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REVIEW ARTICLE

Accelerating AI-driven solutions for insect pest detection in Indian agriculture: A systematic review

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Abstract

The increasing demand for agricultural production is heavily constrained by biotic stresses such as insect pests, diseases and nematodes, which significantly reduce crop productivity. Traditional pest monitoring methods, which are often manual, time-consuming, labour-intensive and reliant on expert identification, are prone to human error and unsustainable for large-scale implementation. With the advent of digital agriculture, artificial intelligence (AI) has become a transformative tool for enhancing pest detection and management. AI-driven technologies, particularly those integrating computer vision, deep learning and machine learning, offer automated and accurate identification of pests, minimizing the misuse of chemical inputs and reducing ecological damage. Smart devices and sensor networks equipped with AI capabilities enable real-time surveillance of both biotic and abiotic stresses, promoting efficient, targeted and environmental conscious pest control strategies. This review systematically explores the historical development of AI based insect pest detection in India, highlighting their potential to enhance precision monitoring, reduce reliance on conventional practices and support sustainable crop protection. Furthermore, it addresses the key challenges associated with AI adoption in the identification of insect pests and outlines future research directions to accelerate the development and deployment of intelligent pest management systems.

Keywords: artificial intelligence; insect identification; pest detection; precision pest management; smart agriculture

Introduction

Insect pests are considered one of the essential biotic factors that contributing to huge crop damage and yield loss. Monitoring pest populations is the first step in the decision- making process to achieve successful control of any target pest. Traditional monitoring methods, such as placing light traps, sticky traps and manual counting, are labour-intensive and prone to error (1). Moreover, traditional methods often require the involvement of field experts. Hence, there is a need for technological advancement to overcome these difficulties. After scientific advancements in the last century, with computers gaining entry in every of agriculture. They tend to solve existing problems using different approaches, starting from the database (2) to decision support systems (3). During the 21st century, artificial intelligence (AI) has started revolutionizing agriculture worldwide with AI-based tools. Since agriculture is dynamic, situations cannot be generalized to suggest a common solution. AI models can train themselves using the intricate details of each situation and solve the problem by finding an appropriate solution.

Despite steady advances worldwide, India's progress in AI -driven pest monitoring has unfolded more cautiously and can be grouped into three overlapping phases. Phase 1 (≈approximately 2005-2015) relied on classical image-processing pipelines, including thresholding, colour segmentation and shape analysis, to automate counting on sticky or light-trap images. These rule-based systems cut labour and observer bias but struggled whenever lighting, camera angle, or pest species changed. Phase 2 (≈2016- present) marked the shift to deep learning: pre-trained CNN models such as VGG (Visual Geometry Group), ResNet (Residual Network), EfficientNet (Efficient Network) and YOLO (You Only Look Once) now learn their own features from thousands of labelled photographs, pushing single -image detection accuracies above 90 % in large public datasets like IP102 and iNaturalist and in local field trials on cotton, rice and storage pests. Most recently, Phase 3 systems integrate these models into IoT (Internet of Things)-enabled smart traps, drones and proximal or satellite remote-sensing platforms, providing real-time surveillance over large areas while reducing connectivity costs through on-device (edge) inference.

Even so, India's on-ground deployment remains patchy. Fragmented land holdings, limited rural internet connectivity, the high cost of rugged sensor hardware and the lack of annotated, region-specific image and sound datasets continue to hinder the widespread adoption of AI and IoT technologies in agriculture. Institutions such as the Indian Council of Agricultural Research (ICAR) and the National Bank for Agriculture and Rural Development (NABARD) have begun funding data collection drives and pilot networks of smart pheromone or light traps. Still, most systems are confined to research plots or proof-of-concept studies on a handful of crops like cotton, tomato, maize and stored grains being the main beneficiaries so far. Bridging this "lab-to-land" gap will require low-cost edge devices, shared national datasets and extension programmes that expose AI tools for farmers and field staff. Against this backdrop, the present review attempts the following (i) consolidating two decades of Indian work on AI-based insect detection, (ii) analyzing the made in the three developmental phases outlined above, (iii) identifying the technical and socio-economic bottlenecks unique to Indian context and (iv) planning towards isolated prototypes to farmer-ready decision support.

Developmental Phases of Artificial Intelligence for Insect Detection in India

Phase 1: Image processing era (≈2005- 2015): Basic computer vision applications

The earliest application of artificial intelligence in insect pest detection research in India began with basic image processing techniques (Table 1). Researchers utilized traditional computer vision tools, including thresholding, colour segmentation, shape detection and morphological operations, to detect and count insects from images captured via light traps, sticky traps, or scanned leaf images, which served as the foundation for detection techniques (4-7). These methods were rule-based and relied heavily on handcrafted features, requiring researchers to define specific visual parameters (e.g., insect body colour, size, contour shape) for each species. For instance, colour-based segmentation was used to detect whitefly populations on yellow sticky traps. At the same time, edge detection and shape matching were applied to distinguish leaf miner trails or holes caused by bollworms. They have proven to be effective in machine vision systems for detecting and identifying insects in crops such as wheat, soybean and paddy (8).

