

Automatic insect identification, counting, and monitoring techniques: a review

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Abstract

BACKGROUND: Insect pests threaten agricultural productivity, while conventional surveillance is labour-intensive and excessive pesticide use creates environmental and health risks. This review evaluated automated insect detection, counting, classification and monitoring technologies, focusing on machine-learning integration, field transferability, and operational readiness.

RESULTS: A PRISMA 2020-guided formal search covering publications from 2010 to 2024 identified 313 records relevant to the technological and methodological scope of the review. After title/abstract screening and full-text eligibility assessment, 116 publications were retained. The evidence encompassed camera- and vision-based systems; acoustic, infrared, and opto-electronic sensors; electrostatic and physical approaches; non-lethal photonic monitoring; radar and biosensing technologies; Internet of Things-enabled platforms; and machine- and deep-learning methods. Camera- and vision-based systems were among the most extensively documented and field-oriented approaches, particularly when integrated with remote image acquisition, communication networks, and automated classification. Acoustic systems provided complementary options for continuous or low-power monitoring, whereas radar, biosensing, and other emerging approaches broadened applications toward biodiversity assessment, large-area surveillance, and early detection. Reported performance was not directly comparable across publications because metrics, acquisition conditions, and validation levels differed substantially, ranging from laboratory or dataset benchmarks to semi-field trials, field validations, and operational deployments.

CONCLUSION: No single technology is optimal for all monitoring objectives. Operational adoption requires standardized task-specific reporting, independent and sustained field validation, representative datasets, improved transferability across crops and environments, and system-level assessment of robustness, energy autonomy, connectivity, maintenance, and cost. Sensor fusion, edge artificial intelligence, and domain-adaptive or uncertainty-aware models are promising when they provide measurable decision-support benefits.

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1 INTRODUCTION

Pesticides play a central role in modern agriculture, serving as a vital component in pest management, crop protection, and the enhancement of agricultural productivity. They are essential for ensuring food security and supporting farmers' livelihoods.¹ However, their use comes with significant environmental and health risks, including soil and water contamination, harm to non-target organisms, and long-term ecological damage from persistent compounds like DDT and lindane.^{2,3} Human health impacts, such as neurological and hormonal disruptions, further underscore the need for sustainable pest management strategies.¹ Early pest detection is key for mitigating these risks, enabling timely interventions to minimize damage to agriculture, ecosystems, and human health.⁴ While public participation in pest detection can be valuable, formal surveillance efforts remain essential, particularly in agriculturally significant regions. Integrating public engagement with scientific data is key to safeguarding against invasive species and supporting early-warning systems within integrated pest management frameworks.

Traditional pest monitoring methods, such as visual inspections and traps, have been widely used but face significant limitations. Visual inspections are often inefficient due to human factors (e.g., fatigue, varying expertise), environmental conditions (e.g., poor lighting), and challenges in detecting smaller or low-contrast pests.⁵ Traditional traps, including water traps, sticky traps, suction traps, interception traps, and funnel or cone traps, provide valuable data on pest abundance and distribution but are limited by their passive attraction mechanisms, manual data collection requirements, and susceptibility to environmental factors.⁶ These limitations highlight the need for more advanced, automated pest monitoring systems capable of providing timely,

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reproducible, and scalable information for pest management decision-making.

Recent advancements in technology, such as electronic sensors, machine learning, and real-time data processing, offer promising solutions to overcome these challenges.^{7,8} Consequently, automated systems can address issues such as labour-intensive data collection, limited specificity, and false negatives, providing more reliable and scalable automatic insect pest identification for modern pest management. This review focuses on field-oriented applications of automated insect pest monitoring systems that integrate optical, acoustic, and image-based sensors, exploring their potential to support more precise, data-driven, and sustainable pest management practices. Because automated monitoring technologies are currently at various stages of development, the review considers systems ranging from laboratory prototypes and semi-field validations to operational field deployments, while critically discussing their transferability to real agricultural conditions.

Previous literature reviews have explored automated pest monitoring; however, this review distinguishes itself by focusing on field applications and examining the integration of various advanced sensor technologies. Thus, previous reviews focused on the use of deep learning for insect pest field-image classification but did not address the integration of multiple sensor technologies,⁸ analysed image-based insect detection methods but in the context of confined laboratory settings,⁹ highlighted sensor-based systems but did not discuss operational field integration and optimization,¹⁰ and centred on image analysis but did not explore broader sensor technologies. In contrast, this review extends beyond image-based systems to include optical and acoustic sensors, emphasizing their integration into field applications and their relevance for automated monitoring, counting, and decision support in pest management.⁷

Accordingly, this review aimed to (i) synthesize sensor- and computation-based technologies for automated insect detection, counting, classification, and monitoring; (ii) distinguish laboratory or dataset benchmarks, semi-field trials, field validations, and operational deployments; (iii) compare their taxonomic resolution, robustness, scalability, energy and maintenance requirements, and operational readiness; and (iv) identify research priorities for their transfer to agricultural and other relevant entomological monitoring contexts.

2 METHODOLOGY

This section outlines the systematic methodology employed to review studies on automatic insect detection and identification systems in crops. The process was guided by the PRISMA 2020 framework, with the steps summarized as follows:

2.1 Search strategy

A systematic literature search was conducted using Scopus and Web of Science as the primary bibliographic databases. PubMed and Google Scholar were additionally used for supplementary literature checking and citation tracing. The formal database search covered records published or first made available online between 1 January 2010 and 31 December 2024, and focused on English-language literature relevant to automated insect detection, counting, classification, and monitoring. The following core search expression was used and adapted, where necessary, to the search fields available in each database:

'Automatic detection of insects' AND (insect traps OR classification OR detection).

The formal database search identified 278 records. After removal of 23 duplicate records, 255 unique records remained. To complement this search and adequately characterize the technological approaches identified, supplementary citation searching and methodological reference checking were performed. This process contributed 35 additional unique publications, including publications describing enabling sensing principles, computational architectures, algorithms, datasets, and analytical or evaluation methods used in automated insect monitoring. These supplementary sources were considered part of the technological and methodological synthesis when they were directly required to describe, interpret, or compare the reviewed approaches.

The combined evidence pool therefore comprised 290 publications. Following title, abstract, and relevance screening, 172 records were excluded because they did not meet the topical or methodological scope of the review, leaving 118 reports for full-text assessment. Two reports were subsequently excluded because they provided insufficient methodological or performance information for the planned synthesis. Consequently, 116 publications were retained to inform the technological and methodological synthesis presented in this review, as summarized in Fig. 1.

The predefined 2010–2024 publication window applied to the formal database search; however, earlier foundational or methodological sources identified through supplementary reference checking were retained when needed to explain relevant technologies, algorithms, analytical methods, or evaluation frameworks, without being considered primary evidence of contemporary field performance. When records identified within the search period were subsequently published as peer-reviewed articles before completion of the review, the final version of the record was used, with both versions treated as the same publication. Overall, 116 publications directly informed the technological and methodological synthesis, while 11 additional references provided background, methodological, or contextual information and were excluded from the PRISMA synthesis corpus, resulting in a total reference list of 127 publications.

2.2 Inclusion criteria

Studies were included when they met the following criteria: (i) they addressed automated insect detection, counting, classification, or monitoring; (ii) they were relevant to insect pests, agricultural or stored-product pest management, vector surveillance, or transferable entomological monitoring technologies; (iii) they were published as peer-reviewed journal articles or conference proceedings at the time of the final evidence synthesis (preprints and other non-peer-reviewed documents were excluded from the systematic evidence set or retained as supplementary sources when necessary); and (iv) they provided sufficient methodological or performance information to characterize the technological approach.

To account for differences in validation conditions and deployment readiness, studies were classified into four levels: (i) laboratory or dataset benchmark, including controlled experiments, curated datasets, or offline evaluations; (ii) semi-field trial, conducted in partially controlled environments such as greenhouses, enclosures, or flight tunnels; (iii) field validation, involving

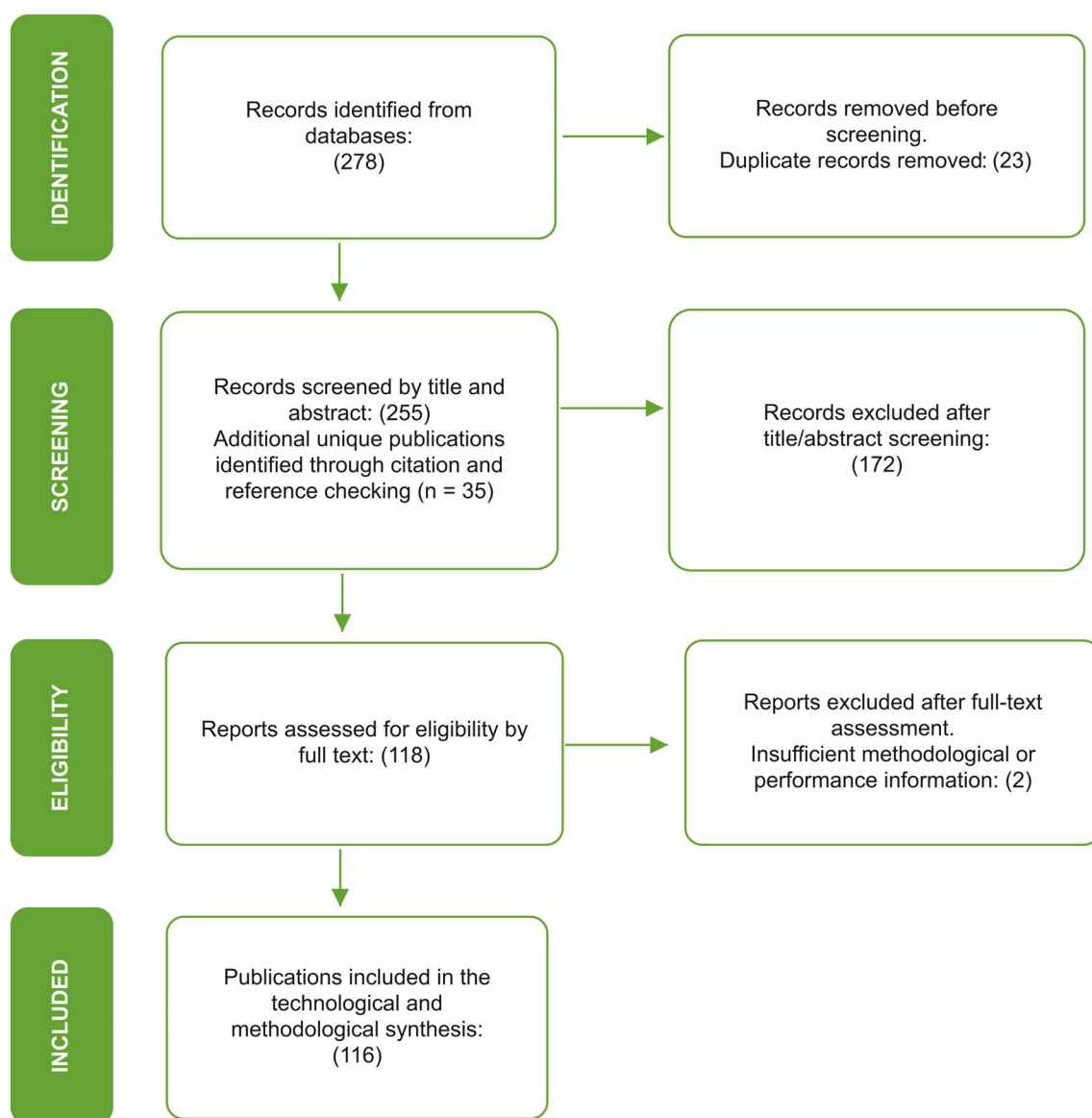


Figure 1. PRISMA-based flow diagram summarizing the identification, screening, eligibility assessment, and inclusion of studies in the present review. Adapted from the PRISMA 2020 flow diagram.¹¹

testing under real-world or operationally relevant conditions for a limited period or at specific sites; and (iv) operational deployment, involving sustained or recurrent use under routine real-world monitoring conditions. Studies from all four levels were retained because laboratory and semi-field studies often provide relevant sensing principles, algorithms, and proof-of-concept evidence for later field applications. However, performance obtained under controlled conditions was not considered equivalent to performance demonstrated in field validation or operational deployment. The assigned validation level is reported in the summary tables and is used in section 4 to support cross-technology comparison.

Performance outcomes were reported using the terminology of the original studies, including accuracy, detection rate, counting accuracy, sensitivity, specificity, and capture or trapping efficiency. Because these metrics may represent different outcomes and were obtained under heterogeneous datasets, tasks, and

validation conditions, they were not assumed to be directly comparable across studies. These limitations are discussed further in section 4.

2.3 Exclusion criteria

Publications were excluded if they were outside the scope of automated insect or arthropod detection, counting, identification, classification, or monitoring, or if they lacked sufficient technological, methodological, or performance information for the synthesis. After screening, 118 reports underwent full-text assessment, of which two were excluded for insufficient methodological or performance information. The language and publication-type criteria defined for the formal database search were applied as specified in section 2.2, while supplementary methodological or foundational sources were retained only when they were directly relevant to the interpretation of the reviewed technologies.

Following full-text assessment, 116 publications were included in the technological and methodological synthesis, as summarized in Fig. 1.

3 RESULT AND DISCUSSION: CURRENT TECHNOLOGIES FOR AUTOMATED INSECT MONITORING

In response to the increasing demand for scalable and precise pest monitoring tools, recent studies have explored a wide range of novel methodologies for the automatic identification and classification of insect pests in agricultural settings. This section reviews current advances from two complementary perspectives: the physical and sensor-based systems used for insect detection under laboratory, semi-field, and field conditions, as well as the computational approaches employed to process, classify, and interpret the captured data. By examining both detection technologies and data-driven analysis frameworks, this overview provides insight into how integrated systems are evolving to meet the challenges of modern, data-intensive pest management, while also highlighting differences in technological maturity, validation conditions, and operational readiness across approaches.

