GMR
The Original

ARTIFICIAL INTELLIGENCE-POWERED INTEGRATED FARMING AND PEST MANAGEMENT: A COMPREHENSIVE REVIEW FOR SUSTAINABLE AGRICULTURE

[1]Dr Geetanjli Sahni, 2[*]Hardeep Jhanjohtra, [3]Ridhanye Dhawan [4]Prerna Gaba, [5]Sunita, [6]Nisha Rani,

[1]Associate Professor, Head and Associate Professor, Department of Zoology, Arya PG College, Panipat-132103, Haryana, India. geetanjlisahni8@gmail.com
[2*]Assistant Professor, Department of Zoology, Arya PG College, Panipat-132103, Haryana, India hardeep.envt@kuk.ac.in, https://orcid.org/0009-0009-1360-7577
[3]Department of Zoology, Arya PG College, Panipat-132103, Haryana, India. ridhidhawan66@gmail.com
[4]Assistant Professor, Department of Zoology, Arya PG College, Panipat-132103, Haryana, India prernagaba2003@gmail.com
[5]Department of Zoology, Arya PG College, Panipat-132103, Haryana, India csunita19440@gmail.com
[6]Department of Zoology, Arya PG College, Panipat-132103, Haryana, India. nisha19441@gmail.com

ABSTRACT
Artificial Intelligence (AI) plays a transformative role in enhancing Integrated Pest Management (IPM) by facilitating rapid pest identification, predicting potential outbreaks, and enabling precise pesticide application. Using machine learning, computer vision and internet monitoring. AI helps to reduce chemical use while promoting informed decision-making, thereby supporting sustainable agricultural practices and strengthening ecological resilience. Recent studies indicate that AI significantly enhances the accuracy of pest monitoring and optimizes resource use in precision farming, which is crucial for protecting beneficial organisms and improving crop yields. Many AI applications primarily emphasize pest detection, often overlooking the broader IPM framework that encompasses biological control methods, ecological interactions, and socio-economic considerations.

KEYWORDS: Artificial intelligence, Integrated pest management, Biosensor, Ecosystem and Sustainable management.

1. INTRODUCTION

A pest poses a significant threat to human activities, impacting our economy and well-being by causing financial losses, reducing the yield and quality of crops, spreading harmful diseases, and damaging essential stored products, livestock, or property (Azeele *et al.*2022). Effective pest management is crucial in counteracting these challenges, and it involves a systematic application of diverse strategies that encompass biological, cultural, physical, mechanical, genetic, and chemical methods (Nehul,2025). The primary goal is to prevent, suppress, or maintain pest populations below the Economic Injury Level (EIL) while ensuring that human health, beneficial organisms, and the environment are safeguarded. In the realm of contemporary agriculture and pest control, there is a strong push for Integrated Pest Management (IPM), a holistic approach that integrates multiple compatible strategies rooted in ecological principles (Ahmed *et al.* 2024). This innovative method not only addresses pest issues effectively but also promotes sustainable practices that balance productivity with environmental stewardship. By adopting IPM, we can protect our crops, enhance our agricultural resilience, and prioritize the health of our planet for future generations (Das *et al.,* 2024).

Global agricultural systems suffer significant yield losses from insect pests, plant pathogens, and weeds, accounting for 30–40% of total crop production losses annually (Junaid and Gokce, 2024). Conventional pest management practices based on prophylactic pesticide applications have led to pesticide resistance, environmental contamination, the resurgence of secondary pests, and the destruction of beneficial organisms (Chaudhary *et al.,* 2024). Integrated Pest Management (IPM) was developed as an ecological approach that combines biological, cultural, mechanical, and chemical methods to maintain pest populations below economic threshold levels. Despite its ecological advantages, traditional IPM requires intensive field monitoring, expert knowledge, and timely decision-making (Choudhary *et al.* 2026). Traditional control methods including cultural control methods, are vital for sustainable agriculture and include practices such as crop rotation, selecting resistant plant varieties, and maintaining proper sanitation to reduce pest populations (Istatu *et al*. 2025). Biological control involves using natural enemies of pests, such as predators, parasitoids, and pathogens, to manage pest outbreaks effectively and minimize reliance on synthetic chemicals. (Sutherland *et al.* 2017). Mechanical and physical methods incorporate tools such as traps and barriers to physically prevent pests from damaging crops. Finally, judicious chemical control refers to the careful and targeted use of pesticides, ensuring that they are applied only when necessary and in a manner that minimizes harm to the environment and non-target organisms (Angon *et al*. 2023). The emergence of Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL) and Unmanned Aerial Systems (UAS) has revolutionized pest management by enabling automated pest identification, outbreak forecasting, and site-specific pesticide application. AI-enabled IPM supports sustainable agriculture by improving productivity while minimizing environmental impacts.