These approaches dramatically reduced counting time and inter-observer variability, making them a popular, low-cost entry point for many research stations and State Agricultural Universities. Moreover, these models were often limited to single -species detection and could not learn or adapt to new scenarios without manual redesign. Despite these limitations, Phase 1 laid the groundwork for automating pest monitoring and introduced the concept of digitizing entomological observations in India.

Phase 2: Deep learning era (≈2016- present): Shift to data-driven detection

Deep learning surpasses image processing in insect detection by automatically learning complex features, handling variations in lighting and posture and providing higher accuracy and scalability. With the increasing accessibility of GPUs (Graphical Processing Units), annotated pest datasets and pre-trained convolutional neural networks (CNNs) like VGGNet, ResNet, EfficientNet, MobileNet and YOLO, researchers have begun transitioning from rule-based models to data-driven frameworks. It adapts easily to new species, making it ideal for precision detection and real-time pest monitoring. These models were capable of automatically learning spatial features from thousands of images, improving classification accuracy and enabling multi-class and multi-object detection (9-12).

Deep learning enabled the identification of pests at different life stages, including adults, larvae and symptoms such as leaf curling, mines and boreholes. For example, CNN-based models were trained to detect leaf damage symptoms of *T. absoluta* (13) and larval images of fall armyworm, African armyworm, maize stem borer, etc. (14). These models showed enhanced performance in terms of accuracy, precision, recall and generalization, especially under varying field conditions (Table. 2 and Table S1). Not only images were used for detecting and classifying insects, but also sounds produced by insects were utilised. They are recorded using acoustic sensors and a deep learning algorithm is employed to identify and classify insect-

Table 1. Image processing-based insect detection studies conducted in India

Crops	Insects detected	Technique used	Detection accuracy (%)	Year	Reference
Sugarcane	Sugarcane pyrilla, Sugarcane whitefly, Mealybug Top Shoot Borer, Sugarcane Aphid	Sobel edge detection for segmentation and MATLAB 2015b with Image Processing Toolbox	Not specified	2017	(46)
Mustard and faba bean	Fluffy caterpillar	Wavelet transformation, Oriented FAST, rotated BRIEF (ORB) and MATLAB 2019a	91.89	2021	(47)
Field crops	Xie insect dataset (48), Wang insect dataset (49), Butterfly image dataset	Histogram of oriented gradients (HOG) and global image descriptor (GIST) for image processing. Naïve Bayes (NB), Support Vector Machine (SVM), K-Nearest Neighbour (KNN) and Multi-Layer Perception (MLP) as base classifiers.	Xie dataset- 92.1, Wang dataset- 96.5, Butterfly dataset- 92.3	2021	(8)
Greenhouse crops- Rose, Cucumber, Tomato, Gerbera, Capsicum etc.,	Whiteflies, thrips and aphids	Support Vector Machine (SVM) classifier	100	2013	(50)
Greenhouse	Whitefly	MATLAB 7.1 2011a	96	2010	(51)
Soybean	Aphids	MATLAB R2014a	96	2017	(52)
Paddy	Green leaf hopper	SVM classifier, Colour histogram and contour detection for feature extraction, k-fold and Bootstrapping for validation.	Not specified	2019	(53)
Paddy	Ants, Black bugs, Cricket, Armyworm, Mealybug, Cutworm, Hispa, short-horned Grasshopper, Brown Plant Hopper, Thrips, Yellow stem borer, Caseworm, White backed plant hopper, zig-zag leaf hopper, Leaf folder, Gall midge	Otsu's method, scale-invariant feature transform (SIFT), speeded-up robust features (SURF), SVM classifier	90	2014	(54)
Bhendi, Paddy	Whitefly	Verilog implementation, MATLAB R2011b	90	2017	(55)

Table 2. Deep learning approaches applied for insect pest detection in indian agriculture

