

Artificial Intelligence in Entomological Developments: Uses and Prospects for Research on Insect and Pest Management: A Review

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Abstract

Artificial intelligence (AI) is transforming entomology, changing how insects are identified, monitored, forecast, and managed in agriculture, forestry, and public health. Advances in machine learning, deep learning, computer vision, bioacoustics, robotics, the Internet of Things (IoT), and, more recently, generative AI and large language models (LLMs) offer scalable solutions to problems long constrained by expert scarcity, labour-intensive scouting, and delayed decision-making. Convolutional neural networks and object detectors such as YOLO and Faster R-CNN often exceed 90% classification accuracy, reaching 99% under controlled conditions, while ensemble and explainable deep-learning models extend the lead time and reliability of outbreak forecasts. Integration with UAV remote sensing, smart traps, bioacoustic sensors, and edge computing is enabling real-time, in-field decision support, and LLM-based advisory tools are beginning to turn model outputs into farmer-facing guidance. Nonetheless, small-object detection, data scarcity, class imbalance, poor cross-domain generalisation, limited interpretability, infrastructural constraints, and uneven adoption in resource-limited settings restrict real-world impact. Priority directions include multimodal data fusion, lightweight explainable models for edge deployment, open standardised benchmark datasets, and closer collaboration among entomologists, data scientists, and policymakers, which will determine whether AI moves from research prototypes to dependable tools for sustainable pest management.

Keywords: *artificial intelligence; machine learning; deep learning; entomology; insect pest management; precision agriculture; computer vision; Integrated Pest management (IPM)*

1. Introduction

Insects matter to agriculture and health in two opposite ways. A few species do outsized damage to crops, stored food and people, while the great majority pollinate plants, break down dead material and keep pest numbers down naturally. The FAO estimates that insect pests destroy between 20 and 40% of the world's crops every year [1,2]. Resistance to insecticides, pests extending their ranges as the climate warms, and the slow work of scouting and identifying them add to the burden. Conventional practice is slow, depends on individual judgement and is hard to scale up [2,3].

We use AI as a broad label for data-driven methods (machine learning, deep learning, computer vision, language processing and robotics) that learn from examples and support decisions with limited human intervention [1]. Interest took off around 2015 as large annotated datasets, affordable sensors, edge computing and improved model designs became available, and the pace has quickened markedly since 2020 [4,5].

This review does three things. It maps the main AI applications in entomology and pest management, it examines what stops them from becoming practical field tools, and it points to where research effort is best directed. We drew mainly on studies from 2018 to 2026 found through Scopus, Web of Science, ScienceDirect, Springer Nature, Frontiers, MDPI, IEEE Xplore, PubMed/PMC, arXiv and bioRxiv.

2. Methods behind the Applications

Several families of method recur across the literature. Conventional machine learning, such as support vector machines, random forests and gradient boosting, is still common when the task is predicting outbreaks or modelling habitat [6]. Tasks involving images or sound are dominated by deep learning, in particular convolutional neural networks (CNNs) [7].

For detecting insects in a photograph, single-stage detectors (YOLO, RetinaNet, SSD) can find many individuals in one pass and run in real time. YOLO in particular has seen more than twelve versions, and several use compact backbones that suit edge devices [8,9]. Transformer models (ViT, Swin, DETR) are better at capturing relationships across a whole image, at the price of more training data and computing [10].

Forecasting work usually turns to ensembles or hybrid CNN-LSTM and attention networks [11,12]. To make such models easier to trust, researchers add explainability tools like Grad-CAM and SHAP [13]. Generative AI and large language models (LLMs) are the newest arrivals, being tried for data augmentation and decision support [14,15].

3. Identification and Taxonomy

Recognising insects from photographs is where AI is most mature. With taxa that have plenty of training images, deep CNNs can match or surpass trained taxonomists, and they do so far faster and across far more material [1,5]. Much of the detection literature rests on IP102, which offers over 75,000 images in 102 pest categories [16]. EfficientNet and InceptionV3 are reported to exceed 98 to 99% accuracy on carefully assembled datasets, but their performance declines markedly with tiny insects, busy backgrounds or images taken in the field [17,18].

Aphids, thrips and whiteflies are especially hard because they occupy so few pixels. Researchers have responded with detection heads tuned to fine detail, attention modules and super-resolution preprocessing [19,20]. Since a handful of species are common and most are rare, few-shot and open-set learning have been brought in to handle the rare tail [21,22].