Artificial intelligence is advancing Integrated Pest Management (IPM) by enabling real-time pest detection, outbreak prediction, and targeted pesticide application. Technologies such as machine learning, computer vision, and information

technology-based monitoring reduce chemical use, improve decision-making, and support sustainable agriculture. (Javed *et al.* 2025). AI-driven tools, including automated image analysis, drones, and climate-based predictions, enhance pest monitoring accuracy and resource efficiency, contributing to precision farming (Hoque *et al.* 2026). These systems also help minimize unnecessary pesticide use, protecting pollinators and natural enemies, and improving crop yields and economic outcomes. Decision-support systems that use real-time field data enable flexible, threshold-based pest control, which is more effective than traditional calendar-based spraying. However, most AI models are developed in controlled environments and may not perform consistently across different crops, climates, or small-scale farms. Additionally, many AI tools focus primarily on pest detection and do not fully address other IPM components, such as biological control, ecological interactions, and socioeconomic factors. However, it is important to note that most current AI models are developed within controlled environments, which limits their adaptability to diverse crops and farming systems. This paper aims to examine how Artificial Intelligence (AI) can enhance Integrated Pest Management (IPM) frameworks. The focus will be on its contributions to maintaining ecological balance, conserving biodiversity, and promoting agricultural practices that are resilient to climate change. The swift progression of Artificial Intelligence (AI) has greatly altered traditional agricultural methods, especially Integrated Pest Management (IPM), by facilitating data-informed, accurate, and environmentally friendly pest control techniques. Conventional pest management methods rely on regular field inspections and scheduled pesticide applications, often leading to excessive chemical use, pest resistance, reduced biodiversity, and environmental pollution. AI-powered technologies offer real-time surveillance, predictive analysis, and automated decision-making, thus enhancing the effectiveness and ecological sustainability of IPM. Machine learning (ML) and Deep Learning (DL) techniques are demonstrating significant effectiveness in the areas of pest detection, classification, and forecasting their populations. The application of Convolutional Neural Networks (CNNs) for identifying pests through images has achieved remarkable accuracy in both controlled settings and real-world scenarios. This ability enables the quick distinction between pest species and beneficial organisms, greatly reducing the dependence on manual identification methods and supporting timely intervention measures (Abdalla *et al.* 2021; Wang *et al*. 2024). Furthermore, ML models that examine historical pest information together with climatic factors have the potential to forecast pest outbreaks. This capability allows farmers to take preventive actions rather than relying on reactive pesticide treatments (Liakos et al., 2020). The fusion of AI with internet-connected devices has revolutionized real-time pest surveillance systems. Advanced smart pheromone traps, equipped with cutting-edge sensors and wireless communication technologies, provide continuous monitoring of insect populations while seamlessly transmitting data to cloud-based platforms (Chaudhary *et al.* 2026). This capability empowers farmers to make immediate, threshold-based pest management decisions, resulting in practices that are not only more efficient but also much kinder to the environment compared to outdated scheduled spraying methods (Saeed *et al*. 2022). Additionally, Unmanned Aerial Vehicles (UAVs) equipped with AI-driven image analytics enable large-scale pest monitoring, drastically cutting labor costs and significantly enhancing the spatial accuracy of pest detection (Yang *et al.* 2022). AI-driven precision spraying technologies signal a pivotal advancement in Integrated Pest Management (IPM). By employing computer vision, these sprayers can accurately detect pest-infested areas and apply pesticides selectively, thus dramatically reducing chemical usage and lessening impacts on non-target organisms. This targeted approach not only aids in pest control but also promotes pollinator conservation, supports natural predators, and sustains soil microbial health, thereby contributing to the overall biodiversity of agroecosystems (Talaviya *et al.* 2023). Furthermore, AI-based Decision Support Systems (DSS) empower farmers with real-time guidance on pest management strategies tailored to crop development stages, pest populations, weather patterns, and economic considerations. From a sustainability perspective, AI-enabled IPM aligns seamlessly with climate-smart agricultural practices, enhancing resource-use efficiency, reducing greenhouse gas emissions associated with pesticide production and use, and bolstering crop productivity amid shifting climatic conditions. The ecological benefits are profound, including reduced pesticide residues in our soils and waterways, safeguarding of beneficial insect species, and the revitalization of natural pest-predator interactions (Angon *et al.* 2023; Jha *et al.* 2023). The following models of integrated pest management and AI -based pest management were reported in Table 1 as follows.