3.1 Detection methods for automated insect traps

3.1.1 Camera and vision-based techniques

An automated pest management system has been developed that integrates artificial intelligence (AI) and Internet of Things (IoT) technologies to support sustainable agriculture. The IoT-enabled trap incorporates an embedded camera for continuous field monitoring, capturing daily images of crops and surrounding areas. These images are analysed using machine-learning algorithms to detect insect species, assess crop damage, and generate real-time alerts through a cloud-based platform. Additionally, the system provides data-driven pest control recommendations, enabling farmers to implement targeted and environmentally sustainable interventions. This approach may contribute to reducing unnecessary pesticide applications by supporting earlier detection, remote surveillance, and more targeted decision-making.¹²

A remote insect monitoring and detection system has been developed based on a four-layer IoT architecture that integrates communication and monitoring technologies. The framework consists of (i) a perception layer that captures insect images using low-power wireless cameras; (ii) a transport layer that ensures real-time and reliable data transmission via Wi-Fi and Transmission Control Protocol/Internet Protocol (TCP/IP) protocols; (iii) a processing layer that employs deep-learning algorithms, such as Faster RCNN ResNet50,¹³ to classify insects and diseases with an accuracy of up to 94%¹⁴; and (iv) an application layer offering user-friendly interfaces for remote access through web and mobile platforms. This system utilizes real-time image processing and deep learning to facilitate accurate insect detection, enabling remote monitoring for informed pest control decision-making. Its performance is validated using metrics such as accuracy, precision, recall, F1 score, and intersection over union (IoU), although the interpretation of these values depends on the dataset, target organisms, image acquisition conditions, and validation protocol used in the original study.¹⁴

Camera-equipped insect traps have been developed by integrating conventional trap designs – such as sticky, bucket, and delta-shaped traps – with hardware components, including

cameras (1–5 MP), communication modules for remote image transmission, and solar-powered batteries. These systems are typically tailored to monitor specific pest species and capture high-resolution images at regular intervals. The images are transmitted to centralized servers, where automated insect identification is performed using image recognition algorithms, supplemented by manual verification when needed. Camera-equipped trapping systems can enhance real-time pest monitoring by enabling remote image acquisition, wireless data transmission and, in some cases, integration of environmental data such as temperature and humidity through web-based platforms.^{15–17} However, their practical deployment may still be constrained by cost, power autonomy, image quality, and the need for further improvements in fully automated detection and counting algorithms.¹⁶

An intelligent, motor-driven e-trap system has been designed for citrus pest management, integrating computer vision to enable autonomous, cost-effective, and precise insect monitoring. The trap features a motorized mechanism that automatically replaces yellow sticky paper, allowing uninterrupted operation without the need for manual maintenance. Real-time images of trapped insects are analysed using computer vision algorithms, including local binary pattern methods for pest density assessment and a multi-attention and multi-part convolutional neural network (CNN), which achieves a recognition accuracy of 95.6% for *Bactrocera minax* and *Bactrocera dorsalis*. With an overall detection accuracy of 99.3%, the system reported high identification performance and reduced the need for manual trap inspection under the conditions evaluated. Priced at an estimated \$150 per unit and adaptable to various pest species through customizable attractants, this e-trap offers a potentially scalable option for citrus orchards, although its broader applicability depends on crop context, target species, maintenance requirements, and field robustness.¹⁸

A deep-learning-based method has been proposed for accurate multiclass insect counting and identification under real-field conditions, utilizing density maps and CNNs.^{19–21} This approach addresses common challenges in field image analysis, such as overlapping insect clusters and occlusion, delivering high accuracy, achieving R^2 values of up to 0.98 in the counting of larger nymphs.¹⁹ The model is packaged within a containerized and remotely accessible software environment,²² enabling deployment on mobile devices. This facilitates real-time field application and supports data-driven pest management by accurately assessing infestation levels and informing timely intervention strategies.¹⁹ Nevertheless, the transferability of such models to other crops, pest species and image acquisition conditions depends on dataset diversity, annotation quality, and model adaptation.

Electronic traps (e-traps) have been developed to enable real-time monitoring of fruit fly populations by integrating communication systems and image-based techniques. Designed to target species such as *Ceratitidis capitata* and *Bactrocera oleae*, these traps utilize pheromones and visual attractants to lure insects, capturing high-resolution images of the trapped specimens for remote analysis and identification. Automated classification algorithms achieve an accuracy of over 88%, as validated through field trials conducted across Mediterranean agricultural environments, showing agreement with manual counts. Wireless communication via Wi-Fi and ZigBee, adapted to field-specific conditions, facilitates reliable data transmission.²³ Additionally, energy-efficient features such as solar power and hibernation modes enable continuous operation in remote locations. Centralized

data processing can reduce the need for frequent manual trap inspections and support more timely pest management decisions. Challenges related to transmission delays were mitigated through adaptive network configurations, improving system performance in variable field conditions.²⁴

In a complementary advancement, an enhanced insect pest counter has been proposed to improve detection and counting accuracy from digital images of yellow sticky traps. The system employs saliency maps that generate candidate insect regions and reduce the influence of irrelevant background areas, followed by a CNN for classification of pests and non-pests. An improved non-maximum suppression algorithm is implemented to address redundant detection bounding boxes. At the same time, a dual-path architecture – combining the saliency-map-based counter with faster R-CNN²⁵ – enhances detection in complex scenarios with insects located close to one another. Pest counts are obtained by counting the processed detection bounding boxes, each corresponding to one insect pest.²⁶

The automated McPhail trap designed by Doitsidis *et al.*¹⁵ integrates modern electronic components into the traditional McPhail trap to monitor *Bactrocera oleae* populations. It features a low-cost, scalable system equipped with a 2-MP camera controlled by a low-power microcontroller, which captures and stores images locally on an SD card and transmits them wirelessly via a Global System for Mobile Communications (GSM) module to a remote server for real-time monitoring and analysis. The system includes automated insect counting software (75% accuracy) to reduce human error, operates efficiently on a 12 V battery (7000 mAh) for long-term use, and was designed for field operation under outdoor conditions. Field tests demonstrate comparable pest attraction to traditional traps while offering potential advantages in reducing manual monitoring effort and supporting more timely decisions on pest control interventions.

An insect detection system has been developed that integrates a synchronized stereo-camera setup combining an red, green and blue (RGB) camera with a dynamic vision sensor (DVS), a neuro-morphic, event-based sensor capable of capturing rapid changes in brightness. This configuration is particularly effective for tracking small, fast-moving insects in dynamic and complex outdoor environments. The DVS continuously monitors scene changes and triggers the high-resolution RGB camera only when it detects insect motion, thereby improving power efficiency and optimizing data storage. A custom algorithm processes the asynchronous event data and full-frame images, effectively distinguishing insect activity from background disturbances such as plant movement or varying light conditions. Evaluated on a dataset of over 81 000 annotated frames, the system demonstrated superior accuracy compared to conventional deep-learning approaches while simultaneously reducing computational and energy requirements.²⁷ As with other image-based systems, its broader operational applicability should be interpreted in relation to the range of target species, crop backgrounds, and environmental conditions considered during validation.

ICount, a software tool developed by Gaburro *et al.*,²⁸ automates the counting of *Aedes aegypti* eggs, a mosquito vector associated with arboviruses such as dengue, Zika, and chikungunya. The tool employs digital image analysis techniques, utilizing thresholding for image segmentation to identify and count mosquito eggs. It offers both automatic and semi-automatic modes, providing flexibility for different counting workflows. When validated against manual counts,²⁹ ICount demonstrated statistically comparable results, supporting its use for rapid egg-count analysis. Key

features include a user-friendly interface, low computational demands, and adaptability to various image types, making it accessible to both experts and non-experts. Available for free, ICount was evaluated across different egg densities and may be particularly useful in resource-constrained environments for consistent mosquito egg counting, supporting mosquito population monitoring and control efforts.

A smartphone-based image processing system developed by Zhu *et al.*³⁰ enables the detection and counting of insects in stored grain environments, achieving up to 95% accuracy in pest enumeration. The system employs a dynamic threshold adjustment mechanism, utilizing sliding window binarization, to account for uneven lighting conditions and segment insect images through connected domain analysis. It integrates modular components for image capture, pre-processing, statistical analysis, and data visualization within an Android framework. This portable and cost-effective tool enables real-time pest monitoring on standard smartphones, offering an efficient solution for timely pest management in grain storage facilities without the need for expensive equipment.

An automated e-trap system for managing Lepidopteran pests in agriculture has been developed by Saradopoulos *et al.*³¹ Based on a traditional funnel trap design, the system integrates image acquisition, onboard processing, and wireless communication for automated pest monitoring. Retaining the effective moth attraction capabilities of conventional pheromone-based traps, the system incorporates several key innovations. A single-board computing unit manages image processing and system control, and a high-resolution 5-MP camera captures daytime images. The trap features a self-disposal mechanism powered by a servomotor to remove accumulated insects and reduce overlap during long-term operation. Its three-dimensional-printed housing provides protection for the electronics, ensuring durability and portability. Designed for battery efficiency, the trap supports long-term autonomous operation. Embedded deep-learning algorithms, such as YOLOv7/8, analyse insect images for pest detection, counting, and wireless data transmission for further analysis. With its scalability, affordability, and open-source framework, this system represents a potentially scalable approach for precision pest monitoring, particularly where long-term autonomous trap operation is required.

An automated image analysis technique developed by Ghods and Shojaeddini³² supports integrated pest management (IPM) by providing counts of whiteflies on crop leaves. This method employs unsupervised image processing, combining grayscale conversion, granulometry, and morphological tophat transforms to isolate whiteflies. Segmentation is then performed using histogram-based thresholding, while entropy-based texture analysis further refines detection, particularly in high-density infestations, thereby minimizing over-segmentation. The approach, which requires minimal ground truth data, is potentially adaptable to various crop conditions, making it a useful contribution to image-based pest monitoring within IPM contexts.

An optical insect counter (OIC), developed by Hoffmann *et al.*,³³ provides monitoring and quantification of mosquito movement in response to attractants and repellents within a controlled flight tunnel. The OIC utilizes a line-scan camera combined with a vertical light sheet to capture both spatial and temporal data as mosquitoes traverse a designated plane. Positioned within a Plexiglas tunnel with controlled airflow and humidity, the system monitors mosquito behaviour stimulated by attractants such as human breath. It analyses flight patterns to assess attraction or repulsion.

This laboratory-based system provides a reliable method for recording the number, position and timing of mosquitoes crossing a defined plane, offering useful behavioural information that may inform the development of optical monitoring approaches for pest management.

A precision agriculture system for ecological monitoring of the oriental fruit fly (*Bactrocera dorsalis*) was developed by Jiang *et al.*,³⁴ integrating wireless communication, automated data collection, and real-time analysis. The system utilizes remote monitoring platforms equipped with a low-power microcontroller to manage sensors (e.g., temperature, humidity, wind speed) and automated fly-trapping and counting devices. These platforms transmit environmental and pest population data via GSM-SMS (Short Message Service) to a centralized host control platform, which receives, stores, displays, and analyses the data online, providing real-time visualization, query functionality, and alerts for pest population thresholds or system errors. This system facilitates long-term data collection and enables real-time monitoring while also allowing for correlation analysis between environmental factors and pest dynamics, supporting timelier and spatially resolved pest management decisions. Key findings from the studies reviewed in this section are summarized in Table 1.

In summary, camera- and vision-based systems support automated insect counting and classification through remote image acquisition and analysis. Their comparative maturity, operational limitations, and field-transferability are discussed in section 4.

3.1.2 Acoustic, ultrasonic, and infrared-based methods

The development of pest monitoring technologies has increasingly incorporated sensing systems capable of capturing physical phenomena associated with insect movement and behaviour. Among these, acoustic, ultrasonic, and infrared-based methods have shown potential because of their capacity for non-invasive, real-time detection and classification of insect activity under diverse environmental conditions. These systems rely on measurable parameters such as wingbeat frequency, body heat emission, and motion-induced signal occlusion and are implemented through a variety of optoelectronic and microcontroller-based configurations. Integrated into autonomous platforms, they can support insect identification, reduce manual inspection needs, and facilitate remote data acquisition and transmission. The following subsections review a series of representative approaches that exemplify the versatility and applicability of these sensing modalities in both agricultural and ecological pest management contexts, while also considering differences in validation conditions, target organisms, and operational maturity.

Wang *et al.*³⁵ developed two optical mosquito-counting systems based on light backscattering and light attenuation/shadowing, respectively, to record wingbeat signals from mosquitoes crossing an light-emitting diode (LED)-based detection area. The system integrates LED-based scattering and photodiode shadowing technologies with commercial mosquito traps, allowing real-time detection and the analysis of wingbeat frequency in *Aedes albopictus* and *Culex pipiens*. The study showed that wingbeat frequency could distinguish males from females within the tested species, although it was less dependable for distinguishing *A. albopictus* from *C. pipiens* of the same sex because of overlapping frequency ranges.

Goldshtein *et al.*³⁶ developed an automated trap for monitoring Mediterranean fruit fly (*Ceratitis capitata*) as a sensor-based system for sequential, remote monitoring in citrus orchards. The cylindrical trap combines the para-pheromone trimedlure with a

4% Dichlorvos 2,2-dichlorovinyl dimethyl phosphate (DDVP; dichlorvos) toxicant strip, attracting and eliminating male flies^{37,38}

An optoelectronic infrared sensor counts captured insects, providing automatic count data without relying on weekly manual inspection. Data are transmitted via a single-board computer-based logger with solar power. Field tests showed trapping efficiency comparable to Steiner traps,³⁹ with improved performance using larger pheromone-release apertures. Counting accuracy ranged from 88% to 100%, with overcounts caused by ants or rain mitigated through trap adjustments. Notably, real-time monitoring allowed growers to avoid three of eight planned pesticide applications in pilot trials, although the authors indicate that more extensive field experiments are needed to confirm its contribution to reducing insecticide applications without compromising yield.³⁶

Telaumbanua *et al.*⁴⁰ present an automatic pest trap for cucumber plants featuring a yellow LED baiting system, solar-powered operation for field independence, and an infrared proximity sensor for pest detection. On detecting insects, an airflow mechanism directs them into a water-filled reservoir, where they are retained. Field tests over 6 days showed an 80.87% capture efficiency, with an average capture time of 130 s. The system combines yellow-light attraction, infrared detection, solar power, and mechanical capture; however, its validation was limited to a six-day field test, so its robustness across seasons, pest densities, and crop conditions remains to be further evaluated.

Vasconcelos *et al.*⁴¹ developed a prototype IoT-based system for automated mosquito population monitoring, leveraging bioacoustic sensing and machine learning to address the limitations of traditional, labour-intensive trapping methods. The system captures mosquito wingbeat frequencies using audio sensors, processes the data with an embedded microcontroller, and employs Long Range (LoRa) communication for long-range, low-power data transfer from remote areas. Trained machine-learning models analyse wingbeat patterns for species identification, although the study reports the prototype architecture, preliminary field testing, and remaining challenges for deployment in noisy, physically demanding field environments. The architecture includes environmental sensors, backup storage, and real-time clock functionality, enabling operation in tropical and subtropical conditions. Preliminary field tests demonstrate the system's potential for continuous, remote mosquito monitoring, providing a basis for scalable vector surveillance systems in regions affected by malaria and dengue.