Crop/ Source	Insects detected	Techniques used	Size of the dataset	Detection accuracy (%)	Year	Reference
iNaturalist and BugGuide	Insects of the order Coleoptera, Hemiptera, Hymenoptera, Lepidoptera, Odonata, Diptera,	YOLO v5s, YOLO v5m, YOLO v5l, YOLO v5x, YOLO v5x (new version)	15000 images	93.0	2023	(7)
IP102 dataset	102 insect classes	Faster R- CNN Efficient Net B4, Faster R- CNN Efficient Net B7	Total- 75000 images 5 insect classes- 14490 images 10 insect classes- 29210 images 15 insect classes- 43210	5 insect class- 99.0 10 insect class- 96.0 15 insect class- 93.0	2022	(33)
Diverse agricultural fields	Various insects	Pelican Optimization Algorithm with Deep Learning (AIDC-POADL), DenseNet-121, multilayer perceptron (MLP) model	Not specified	Not specified	2024	(56)
IP102 dataset	102 insect classes	EfficientNetB4 deep CNN model.	Not specified	95 %	2023	(57)
IP102 dataset	102 insect classes	VGG16, VGG19 and ResNetv50	75000 images	82.5	2023	(58)
Survey	Locust	CNN and Deep Learning model	Not specified	83.0	2020	(59)
Diverse agricultural fields	*Phyllophaga* sp., *Helicoverpa armigera, Spodoptera litura*	SSD Inception, SSD MobileNet, Faster R- CNN	593 insects	95.33	2019	(60)
IP102 dataset	Aphids, Flea beetles, Cicadellidae, Flax Budworm, Red spider mite	Inception V3, Xception, VGG19 and ResNet Models as backbone architectures. CNN, Fast R- CNN, Faster R- CNN and YOLOv5 as algorithms.	Not specified	93	2022	(61)
Diverse agricultural fields	72 insect pests	Butterfly filter, Blackman and Flattop window, Ultraspherical filter, Rife-Vincent Window, Cosine-Tapered Window, PID sensors for sound recordings. HFDLNet for training the dataset.	7200 pest sounds	99.87	2024	(62)
Grain storage	*Tribolium castaneum* and *Rhyzopertha dominica*	YOLO v7 (YOLO v7 and x), YOLO v8 (l/m/x/s/n)	Not specified	*T. Castaneum*- 97.7 *R. dominica*- 96.2	2025	(63)
Kaggle notebook dataset of Simran Volunesia	Not specified	EfficientNetB7, Xception, MobileNet and MobileNetV2	Not specified	95.15	2022	
IP102 Dataset	105 insect classes	YOLO	75000 images	87	2023	(64)
Soybean crops	Not specified	YOLO v3, v4, v5	Not specified	99.5	2021	(65)
Wang dataset	*Locusta migratoria, parasa lepida*, Gypsy moth larva, *Empoasca flavescens, Spodoptera exigua, Chrysochus chinensis, Laspeyresia* pomonella larva, *Atractomorpha sinensis, Laspeyresia pomonella*	Random Forest (RF), Logistic regression (LR), K- mean clustering and CNN for classification, GLCM for feature extraction	Not specified	93.9	2021	(66)

produced sounds automatically. An IoT framework was developed to capture sounds produced by insects and deep learning was integrated to classify and detect these insects.

However, significant challenges persisted, including the need for large, annotated datasets, high training times and limited generalization across regions or pest species. Most models remained confined to academic experiments or controlled trials, with limited real-world deployment. Nonetheless, Phase 2 marked a significant leap in research sophistication, laying the groundwork for integrating AI into decision-support systems in pest management.

Phase 3- IoT and remote-sensing integrated AI (≈2020- Future): Towards precision pest surveillance

The third and most advanced phase in the development of AI-based insect pest monitoring in India involves integrating IoT, remote sensing, cloud computing and edge AI technologies. This phase marks a shift from static, post-hoc analysis to real-time, automated and continuous pest surveillance systems. Smart traps equipped with cameras and sensors have been developed to monitor nocturnal pests, including *T. absoluta*, *H. armigera* and *S. litura*. These devices are equipped with solar-powered units, GSM (Global System for Mobile Communications)/4G modules and low-power microcontrollers (e.g., Raspberry Pi, Arduino) that can run deep learning models, such as YOLOv5 or MobileNet, directly on the device. These edge AI models can detect, classify and count pest species instantly without relying on cloud servers, making them particularly useful in remote or rural agricultural areas with limited internet connectivity.

IoT and sensor-based insect pest detection: IoT devices, such as mobile phones, drones and robots, along with AI algorithms, monitor pest activity in agricultural fields. These detect and count the insects caught on the traps. These tools help farmers make decisions about pest management by providing real-time data on insect pests (15). Sensors are devices that can detect and convert chemical and physical cues of a living organism into a format that a computer can analyze. They can gather information by taking pictures using cameras, recording sounds using microphones, measuring distance using LiDAR and radar sensors (16). ML is frequently used to train AI systems to read sensor data and make decisions based on it (17). Sensors combined with AI, ML and DL models are effective in detecting insect pests and advising control measures (15). On the other hand, acoustic sensors are integrated into insect traps to detect insects based on acoustic sounds. For example, Acoustic sensors, PID sensors, algorithms like LPC, FFT, STFT and Welch method, as well as the Chebyshev filter integrated with traps showed 99.78 % accuracy, 99.64 % specificity, 99.91 % sensitivity and 99.85 % precision for sound detection of 800 pests when compared to pre- trained models like YOLOv5, VG-16, DenseNet and ResNet-50, the Multilayer Perceptron (MLP) (18).