MATERIAL AND METHODS

The model encompassed an equivalent of two acres of land, divided into distinct sections for optimal agricultural productivity. One acre was dedicated to the main crop, while the remaining acre featured a diverse mix: fifty percent was allocated for forage crops and the balance was utilized for a fisheries pond and poultry. Surrounding the entire field, a perimeter of strategically planted fruit and timber trees served as a windbreak, enhancing the microclimate and overall sustainability of the area. To ensure proactive pest management, the field was equipped with poles that hold LED lights connected to sensors. These sensors were programmed with audio and visual information about various pests, both beneficial and harmful. When a pest was detected, an alert was immediately sent to farmers, enabling them to take timely preventive measures and protect their crops effectively as shown in Figure 1.

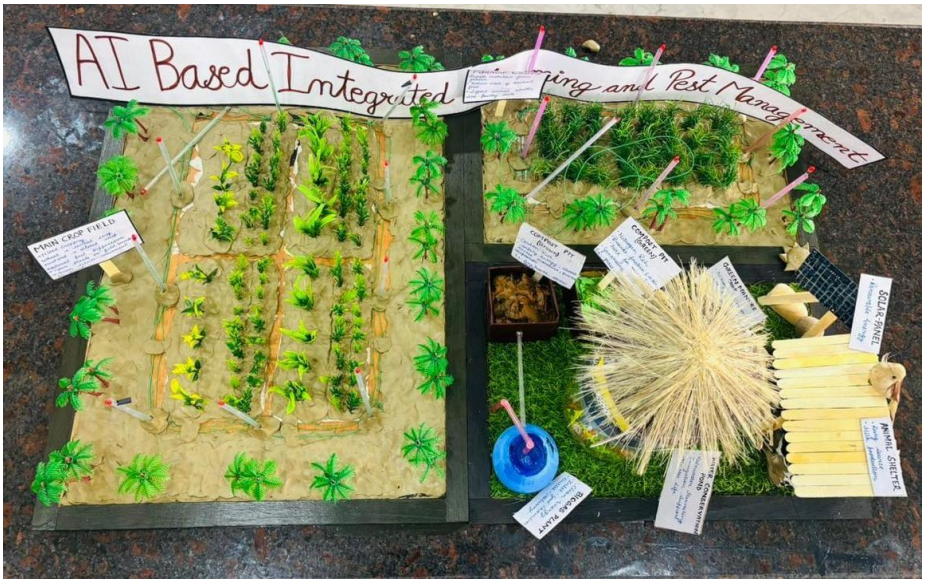


Figure 1: AI-based Integrated farming and pest management model

Literature and Review

Table1: Year-wise comparison of models

Year	Authors	Model/Approach	AI/Technology used	Major Application	Key Contribution /strength	Major Limitation
1998	Kogan	Integrated Pest Management (IPM) Framework	Knowledge based decision–making, ecological principles	Crop protection and pest management	Established IPM as an integrated approach combining multiple pest control strategies	Relatively dependent on expert knowledge and field scouting
2015	Barzman et al.	IPM principles framework	Decision rules, monitoring and ecological approaches	Sustainable pest management	Formalized eight principles for implementation of IPM	Requires continuous monitoring and context-specific decisions
2016	Mohanty et al.	Deep learning plant tissues model	Convolutional Neural Network (CNN)	Plant disease identification	Demonstrated strong potential of deep learning for automated disease classification	Performance can decline under field conditions compared with controlled images
2017	Kamilaris and Prenafeta-Boldu	Deep learning in agriculture	Deep neural networks/CNN	Crop, soil and disease-related applications	Demonstrated broad potential of deep learning in agricultural applications	Large annotated datasets and computational resources are required
2018	Ferentinos	Deep-learning disease detection	CNN	Plant diseases diagnosis	Developed high-performing deep-learning models for plant disease recognition	Primarily focused on image-based diagnosis rather than complete farm management
2019	Koirala et al.	Deep-learning fruit detection	Faster R-CNN	Fruit detection and yield estimation	Enabled automated crop monitoring and yield-related assessment	Model performance affected by field illumination and occlusion
2020	Patricio and Reider	AI-based disease detection	Deep learning and computer vision	Plant disease classification	Reviewed AI approaches for automated diseases recognition	Need for standardized and diverse datasets
2021	Ferentinos et al.	AI-enabled	Computer vision	Crop disease	Improved	Generalization across

		agricultural diagnosis	and deep learning	and pest-related diagnosis	automated identification capabilities	crops and geographical regions remains a challenge