Sound is a second source of identification. Spectrogram-based classifiers can distinguish singing insects, mosquitoes and pollinators, and public collections such as InsectSet459 (more than 26,000 recordings, 459 species) give the field a common yardstick [23]. The catch

is that most of these models learned from clean recordings, so they struggle with the noise of unattended field deployment [24]. Photographs contributed by the public, for instance on iNaturalist, ease the lack of expert-labelled data [1]. InsectNet was built this way; it covers over 2,500 species at better than 96% accuracy and withholds an answer when it is uncertain [25].

4. Monitoring and Surveillance

In a smart trap, an image sensor and a network link feed a deep-learning model that detects, counts and classifies whatever is caught. The model may run on the trap itself or in the cloud [26,27]. Designs using ESP32-class microcontrollers, YOLO detectors and 4G connections follow pests including *Spodoptera litura* and fall armyworm almost in real time, at about 90 to 98% accuracy on cheap hardware [20,28].

Drones carrying RGB, multispectral or hyperspectral cameras fill the gap between walking the field and relying on satellites, which are too coarse for many purposes. Deep-learning analysis of drone imagery has been used to spot canopy stress from insect feeding and to grade infestation severity, for example in vineyards [29,30].

Stored grain presents a different problem. Insects there may account for postharvest losses of 12 to 40% [31] and, because they live inside the kernels, cannot be seen. Listening for them has therefore become a leading option: CNN classification of low-cost microphone recordings reaches roughly 84 to 85% accuracy [32,33].

5. Forecasting and Predictive Modelling

Forecasts improve when several algorithms are combined. Ensembles that draw on neural networks, support-vector regression, k-nearest neighbours and random forests, together with weather data, generally beat a single model [6,11]. Neural networks did better than classical time-series methods for predicting fall armyworm numbers in maize [34]. For western flower thrips, machine-learning forecasts achieved 85 to 88% accuracy, but they lost accuracy when their parameters were moved from one production setting to another [35].

Other studies fuse several data types. A hybrid model that used Sentinel-2 satellite images alongside time-series data predicted olive fruit fly activity one week ahead [36]. Separately, an AI-IoT system that blends lightweight CNNs, Grad-CAM and fuzzy logic reached over 98% accuracy while running on Raspberry Pi-class devices [13].

At a larger scale, species distribution models (MaxEnt, random forest, biomod2) estimate where pests and their natural enemies could live today and later [37,38]. They hint that warming may undermine some biological control, since pests and their enemies can fall out of step in timing [39,40], and that some pests may move toward the poles and up mountain slopes [41].

6. Precision Control and Robotics

Robotic sprayers close the loop between seeing and acting: a camera detects the target and the system adjusts spray output at once. Some of these machines have reduced chemical use

by more than 90%, with targeting precision of 88 to 89% in field tests [42,43]. A YOLO-driven robot has been shown to separate crops, weeds and pests as it moves and to control spraying accordingly [44]. For smallholders, early prototypes pair edge-AI detection with inexpensive spraying hardware [45]. The range of platforms is growing quickly, from compact machines such as Tertill and TerraSentia to large autonomous sprayers [46].

7. Disease Vectors and Public Health

Tracking the arthropods that transmit malaria, dengue, Zika and chikungunya is a field of its own, though it shares tools and aims with agricultural entomology [47]. Deep CNNs can tell mosquito species and sex apart from pictures of wings and body features, frequently outperforming manual identification [48]. Wingbeat sound offers a further cue for separating species inside traps [49].

Systematic reviews of 81 studies published between 2010 and 2024 find machine learning increasingly applied to outbreak prediction and spatial risk mapping, with accuracy often higher than 90% when tested under controlled conditions [50,51]. MosAICo illustrates where this is heading: standardised imaging hardware combined with open-set recognition that sends unfamiliar or invasive specimens to a human expert, a useful safeguard given how few medical entomologists are available [52].

8. Biological Control, Behaviour and Ecology

Video analysis with AI can record and classify insect behaviour at volumes no human observer could handle [1]. For biological control, distribution models help choose where to release parasitoids and predators, anticipate risks to non-target species in future climates [39], and judge whether a natural enemy can establish against an invader such as the woodwasp *Sirex noctilio* [40].