Remote sensing enabled AI for insect pest detection: Remote sensing technologies rely on receiving and interpreting information about the Earth's surface without any physical contact (19). Electromagnetic energy is the core component of remote sensing. Various sensors were used to record electromagnetic radiation from the Earth's surface. Sensor instruments include digital cameras, electromechanical scanners, video cameras and radar devices (20). For the successful management of insect pests, forecasting is an important step that should be followed. It can be accomplished on smaller land areas using alternative techniques. However, for larger areas, remote sensing proved to be much more effective in forecasting pests. Remote sensing offers improved spatial and temporal resolution compared to traditional insect monitoring methods, such as sex pheromone traps, light traps and suction traps (21). The wavelength of electromagnetic radiation (EMR) varies depending on its interaction with the plant surface. Thus, the health and vigour of plants can significantly influence the reflectance patterns of their leaves (22).

Artificial intelligence plays a crucial role in understanding remote sensing data like cropping systems, environmental conditions and physical characteristics associated with plant diseases and insects. It perceives the complex patterns in the data and provides suitable solutions. It is widely used to detect infestations by insects, as well as the presence of these insects themselves. Using a near-infrared (NIR) and hyperspectral imaging system, researchers differentiated healthy wheat kernels from insect-damaged ones in storage by employing proximal remote sensing and hyperspectral reflectance profile (23). The stress levels and severity caused by leafhopper attacks on cotton plants were assessed by evaluating chlorophyll content and relative water content (RWC) using ground-based hyperspectral remote sensing (24).

On the other hand, an AI model was developed by combining convolutional neural networks (CNN) with long short-term memory (LSTM) models to analyze raw imagery data for assessing insect damage in wheat crops. The proposed model achieved a significant accuracy improvement of 74 % compared to traditional methods and outperformed other deep learning models by 50 % (25). The GeoAgriGuard is an AI-driven remote sensing system for managing insects and diseases(26). It collects data using multispectral and hyperspectral imagery, as well as drone technology. The system employs a combination of AI models, including ResNet, Transformer, DenseNet and AutoEncoders, to process the gathered data. It achieves an impressive accuracy of 97.81 %. The model generates risk maps, which enable farmers to implement timely management practices.

Prediction Models and Forecasting Using IoT-AI Technology: With further developments in hardware and communication technologies, insect monitoring is advancing to the next level. Insect population can be predicted promptly at different localities in a major region using meteorological factors like temperature, relative humidity, rainfall, etc., In this context, we can predict when the incidence of any insect pest will occur, providing users with sufficient time to respond and reduce the insect pest population (27). In general, pest data were collected by counting the number of insects caught on light traps, sticky traps, etc., However, recent advancements attempt to automatically count insects on traps by installing cameras and sensors. Similarly, meteorological data are obtained from sensors installed in the field and analyzed using machine learning models to forecast insect populations. By combining historical data and weather correlations, we can achieve accurate and timely prediction for effective pest control (28). A prediction model for *Helicoverpa armigera* has been developed that correlates weather parameters (temperature, rainfall, sunshine hours and relative humidity) with pheromone trap catches (29). Recent advancements have been made in developing predictive models for monitoring vectors of major diseases. Predictive models have proven effective in monitoring vectors of various diseases, including *Anopheles* spp., *Aedes* spp., *Culex* spp., triatomine bugs, lice, ticks, fleas and blackflies. Despite the promise, this phase faces challenges such as high initial costs, maintenance requirements, limited connectivity and the need for large annotated datasets to train accurate and regionally adaptable models. Nonetheless, Phase 3 represents the future of pest surveillance in India combining artificial intelligence with automation, mobility and precision farming tools to offer a scalable, field-ready solution for sustainable pest management.

Bibliometric analysis results of AI based insect detection research

Adoption trends of AI across Indian economic sectors

AI adoption is highest in the Banking, Financial Services and Insurance (BFSI) sector (22.4 %) and the Information Technology (IT) sector (20.5 %), driven by strong digital infrastructure and data availability (Fig. 1). Sectors like healthcare (17.2 %) and Fast-moving consumer goods (FMCG) & retail (14.2 %) also show significant adoption due to AI's role in diagnostics, consumer behaviour and supply chain optimization.

In contrast, Agriculture (3.6 %), Media & Entertainment (5.9 %) and Infrastructure (6.9 %) have lower adoption rates, likely due to limited digital access, funding and awareness. This highlights a digital divide, where sectors with higher resources lead in AI integration, while traditional sectors, such as agriculture, lag despite their importance.