An acoustics-based trap for detecting *Lobesia botrana* was developed, characterized by its capacity to identify specific flight sounds using laboratory-characterized acoustic signatures. The system utilizes wireless sensors equipped with microphones capable of capturing a wide frequency range (100 Hz to 125 kHz). It employs matched band-pass filters centred at 8 and 23 kHz for detection. Integrated with pheromone traps, the device autonomously transmits real-time data – including moth counts, location, and time of detection – to a remote server for analysis, thereby reducing manual labour and supporting monitoring efficiency. Validation under both laboratory and field conditions demonstrated that the acoustic detections were consistent with the flying period of *L. botrana* and showed agreement with traditional field traps when compared to traditional traps used by the Chilean Agricultural and Livestock Service.⁴²

Advanced optoacoustic techniques for insect detection and monitoring have also been explored. These systems detect wingbeats by converting interruptions in a light beam into acoustic

Table 1. Summary of reviewed studies on camera- and vision-based systems for insect detection, counting and monitoring

Author	Trap/study	Methodology/technique	Reported metric/value	Validation level
Reddyboina <i>et al.</i> ¹²	AI- and IoT-based insect identification system	Embedded camera with lightweight object detection and CNN-based classification; detected insects or damaged leaves trigger remote alerts to farmers	CNN testing accuracy ranged from 88% to 91% across nine to 15 epochs The object-detection model achieved AP values of 0.624 for black pest, 0.544 for ladha and 0.542 for damaged leaves	Laboratory/dataset benchmark
Ramalingam <i>et al.</i> ¹⁴	Remote insect monitoring and detection system	The monitoring strategy leverages real-time image processing, deep learning for insect detection, and remote monitoring to support decision-making for pest control	Average accuracy of 94% for automatic identification of built-environment insects and farm-field insects; evaluated within the proposed IoT-based remote monitoring framework	Laboratory/dataset benchmark
Preti <i>et al.</i> ¹⁶	Camera-equipped insect traps	The trap captures high-resolution images at intervals, which are transmitted to servers for automated or semi-automated insect identification using image recognition algorithms	Review article; no single performance metric The article discusses advantages and limitations, including image quality, cost, power autonomy, and the need for further improvements in fully automated pest detection	Not applicable, review article
Huang <i>et al.</i> ¹⁸	Intelligent, computer vision-based trap	Employing local binary pattern, multi-attention and multi-part convolutional neural network	Recognition accuracy of 95.6% for citrus fly recognition; overall detection accuracy of 99.3% reported for the proposed e-trap detection/recognition algorithms	Laboratory/dataset benchmark
Bereciartua-Pérez <i>et al.</i> ¹⁹	Density map deep-learning model	Density maps and mobile-accessible software implementation for insect counting	Adult insects: RMSE 0.89–4.47, MAE 0.40–2.15 and R^2 0.86–0.91 depending on species/class BEMITA immatures: R^2 up to 0.98 for larger nymphs; evaluated under real conditions across multiple locations and crops	Field validation
Shaked <i>et al.</i> ²⁴	Electronic trap for real-time monitoring	Uses pheromones and visual cues, capturing high-resolution images of insects for remote analysis	Entomologist classification from transmitted images was >88%; average flies/trap in e-trap grids did not differ from conventional traps operating simultaneously	Field validation
Guo <i>et al.</i> ²⁶	Insect pest counter	Saliency-map-based region proposal, CNN classification and improved non-maximum suppression for insect pest counting	Improved F1 score and lower MAE/MSE compared with reference methods	Laboratory/dataset benchmark
Doitsidis <i>et al.</i> ¹⁵	Electronic McPhail trap	Captures images locally and transmits them wirelessly to a remote server for real-time monitoring and analysis	Mean automatic counting accuracy of 75% compared with manual counting; e-trap attractiveness did not differ significantly from the reference glass-type McPhail trap	Field validation
Gebauer <i>et al.</i> ²⁷	Event-based insect camera trap	Event-based vision sensor used for asynchronous detection and tracking of flying insects, triggering a synchronized high-resolution colour camera only when insect presence is detected	Overall frame-level accuracy was 81.02% across all annotated frames; mean scene-level accuracy was 73.78% with a global parameter configuration and 76.96% with scene-specific tuning Bounding-box F1 ranged from 22.35% to 69.62% depending on scene complexity	Field validation

Table 1. Continued

Author	Trap/study	Methodology/technique	Reported metric/value	Validation level
Gaburro <i>et al.</i> ²⁸	ICount for mosquito egg counting	Image analysis software for automated and semi-automated counting	ICount provided automatic analysis times of 3.8–4.7 s depending on egg density; semi-automatic correction can reduce counting errors to zero Extension to <i>Aedes albopictus</i> eggs showed an average error of 7.4 ± 4%	Laboratory/dataset benchmark
Zhu <i>et al.</i> ³⁰	Mobile dynamic binarization	Mobile image analysis with sliding window binarization	Counting accuracy of 95% (57 insects detected out of 60), compared with 80% using the fixed-threshold method, under the tested smartphone-image conditions	Laboratory/dataset benchmark
Saradopoulos <i>et al.</i> ³¹	Image-based e-funnel trap	Onboard image acquisition and embedded deep learning for insect counting, comparing YOLOv7/8, deep regression, and crowd-counting approaches; a self-disposal mechanism reduces insect accumulation and overlap	Performance varied with insect size, abundance and overlap, and no single method was optimal in all scenarios YOLOv7/8 was recommended as the best overall embedded solution	Laboratory/dataset benchmark
Ghods and Shojaeddini ³²	Automated image analysis system for counting whiteflies on crop leaves	Unsupervised image analysis combining granulometry-based size estimation, intensity, and shape analysis, and local-entropy texture thresholding to separate adjacent whiteflies	Mean F1 score of 85% for low-density images and 74% for high-density images; mean FDRs were 0.7% and 0.6%, respectively, across 200 images	Laboratory/dataset benchmark
Hoffmann <i>et al.</i> ³³	Optical counting in flight tunnel	Spatial and temporal movement analysis	Successfully counted 19 mosquito crossings during a 10-min trial and recorded the time and horizontal position of each crossing; 12 mosquitoes crossed the left side and seven the right side of the light sheet	Semi-field trial
Jiang <i>et al.</i> ^{34*}	Precision agriculture system for monitoring	Remote monitoring platforms equipped with sensors transmit environmental and pest population data to a centralized host control platform	One-year field test demonstrated real-time monitoring of environmental parameters and oriental fruit-fly population dynamics	Field validation

Values correspond to the metrics reported in the original studies and should not be interpreted as directly comparable across systems because the reviewed studies differ in target species, validation setting, dataset size, image acquisition conditions, evaluation protocols, and performance metrics. In this and the following summary tables, the 'Validation level' column indicates, for each study, whether the reported system was evaluated as a laboratory or dataset benchmark, a semi-field trial, a field validation, or an operational deployment, based on the conditions described by the original authors. This classification is intended to help the reader avoid comparing performance figures across studies of markedly different technological maturity.

AI, artificial intelligence; AP, average precision; BEMITA, Bemisia tabaci; CNN, convolutional neural network; FDR, false discovery rate; IoT, Internet of Things; MAE, mean absolute error; MSE, mean squared error; RMSE, root mean squared error.

*Foundational contextual study published before the predefined systematic search period; discussed for technological context but not included in the PRISMA-counted corpus ($n = 116$).

signals, which are then modulated and demodulated to isolate harmonic patterns, allowing for automated identification. High-frequency photodiodes support signal acquisition even in noisy or variable lighting environments. The optical monitoring, combined with a noise-resilient design, supports real-time pest surveillance in both laboratory and field settings. When integrated with automated traps, the system enables remote classification and data transmission, offering potential applications for

automated pest monitoring, although performance depends on trap configuration, signal quality, and validation under field conditions.⁴³

Similarly, laser-based sensing technologies have shown potential in entomological applications. The entomological stand-off optical sensor (ESOS) system, for instance, utilizes near-infrared light and a continuous-wave diode laser to detect flying insects by analysing the backscattered light. It classifies individuals based

on wingbeat frequency and morphological features, enabling the identification of insect groups and behavioural patterns via clustering algorithms. Validation through comparison with Centers for Disease Control and Prevention (CDC) light traps confirmed agreement between ESOS-derived mosquito aerial density and trap-based mosquito counts. With high temporal resolution, autonomous functioning, and non-intrusive operation, the system was used in long-term monitoring of insect density and circadian rhythms in semi-urban environments, registering approximately 60 000 insect detections during field trials.⁴⁴

Puntonet *et al.*⁴⁵ applied the discrete wavelet transform to detect termite acoustic emissions, demonstrating the feasibility of recognizing termite alarm signals under low signal-to-noise conditions. By analysing non-stationary alarm signals through wavelet decomposition and employing entropy-based adaptive filtering, the approach achieved robust noise reduction even at signal-to-noise ratios as low as -30 dB. Signals were acquired using accelerometers and a standard microphone, and then denoised and processed using wavelet-based methods. While the study addresses acoustic/vibratory termite signal recognition in materials such as wood and soil, the method's practical deployment is constrained by the cost and complexity of sensor installation.

In a different context, Santoso *et al.*⁴⁶ developed an IoT-based pest monitoring system for rice fields, combining real-time detection with environmental sensing. The system uses an ESP32-WROOM microcontroller to wirelessly transmit data to the an IoT platform. Key components include a passive infrared (PIR) sensor for motion-based pest detection, ultrasonic emitters to repel pests, and DHT11 sensors for temperature and humidity monitoring. LED and relay mechanisms were incorporated to attract or deter insects as needed. Real-time pest activity and environmental data are displayed on an LCD screen and sent to the cloud platform. The system showed pest detection within a 0–5 m range using the PIR sensor, with low measurement errors (temperature 4.42%, humidity 6.03%). Its integration with IoT platforms enabled responsive updates with reported delays of 0.54–0.67 s depending on the communication provider, demonstrating the system's potential for low-cost IoT-based pest monitoring, although its validation remains limited to the tested configuration and local field conditions.

An integrated pest monitoring platform has also been developed to manage *Spodoptera frugiperda* populations in maize crops, combining key components of IoT-based sensing and spatial analysis. The system utilizes wireless sensor networks to collect real-time data on pest incidence and environmental conditions, which are then transmitted to a central node for processing and analysis. A notable feature is the integration of geographic information systems (GIS), enabling spatial mapping and geostatistical analysis of infestation patterns. Data visualization interfaces provide farmers with accessible insights into pest dynamics, enabling them to monitor trends and make informed decisions. According to the available abstract, the platform is intended to support monitoring, visualization, and prediction through a base station and internet-accessible devices such as smartphones, tablets, or computers. By unifying data acquisition, processing, and interpretation within a remotely accessible digital framework, the system contributes to the broader goal of precision agriculture through enhanced situational awareness and strategic pest control.⁴⁷

Although many sensor-based systems focus on agricultural pest surveillance, similar technological approaches have also been

explored in the field of public health for vector monitoring. A notable example is the use of infrared photoelectric sensor networks for the remote detection of arthropods, particularly *Triatoma infestans*, the principal vector of Chagas disease. In this application, infrared sensors embedded within traps detect the interruption of a light beam caused by insect movement, allowing for real-time monitoring of both flying and crawling arthropods. The captured data are transmitted to a central server, enabling remote access to information on arthropod presence and trap activity. Although primarily intended for epidemiological surveillance, the system demonstrates the potential transferability of infrared-based sensing and remote data transmission for broader entomological applications.⁴⁸

A multi-sensor approach to pest detection was proposed through the development of an IoT-based system that integrates PIR sensing, ultrasonic repulsion, and image processing techniques. In this configuration, motion is first detected using a PIR sensor, which detects variations in infrared radiation, indicating the presence of insects. Image processing is then used to confirm pest presence by capturing field images and comparing them with reference information. After confirmation by PIR sensing and image processing, an ultrasonic generator emits waves intended to repel insects from the agricultural field. The system therefore combines detection, visual confirmation, and repulsion rather than performing acoustic species classification. The integration of these modalities supports the early detection of infestations and may reduce reliance on pesticide applications, although its effectiveness and selectivity would need to be confirmed under field conditions.⁴⁹

The pest trap developed by Akkas *et al.*⁵⁰ integrates infrared detection, sound analytics, and ultrasonic repulsion to detect and repel pests in agricultural fields. Utilizing a passive infrared (PIR) sensor for real-time pest detection based on body heat, coupled with sound analytics based on 1750 pest recordings using the linear predictive cepstral coefficients (LPCC) algorithm, the system achieves a detection accuracy of 99.65%, with sensitivity and specificity of 99.53% and 98.06%, respectively. On confirming the presence of pests, ultrasonic waves at variable frequencies are emitted to repel them, providing a non-chemical pest-control approach intended to reduce pesticide dependence.

Balla *et al.*⁵¹ developed an optoelectronic monitoring system using an infrared sensor ring (IRSR) to detect arthropods across a wide range of sizes and habitats. The system includes two configurations: IRSR-1 for larger arthropods (2–35 mm) and IRSR-2 for microarthropods (0.1–2 mm), both based on arrays of infrared LEDs and photodiodes arranged semicircular to capture light disturbances caused by passing insects. These rings were integrated into pheromone and soil-monitoring trap systems adapted for flying, crawling, or dual-habitat species. Operating within the ZooLog Sensor System, they connect to data loggers and a cloud-based database for real-time monitoring. Laboratory tests confirmed high sensitivity, with detection thresholds of 0.9 mm (IRSR-1) and 0.5 mm (IRSR-2) for some tested microarthropods; the wider sensor ring reached a 95% detectability level with 0.9 mm particles, while the narrower ring reached 95% detectability at 1.1, 0.9, and 0.5 mm depending on the microarthropod species tested. The system offers an automated approach for real-time arthropod activity monitoring, although its performance depends on arthropod size, shape, transparency, position, and trap configuration.

Sandrini-Moraes *et al.*⁵² developed an optoelectronic sensor system designed to detect and classify fruit flies (*Anastrepha*

fraterculus and *Ceratitis capitata*) based on their wingbeat frequencies using a non-invasive infrared setup. The sensor employs an infrared LED emitter and a phototransistor receiver to capture the partial occlusion of the light beam produced by wing motion. Signal acquisition is performed using a trans-impedance amplifier and analog filters and then digitized via an audio interface. Signal processing is conducted through the classification algorithm based on the energy of the autocorrelation, which combines autocorrelation and fast Fourier transform to extract temporal and spectral features. Using a dataset of wingbeat events recorded under laboratory conditions; the authors estimated mean fundamental frequencies of 113.75 Hz for *A. fraterculus* and 160.81 Hz for *C. capitata*. The system demonstrated the feasibility of real-time, automated insect classification. However, signal degradation at higher frequencies – attributed to the phototransistor's limitations – required the implementation of complementary analytical strategies to enhance accuracy.⁵²

An early prototype of an intelligent insect detection device was developed using the electronic McPhail trap, designed to monitor pests such as *Bactrocera oleae* autonomously.⁵³ Based on the traditional McPhail model, the system integrates an optoelectronic sensor comprising an infrared LED and five phototransistors arranged in a reflective infrared sensor module. Wingbeat activity is captured via partial occlusions of the infrared beam as insects pass through the trap's funnel. The analog signal is band-pass filtered (60 Hz–4 kHz), amplified, and processed by a microcontroller, which performs insect counting. A GSM module enables remote data transmission via SMS. Although the prototype was initially limited to detection, it was designed for future implementation of onboard species classification. This low-cost system marked an early step towards automated, field-oriented pest monitoring in agriculture. The main contributions and reported outcomes of the studies reviewed in this subsection are summarized in Table 2.

Taken together, acoustic, infrared, optoelectronic, and multisensory systems provide complementary approaches for real-time or near-real-time insect detection and monitoring. Their differences in validation level, taxonomic resolution, and operational readiness are examined comparatively in section 4.

3.1.3 Electrostatic and physical methods

Electrostatic and other physical sensing approaches represent non-chemical alternatives for insect detection, capture, or monitoring, particularly in contexts where reducing pesticide dependence is a priority. However, the systems reviewed in this subsection differ substantially in their technological basis and maturity: some focus on physical trapping and insecticidal effects, whereas others explore highly sensitive detection of volatile semi-chemicals as a potential tool for future pest surveillance. Matsuda *et al.*⁵⁴ developed a physical pest control system that uses an electrostatic field to trap and eliminate small flying insects such as houseflies (*Musca domestica*). The device consists of two parallel iron plates: a negatively charged, polyvinyl chloride (PVC)-coated, insulated plate and a grounded, non-insulated plate, which together generate a high-voltage electric field through a Cockcroft circuit powered by a negative voltage generator. As insects enter the electric field, they lose electrons and acquire a net positive charge, causing them to be attracted to the negatively charged insulated plate, where electrostatic confinement and electrical discharge effects ultimately contribute to mortality. This discharge is measured using a galvanometer, which enables the quantification of insect-derived transient electric current

during attraction and confinement. The study provides experimental evidence of the insect-capturing and insecticidal function of the apparatus under controlled conditions, although its practical performance for different pest species and field settings would require context-specific validation.

In a complementary application of physical sensing technologies, cantilever-based nanosensors have been reviewed as potential tools to detect volatile pheromones of *Euschistus heros*, a major agricultural pest. These nanosensors, composed of silicon or silicon nitride and functionalized with materials such as graphene oxide, polyaniline, or metal-oxide nanocomposites, respond to trace amounts of pheromones by altering their vibrational frequency or mechanical deflection, thereby generating an electrical signal for volatile-compound detection. The reviewed literature indicates that cantilever-based gas nanosensors can reach very low detection limits, from the femtogram to zeptogram range depending on the sensitive layer and target compound; nevertheless, their transfer from laboratory sensing platforms to robust portable field systems remains an important challenge.⁵⁵ An overview of the reviewed approaches and their reported performance is provided in Table 3.

Together, these studies illustrate distinct physical approaches ranging from electrostatic capture to highly sensitive pheromone detection. Their technological maturity and potential for field deployment are comparatively assessed in section 4.