9. New Directions: Big Data, Edge Computing and Generative AI

Inexpensive sensors, IoT devices and cloud services are producing entomological data at a scale not seen before. That makes thorough monitoring possible, but it creates new difficulties in storing, standardising and sharing the data [1,6]. At the same time, compressed models for low-power hardware such as the Raspberry Pi allow inference to happen in the field, reducing the need for a reliable connection [13,53].

Generative AI and LLMs are being tested as an advisory layer. One approach, retrieval augmentation, ties an LLM's answers to verified pest databases so that it gives fewer wrong recommendations [14,15]. Another is to build small, specialised models that work offline for smallholder use [14,54]. The area is still mostly exploratory, though by 2026 it was among the quickest-growing topics in agricultural AI [15,54].

10. Challenges and Limitations

Five obstacles appear again and again. The first is size: aphids, thrips and whiteflies cover so few pixels that detection is less accurate for them than for larger insects [19,20]. The second is the gap between laboratory and field. Top results usually come from curated datasets or specimens in controlled settings and decline in cluttered real conditions, which has been seen with images, sound and forecasting alike [17,18,24]. The third is data: rare, invasive and regionally important pests have too few examples, and class imbalance makes it worse [21,22].

The fourth obstacle is opacity. Deep models are difficult for growers and regulators to inspect, and explainability tools only partly address this [12,13]. The fifth is access. Unreliable connectivity, modest computing resources and the cost of smart traps, drones and robots keep these tools away from smallholders in low- and middle-income regions, even though food-security risk is often highest there [1,45]. Generative tools bring their own hazard, namely factually wrong output, so they need to be anchored in verified agronomic knowledge [14,15]. Table 1 pairs each approach with its reported strength and its main field limitation.

Table 1. AI approaches in entomology: reported strengths and field limitations

Approach	Reported strength	Main field limitation
Image classification (CNNs)	Over 98-99% accuracy on curated datasets [17,18]	Drops for small, cluttered or field-taken images [17,18]
Small-pest detection	Detail-focused heads, attention, super-resolution [19,20]	Remains less accurate than for larger insects [19,20]
Bioacoustics	Shared benchmarks such as InsectSet459 [23]	Trained on clean audio; fragile outdoors [24]
Smart traps and IoT	Roughly 90-98% accuracy on low-cost hardware [20,28]	Cost and connectivity restrict smallholder use [1,45]
Drone (UAV) sensing	Maps pest severity and canopy stress, e.g. vineyards [29,30]	Drone cost limits uptake in low-income regions [1,45]
Forecasting models	85-88% accuracy for western flower thrips [35]	Accuracy falls when moved between environments [35]
Spraying robots	Pesticide use cut by over 90% in some cases [42,43]	Robot cost limits smallholder access [1,45]
Vector surveillance	Often above 90% accuracy [50,51]	Figures come from controlled evaluation [50,51]
LLMs and	Retrieval grounding gives	Factual unreliability is still a risk

Approach	Reported strength	Main field limitation
generative AI	fewer wrong answers [14,15]	[14,15]

11. Future Prospects

No single data stream is likely to be enough. Merging images, sound, environmental sensors and satellite data should make detection and forecasting more dependable [36]. For real-time AI to reach beyond well-funded commercial farms, models must be light, able to run at the edge and explainable [13,53]. Shared, standardised benchmarks that cover many more taxa, extending IP102, InsectSet459 and citizen-science collections, would reflect the long tail of insect diversity and let studies be compared fairly [16,23].

Climate-aware forecasting and distribution models can show how pest ranges may shift and how robust biological control will be [37,39]. Well-grounded LLMs may eventually bring such insight to smallholders and extension staff [14,15]. None of this will happen without teamwork between entomologists, data scientists, engineers and policymakers, backed by shared infrastructure, data governance and field trials that demonstrate actual benefit in lower pesticide use, protected yields and reduced disease burden [3,51].

12. Conclusion

AI now sits at the centre of methods in applied and public-health entomology, spanning identification, smart trapping, forecasting, robotic control, vector surveillance and biological control. Vision and bioacoustic classifiers often come close to expert identification, and IoT traps, drone sensing and precision robots are turning them into real-time decision support that could trim crop losses and pesticide use. Prototypes are still held back from dependable field use by difficulties with tiny targets, limited data, weak generalisation, opacity and unequal access. With progress in multimodal fusion, edge computing, common benchmarks and grounded generative AI, and with closer collaboration, AI looks set to become an everyday part of sustainable, data-driven pest management worldwide.

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