Applications of AI across agricultural research areas

The deployment of artificial intelligence in agriculture ranges from 5 % to 30 %. Crop disease detection is the most prominent application of AI in agriculture, accounting for 30 % of usage, due to its direct impact on yield and plant health ((Fig. 2). Yield prediction

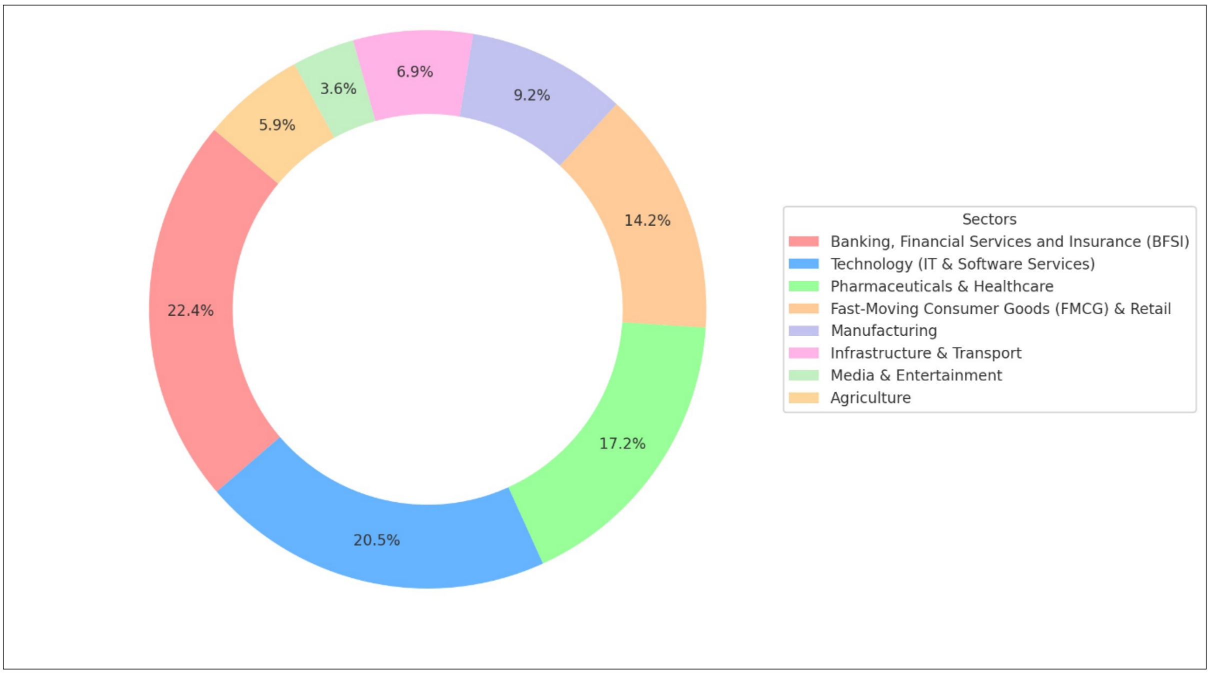

Fig. 1. Sector-wise distribution of AI adoption in India

and pest and insect identification each represent 20 %, highlighting their importance in planning and pest management. Soil health monitoring accounts for 15%, reflecting a growing interest in sustainable farming. Smart irrigation (10 %) and supply chain optimization (5 %) are less explored areas, indicating potential for future development as digital infrastructure improves.

Collaborative networks in AI-driven agricultural pest research

India is engaged with 38 countries across Asia, Europe, North America, Africa and Oceania for collaborative research on AI-based insect detection (Fig. 3 and Table 3). Higher collaboration is observed between India and the USA (14 collaborations), followed by Saudi Arabia (13), China (4), Iraq (3), Oman (3.) and Bangladesh (3). Countries like Egypt, Korea, Malaysia, Norway, Rwanda and the United Arab Emirates also are collaborative partners

Thematic structure of research through keyword co-occurrence analysis

The network analysis (Fig. 4) shows that deep learning is the most central theme in AI-based agricultural research, with strong links to machine learning, image processing and precision agriculture. Key focus areas include plant disease detection, insect detection and pest classification. Technical terms like CNN, MobileNet, SqueezeNet and VGG16 indicate the dominance of neural network models. Clusters also highlight the role of IoT, remote sensing and data segmentation. The emerging focus on insect detection suggests a growing but still developing research area in India.