3.1.4 Machine learning and neural network integration methods

The integration of machine learning and deep neural network architectures into pest monitoring systems has enabled important advances in automated image analysis, particularly for insect detection, classification, and counting tasks. These approaches can extract complex visual patterns from trap images, laboratory samples, and controlled imaging settings, although their performance depends strongly on dataset quality, annotation strategy, target species resolution, and validation conditions. CNNs have been widely applied to object detection and density estimation tasks, supporting automated or near-real-time analysis of trap images, Petri dish samples, and video frames. Recent developments include end-to-end detection frameworks and domain-specific architectures designed to address occlusion, scale variation, and partial visibility. The following studies illustrate how these techniques are being applied to insect detection, counting, and quality-assurance workflows across agricultural and entomological domains, while also highlighting differences between general object-detection frameworks and pest-specific models validated on specialized datasets.

The single-shot multibox detector (SSD) framework introduced by Liu *et al.*⁵⁶ marked a significant advancement in real-time object detection by achieving a balance between speed and accuracy through a single forward pass of a CNN. The SSD leverages multiscale feature maps to detect objects at various resolutions, utilizing default (anchor) boxes with different aspect ratios and scales, and applies convolutional filters to predict bounding boxes and class probabilities simultaneously. Built on a pre-trained VGG-16 architecture⁵⁷ and implemented in the Caffe deep-learning framework,⁵⁸ the model achieves high performance: 74.3% mean average precision (mAP) on the PASCAL VOC2007 benchmark⁵⁹ and 59 frames per second (FPS) on a Titan X GPU with 300 × 300 input resolution. Although SSD is a general-purpose object detector rather than a pest-specific monitoring system,

Table 2. Summary of reviewed studies on acoustic, infrared, optoelectronic, and multisensory systems for insect detection, counting, and monitoring

Author	Trap/study	Methodology/technique	Reported metric/value	Validation level
Wang <i>et al.</i> ³⁵	Optical scattering/shadowing	Wingbeat frequency analysis and shadow characteristics	Sex discrimination based on wingbeat frequency; species discrimination limited by frequency overlap between species of the same sex	Laboratory/dataset benchmark
Goldshtein <i>et al.</i> ³⁶	Automatic monitoring trap for fruit flies	Sensor-based automatic monitoring using infrared sensors	Counting accuracy 88–100%; trapping efficiency comparable to Steiner traps	Field validation
Telaumbanua <i>et al.</i> ⁴⁰	Automatic pest trap using yellow LED as bait	Infrared sensor-based detection, yellow LED light attraction, and automated fan-assisted trapping	Capture efficiency 80.87%; average capture time 130 s in a 6-day field test	Field validation
Vasconcelos <i>et al.</i> ⁴¹	Bio-acoustic IoT for mosquitoes	Species classification through wingbeat frequency	Field test: 13 mosquitoes estimated by the acoustic sensor vs eight captured in reference traps; species classification not achieved under field conditions	Field validation
Hermosilla <i>et al.</i> ⁴²	Wireless acoustic detection sensor for <i>Lobesia botrana</i> moth	Developed an acoustic sensor to detect the wingbeat sounds of <i>Lobesia botrana</i> moths	Acoustic detections consistent with the flying period of <i>L. botrana</i> and in agreement with traditional field traps	Field validation
Potamitis and Rigakis ⁴³	Optoacoustic sensor-based insect wingbeat recording system	Laser- or infrared-emitter system with a photodiode array and high-frequency modulation/demodulation for noise-robust wingbeat recording	Optical recordings closely matched simultaneous microphone recordings Mean log-spectral distances were 1.33 for the laser sensor and 1.21 for the infrared sensor; wingbeat fundamentals and harmonics were resolved for fruit flies, mosquitoes, bees, and insects as small as 2.5 mm	Laboratory/dataset benchmark
Genoud <i>et al.</i> ⁴⁴	Entomological stand-off optical sensor	Measured wingbeat frequency and optical cross-section ratios for insect clustering and aerial density estimation	Approximately 60 000 insect transits recorded over 80 days; entomological stand-off optical sensor-derived mosquito aerial density agreed with CDC light-trap counts	Field validation
Puntonet <i>et al.</i> ^{45†}	Acoustic-based monitoring system	Wavelet-based acoustic filtering for insect detection	Denoising successful up to a signal-to-noise ratio of −30 dB for termite alarm-signal recognition	Laboratory/dataset benchmark
Santoso <i>et al.</i> ⁴⁶	IoT-based insect pest monitoring system	Integrated microcontroller, PIR sensors, ultrasonic sensors, and pest sting modules	Average sensor-reading accuracy 95%; PIR detection range 0–5 m; temperature and humidity errors 4.42% and 6.03%	Field validation
López <i>et al.</i> ⁴⁷	Electronic trap network for fall armyworm detection and mapping	Camera-equipped electronic traps connected through a wireless sensor network, with image processing for insect detection and counting and spatial mapping of infestation data	Field prototype successfully captured, processed, and counted <i>Spodoptera frugiperda</i> in trap images and transmitted the data for remote monitoring; no quantitative detection or counting accuracy was reported, and the authors identified ground-truth validation as future work	Field validation

Table 2. Continued

Author	Trap/study	Methodology/technique	Reported metric/value	Validation level
Gaona <i>et al.</i> ⁴⁸	Infrared-photoelectric sensor network	Pheromone-baited traps equipped with infrared photoelectric sensors, wireless RF communication, and Internet-based remote monitoring	More than 750 intrusion events were recorded over 9 months across 20 dwellings; the system operated robustly under arid field conditions and detections showed a strong association with <i>Triatoma infestans</i> or other triatomine activity	Field validation
Saranya <i>et al.</i> ⁴⁹	IoT-based pest-repelling system	Infrared motion detection, image processing, and ultrasonic pest-repellent	Reported accuracy 87% in the tested pastureland setting; this refers to the proposed detection/repelling system, not to species-level classification accuracy	Field validation
Akkas <i>et al.</i> ⁵⁰	AI-enabled pest detection and ultrasonic repulsion system	PID infrared sensing combined with LPCC-based sound analytics from 1750 pest recordings and DenseNet classification	Accuracy 99.65%; sensitivity 99.53%; specificity 98.06%; F1 score 98.87%	Laboratory/dataset benchmark
Balla <i>et al.</i> ⁵¹	Infrared optoelectronic sensor ring for arthropod detection	Infrared photodiodes for motion detection in a light gate setup	The wider sensor ring reached 95% detectability for 0.9-mm particles and detected 95–100% of the tested macroarthropods ≥ 1.4 mm The narrower ring reached 95% detectability at 1.1, 0.9 and 0.5 mm for <i>F. candida</i> , <i>H. nitidus</i> , and <i>H. aculeifer</i> , respectively	Laboratory
Sandrini - Moraes <i>et al.</i> ⁵²	Infrared optoelectronic sensor for real-time fruit fly classification	Infrared light occlusion and signal processing for species classification	Mean fundamental frequencies estimated at 113.75 Hz for <i>A. fraterculus</i> and 160.81 Hz for <i>C. capitata</i> ; classification performance to be specified if required	Laboratory/dataset benchmark
Potamitis <i>et al.</i> ⁵³	Optoelectronic sensor-embedded McPhail trap	Infrared light occlusion and wingbeat frequency detection	High-quality wingbeat recordings; hardware-focused prototype for insect detection/counting and future onboard classification	Laboratory validation

Values correspond to the metrics or outcomes reported in the original studies and should not be interpreted as directly comparable across systems because the reviewed studies differ in sensing modality, target species, validation setting, environmental conditions, experimental duration, performance metrics, and technological maturity. CDC, Centers for Disease Control and Prevention; IoT, Internet of Things; LED, light-emitting diode; LPCC, linear predictive cepstral coefficients; PIR, passive infrared; RF, radio frequency.

its single-stage design, use of multiscale feature maps, and speed–accuracy trade-off have made it relevant as a methodological basis for automated insect detection pipelines. SSD also incorporates techniques such as hard negative mining and aggressive data augmentation, which were used to improve training stability and robustness to variation in object size and appearance.

Lee and Son⁶⁰ proposed Mada-CenterNet, a multiscale and deformable attention architecture tailored for pest counting in light trap images. The model combines object detection and density estimation by integrating low- and high-resolution heatmaps, deformable convolutions, and skip connections between hourglass modules. These architectural enhancements address challenges such as occlusion, scale variation, and diversity in insect poses in trap-based imagery. Evaluated using mAP and

customized counting metrics, Mada-CenterNet outperforms conventional detectors and crowd-counting models in the trap-image datasets evaluated in the study. The system is implemented in PyTorch,⁶¹ with publicly available code supporting reproducibility and future adaptation to related trap-based pest-counting tasks.

In the context of the sterile insect technique (SIT), Ovadia *et al.*⁶² developed a CNN based on the InceptionV3⁶³ architecture to perform patch-based image analysis of *Aedes aegypti* mosquitoes. The model enables automated mosquito counting and female detection from Petri dish images using fractional counting techniques to account for partial insect visibility. The system achieves specificity values above 90% at 95% sensitivity in the reported female-detection experiments, with counting performance

Table 3. Comparative overview of electrostatic trapping and physical sensing approaches for insect detection and monitoring

Author	Trap/study	Methodology/technique	Reported metric/value	Validation level
Matsuda <i>et al.</i> ⁵⁴	Electrostatic field trap	High-voltage electric field via a Cockcroft circuit	100% capture achieved within specific voltage ranges; insect-derived transient current increased with applied voltage and was associated with confinement and mortality under controlled conditions	Laboratory
Martinazzo <i>et al.</i> ⁵⁵	Nanosensors for detecting pheromones	Review of gas nanosensors and cantilever-based sensing platforms for detecting insect pheromones, particularly volatile compounds associated with <i>Euschistus heros</i>	Detection limits reported in the reviewed literature range from femtogram to zeptogram levels depending on the sensitive layer and target compound; field-ready performance not established	Not applicable, review article

Note: Values correspond to the metrics or outcomes reported in the original studies and should not be interpreted as directly comparable across systems because the reviewed studies differ in sensing modality, target species or compounds, validation setting, experimental conditions, and technological maturity.

depending on patch size and interpolation strategy, which is critical for quality assurance in SIT programs. By reducing manual inspection and improving operational scalability, this approach could support quality-assurance workflows in mosquito SIT programs, while still relying on human technician review of detected female candidates. Table 4 provides a comparative summary of the methodologies discussed above.

Collectively, machine-learning and neural-network approaches provide versatile tools for insect detection, counting, and classification across different application contexts. Their performance should be interpreted according to the specific task, dataset, and validation setting, as discussed further in section 4.

3.1.5 Ecological and non-lethal approaches

The pursuit of ethically responsible and environmentally sustainable insect monitoring has led to the advancement of non-lethal methodologies capable of generating high-resolution data without compromising specimen viability. These approaches integrate optical, photonic, and statistical techniques to enable automated detection, behavioural assessment, and population estimation under minimally invasive conditions. Technologies employing image acquisition, infrared sensing, laser speckle contrast imaging, and photonic backscatter analysis have demonstrated potential to complement conventional catch-based systems, particularly when high temporal resolution, reduced manual effort, or reduced specimen mortality are priorities. The following studies exemplify how these methods contribute to entomological research, pest surveillance, and biodiversity assessment, offering various levels of ecological applicability, ranging from non-lethal abundance monitoring and photonic biodiversity proxies to physiological imaging and statistical interpretation of trap catches.

Möglich *et al.*⁶⁴ evaluated the performance of an automated moth trap (AMT) as a non-lethal alternative to conventional light traps for monitoring moth abundance. The AMT was built using consumer-grade components and included a low-power ultraviolet (UV) LED light source, a white LED-illuminated resting screen, and an automated camera system for image acquisition and data transfer. In contrast, the conventional trap utilized a UV light

source and a chloroform killing jar. Field deployment across 16 plots revealed that, although the AMT recorded fewer individuals overall, both trap types captured similar seasonal abundance trends, with an approximate 3% decline per day. These results suggest that the AMT can capture large seasonal abundance patterns in a non-lethal way, although the authors also identified limitations related to image quality, power supply, and data transfer that must be addressed before long-term deployment.

Building on the development of autonomous insect monitoring systems, the ZooLog VARL trap integrates pheromone-based attraction with real-time sensing technology to monitor moth populations. The system is based on a pheromone-baited funnel trap with a funnel structure to prevent insect escape, along with sex pheromone lures to attract male moths. A black infrared sensor ring⁵¹ detects insect passage while minimizing environmental interference. To avoid double counting, a blow-off system transfers captured insects into a light-insulated sample container. Powered by solar energy, the system transmits daily detection data to a web interface, allowing for remote and uninterrupted monitoring. This approach supports remote pest surveillance by combining pheromone attraction, infrared detection, and automated data transmission; however, the study also indicates that further evaluation of trapping efficiency is needed under field conditions.⁶⁵

To support scalable and non-invasive biodiversity assessments, Rydmer *et al.*⁶⁶ evaluated a photonic monitoring system based on a commercial photonic sensor that emits modulated near-infrared light (810 and 970 nm) and records insect backscatter signals using a quadrant photodetector. Operating within a measurement volume of approximately 70 liters, the system captures wingbeat frequency and body-to-wing ratios of insects in flight, transmitting the data to a cloud platform via 4G for classification. A proprietary neural network filters out non-insect signals before clustering algorithms (Density-Based Spatial Clustering of Applications with Noise (DBSCAN)⁶⁷ and hierarchical cluster analysis (HCA)⁶⁸) are applied to estimate species richness. Field validation across five sites demonstrated that richness estimates derived from photonic clustering were consistent with variation observed in concurrent Malaise trap samples, which served as a

Table 4. Summary of machine learning and neural network applications in automated insect detection, counting, and classification

Author	Trap/study	Methodology/technique	Reported metric/value	Validation level
Liu <i>et al.</i> ⁵⁶	Single shot multibox detector	Single-stage object detection using default boxes and multiscale feature maps; general-purpose detector used as a methodological basis for insect-detection pipelines	74.3% mAP on PASCAL VOC2007 and 59 FPS with 300 × 300 input on Titan X GPU	Laboratory/dataset benchmark
Lee and Son ⁶⁰	Mada-CenterNet for trap-based pest counting	Two-stage multiscale heatmap generation with internal low- and high-resolution joint feature learning, deformable convolution, and multiscale attention for light-trap images	The proposed model achieved an MAE of 3.92 and an RMSE of 5.63 on the KLPest dataset, outperforming the evaluated object-detection and crowd-counting baselines	Laboratory/dataset benchmark
Ovadia <i>et al.</i> ⁶²	Patch-based CNN	Patch-based InceptionV3 CNN for mosquito counting and female detection in Petri dish images	Specificity of 93.61–94.67% at 95% sensitivity in the context-region experiments; counting RMSE improved from 22 without context to 14 with context and 12 with context plus a focus-region mask In the hyperparameter experiments, counting RMSE ranged from 1.7 to 15.4 for valid configurations	Laboratory/dataset benchmark

CNN, convolutional neural network; FPS, frames per second; GPU, graphics processing unit; MAE, mean absolute error; mAP, mean average precision; RMSE, root mean squared error.

morphological baseline. Despite some divergence in absolute counts, the photonic system showed potential as a non-destructive approach for estimating variation in insect abundance and diversity, although species-level taxonomic resolution and absolute abundance estimation remain challenging.⁶⁶

Yordanov *et al.*⁶⁹ adapted laser speckle contrast imaging (LSCI), a technique originally developed for biomedical applications, to monitor biomechanical activity in live aphids through non-invasive optical imaging. Their customized setup includes coherent laser illumination, optical components, and a camera-based imaging system to capture speckle patterns generated by internal movements within the aphid body. These patterns arise from coherent light scattered by dynamic elements, such as muscle fibres or flowing haemolymph. They are processed using spatial laser speckle contrast analysis (LASCA) algorithms⁷⁰ to produce temporal activity maps. The system enabled visualization of muscle contractions, rhythmic pulses, and potential fluid transport during feeding, all without physical contact or behavioural disturbance. The study demonstrated LSCI's capacity to provide contactless optical mapping of biomechanical activity in aphids, although its application is currently more directly aligned with physiological and behavioural research than with operational pest population monitoring.

