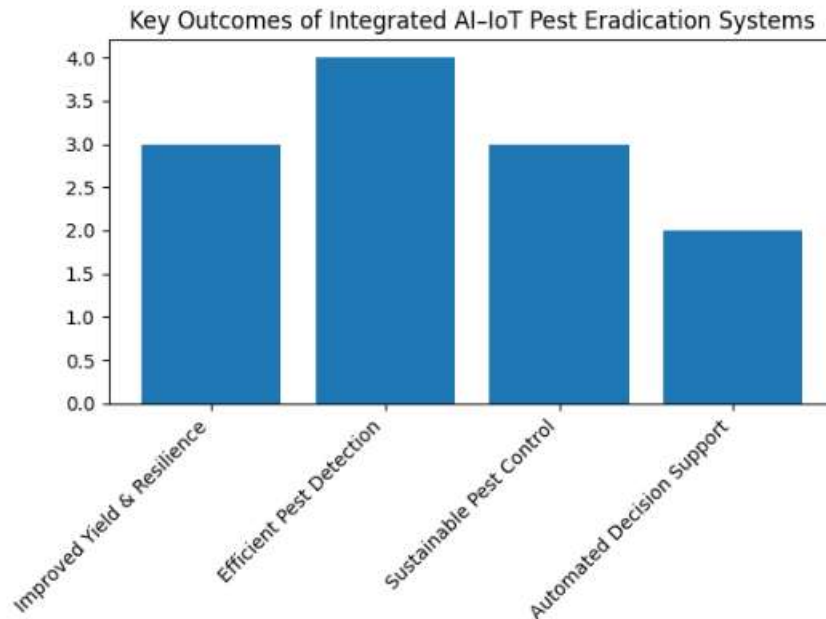


Figure 11: Key Outcomes of Integrated AI-IoT Pest Eradication Systems

In summary, integrated AI-IoT frameworks represent the future of pest management by unifying intelligent sensing, predictive analytics, automated intervention, and sustainability principles. Addressing technical, economic, and social challenges through inclusive design and policy support will be crucial for widespread adoption and long-term impact. This table 4 summarizes end-to-end AI-IoT systems emphasizing sustainability, resource efficiency, and real-time pest management.

Table 4: Integrated AI-IoT frameworks for sustainable pest eradication.

Author (Year)	System / Application Type	Technologies Integrated	Sustainability Aspect	Key Outcome
Iyanda et al. (2025)	Precision agriculture framework	IoT sensors + AI models (ANN, DT)	Efficient water & chemical use	Improved crop resilience, yield, and resource efficiency in stress-prone regions
Benhoussa et al. (2025)	Smart camera network	Federated Learning + CNN + IoT	Low energy consumption & data privacy	Achieved energy-efficient, privacy-preserving bird pest detection
Manduca et al. (2025)	Biological pest control system	AI + Microfluidics + CNN	Eco-friendly biocontrol optimization	Enhanced understanding and deployment efficiency of entomopathogenic nematodes
Li et al. (2025)	Unified pest prevention system	AIoT + Lightweight YOLO variants	Low-cost & energy-efficient pest control	Enabled scalable, accurate, and sustainable pest prevention
Maraveas et al. (2023)	Smart greenhouse systems	AI + Robotics + IoT + UAVs	Reduced pesticide and resource use	Demonstrated sustainability benefits of AI-driven greenhouse management
Chavula et al. (2024)	Climate-smart agriculture	AI + ML + NLP + IoT	Climate resilience & food security	Highlighted AI-IoT role in reducing climate-related pest risks
Kitole et al. (2024)	Agricultural digitalization	Digital platforms + AI tools	Socio-economic sustainability	Showed improved pest management and farmer welfare through digital adoption
Azizi et al. (2024)	Precision farming systems	AI + IoT + Data analytics	Reduced environmental impact	Improved pest control decisions, yield prediction, and farm profitability
Yuan et al.	Intelligent	IoT + Large	Knowledge	Automated pest

(2025)	recommendation system	Language Models (LLMs)	scalability & efficiency	management recommendations with reduced expert dependency
Toscano et al. (2024)	UAV-based pest monitoring	UAVs + AI + Computer Vision	Optimized chemical application	Enabled large-scale, precise pest monitoring and intervention
Rosado et al. (2022)	Mobile pest monitoring platform	Mobile AI + CV + IoT sensors	Reduced pesticide misuse	Provided real-time pest detection and decision support in viticulture
Amrani et al. (2024)	Traceable IPM framework	AI + Blockchain + Image analytics	Data integrity & trust	Ensured transparent and reliable pest management through traceability