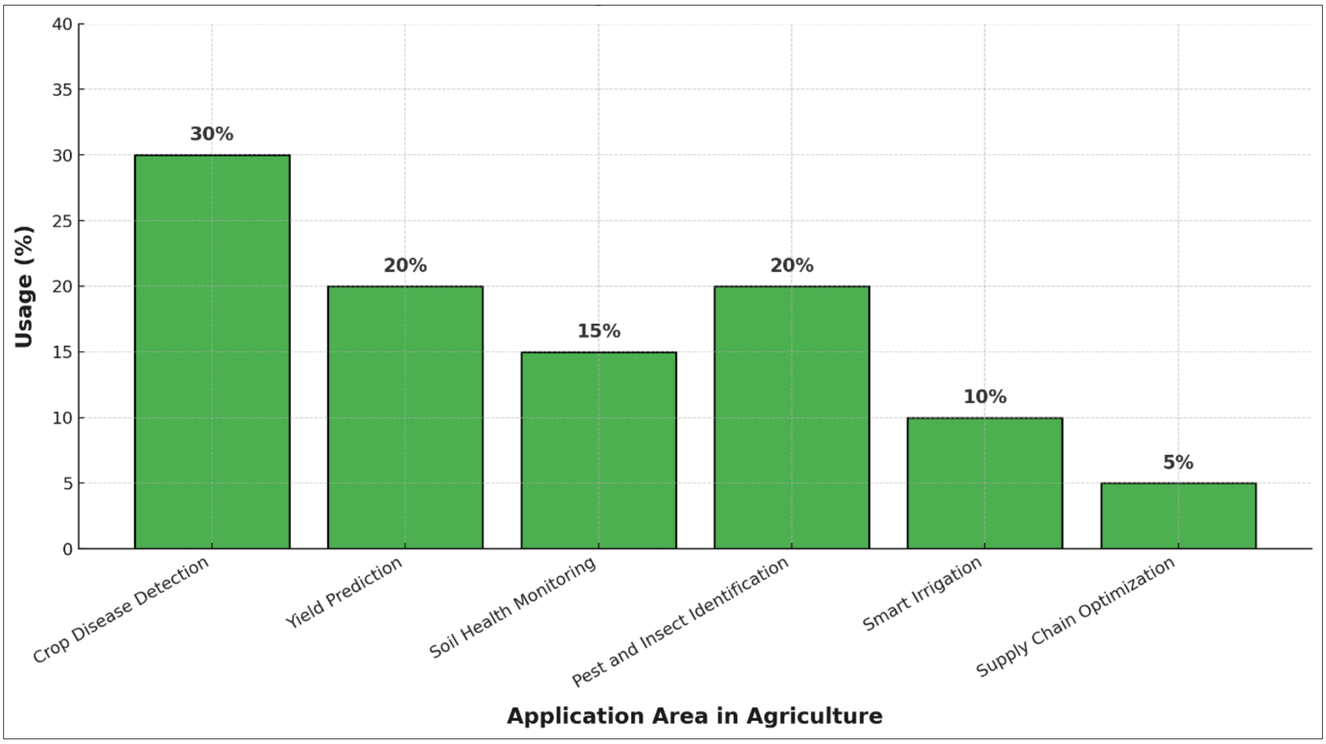

Fig. 2. Adoption rate of AI technologies across agricultural research activities

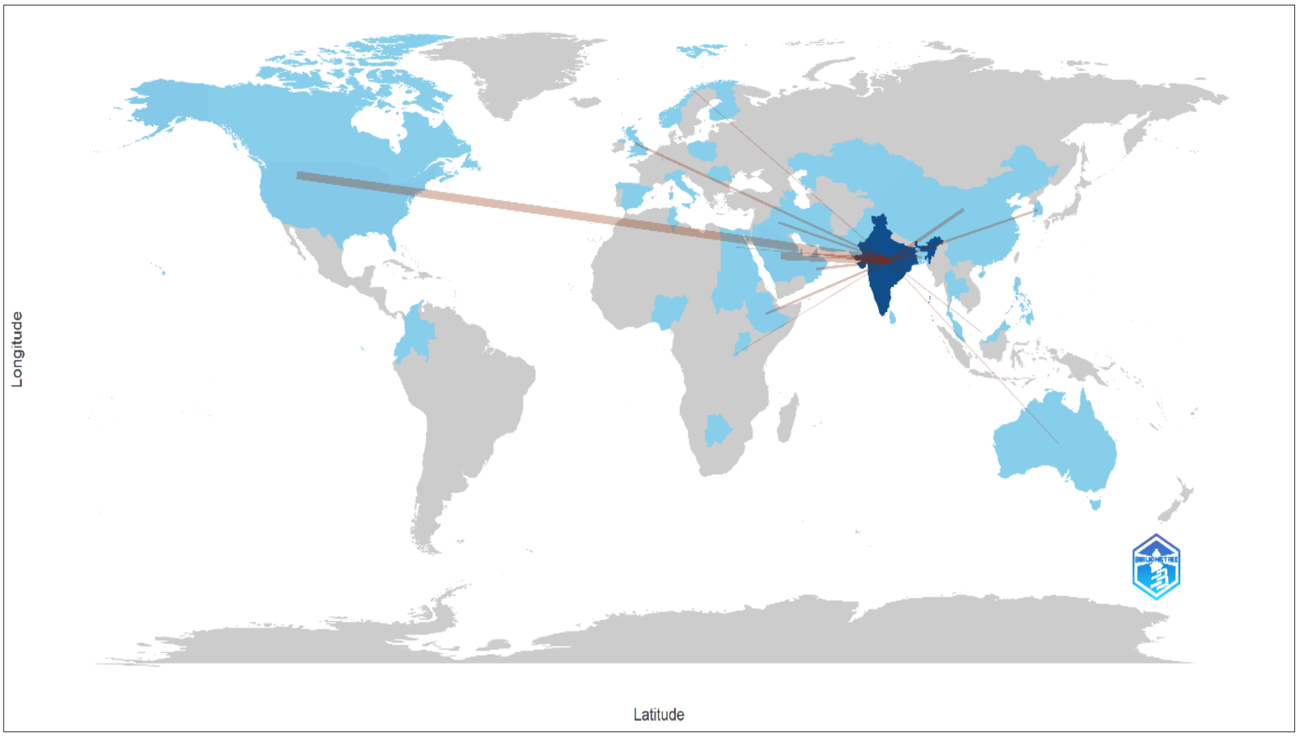

Fig. 3. Global map of international collaborations in AI-driven insect pest detection research