2022	Kamilaris et al.	AI-enabled smart farming	AI Internet network, sensors and remote sensing	Precision agriculture	Supported real-time and data-driven agricultural management	Infrastructure, interoperability and data-management issues
2024	Recent AI-based pest-detection studies	AI pest recognition	CNN, YOLO and computer vision	Automated insect/pest detection	Rapid and non-destructive pest identification	Requires large, representative field-image datasets
2025	Recent precision-IPM studies	AI-enabled precision IPM	ML/DL + remote sensing + IoT +DSS	Pest prediction and site-specific intervention	Moves pest management from reactive to predictive approaches	Field validation, explainability and integration remain important challenges

Advantages

AI-based pest monitoring significantly improves IPM decision-making efficiency, reduces pesticide consumption, influences crop productivity with precision and enhances ecological sustainability. AI could create a bond between pesticide and biodiversity conservation. Reduces pesticide resistance and pest resurgence, minimizes environmental pollution, protects non-target organisms and biodiversity, improves long-term agricultural sustainability and is cost-effective for farmers. This study aims to explore how Artificial Intelligence (AI) can improve decision-making in Integrated Pest Management (IPM). It will analyze the effects of AI-driven IPM strategies on pesticide usage and crop productivity. Additionally, the research will assess the role of AI-based IPM in promoting biodiversity conservation and ecological sustainability. Finally, the study seeks to develop a structural model that supports sustainable pest management through AI technologies (Eromosele *et al.* 2013).

AI-enabled pest detection through cameras and computer vision can provide early and accurate identification of pest species and infestation levels, while network sensors continuously collect real-time information on temperature, humidity, soil moisture, rainfall, crop conditions and other environmental variables. These data can be combined with historical pest records and weather information to generate early pest-risk forecasts, allowing farmers to shift from reactive pesticide application toward preventive and evidence-based management. The resulting IPM decision system can recommend precision interventions only when pest populations approach economically or ecologically meaningful thresholds, thereby reducing unnecessary pesticide use, input costs, crop losses and environmental contamination. From an economic perspective, the framework can improve farm profitability by reducing expenditure on pesticides, water, labour and repeated field scouting while protecting crop yield and quality. From a social perspective, accessible AI-assisted decision support can reduce dependence on highly specialized pest-management expertise, improve farmers' access to timely information, support safer working conditions by reducing unnecessary pesticide exposure, and contribute to more resilient livelihoods, particularly where agricultural resources are limited. From an ecological perspective, targeted interventions can conserve beneficial insects and natural enemies, reduce pesticide residues and soil and water contamination, protect biodiversity, and support long-term ecosystem stability.