Onufrieva and Onufrieva⁷¹ introduced a statistical model for estimating insect population density using single trap catch data, leveraging probabilistic relationships between catch rates and trap proximity. Validated across diverse datasets and species, the method achieves a reported correlation of $R = 0.91$ across the evaluated datasets and provides confidence intervals for population estimates. This approach does not constitute a non-lethal monitoring technology itself, but it provides a quantitative

framework for interpreting trap catches and estimating absolute population density with statistical bounds. Its applicability depends on the assumptions of the trapping model, trap type, and availability of suitable calibration data. Table 5 summarizes the main contributions and outcomes of the reviewed studies.

From an ecological perspective, non-lethal approaches extend automated monitoring toward abundance, biodiversity, and behavioural assessment while reducing specimen mortality. Their complementary roles and differences in operational applicability are discussed in section 4.

3.1.6 Other methods

In addition to mainstream optical and acoustic systems, recent research has explored a diverse set of approaches for insect detection, monitoring, and classification. These methods incorporate emerging technologies, including embedded AI devices, organic electronics, gas sensing, radar imaging, and biosensing platforms. Spanning edge image processing, volatile-compound detection, pheromone-receptor biosensing and radar-based observation, these approaches illustrate the technological diversity of automated insect monitoring but differ substantially in purpose, maturity, and validation setting. The studies reviewed in this section demonstrate the breadth of technological experimentation applied to entomological surveillance, while also highlighting the need to distinguish between operational systems, early-stage prototypes and methods originally developed for atmospheric or ecological research.

An autonomous insect counting system was developed using an embedded camera-based microcontroller platform for local image acquisition and insect counting in sticky traps. The device integrates a deep-learning model implemented onboard,

employing a MobileNetV2 CNN trained on pest-specific features, particularly for the detection of *Cydia pomonella*. The detection pipeline incorporates a sliding window method for image segmentation, followed by clustering and post-processing using non-maximum suppression (NMS) and soft-NMS to reduce overlapping detections. Data augmentation strategies were employed to address the limited availability of training images and reduce false detections. Designed for deployment in isolated environments, the system captures daily images of sticky traps, processes detections locally, and stores the results without requiring external power or continuous network connectivity. Field validation demonstrated the feasibility of embedded trap-image processing for insect counting, although performance depends on image quality, trap conditions, and the availability of representative training data.⁷²

Petrauskas *et al.*⁷³ introduced a feasibility study on the potential use of organic electronics for insect sensing and selective physical pest control. The proposed reusable, low-cost trap integrates organic field-effect transistors to deliver precise electrical discharges for pest inactivation, electrical impedance sensors to identify insect presence and species based on dielectric properties, polymer piezoelectric transducers to analyse vibrations from

insect movement, and flexible organic light-emitting diode (OLEDs) and UV LEDs for species-specific light attraction. Additionally, pheromone and volatile organic compound dispensers enhance species targeting, while solar panels and rechargeable batteries provide sustainable energy. Although the study provides experimental evidence supporting the compatibility of organic electronic components with insect sensing and inactivation, the complete trap remains a conceptual system requiring further integration, selectivity testing, and field validation before it can be considered an operational replacement for chemical insecticides.

An autonomous pheromone-receptor-based biosensing platform was developed using a capacitive micromachined ultrasonic transducer structure incorporating a boron-doped diamond (BDD) membrane. The membrane was fabricated via microwave plasma-assisted chemical vapor deposition using a diamond growth process, producing a high-frequency resonator with a Young's modulus exceeding 1000 GPa. Pheromone receptors were immobilized on the BDD surface through a nitrilotriacetic acid linker, enabling site-specific coordination to histidine-tagged proteins via Ni²⁺ chelation. Binding events between volatile insect pheromones and receptor proteins induce measurable shifts in the resonance frequency of

Table 5. Summary of ecological, non-lethal, and quantitative approaches for insect monitoring and population assessment

Author	Trap/study	Methodology/technique	Reported metric/value	Validation level
Möglich <i>et al.</i> ⁶⁴	Comparison of two trap systems	Automated non-lethal moth trap based on image capture from an illuminated resting surface, compared with a conventional lethal light trap	AMTs recorded fewer individuals than conventional traps, but both trap types showed a similar seasonal abundance decline of approximately 3% per day	Field validation
Flórián <i>et al.</i> ⁶⁵	Automated funnel trap	Pheromone-baited funnel trap with infrared sensor ring, blow-off mechanism to reduce multiple counting, and automated data transmission	Average detection accuracy ranged from 84% to 92% across six moth species; ANN filtering accuracy was >60% and reached 90% for larger-bodied species	Field validation
Rydhmer <i>et al.</i> ⁶⁶	Photonic sensor for non-destructive insect biodiversity monitoring	Near-infrared backscatter sensing of flying insects, followed by signal filtering and clustering to estimate richness proxies	84 770 reference recordings from 42 known species and 238 584 field recordings; photonic cluster richness reflected variation in Malaise-trap family richness, but species-level identification and absolute abundance estimation remain limited	Field validation
Yordanov <i>et al.</i> ⁶⁹	Non-invasive optical technique	Laser speckle contrast imaging for contactless monitoring of biomechanical activity in live aphids	No classification accuracy reported; LSCI enabled optical mapping of activity patterns related to feeding, muscle contractions, haemolymph movement or stylet flow under experimental conditions	Laboratory
Onufrieva and Onufrieva ⁷¹	Density estimation model	Probabilistic trap-catch modelling	Reported relationship between catch probability and distance described 10 trapping datasets with $R = 0.91$; model estimates absolute population density and statistical bounds from trap catches	Laboratory/dataset benchmark

AMT, Automated Moth Trap; ANN, artificial neural network; LSCI, laser speckle contrast imaging.

the membrane, allowing label-free pheromone-receptor-based sensing in principle. The system demonstrates a promising biosensing concept for early pest detection; however, the reported work represents an early-stage development in which receptor production and testing were still ongoing.⁷⁴

The pest detection system developed by Sheema *et al.*⁷⁵ combines multiple sensing modalities and deep-learning algorithms to explore IoT-based detection of pest infestation, particularly targeting *Spodoptera frugiperda* in maize crops. Central to the system is an odour-based detection module that utilizes gas sensors to identify volatile compounds emitted by pests, such as ammonia, methyl acetate and formic acid, which serve as olfactory indicators of infestation. This is complemented by an image-based pest analysis using deep learning methods. Image data are analysed using a combination of Faster R-CNN²⁵ and a custom-developed algorithm, the Speckle Warner Feature Region Network, designed to enhance classification accuracy and reduce false detections. The model leverages CNNs and region proposal mechanisms for feature extraction and object localization. IoT connectivity enables continuous monitoring and remote access to pest data, although the reported validation and sensor-specific performance should be interpreted cautiously because the study provides limited detail on field-scale deployment, dataset structure, and external validation.⁷⁵

A radar-based method for distinguishing insect echoes from hydrometeor signals has been developed using a Ka-band (35 GHz) vertically pointing polarimetric Doppler radar. The system, integrated into an atmospheric observation network, employs two spectral analysis algorithms: one based on Doppler velocity spectrum texture and another on the linear depolarization ratio. These techniques enable the classification of radar targets by exploiting the asymmetric scattering characteristics of insects compared to hydrometeors. The radar records co-polarized and cross-polarized signals, enabling precise spectral discrimination. This technique filters insect clutter from atmospheric observations, improving cloud microphysical retrievals and demonstrating that atmospheric radar datasets may contain useful insect-related information, although the method was primarily developed for atmospheric classification rather than pest monitoring.⁷⁶

The vertical-beam entomological radar is a non-invasive system designed for long-term monitoring of insect biodiversity using X-band (9.4 GHz) radar. The upgraded insect monitoring radar (IMRU), installed in Hay, New South Wales, Australia, operates continuously and autonomously to detect insects larger than 10 mg across altitudes from 150 to 2550 m. By analysing radar cross-sections, wingbeat frequency, and polarization patterns, the system estimates insect abundance, biomass, and biodiversity indices, such as Shannon–Wiener and Simpson metrics.^{77,78} Although species-level resolution is not achievable because of wavelength limitations, the radar provides ecologically meaningful data on population dynamics and their correlation with climatic events. The IMRU represents a potentially valuable component of long-term insect monitoring, particularly for larger flying insects and biomass estimation, but its taxonomic resolution and altitude-specific sampling constraints limit its use as a stand-alone biodiversity assessment method.⁷⁹ Table 6 presents a structured summary of the systems and methods reviewed.

In summary, these alternative methods illustrate the growing diversification of automated insect monitoring beyond conventional optical, acoustic, and trap-based systems. Their differing levels of technological maturity and transferability to operational pest management are synthesized in section 4.

3.2 Computational strategies for data processing during insect counting and identification

The development of automated insect monitoring has increased the need for computational strategies capable of processing image, sensor, and trap-derived data for insect counting and identification. These systems increasingly rely on computational strategies to process the large and heterogeneous datasets generated during insect counting and identification. This section reviews the diverse computational approaches currently employed in this field, highlighting their methodologies, strengths, and limitations in extracting meaningful information from sensor data, contributing to more timely pest surveillance, biodiversity monitoring, and decision-support workflows.

3.2.1 YOLO techniques

One of the most prominent approaches is the YOLO (You Only Look Once) architecture, which is illustrated in Fig. 2.

Redmon *et al.*⁸⁰ introduced YOLO, a single-stage framework for real-time object detection that reformulates detection as a single regression problem. The model employs a unified architecture comprising 24 convolutional layers and two fully connected layers, simultaneously predicting bounding boxes and class probabilities for entire images. It achieves real-time performance, processing images at 45 frames per second on an NVIDIA Titan X GPU. Key advantages of YOLO include its speed and efficiency, end-to-end training without complex pipelines, use of full-image contextual information, and reported generalization across diverse datasets, including unconventional domains such as artwork. However, the original YOLO model also presents limitations, particularly lower localization accuracy and reduced performance for small objects compared with some two-stage detectors, which is relevant when adapting YOLO-based approaches to insect images.⁸⁰

Thanh-Nghi⁸¹ explored the application of deep-learning models from the YOLO family,^{82,83} including YOLOv3, YOLOv4, YOLOv5, and YOLOX for large-scale insect pest detection, classification, and counting. These models, optimized for real-time applications, were fine-tuned through transfer learning on two datasets, Insect10 (2335 images of 10 species) and IP102⁸⁴ (75 222 images of 102 species), utilizing techniques such as data augmentation (rotation, flipping, and color adjustments) to enhance robustness. YOLOX-S achieved the best performance on Insect10 (mAP 84.84%), while YOLOX-M excelled on IP102 (mAP 54.19%). These results indicate that YOLO-based models can be adapted to insect pest datasets, but they also show that performance is strongly dataset-dependent, decreasing in the larger and more taxonomically diverse IP102 dataset, therefore the results should be interpreted as evidence of methodological potential rather than direct proof of field-ready pest monitoring performance.⁸¹

Expanding the capabilities of YOLO-based detection, Amrani *et al.*⁸⁵ proposed an enhanced YOLOv3 model incorporating an adaptive feature fusion (AFF) convolutional module⁸⁶ to improve insect detection, identification, and counting in complex visual conditions. The model leverages the Darknet-53 backbone⁸³ for multiscale feature extraction and integrates AFF to resize and fuse features across scales, with the aim of improving the detection of small insect targets. The network was trained on the Pest24 dataset, comprising 25 878 annotated images of 24 insect species, using data augmentation techniques such as random cropping, horizontal flipping, and resizing. The proposed model achieved a mAP of 72.10% and an inference speed of 63.8 frames per

second, outperforming established detectors such as SSD, Retina-Net, and Faster-RCNN. The study is particularly relevant because Pest24 includes small objects, non-target insects, class imbalance, dense distributions, occlusion and illumination-related artefacts; nevertheless, the reported performance remains specific to this dataset and evaluation protocol.⁸⁵

Extending the use of YOLO architectures to ecological monitoring, a recent study presents a large-scale, real-time insect identification system designed to address the global decline in biodiversity. The model, developed by Venverloo and Duarte,⁸⁷ is based on YOLOv8 and trained on a dataset of 1.93 million images representing 2584 insect species, sourced primarily from web-scraped images and the Global Biodiversity Information Facility (GBIF). The system achieved an 82.3% accuracy, demonstrating the potential of YOLOv8 for large-scale insect species identification. To assess the model's robustness, the authors conducted an in-depth analysis of long-tailed class distributions, highlighting performance drops on rare species and proposing solutions such as reweighting during training. Additionally, they developed an open-source tool to facilitate regional customization of YOLOv8-based insect detection systems using local species lists and GBIF images, promoting scalability and accessibility for biodiversity monitoring applications. Although this study is oriented towards broad insect biodiversity monitoring rather than agricultural pest control, its large-scale YOLOv8 framework is relevant to pest detection because it illustrates how regional species lists and large image repositories can be used to customize insect-identification models. However, performance remains dependent on image availability per species and may decrease for underrepresented taxa.⁸⁷

Building on the evolution of YOLO-based detectors, recent advances have focused on enhancing their performance in complex agricultural settings, particularly for detecting small objects, such as pests. In this context, Xiang *et al.*⁸⁸ proposed *Yolo-Pest*, a lightweight and specialized detection algorithm designed to address key challenges agricultural pest image detection, including limited training samples, model complexity, and environmental interference. *Yolo-Pest* builds on the YOLOv5s architecture by incorporating the CAC3 module (Convolution Attention C3) to improve feature extraction for small objects, a CSPDarknet53-based backbone enhanced with ConvNeXt blocks⁸⁹ and squeeze-and-excitation (SE) attention mechanisms⁹⁰ for efficient multiscale feature fusion, and multiple detection heads to manage scale variation. The model also leverages targeted data augmentation strategies, such as random background enhancement and copy-paste techniques, to mitigate class imbalance. Evaluated on the Teddy Cup pest dataset, *Yolo-Pest* achieved a mAP_{0.5} of 91.9%, outperforming YOLOv5s by 8%, and showing improved performance for small-target pest detection within the evaluated dataset. However, its operational performance in field-deployed monitoring systems would still require validation under different crops, imaging devices, and environmental conditions.

Complementing efforts focused on agricultural pest detection, other studies have explored broader ecological contexts, highlighting the transferability of deep-learning approaches in natural environments. Bjerger *et al.*⁹¹ developed an image-based insect monitoring system that utilizes time-lapse cameras and deep-learning models to detect, count, and classify insects on green roofs with *Sedum* plants. The dataset comprised over 2 million high-resolution images, manually annotated and supplemented with citizen science contributions, focusing on nine

dominant species. YOLO deep-learning models, including YOLOv3 and YOLOv5, were trained in object detection, achieving an average precision of 92.7% and recall of 93.8% in detection and classification across species. Temporal analysis revealed seasonal variations in insect activity, highlighting the system's potential for ecological applications, with future improvements suggested for broader environmental contexts and refined classification techniques. Although the study is not focused specifically on agricultural pest control, it is relevant to pest detection because it demonstrates the feasibility of YOLO-based detection of small insects in complex vegetated backgrounds, a common challenge in field monitoring.