6. Discussion

This systematic review highlights recent advances in AI-based pest detection, prediction, and eradication systems that are reshaping modern pest management practices through AI. The analysis of 51 peer-reviewed journal articles published from 2020 to 2025 indicates a clear transition away from traditional reactive approaches toward intelligent data-driven proactive systems. Findings show that DL models based on computer vision dominate research into pest detection due to their high accuracy, scalability, and suitability for real-time deployment in the field. Increasing use of mobile platforms, UAVs, and IoT-enabled sensors reflects an emphasis on practical solutions in the field supporting early detection and reducing dependency on manual surveillance. Beyond detection; AI-driven prediction and decision-support systems leverage climatic, environmental, and crop data to forecast outbreaks of pests recommending targeted interventions significantly increasing the effectiveness of Integrated Pest Management (IPM).

One of the most important things we learned based on this review is the increasing significance of integrated AI and IoT solutions. This is a framework where sensing, analytics, automation, and sustainability rules are brought together to create end-to-end pest eradication solutions. The advantages of this framework are quite tangible, including reduced pesticide usage, optimized resource utilization, improved plant hardiness, and reduced environmental degradation. New advances such as federated learning, Explainable AI, UAVs, Blockchain, and large language models have all improved scalability, explainability, and usage rates of these solutions. However, a number of challenges were also identified, including lack of data within these solutions, the high costs of deployment, as well as the ability to address infrastructure and technology gaps, particularly within developing countries. Based on this review of literature, it is clear that pest management solutions enabled by AI have grown significantly and are now reliable and sustainable. Indeed, this is a technology that promises to improve agricultural productivity and environmental sustainability in the coming years.

7. Future Scope

Here is a Future Scope section presented in clear bullet points:

- The pest management systems of the future will be able to combine image, video, acoustic, climatic, soil and satellite data to enhance detection ability, strength, and early warning of pests under unique agro-ecological environments.
- Greater focus on explainable AI (XAI): This will be critical to increase transparency, interpretability, and trust in AI-driven pest predictions and recommendations, allowing the stakeholders to comprehend, make appropriate decisions based on them.
- Latency, energy usage, and cost of deployment can be minimized with the creation of lightweight models targeted at edge devices (smartphones, microcontrollers, and drones), allowing them to be deployed in resource-constrained areas.
- By extending federated learning models, it will become possible to engage in model training at farms and regions without exchanging raw data, which ensures data privacy and enhances model generalization.
- With AI-IoT systems coupled with LLMs, it can be made possible to interact in the natural language, have automated advisory services, and context-based pest management recommendations to locals based on farming practices.
- Future systems could combine reinforcement learning and robotics, UAVs and variable rate spraying technologies to allow fully autonomous and adaptive and precision control of pests with little human intervention.
- AI models that explicitly incorporate climate change scenarios can improve long-term pest risk assessment, supporting climate-smart agriculture and sustainable food production.
- Future research should align technological advances with policy support, digital literacy programs, and socio-economic considerations to ensure equitable adoption and long-term sustainability of AI-based pest management systems.

8. Conclusion

This systematic review points to the high pace of development of AI-driven pest eradication systems and their increased role in sustainable agriculture. The articles included in the review have shown that AI-based pest detectors, predictors, and decision support systems contribute to the accuracy, timeliness, and scalability of pest management under various agricultural environments. Deep-learning-based computer-vision models, IoT-based sensing infrastructures, and predictive analytics that are driven by data have all changed conventional reactive pest management practices to proactive and precision-oriented practices. Additionally, the combination of AI with IoT technologies provides end-to-end pest management systems that can be used to optimize resource usage, minimize the reliance on pesticides, and ensure environmental sustainability. New paradigms explainable AI, federated learning, edge computing, and large language models reinforce the transparency of systems, their efficiency, and their accessibility even further. In spite of these developments, issues of high implementation costs, lack of data, use of inadequate infrastructure, and disproportionate use of technology, still exist especially in the developing areas. In general, AI-based pest eradication systems present a viable solution in the direction of sustainable, climate-resilient, and climate-smart agriculture. Ongoing interdisciplinary studies, inclusive design approaches and supportive policy will be necessary to speed up mass implementation, as well as, maximizing the potential of intelligent pest management systems in ensuring global food security and environmental conservation.

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