Table 3. Country-wise research collaborations on AI-based insect pest detection

Rank	Country Pair	Frequency
1	India - USA	14
2	India - Saudi Arabia	13
3	India - China	4
4	India - Iraq	3
5	India - Oman	3
6	India - Bangladesh	3
7	India - Egypt	2
8	India - Korea	2
9	India - Malaysia	2
10	India - Norway / India - Rwanda / India - UAE	2 each

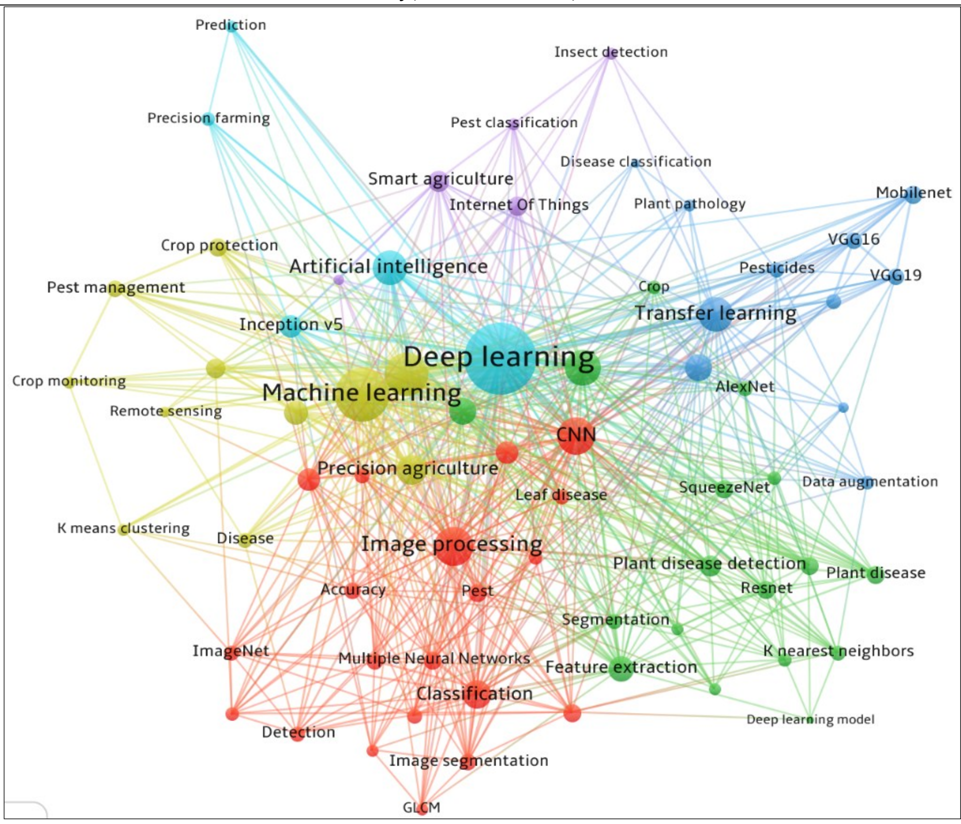

Fig. 4. Network map of frequently co-occurring keywords in the domain

Case studies highlighting AI-based insect pest monitoring

Case study 1: Image processing in insect detection

Digital image processing techniques were used to detect insects in sugarcane crop. In this study, images were subjected to pre-processing, segmentation and feature extraction to detect the shape of the insect. The Sobel edge detection method (a gradient-based edge finder) was applied to extract insect boundaries from their background and the entire work was implemented using MATLAB 2015b with the Image Processing Toolbox software. The final model was able to detect the insect outlines with high accuracy. Similar to this study, image processing techniques were integrated with support vector machine (a subset of machine learning) to classify pests like Green Leaf Hopper, Grasshopper, Swarming Caterpillar, etc., wherein the features of the insects were extracted using colour histogram and contour detection and classified using support vector machine architecture with high detection accuracy (30).