Further optimizations of the YOLO architecture have focused on achieving a better balance between accuracy, inference speed, and computational efficiency, particularly in crop-specific pest detection tasks. Yang *et al.*⁹² developed Maize-YOLO, an improved YOLOv7 algorithm specifically designed for detecting pests in maize crops. By integrating CSPResNeXt-50⁹³ and VoVGSCSP modules⁹⁴ into the architecture, the model enhances feature extraction and reduces computational complexity without compromising accuracy. Maize-YOLO was tested on the IP102 dataset (IP13),^{84,92} which includes 4533 images across 13 common maize pest species. Maize-YOLO achieved a mAP of 76.3% and a recall of 77.3% while reaching an inference speed of 67 FPS. These results indicate a favourable accuracy-speed trade-off for maize pest detection on the selected IP102 subset, although the findings remain tied to the dataset composition, selected pest classes, and evaluation protocol.

In parallel to advances in convolutional architectures, hybrid systems that combine deep-learning and traditional machine-learning methods have also been investigated in edge computing scenarios within smart agriculture. Zhong *et al.*⁹⁵ introduced a vision-based system for intelligent agriculture capable of detecting, counting, and identifying flying insects using a combination of YOLO for coarse detection and support vector machines (SVMs) for fine-grained classification. The system treats all flying insects as a single class for initial detection, thereby improving detection simplicity in noisy outdoor environments and reducing the need for species-specific annotations. Subsequent classification into six species—including bees, flies, mosquitoes, moths, chafers, and fruit flies—is performed using an SVM trained on global (shape, texture, and color) and local histogram of oriented gradients features. The model was trained on over 10 000 images and implemented on a low-cost embedded computing platform, allowing for edge processing and integration into an agricultural monitoring platform. Compared with traditional methods like connected components labelling, the system achieved higher detection accuracy (YOLO 93.71%, connected components labelling (CCL) 87.63%) and classification accuracy (SVM 90.34%). These results support the feasibility of combining YOLO-based detection with classical classifiers for embedded insect monitoring, although performance should be interpreted in relation to the selected six insect categories and the imaging conditions used in the study.⁹⁵

As the YOLO framework continues to evolve, recent approaches have focused on modular refinements to enhance its adaptability to the complexities of large-scale pest image detection, particularly in scenarios involving class imbalance and fine-grained species differentiation. Wei *et al.*⁹⁶ presented AEC-YOLOv8n, an enhanced YOLOv8n deep-learning model specifically designed for efficient multi-pest detection. This model incorporates several advanced modules, including EMSFEM (Efficient Multiscale

Table 6. Summary of alternative and emerging methods for automated insect detection, sensing, and monitoring

Author	Trap/study	Methodology/technique	Reported metric/value	Validation level
Sütő ⁷²	Embedded sticky-trap insect-counting system	Embedded camera-based trap with MobileNetV2-based moth classifier, selective search for object proposals, and NMS/soft-NMS for reducing overlapping detections	Selective-search object proposal accuracy of 82% on the test set; lowest reported soft-NMS counting loss was 0.164 Performance depends on the difference between training images and field trap images	Laboratory/ dataset benchmark
Petrauskas <i>et al.</i> ⁷³	Organic-electronics-based pest sensing and inactivation concept	Feasibility study combining impedance sensing, piezoelectric transducers, and organic electronic components for insect detection, characterization, and potential selective inactivation	No single field-performance accuracy reported; impedance was measured across 14 insect species, and most insect integuments showed breakdown voltages below 200 V	Laboratory/ dataset benchmark
Zaki <i>et al.</i> ⁷⁴	Pheromone-receptor-based biosensor	Diamond-based capacitive micromachined ultrasonic transducer gravimetric resonator functionalized for pheromone-receptor immobilization and label-free sensing	No detection accuracy reported; receptor immobilization protocol was optimized, the suspended diamond membrane showed resonance frequencies of 125–160 kHz in water, and PR detection measurements were still in progress	Laboratory/ dataset benchmark
Sheema <i>et al.</i> ⁷⁵	Odor-based detection system	IoT-based pest detection combining odour/gas-sensor analysis with image-based deep learning, including Faster R-CNN and SWFRN	Reported mAP values: SSD 78.09, faster R-CNN 95.02, R-FCN 85.50, and SWFRN 96.98 on the dataset used in the study; external field validation remains limited	Laboratory/ dataset benchmark
Williams <i>et al.</i> ⁷⁶	Polarimetric Doppler radar	Ka-band vertically pointing polarimetric Doppler radar using CoPol spectral texture and linear depolarization ratio-based algorithms to distinguish insects from hydrometeors	Over 70% of hydrometeor-mask column bottoms were within ± 100 m of simultaneous ceilometer cloud-base heights; the method was designed to remove insect clutter from atmospheric radar observations	Field validation
Drake <i>et al.</i> ⁷⁹	Vertical-beam entomological radar	Vertical-beam entomological radar for detecting larger flying insects and estimating numbers, size, mass, biomass, and diversity indices from radar observations	Detects individual insects larger than 10 mg at 150–2550 m altitude; provides count, biomass, and Simpson/Shannon–Wiener index estimates, but not species-level biodiversity measures	Field validation

IoT, Internet of Things; mAP, mean average precision; NMS, non-maximum suppression; PR, pheromone receptor; R-CNN, region-based convolutional neural network; R-FCN, region-based fully convolutional network; SSD, Single Shot MultiBox Detector; SWFRN, Speckle Warner Feature Region Network.

Feature Extraction Module), which uses asymmetric convolutions and variable dilation rates to enhance multiscale feature extraction, AFEM_SIE (Add Feature Enhancement Module for Spatial Information Exchange) for improved spatial information exchange through self-attention and channel attention mechanisms, Concat_Weighting feature fusion strategy that applies learned weights for more effective integration of feature maps, and SPPELAN (Series Pooling Pyramid Enhanced Local Attention Network), a pooling-enhanced module that replaces the standard SPPF in YOLOv8n with multiple pooling operations of varied kernel sizes to better capture pest features across scales. Utilizing the challenging IP102 dataset,⁸⁴ which features imbalanced classes and high intra-class variability, AEC-YOLOv8n achieves

reported improvements in detection accuracy (+6.8%) and recall (+6.3%), outperforming the standard YOLOv8n with higher mAP50 and mAP50-100 metrics. These findings suggest that feature enhancement and weighted fusion modules can improve YOLOv8n performance on large-scale pest datasets, although external validation across independent field datasets would be needed to confirm generalizability.

Kathhole *et al.*⁹⁷ introduced an IoT-based pest detection system designed for agricultural fields, utilizing the YOLOv3 algorithm for identifying pests in real-time images captured by IoT devices. For classification, they employ a convolution neural long short-term memory (CNLSTM) network, which is optimized using the adaptive honey badger algorithm (AHBA) to enhance detection

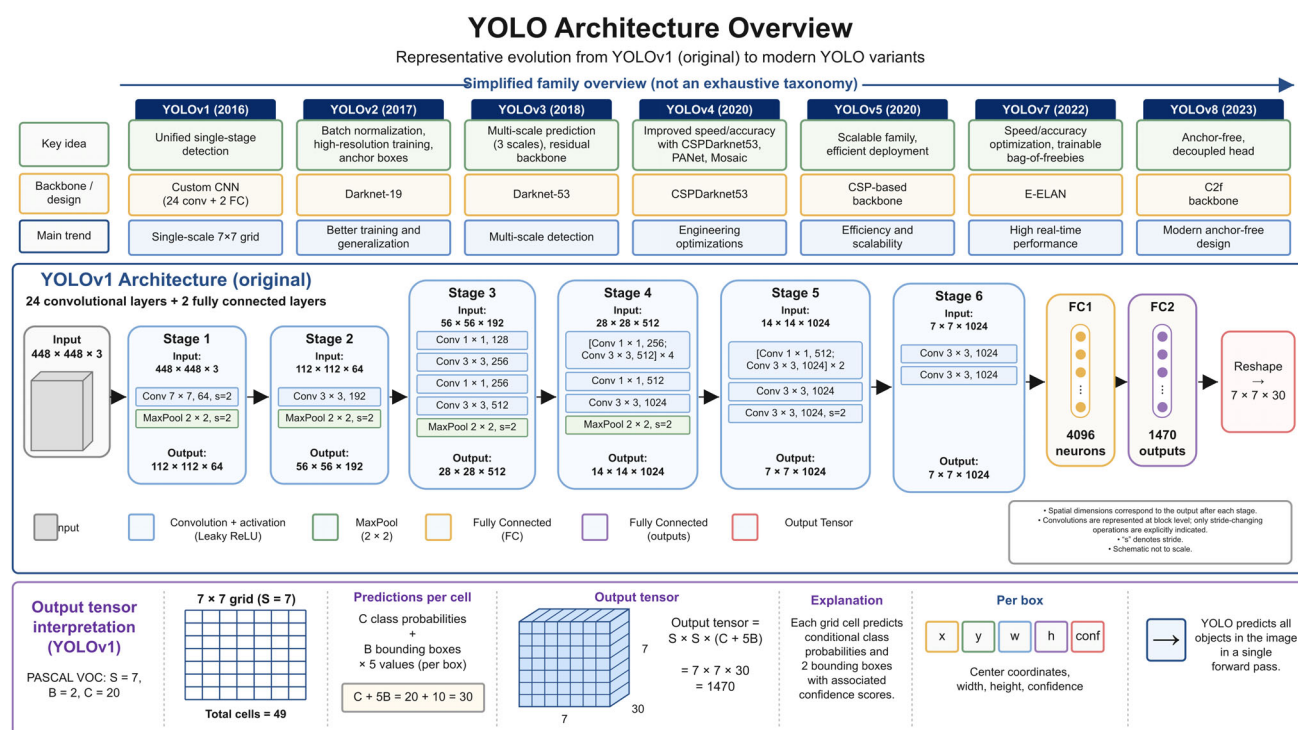


Figure 2. YOLO architecture overview: (a) YOLOv1 network; (b) evolution of YOLO variants, 2016–2023; (c) output tensor: an $S \times S$ grid predicts B bounding boxes and C class probabilities per cell. Arrows: data flow.

and classification efficiency. The method combines IoT-based image acquisition, YOLOv3 object detection, CNN-based feature extraction, and CNLSTM classification with AHBA-based hyperparameter optimization. Performance was assessed using standard classification metrics, with the proposed framework showing improved pest identification and classification compared with the evaluated baseline approaches. This integrated approach illustrates the potential of combining object detection, deep feature extraction, temporal classification, and metaheuristic optimization for IoT-assisted pest monitoring in agricultural settings. The core methods and findings addressed in this subsection are outlined in Table 7.

In this context, YOLO-based approaches provide adaptable and computationally efficient solutions for automated insect detection across diverse imaging scenarios. Their operational reliability and dependence on dataset quality and external validation are discussed comparatively in section 4.

3.2.2 Deep learning

The utilization of CNNs has become widely established in image-based insect identification within agriculture, ecology, and biodiversity conservation due to their capacity to learn visual features directly from images and support automated classification or detection tasks. Unlike traditional methods, which are labor-intensive and require expert knowledge, CNNs can help address variations in insect size, color, shape, and texture, enabling the rapid and scalable processing of extensive image datasets. This automation can reduce manual workload in pest monitoring and ecological assessment, although real-time applicability depends on model size, hardware, image resolution, and deployment conditions. Furthermore, CNN-based models can be integrated into mobile and edge computing devices, providing field

researchers, farmers, and ecologists with accessible and effective tools for on-site insect identification. Consequently, CNNs represent an important computational basis for automated insect identification, but their performance remains strongly dependent on dataset quality, taxonomic coverage, annotation strategy, and external validation. This process is illustrated in Fig. 3, which outlines the key stages involved in CNN-based insect identification.

Hasan *et al.*⁹⁸ leveraged transfer learning and deep learning to enhance insect counting, detection, and identification to classify insect diversity for agricultural and ecological applications. They utilized the ResNet152V2 CNN, which achieved reported training and testing accuracies of 99% and 97%, respectively, with an overall accuracy of 96%, by extracting hierarchical features from insect images. The study also explored other pre-trained models, such as Xception and MobileNetV2, as well as a custom CNN. ResNet152V2 showed the best performance among the evaluated architectures, including accuracy, precision, recall, and F1 score. The researchers employed a dataset of 4509 images spanning nine insect classes, with pre-processing steps such as noise removal, resizing, and normalization to standardize image quality and support model training. Data augmentation techniques further enriched the dataset and helped reduce overfitting risk, although the limited number of classes and images should be considered when interpreting generalizability. Evaluation using a confusion matrix supported the ability of ResNet152V2 to distinguish between the evaluated insect classes, while Grad-CAM provided additional interpretability by highlighting image regions that contributed to model decisions.

Cleetus *et al.*⁹⁹ evaluated the performance of several deep-learning models in detecting and classifying insect pests affecting tomato crops using publicly available high-resolution datasets. One dataset contained tomato leaf disease images, while the

Table 7. Characteristics of studies applying YOLO-based and YOLO-assisted models for insect detection, counting, and identification

Author	Trap/study	Methodology/technique	Reported metric/value	Validation level
Redmon <i>et al.</i> ⁸⁰	YOLO model	Single-stage object detection architecture with 24 convolutional layers and two fully connected layers; methodological basis for later YOLO-based pest detection models	45 FPS with the base YOLO model on Titan X GPU; fast YOLO reached 155 FPS General object-detection model, not insect-specific	Laboratory/ dataset benchmark
Thanh-Nghi ⁸¹	YOLO models, insect datasets	YOLOv3, YOLOv4, YOLOv5, YOLOX; transfer learning	YOLOX-S: 84.84% mAP on Insect10; YOLOX-M: 54.19% mAP on IP102	Laboratory/ dataset benchmark
Amrani <i>et al.</i> ⁸⁵	YOLOv3-AFF, Pest24 dataset	YOLOv3 with adaptive feature fusion for small objects	72.10% mAP; 63.8 images/s on the evaluated Pest24 subset	Laboratory/ dataset benchmark
Venverloo and Duarte ⁸⁷	YOLOv8, large dataset	YOLOv8 trained on 1.93 million images representing 2584 insect species; long-tailed distribution analysis used to assess performance on underrepresented taxa	82.3% accuracy on the validation dataset	Laboratory/ dataset benchmark
Xiang <i>et al.</i> ⁸⁸	Yolo-Pest, Teddy Cup pest dataset and IP102 evaluation	YOLOv5s-based pest detector with CAC3 module, ConvNeXt blocks, SE attention, and targeted data augmentation for small pest detection	91.9% mAP0.5 on Teddy Cup pest dataset; 8% improvement over YOLOv5s	Laboratory/ dataset benchmark
Bjerge <i>et al.</i> ⁹¹	YOLOv3 and YOLOv5, green roof cameras	YOLO models on time-lapse imagery	Average precision 92.7%; recall 93.8% across nine insect taxa	Field validation
Yang <i>et al.</i> ⁹²	Maize-YOLO, IP102 dataset	CSPResNeXt-50, VoVGSCSP	76.3% mAP; 77.3% recall; 67 FPS on the selected maize pest subset of IP102	Laboratory/ dataset benchmark
Zhong <i>et al.</i> ⁹⁵	Vision-based system	YOLO for coarse flying-insect detection and counting, followed by SVM classification using global and histogram of oriented gradients features	YOLO detection accuracy 93.71%; SVM classification accuracy 90.34%; average counting accuracy 92.50%	Field validation
Wei <i>et al.</i> ⁹⁶	AEC-YOLOv8n	Enhanced YOLOv8n with EMSFEM, AFEM_SIE, Concat_Weighting, and SPPELAN modules, evaluated on IP102	Compared with YOLOv8n: mAP50 increased by 8.9%, accuracy by 6.8%, and recall by 6.3%	Laboratory/ dataset benchmark
Kathole <i>et al.</i> ⁹⁷	IoT-based pest detection system	YOLOv3, convolution neural long short-term memory	IoT-assisted framework combining YOLOv3 detection, CNN feature extraction, CNLSTM classification, and AHBA optimization; reported performance improved over evaluated baseline approaches	Laboratory/ dataset benchmark

AFEM_SIE, Add Feature Enhancement Module for Spatial Information Exchange; AHBA, Adaptive Honey Badger Algorithm; CNLSTM, Convolution Neural Long Short-Term Memory; CNN, convolutional neural network; EMSFEM, Efficient Multiscale Feature Extraction Module; FPS, frames per second; IoT, Internet of Things; mAP, mean average precision; SPPELAN, Series Pooling Pyramid Enhanced Local Attention Network; SVM, support vector machine; YOLO, You Only Look Once.

other consisted of 1669 images across four pest categories: fruit piercing moth, gall flies, locust, and stem borer. The study employed pre-processing steps, including image normalization, conversion to NumPy arrays, and augmentation techniques such as zooming, shifting, and flipping to increase data variability during training. Several CNN architectures were tested, including custom CNNs and pre-trained models via transfer learning,

specifically VGG16,⁵⁷ InceptionV3,⁶³ and Xception.¹⁰⁰ Among these, the Xception model, which utilizes depthwise separable convolutions and residual connections, achieved the highest classification accuracy of 77.90% on the test dataset. These results suggest that transfer learning can support pest classification when training data are limited, although the moderate accuracy obtained for the pest dataset indicates that performance may

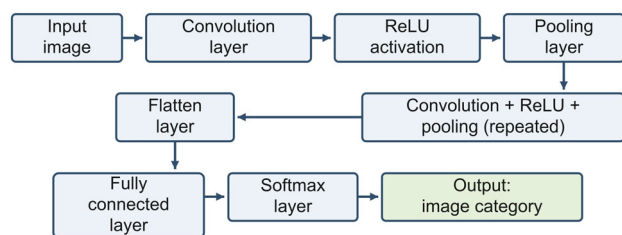


Figure 3. CNN-based identification process. An input image is processed through repeated convolution–ReLU–pooling stages, then flattened and classified by fully connected and softmax layers into an image category. Rectangles: processing stages; arrows: data flow.

remain constrained by dataset size, class diversity, and image acquisition conditions.