Thus, the interlinking of pest detection → IoT environmental monitoring → pest forecasting → IPM-based decision-making → precision intervention → ecological and economic

feedback creates a positive feedback loop in which efficient resource use, farmer welfare, economic sustainability, biodiversity conservation, and crop productivity reinforce one another. In this way, Agrofusion-AI represents a transition from conventional reactive pest control toward predictive, site-specific, resource-efficient, socially responsible and ecologically sustainable precision IPM.

Challenges

The implementation of this technology necessitates a solid understanding of technical concepts and ongoing oversight. Additionally, there has been a slow uptake in developing countries, highlighting the need for comprehensive training for farmers and robust institutional support to facilitate successful integration (Rasyid et al. 2024). Yet, despite these significant innovations, challenges remain that impede the broad adoption of AI in IPM. Many current AI models are based on datasets gathered from developed nations and controlled environments, which limits their applicability across diverse agroecological contexts, particularly among smallholder farmers. Additional hurdles such as a scarcity of labeled pest image datasets, insufficient digital infrastructure, high initial investment costs and a lack of technical expertise among farmers further hinder progress. Moreover, existing research has predominantly focused on pest detection and classification, neglecting the integration of ecological metrics, socioeconomic elements, and biological control strategies within AI methodologies. To move forward, there is an urgent need to develop location-specific, scalable and farmer-friendly AIIPM models that incorporate ecological sustainability indicators and address behavioral adoption factors. Crafting such integrated frameworks is essential for promoting sustainable agricultural practices while ensuring biodiversity conservation and the security of our food systems for the future.

Ecological Benefits

IPM practices help maintain diverse ecosystems, which are crucial for the overall health of the environment. By using a variety of pest control strategies, IPM supports a wide range of species, promoting resilience in agricultural systems. By managing primary pest populations effectively, IPM reduces the risk of secondary pest outbreaks. This approach minimizes the chances of pest resistance and enhances the stability of agro-ecosystems. IPM emphasizes the use of environmentally friendly pest control methods, which decreases the reliance on chemical pesticides. This results in lower levels of environmental pollutants, safeguarding water sources, soil health, and non-target organisms. Healthy ecosystems provide essential services such as pollination, soil fertility and pest regulation. IPM practices contribute to the enhancement of these services, which are vital for sustainable agriculture and overall ecological balance. Through effective pest management strategies, IPM promotes long-term sustainable crop yields. By ensuring that pests are kept in check without harming the environment, farmers can achieve productivity while conserving natural resources. Combining Biology, Ecology, and Agriculture for Sustainable Pest Control (Tiwari et al. 2024) noted that excessive use of conventional pesticides often harms natural pest predators, leads to pest resurgence and contaminates soil and water resources.

CONCLUSION

Integrated Pest Management (IPM) is a critical framework for sustainable pest control that not only safeguards agricultural productivity but also emphasizes environmental sustainability and ecological balance. It's role in enhancing long-term food security is increasingly recognized. The document highlights that climate change significantly alters pest dynamics, thereby necessitating the development of flexible and knowledge-driven IPM strategies. Despite the well-documented ecological and economic advantages of IPM, its global adoption remains inconsistent, hindered by factors such as inadequate farmer education, policy shortcomings, high initial knowledge requirements, and insufficient extension services. Future IPM initiatives must leverage technology to build resilience against climate change and be underpinned by advancements in digital agriculture and artificial intelligence (AI). Additionally, participatory governance will be crucial for effectively achieving sustainable crop protection and ensuring food security. The core objective of IPM lies not only in controlling pest populations efficiently but also in promoting ecological health and sustainable agricultural methods. AI's impact on IPM is profound, transitioning crop protection strategies from traditional reactive chemical applications to proactive, precision-driven and ecosystem-centered approaches. AI-enhanced IPM strategies reduce reliance on pesticides, conserve biodiversity, increase agricultural productivity and align with environmentally sustainable farming practices. However, it is important to note that most current AI models are developed within controlled environments, which limits their adaptability to diverse crops and farming systems. Additionally, the successful implementation of these innovative methodologies calls for interdisciplinary research, scalable technologies and inclusive digital policies to ensure broad access and effectiveness in pest management.