Case study 2: Deep learning in insect detection

Using the CNN method, a comparative study of eleven different pre-trained models was performed and the ResNet-152 model was proven to be more efficient in classifying butterfly images belonging to 315 species from India (31). Modern machine learning techniques, such as artificial neural networks (ANN), support vector machines (SVM), k-nearest neighbour (KNN), naïve Bayes (NB) and CNN, were used to detect and classify nine and 24 insect classes from the Wang and Xie datasets. In conclusion, CNN model achieved a highest detection accuracy of 91.5 % and 90 % for both datasets (32). A YOLO v5 deep learning pre- trained model has been trained for online available datasets (nearly 15000 images) of different insect orders *viz*., Coleoptera, Hymenoptera, Hemiptera, Lepidoptera, Odonata, Diptera and Araneae. The datasets were annotated, augmented and trained using YOLO v5. The model was able to detect insects with an highest accuracy of 93 % (33).

Case study 3: IoT- based insect detection

For accurate monitoring of agricultural and environmental insect pests, remote insect trap monitoring system has been developed using IoT and Deep Learning framework. Ramalingam, Mohan (34) using faster R-CNN (Region- based CNN) and ResNet50 (Pre-trained deep learning model) for the detection of insects caught on sticky traps. The model achieved a higher accuracy of 94 %. It proved to be efficient in early monitoring of insect pests. By taking insect odour as a key consideration, gas sensors are used to collect the five different odours of insects, including pungent, misty, sweet and musty smells, associated with Fall Army Worm (FAW)- infested maize crops. The data were trained using Faster R-CNN to classify insects based on its odour. The model shows an accuracy of 98 % (35).

Limitations Hindering AI Integration in Pest Detection Systems

Artificial intelligence (AI) presents a promising alternative to conventional approaches for monitoring insect pests, yet its implementation faces several challenges that must be addressed. Foremost is the scarcity of high-quality agricultural data: farming environments are diverse and sparsely sampled and many rural areas lack the infrastructure needed to generate and share reliable, comprehensive datasets (15, 36-38). Agriculture's inherent dynamism, shaped by interacting variables such as weather, soil properties, pest population dynamics and crop genetics, further complicates model development (39). Data privacy and security are additional concerns, sensitive information on farm operations and farmer identities must be protected from unauthorized access and misuse (40, 41). AI models must also be flexible enough to adapt to different farm sizes and cropping systems and they should allow rapid updating and refinement as conditions change (42, 43). Because most AI tools depend on stable internet connections, their deployment in remote or poorly connected regions remains challenging (44). Funding constitutes another major bottleneck. Developing and scaling robust AI solutions requires resources that individual researchers often cannot secure., Support from national institutions and funding through international collaborations could help bridge this gap. Ultimately, effective training and extension services are crucial to ensure that farmers and field staff can effectively adopt and benefit from AI-enabled pest-monitoring systems.

Future prospects

The integration of artificial intelligence (AI) in insect pest monitoring holds immense potential to revolutionize Indian agriculture. As farmers heavily rely on environmental and weather conditions for crop production, AI can serve as a forecasting tool by providing timely insights on insect pest outbreaks (45). By delivering pest and climate risk information in advance, AI can help farmers adapt to changing weather patterns and make proactive decisions to protect their crops (12, 45). A notable initiative in this space is the collaboration between United Phosphorus Limited (UPL) and Microsoft, which led to the development of a pest forecasting application that uses AI and machine learning to predict insect pest attacks (15). The advancement of region-specific AI models integrated with Internet of Things (IoT) devices, Unmanned Aerial Vehicles (UAVs) and remote sensing technologies has the potential to facilitate precise pest monitoring, even in remote and resource-limited farming regions.

Moreover, integrating AI platforms with farmer-friendly mobile applications and existing government pest advisory systems can bridge the gap between research innovation and on -ground implementation. To ensure scalability and equitable access, investments in digital infrastructure, capacity building for extension workers and strong policy support are essential. In the future, AI-powered pest monitoring systems are expected to play a pivotal role in achieving sustainable crop protection. These systems can enhance productivity, reduce reliance on chemical pesticides and mitigate environmental impact, thereby contributing to more resilient and eco-friendly agricultural practices.

Conclusion

Artificial intelligence is emerging as a powerful tool in transforming surveillance and insect pest monitoring in Indian agriculture. By enabling faster, more accurate and cost-effective pest detection, AI addresses many limitations of traditional monitoring methods. From image-based identification to predictive modelling and automated surveillance, AI enhances early warning systems and supports timely pest management decisions. While several challenges such as data quality, infrastructure gaps and user awareness do exist, advancements and collaborative efforts between researchers, policymakers and farmers are paving \way for practical implementation. Embracing AI-based solutions will be crucial in achieving sustainable pest management, reducing crop losses and securing the future of Indian agriculture in an era of climate variability and increasing food demand.

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Authors' contributions

NP and ET prepared the design of the study and drafted the manuscript. MM, BK, ST and TC conceived the study and participated in its design and coordination. All the authors read and approved the final version of the manuscript.

Compliance with ethical standards

Conflict of interest: The Authors do not have any conflicts of interest to declare.

Ethical issues: None

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