Recent work has explored transformer-based architectures for pest detection in complex agricultural scenarios. Sushma *et al.*¹⁰¹ developed a hybrid framework combining CNNs with an enhanced vision transformer architecture (EVITA) and a moth flame optimization (MFO) algorithm.¹⁰² The model was trained on images of aphids, wireworms, and gram caterpillars from IP102,⁸⁴ applying pre-processing (grayscale conversion, edge detection, bounding boxes) and data augmentation. CNNs extracted spatial features, while MFO was used for feature selection or optimization. EVITA segmented pest images into patches processed through a multiscale transformer encoder with positional embeddings. Compared to a baseline CNN (91.65% accuracy), the EVITA-MFO model achieved 98.47% accuracy, 98.29% precision, and 97.92% recall, showing improved performance in the reported evaluation. These findings indicate the potential of combining CNNs, transformer-based representations, and optimization algorithms for pest image classification, although the results should be interpreted in relation to the relatively small dataset size and the specific pest categories evaluated.¹⁰¹

Building on recent transformer-based models, earlier studies have demonstrated the potential of enhanced convolutional architectures for insect localization and classification. Xia *et al.*¹⁰³ developed an insect detection system for agricultural environments using a modified VGG19 CNN.⁵⁷ To address variability and limited data, they expanded their dataset from 600 to 4800 images through augmentation techniques such as rotation and noise addition. A region proposal network (RPN) with multiscale anchors generated bounding boxes, focusing computation on relevant regions. The VGG19-based CNN extracted features for species classification and localization via bounding box regression. A multi-task loss function combining classification and IoU optimized detection performance. Training followed a two-stage process: RPN first, then VGG19 fine-tuning with stochastic gradient descent. The model achieved a mAP of 89.22%, outperforming SSD and Fast R-CNN in the reported comparison. However, the dataset was expanded through augmentation from a limited number of original images, so performance should be interpreted in the context of the dataset construction and evaluation protocol.¹⁰³

In addition to CNN-based and transformer models, accessible machine-learning platforms have recently enabled researchers to develop classifiers without requiring coding expertise. A supervised learning approach was developed using a graphical user interface-based tool. The study focused on two edible cricket species, *Acheta domesticus* and *Gryllus bimaculatus*, extracting high-resolution images from 4000 video recordings. Images were

pre-processed into standardized JPEG format and organized into four classes. A total of 2646 images were used, split into 85% for training and 15% for testing. The model was trained over 100 epochs with a batch size of 16. Using Google Teachable Machine (GTM's) built-in deep-learning infrastructure, the model achieved 100% classification accuracy, as confirmed by the confusion matrix, for both species and their respective sexes. This approach relied on supervised learning with image augmentation to increase variability in the training data. The results suggest that such low-code tools can support preliminary insect classification and could be integrated into web or mobile applications, although the reported performance should be interpreted in relation to the controlled image acquisition conditions, limited number of species and restricted class structure.¹⁰⁴

Further extending deep-learning approaches to large-scale biodiversity monitoring, recent research has explored species-level classification at large taxonomic breadth. Chiranjeevi *et al.*¹⁰⁵ introduced InsectNet, a deep-learning model designed to identify over 2500 insect species, encompassing both beneficial pollinators and predators as well as harmful pests. Utilizing a dataset from iNaturalist, which includes 13 million images across 100 000 species and a focused subset of 2526 agriculturally relevant species with 6 million images, InsectNet was trained to classify both rare and common insects. The model employs techniques, including self-supervised learning, out-of-distribution (OOD) detection, and conformal predictions, to address challenges related to intra-species dissimilarity and inter-species similarity, achieving an overall classification accuracy of 96% and a per-species mean accuracy of 94%. Additionally, the integration of AlphaNet enhances the prediction accuracy for species with limited data from 79.7% to 87.6%. InsectNet leverages CNNs for image-based recognition and improves reliability by deferring uncertain predictions for human review, thereby increasing trustworthiness for high-confidence predictions. Although the system is relevant to pest identification, it is better interpreted as a broad insect-identification pipeline that can support agricultural and ecological applications rather than as a pest-monitoring system alone.

Kargar *et al.*¹⁰⁶ developed an edge AI-based insect monitoring system specifically for agriculture, targeting the brown marmorated stink bug (BMSB), a major crop pest. Utilizing machine vision and a lightweight CNN, the system processes images locally on a low-power microcontroller with an integrated camera, thereby reducing reliance on cloud resources and conserving bandwidth by transmitting data only when a pest is detected. The double-sided trapping and rotational imaging strategy enhance detection coverage compared to traditional single-sided methods. Designed for affordability and integration into orchards and crop fields, the device offers field-oriented automated pest identification, achieving over 70% classification accuracy in field tests. This system shows the feasibility of edge-based pest monitoring for BMSB, although the reported accuracy indicates that further optimization and validation would be needed before large-scale operational deployments.

In their study, Saha *et al.*¹⁰⁷ deployed the eBoss entomological optical sensor, which utilizes a near-infrared laser, to conduct a 9-month field campaign monitoring insect abundance and biomass density in relation to atmospheric conditions. The eBoss system continuously captured data on insect density and behavior by detecting transits through changes in light intensity and wing-beat frequencies. By integrating meteorological data such as temperature, humidity, and wind speed from an on-site weather

station, the researchers correlated insect population trends with environmental factors. The campaign generated 302 093 insect observations and derived aerial density and biomass density at 1-min resolution. These results demonstrate the potential of photonic sensors for long-term, non-destructive monitoring of flying insect abundance, although the study focuses on abundance and biomass trends rather than species-level pest identification.

To optimize model selection for varying image complexities, Li *et al.*¹⁰⁸ benchmarked multiple deep-learning architectures using the Baidu AI Insect Detection Dataset (simple backgrounds) and the IP102 Dataset (complex field images).⁸⁴ Images were manually labelled in Common Objects in Context (COCO) format and processed with an image annotation tool. The models evaluated included YOLOv5 (Darknet53)⁸² for one-stage detection, Faster R-CNN (ResNet50)¹³ for two-stage detection, and Mask R-CNN¹⁰⁹ for pixel-level segmentation. Supporting techniques such as RPNs²⁵ and ROI Align¹⁰⁹ were also applied. YOLOv5 achieved the highest processing speed (53.2 FPS) and high accuracy (99.54%) on simpler images, while Faster R-CNN and Mask R-CNN showed better performance (~99%) on complex scenarios with multiple insect categories and overlapping objects. Thus, the study suggests that model choice should be matched to dataset complexity: one-stage detectors may be preferable when speed is prioritized in simpler scenes, whereas two-stage or segmentation-based models may be more suitable when backgrounds, overlap, and class diversity increase.¹⁰⁸

Complementary to model-centric improvements, some studies have focused on enhancing training data through biologically inspired preprocessing strategies such as visual saliency. A method proposed by Nanni *et al.*²¹ integrates saliency techniques with CNNs to improve pest recognition for crop protection. They utilize three saliency algorithms, graph-based visual saliency, cluster-based saliency detection, and spectral residual, to identify important regions in images through pixel dissimilarity, clustering patterns, and Fourier analysis. By applying saliency maps for data augmentation, the method generates diverse training samples, thereby improving CNN performance. Multiple CNN architectures, including AlexNet,¹¹⁰ GoogLeNet,¹¹¹ MobileNetv2,¹¹² and DenseNet201,¹¹³ are trained and ensembled to achieve reported accuracies of 92.43% on a small dataset and 61.93% on the IP102 dataset.⁸⁴ The contrast between the two datasets shows that performance decreases substantially when moving from smaller or more controlled datasets to the larger and more heterogeneous IP102 dataset. Therefore, saliency-based augmentation appears useful for CNN-based pest recognition, but its effectiveness remains dependent on dataset scale, class imbalance, and intra-class variability.²¹

Building on the trend of integrating synthetic data generation and attention mechanisms, recent studies have explored additional strategies for insect pest detection using generative and semi-supervised approaches. Agarwal *et al.*¹¹⁴ developed a deep-learning-based framework to improve the detection, counting, and classification of insect pests using the large-scale IP102 dataset,⁸⁴ which includes over 75 000 images spanning 102 pest categories. The study introduced a sliding window cropping method to preserve critical pest features during pre-processing, with the aim of reducing information loss during image resizing and preprocessing. Gabor filters¹¹⁵ were employed to extract fine-grained textural details, facilitating the discrimination of insects from complex backgrounds. A modified ResNet architecture, pre-trained via transfer learning, was used as the feature extractor. Central to the approach is the attentive deep

convolutional generative adversarial network (ADCGAN), which incorporates a CycleGAN¹¹⁶ paired activation reconstruction module to generate synthetic pest images. This enhanced training data through semi-supervised learning. Experimental results demonstrated that ADCGAN outperformed conventional models, such as SVM, k-nearest neighbors (KNN), and anchor-free region convolutional neural network (AF-RCNN), achieving 94% accuracy, 93% precision, 92% recall, an F1 score of 89%, and an AUC of 91%, thereby indicating improved performance within the evaluated IP102-based experimental setting. However, the operational robustness of this approach for field-deployed pest monitoring would require external validation across independent image sources and acquisition conditions.¹¹⁴

Badirli *et al.*¹¹⁷ developed a Bayesian deep-learning framework that classifies insects, including those not present in the training dataset, by integrating image and DNA barcode data within a hierarchical model. Utilizing a ResNet-101¹³ for image feature extraction and a CNN for encoding DNA sequences, the two-layer hierarchy comprises a global prior for all species and a local prior for species within the same genus, facilitating the classification of undescribed species by linking them to known genera. Data augmentation with both image and DNA barcode inputs was used within the modelling framework, which reported 96.66% accuracy for known species and 81.39% for genus-level classification of unknown species, balanced by the harmonic mean. This framework addresses the limitations of traditional machine-learning systems in open-set conditions, enabling the identification of a broader range of insect taxa, including described and undescribed species. Although its focus is primarily biodiversity and taxonomic identification rather than operational pest monitoring, the approach is relevant to pest detection because it addresses open-set recognition, a key limitation of closed-class image classifiers.

Recent developments in hybrid neural network architectures and adaptive segmentation methods have further contributed to improving detection performance in complex pest imagery. Epsy and Radha¹¹⁸ propose a deep-learning-based framework for pest monitoring, achieving a detection accuracy of 98.5%. The methodology integrates a superior multilayer perceptron model for image pre-processing and noise reduction, which is intended to improve image quality before segmentation and classification. A hybrid neural network combining ResNet50¹⁰⁹ as a feature extractor and a CNN for feature extraction optimizes classification. This is further refined by belief propagation Adam optimization¹¹⁹ to enhance convergence and avoid overfitting. For segmentation, a cascaded U-Net architecture,¹²⁰ which leverages skip connections and domain adaptation, provides high pixel-level accuracy across diverse datasets. The reported metrics suggest promising performance for the evaluated pest images, but the generalizability of the approach depends on dataset diversity, independent validation, and the reproducibility of the denoising-segmentation-classification pipeline.

Saadati *et al.*¹²¹ focused on enhancing insect detection and classification in agriculture using machine learning (ML) and OOD detection techniques. Traditional manual methods have been complemented by automated systems, progressing from classical ML approaches like support vector machines, which required manual feature extraction, to deep-learning models such as Inception-v3,⁶³ ResNet50,¹⁰⁹ and VGG19,⁵⁷ achieving up to 98% accuracy. To improve trustworthiness under unfamiliar inputs, three OOD detection methods were explored: maximum softmax probability,¹²² Mahalanobis distance,¹²³ and energy-based models.¹²⁴ These

methods help models avoid erroneous predictions when encountering unfamiliar inputs, which is critical for agricultural applications. The study utilized a dataset of 2 million images representing 142 insect species, along with curated OOD datasets, to evaluate model performance using AUROC and FPR95 metrics, showing that OOD detection can support safer deployment by enabling classifiers to abstain from uncertain predictions rather than forcing potentially incorrect species assignments.

Ren *et al.*²⁵ present an efficient deep-learning framework for insect detection, counting, and classification based on Faster R-CNN, a general object-detection framework based on RPNs. The RPNs generate region proposals using anchors—reference boxes with varying scales and aspect ratios—to identify potential objects, such as insects, and apply bounding box regression for precise localization. Shared convolutional layers extract feature maps for both RPN and classification tasks, reducing computational costs. A sliding window approach predicts objectness scores and bounding boxes for insect-sized regions. The system employs multi-task loss to optimize classification and localization accuracy, while NMS removes redundant detections. Finally, the approach limits proposals to a manageable number (e.g., 300) for computational efficiency, enabling efficient object detection and providing a methodological basis for later insect and pest detection models.

Kundur and Mallikarjuna¹²⁵ demonstrated the application of deep learning for insect pest detection and classification using image-based methods, primarily leveraging the Faster R-CNN²⁵ framework combined with EfficientNet architectures (B4 and B7)¹²⁶ for feature extraction. The Faster R-CNN model integrates an RPN, bounding box regression, and a classification layer for efficient pest localization and identification. Image pre-processing (scaling, normalization) and data augmentation (rescaling, zooming, flipping) were used to increase image variability during training. Performance metrics, including accuracy, precision, recall, and F1 scores, revealed strong reported performance, with the EfficientNet B7 backbone achieving a classification accuracy of 99% for five pest classes. IoU evaluated bounding box precision, while non-maximum suppression reduced overlapping detections. Confusion matrices identified misclassification patterns, guiding the optimization of the model. These results indicate that Faster R-CNN with EfficientNet backbones can perform well on selected IP102 class subsets, although performance decreases as the number of pest classes increases and should be interpreted in relation to the chosen subset and evaluation protocol.