Acknowledgements: The authors would like to express their sincere thanks to the Arya PG College, Panipat-132103, Haryana, India for providing laboratory facilities.

Ethical Approval: The authors declare that this study did not involve Humans or Animals.

Consent to Participate: All co-authors have agreed.

Consent to Publish: All co-authors have agreed

Data Availability Statement: Data will be available on demand.

Authors' Contributions: Hardeep Jhanjohtra conducted conceptualization, Data curation, Formal analysis and prepared the original draft of the manuscript. Prerna Gaba assisted in editing the manuscript, compiling the data and making final corrections. Ridhanye Dhawan assisted in editing the manuscript, removing plagiarism and making final corrections. Dr. Geetanjli Sahni developed the concept, supervised the research, and edited the manuscript. Sunita and Nisha Rani constructed the model and provided different designs. All authors reviewed and approved the final version of the manuscript.

Funding: No funding was received to conduct this research.

Competing Interests: All authors affirm that they have no competing financial or personal conflicts of interest that could potentially have an impact.

REFERENCES

1. Ahmad MF, Ahmad FA, Alsayegh AA, Zeyaullah M, AlShahrani AM, Muzammil K, Saati AA, Wahab S, Elbendary EY, Kambal N, Abdelrahman MH, Hussain S.: Pesticides impacts on human health and the environment with their mechanisms of action and possible countermeasures. Heliyon. Apr 4;10(7): (2024). e29128PMID: 38623208; PMCID: PMC11016626. doi: 10.1016/j.heliyon. 2024.e29128.
2. Angon, P. B., Mondal, S., Jahan, I., Datto, M., Antu, U. B., Ayshi, F. J., and Islam, M. S.: Integrated pest management (IPM) in agriculture and its role in maintaining ecological balance and biodiversity. Advances in Agriculture, (1), 5546373.2023.
3. https://doi.org/10.1155/2023/5546373.