Gupta *et al.*¹²⁷ present a hybrid model that integrates a weighted multipath CNN and a generative adversarial network (GAN) to support insect identification. The multipath CNN iteratively processes images to extract refined features, while weighted paths prevent redundancy. GANs augment the Xie2 dataset by a factor of 30, significantly expanding the diversity of the training data. The model achieves an accuracy of 98.16%, outperforming benchmarks like AlexNet,¹¹⁰ ResNet50,¹³ GoogleNet,¹¹¹ and VGG-16,⁵⁷ with a 3.75% improvement over AlexNet. This result suggests that combining GAN-based data augmentation with multipath CNN feature extraction can improve insect classification on the evaluated dataset, although the use of synthetic expansion and a specific benchmark dataset should be considered when assessing transferability to other pest-monitoring contexts. A synthesis of the reviewed literature, including objectives and results, is shown in Table 8.

More broadly, deep-learning approaches have expanded the computational options available for automated insect detection, classification, and monitoring. Their context-dependent

performance and requirements for broader field validation and transferability are examined in section 4.

4 CROSS-TECHNOLOGY SYNTHESIS, DEPLOYMENT READINESS, AND FUTURE RESEARCH ROADMAP

Automated insect monitoring is evolving through the convergence of sensing hardware, communication infrastructure, and machine-learning-based interpretation, but technological maturity varies substantially and performance under control conditions should not be equated with routine field readiness. Camera- and vision-based systems are among the most extensively documented and field-oriented approaches, integrating conventional traps with remote image acquisition, wireless communication, automated counting and cloud-based management.^{15,16,24,34} More advanced configurations combine autonomous traps with computer vision, CNNs, and YOLO-based models for simultaneous counting and taxonomic identification.^{19,31,113} Their main advantage is visual auditability, although performance and transferability remain constrained by illumination, background variability, occlusion, insect overlap, connectivity, power autonomy and representative annotated datasets.^{19,26,27,30}

Acoustic, infrared, and optoelectronic systems provide complementary alternatives based on wingbeat frequency, flight sounds or light-beam interruption, enabling continuous or near-real-time monitoring with potentially lower data-processing and transmission requirements.^{36,41,43,93} Several have been field validated with autonomous power and remote communication^{36,40,51} but their maturity is heterogeneous: passage detection and counting may be reliable while species discrimination often requires additional signal processing or machine learning.^{52,53,93} Bioacoustics approaches also remain sensitive to environmental noise and signal quality.^{41,42,45}

Other technologies remain less operationally consolidated. Electrostatic trapping has been demonstrated under controlled conditions,⁵⁴ whereas cantilever nanosensors offer highly sensitive pheromone detection but still face challenges in transfer to robust field platforms.⁵⁵ Non-lethal automated traps and photonic sensors have reached field evaluation for abundance and biodiversity assessment, while laser speckle imaging remains more closely aligned with physiological research.^{64,66,69} Radar can extend monitoring to larger spatial and altitudinal scales, although with different taxonomic resolution and application objectives from species-specific crop monitoring.^{76,79}

Computational maturity must likewise be distinguished from system-level maturity. YOLO, CNNs, ResNet, and related architectures are established computational tools, but many insect-monitoring applications remain validated primarily on laboratory or dataset benchmarks. Field-oriented YOLO and edge-AI systems demonstrate deployment feasibility, but high algorithmic performance does not necessarily imply equivalent operational readiness.^{91,106}

Cross-study comparison is limited by substantial heterogeneity in both monitoring tasks and performance metrics. Camera-based studies report classification or counting accuracy, F1 score, MAE, RMSE or R²,^{18,19,26} sensor-based studies report counting accuracy, capture efficiency, detectability thresholds, signal-processing outcomes or agreement with conventional traps,^{36,40,44,51} ecological approaches evaluate abundance trends, richness proxies or population-estimation uncertainty,^{64,66,71} and computational studies additionally use mAP, precision, recall, inference speed, Top-1/Top-5 accuracy, AUROC or FPR95.^{81,108,121}

Table 8. Characteristics of deep-learning and hybrid computational approaches for insect detection, classification, and monitoring

Author	Trap/study	Methodology/technique	Reported metric/value	Validation level
Hasan <i>et al.</i> ⁹⁸	Transfer-learning model for insect diversity classification	Transfer learning with ResNet152V2	Overall classification accuracy of 96% on a dataset of 4509 images representing nine insect classes	Laboratory/dataset benchmark
Cleetus <i>et al.</i> ^{99†}	Deep-learning classification of crop pests and plant diseases	Comparison of convolutional neural networks and transfer-learning architectures	Xception achieved 77.90% classification accuracy on the pest dataset	Laboratory/dataset benchmark
Sushma <i>et al.</i> ¹⁰¹	EVITA with MFO, pest datasets	CNN feature extraction, MFO-based optimization, and enhanced vision transformer architecture for pest image classification	EVITA-MFO achieved 98.47% accuracy, 98.29% precision, and 97.92% recall on the evaluated aphid, wireworm, and gram caterpillar datasets	Laboratory/dataset benchmark
Xia <i>et al.</i> ¹⁰³	Insect detection and identification system	Modified VGG19 convolutional neural network	89.22% mAP after expanding the dataset from 600 to 4800 images through augmentation	Laboratory/dataset benchmark
Homchan and Gupta ¹⁰⁴	Machine-learning model for cricket species and sex classification	Graphical-interface-based transfer-learning tool trained on controlled cricket images	100% classification accuracy for two cricket species and sex classification using 2646 images under controlled image acquisition conditions	Laboratory/dataset benchmark
Chiranjeevi <i>et al.</i> ¹⁰⁵	InsectNet for large-scale insect-species identification	Self-supervised learning with conformal predictions	>96% classification accuracy for 2526 insect species; per-species mean accuracy reported as 94%; prediction deferral used for uncertain cases	Laboratory/dataset benchmark
Kargar <i>et al.</i> ¹⁰⁶	Edge-AI smart sticky-trap system for brown marmorated stink bug monitoring	Resource-constrained camera system mounted on a double-sided sticky trap; onboard image cropping and lightweight CNN classification, with remote transmission of relevant detections	Preliminary classification accuracy above 70% on a custom brown marmorated stink bug dataset; the prototype was deployed in an Italian fruit orchard	Field validation
Saha <i>et al.</i> ¹⁰⁷	Entomological optical sensor	Near-infrared optical sensing for flying-insect abundance and biomass monitoring	302 093 insect observations over nine months; aerial density and biomass density derived at 1-min resolution; not a species-level pest classifier	Field validation
Li <i>et al.</i> ¹⁰⁸	Comparison of deep-learning detectors for insect-pest detection	Benchmarking of YOLOv5, faster R-CNN and mask R-CNN on simple and complex insect pest datasets	Baidu AI dataset: YOLOv5 99.5%, faster R-CNN 98.1%, mask R-CNN 98.4%; IP102: faster R-CNN and mask R-CNN approximately 99%, YOLOv5 approximately 97%	Laboratory/dataset benchmark
Nanni <i>et al.</i> ²¹	Saliency with CNN and DenseNet	Saliency methods and data augmentation	92.43% accuracy on a small pest dataset and 61.93% on IP102	Laboratory/dataset benchmark
Agarwal <i>et al.</i> ¹¹⁴	Transfer-learning-based agricultural pest classification model	Sliding-window image cropping, texture-feature enhancement and an attentive generative adversarial network combined with transfer learning	94% accuracy, 93% precision, 92% recall, 89% F1 score, and 91% AUC on the evaluated IP102-based setting	Laboratory/dataset benchmark
Badirli <i>et al.</i> ¹¹⁷	Deep hierarchical Bayesian insect-identification model	Hierarchical Bayesian classification combining insect-image features and DNA-barcode features to classify described species and assign undescribed species to a genus	96.66% species-level accuracy for described species; 81.39% genus-level accuracy for undescribed species using combined image and DNA barcode data	Laboratory/dataset benchmark

Table 8. Continued

Author	Trap/study	Methodology/technique	Reported metric/value	Validation level
Epsy and Radha ¹¹⁸	Image-based pest detection and segmentation system	Image denoising followed by cascaded semantic segmentation and residual convolutional classification, with adaptive optimization	Reported detection accuracy of 98.5% for the evaluated pest image dataset	Laboratory/dataset benchmark
Saadati <i>et al.</i> ¹²¹	OOD detection for insect classifiers	Comparison of confidence-, distance- and energy-based OOD methods wrapped around trained insect classifiers	OOD methods evaluated using AUROC and FPR95 on insect classifiers; study focuses on abstaining from uncertain or unfamiliar inputs rather than improving classification accuracy alone	Laboratory/dataset benchmark
Ren <i>et al.</i> ²⁵	Faster R-CNN object-detection framework	Region proposal network with shared convolutional features, anchors, bounding-box regression, and fast R-CNN detection head	General object-detection framework; 5 FPS with VGG-16 and 300 proposals per image reported on general object-detection benchmarks, not insect-specific	Laboratory/dataset benchmark
Kundur and Mallikarjuna ¹²⁵	Faster R-CNN with EfficientNet feature extraction	Two-stage object detection using region proposals and EfficientNet-B4/B7 backbones for pest localization and classification	Faster R-CNN EfficientNet-B7 achieved 99%, 96%, and 93% average classification accuracy for 5, 10, and 15 IP102 pest classes, respectively	Laboratory/dataset benchmark
Gupta <i>et al.</i> ¹²⁷	Weighted multipath CNN and GAN for insect identification	GAN-based data augmentation and weighted multipath CNN feature extraction	98.16% accuracy on the Xie2 dataset; 3.75% improvement over AlexNet; dataset augmented 30-fold using GAN	Laboratory/dataset benchmark

AI, artificial intelligence; AUC, area under the curve; AUROC, area under the receiver operating characteristic curve; CNN, convolutional neural network; EVITA, Enhanced Vision Transformer Architecture; GAN, generative adversarial network; IoT, Internet of Things; mAP, mean average precision; MFO, Moth Flame Optimization; OOD, out-of-distribution; R-CNN, region-based convolutional neural network; YOLO, You Only Look Once. †Preprint.

These values are also obtained under markedly different conditions, from curated datasets and laboratory experiments to semi-field trials, short field validations, and operational deployments. Consequently, direct ranking based on percentages is misleading. Performance should be interpreted jointly according to task, target taxa, dataset composition, acquisition conditions, environmental variability, experimental duration, evaluation protocol, and validation level. Standardized, task-specific reporting and explicit differentiation between laboratory/dataset benchmarks, semi-field trials, field validations, and operational deployments are therefore essential for meaningful comparison.

No single technology simultaneously maximizes taxonomic resolution, temporal resolution, energy efficiency, robustness, scalability, and cost-effectiveness. Camera systems offer strong visual auditability and compatibility with modern detection algorithms, but depend heavily on image quality and impose greater processing and communication requirements.^{16,19,27} Infrared, optoelectronic, and acoustic systems can provide continuous, relatively low-power monitoring without full image capture,^{36,41,43} but often trade taxonomic resolution for simpler detection, as illustrated by overlapping wingbeat-frequency ranges between some species.⁹³

Photonic sensing prioritizes non-destructive, high-temporal-resolution abundance, and biodiversity information, although species-level identification and absolute abundance remain

challenging.^{66,107} Radar extends surveillance to much larger spatial scales but generally provides lower taxonomic resolution and is better suited to movement, abundance or biomass monitoring.⁷⁹ Computationally, one-stage detectors such as YOLO favour speed, whereas more complex detection or segmentation architectures may better address difficult backgrounds and overlapping insects.¹⁰⁸ Edge-AI and lightweight CNNs can reduce bandwidth and cloud dependence, but introduce constraints associated with embedded hardware.^{72,106}

The evidence therefore supports task-oriented technology selection: low-power infrared or optoelectronic sensing for counting, camera-plus-deep-learning systems for taxonomic identification, and photonic or radar approaches for broader abundance and biodiversity monitoring. Multisensory systems may combine complementary strengths, provided that added complexity translates into improved pest-management information.^{49,50,75}

The principal deployment challenge is maintaining reliable performance across time, locations, species, and environmental conditions. Scalability requires adequate energy autonomy, connectivity, and manageable maintenance. Solar power, low-power electronics, hibernation modes, GSM, Wi-Fi, ZigBee, and LoRa have been explored for autonomous remote monitoring,^{15,24,36,41} while edge processing can reduce communication requirements through local inference.^{72,106} Hardware solutions such as automatic sticky-surface replacement and insect self-disposal address accumulation and maintenance limitations.^{18,31}

Economic feasibility must be assessed at system level rather than from device cost alone.^{15,18,106} Energy supply, connectivity, storage, maintenance, and model updating all influence scalability. Model transferability is equally critical, as performance may decline when systems are transferred across crops, regions, devices or pest communities; dataset diversity, annotation quality, class imbalance and unfamiliar inputs therefore remain major challenges.^{21,84 114,121} Finally, operational value depends on converting detections into actionable information through alerts, environmental data, GIS or decision-support interfaces.^{12,34,47}

Future research should first strengthen standardized benchmarking and external validation. Shared datasets such as IP102 support methodological comparison but cannot replace validation with independent, field-acquired data from diverse crops, pest populations, devices, and environmental conditions.^{84,108} Benchmark performance should therefore be clearly distinguished from semi-field, field, and operational evidence. Second, sensor fusion should combine complementary information only when it demonstrably improves robustness, reduces false detections, increases taxonomic resolution or enhances decision support.^{34,49,50,75} Third, edge AI offers a route toward autonomous, bandwidth-efficient monitoring, although longer field deployments are needed to quantify trade-offs among computational efficiency, energy consumption, and detection performance.^{72,106}

Finally, model transferability requires greater attention to domain adaptation, dataset diversity, and uncertainty. Transfer learning, augmentation, and domain-adaptive approaches can address distribution shifts, while OOD and uncertainty-aware methods may reduce unreliable predictions on unfamiliar inputs.^{114,118,121} Overall, progress should be assessed less through isolated gains in benchmark accuracy and more through reproducible, interpretable, and actionable performance across realistic deployment conditions.

5 CONCLUSION

This review shows that automated insect monitoring is evolving through the integration of sensing technologies, communication systems, and machine-learning-based data analysis, although no single technological approach is optimal across all monitoring objectives. Camera- and vision-based systems are among the most extensively documented and field-oriented solutions, particularly when combined with automated traps and deep-learning algorithms, whereas acoustic, infrared, and optoelectronic approaches provide complementary options for continuous or low-power monitoring. Photonic, radar, biosensing, and non-lethal technologies further broaden the field toward biodiversity assessment, large-scale surveillance, and alternative detection strategies, but differ in technological maturity, taxonomic resolution, and operational readiness.

A major limitation across literature is the heterogeneity of monitoring tasks, performance metrics, and validation settings. Consequently, results obtained from laboratory or dataset benchmarks should not be directly compared with those from semi-field trials, field validations or operational deployments, and high algorithmic performance should not be considered equivalent to system-level readiness. Future progress will require standardized task-specific reporting, independent and sustained field validation, greater dataset diversity, improved model transferability, and robust performance across crops, species, devices, and environmental conditions. Sensor fusion, edge AI, and domain-adaptive or uncertainty-aware approaches offer promising

development paths when they provide measurable operational benefits. Successful adoption will depend on integrating reliable detection with energy autonomy, connectivity, maintainability, economic feasibility, and actionable decision support, thereby translating technological advances into scalable tools for precision and integrated pest management.

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DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

All authors were actively involved in the development of the review. The planning of the work, including the definition of literature search strategies and selection criteria, as well as the collection, critical reading, and analysis of the selected articles, were conducted jointly by all authors. The first draft of the manuscript was written by JCNP, and all authors reviewed and commented on earlier versions of the text. All authors read and approved the definitive version of the manuscript.

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