4. Azelee, N. I. W., Manas, N. H. A., Hanapi, S. Z., Sarip, S. H. M., Abd Malek, R., El-Enshasy, H. A., and Ngah, M. F.: Removal of pesticides from water and wastewater by agricultural biomass-based adsorbents. In Pesticides Remediation Technologies from Water and Wastewater (pp. 365-384). Elsevier. (2022).
5. Aziz, D., Rafiq, S., Saini, P., Ahad, I., Gonal, B., Rehman, S. A., Rashid, S., Saini, P., Rohela, G. K., Aalum, K., Singh, G., Gnanesh, B. N., & Nabila Iliya, M.: Remote sensing and artificial intelligence: Revolutionizing pest management in agriculture. Frontiers in Sustainable Food Systems, 9, 1551460. (2025). https://doi.org/10.3389/fsufs.2025.1551460
6. Barzman , M., Barberi, P., Birch, A. N. E., Boonekamp, P., Dachbrodt-Saaydeh, S., Graf, B., Hommel, B., Jensen, J. E., Kiss, J., Kudsk, P., Lamichhane, J.R., Messean, A., Moonen, A.-C., Ratandass, A., Ricci, P., Sarah, J.-L., & Sattin, M. Eight principles of integrated pest management. Agronomy for Sustainable Development, 35, 1199-1215. (2015).
7. Chaudhary, M., Jabborova, D.: Smart Sensing Technologies: Monitoring Insect Pests with AI. In: Mitra, D., Pellegrini, M., Sierra, B.E.G. (eds.). Advancements in Entomology. Springer, Singapore. (2026). https://doi.org/10.1007/978-981-95-5214-6_18
8. Chaudhary, V., Kumar, M., Chauhan, C., Sirohi, U., Srivastav, A. L., and Rani, L.:Strategies for mitigation of pesticides from the environment through alternative approaches: A review of recent developments and future prospects. Journal of Environmental Management, 354, 120326. (2024).
9. Choudhary, M., Singh, N., Meena, P. N., Khokhar, M. K., Haldhar, S. M., and Chandervanshi, Y.: Integrated Pest Management (IPM) in the AI era. Smart Agricultural Technology, 102397.
10. Ehi-Eromosele, C. O., Nwinyi, O. C., and Ajani, O. O. (2013). Integrated Pest Management. In Weed and Pest Control - Conventional and New Challenges. InTech. (2026). https://doi.org/10.5772/54476.
11. Fuentes, A. F., Yoon, S., Lee, J., and Park, D. S.: High-performance deep neutral network-based tomato plant diseases and pest diagnosis system with refinement filter bank. Frontiers in Plant Science,9, 1162. (2018) https://doi.org/10.3389/fpls.2018.01162.
12. Fuentes, A., Yoon, S., Lee, M. H., and Park, D. S.:Improving accuracy of tomato plants disease diagnosis based on deep learning explicit control of hidden classes. Frontiers in Plant Science, 12, 682230. (2021). https://doi.org/10.3389/fpls.2021.682230.
13. Hoque, A., Padhiary, M., and Roy, S.: Precision Agriculture Meets Sustainable Chemistry: Innovations for Eco-Friendly Farming. In Sustainable Chemistry and Pioneering Green Engineering Solutions (pp. 233-270). (2026). IGI Global Scientific Publishing.
14. https://doi.org/10.1007/s13593-015-0327-9.
15. Istatu, P. S., Chauhan, S., Rana, A., Sharma, S., and Dhiman, P.: Integrated Pest Management (IPM) Approaches. SUSTAINABLE AGRICULTURE, 15. (2025).
16. Javed, K., Smagghe, G., Wang, Q., Javed, H., and Wang, Y.: Artificial intelligence in crop protection: Revolutionizing agriculture for a sustainable future. Information Processing in Agriculture. (2025).
17. Jha, K., Doshi, A., Patel, P., Shah, M.: A comprehensive review on automation in agriculture using AI. Artificial Intelligence in Agriculture, 2, 1–12. (2019).
18. Junaid, M. D., and Gokce, A. F.: Global agricultural losses and their causes. Bulletin of Biological and Allied Sciences Research, (1), 66 (2024).
19. Kamilaris, A., and Prenafeta-Boldu, F. X.: Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70-90. (2018). https://doi.org/10.1016/j.compg.2018.02.016.
20. Kamilaris, A., and Prenafeta-Boldu, F.X.: Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70-90. (2018).
21. Kogan, M.: Integrated pest management: Historical perspectives and contemporary developments. Annual Review of Entomology, 43, 243-270 (1998).
22. Koirala, A., Walsh, K. B., Wang, Z., and McCarthy, C. Deep learning for real-time fruit detection and orchard fruit load estimation: Benchmarking of 'Mango YOLO'. Precision Agriculture,20,1107-1135.(2019) https://doi.org/10.1007/s11119-019-09642-0
23. Mohanty, S. P., Hughes, D. P., and Salathe, M.: Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419. (2016).
24. Nehul, J. N. Environmental impact of pesticides: toxicity, bioaccumulation and alternatives. Environmental Reports. I, 10. (2025). https://doi.org/10.51470/ER.2025.7.2.14
25. Patricio, D. I., and Rieder, R. Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review. Computers and Electronics in Agriculture, 153, 69-81. (2018). https://doi.org/10.1016/j.compag.2018.08.001
26. Rasyid, H., and Ningsih, G. M. The role of digital technology in the transformation of agriculture toward smart farming. Journal of World Science, 3(1), 1-7.
27. Sutherland, W. J., Barnard, P., Broad, S., Clout, M., Connor, B., Côté, I. M., ... and Ockendon, N. (2017). A 2017 horizon scan of emerging issues for global conservation and biological diversity. Trends in ecology and evolution, 32(1), 31-40. Talaviya, T., Shah, D., Patel, N., Yagnik, H., Shah, M. (2023). Implementation of AI in agriculture for optimisation of irrigation and pest control. Artificial Intelligence in Agriculture, 7, 1–17. (2024).
28. Wei, J., Gong, H., Li, S., You, M., Zhu, H., Ni, L., Chen, M., Chao, H., Sun, Y. Improving the accuracy of agricultural pest identification: Application of AEC-YOLOv8n to large-scale pest datasets. Agronomy, 14(8), 1640. 2024). https://doi.org/10.3390/agronomy14081640