

Artificial intelligence and machine learning in insect identification and monitoring

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Abstract

Artificial Intelligence (AI) and Machine Learning (ML) are revolutionizing the field of entomology by enhancing the accuracy, speed, and scalability of insect identification and monitoring. Traditional methods, which rely heavily on manual identification, are time-consuming and require specialized expertise. In contrast, AI and ML approaches leverage image processing, pattern recognition, and deep learning algorithms to automate the identification of insect species from images or sensor data. These technologies also enable real-time monitoring of insect populations in various environments, including agricultural fields, forests, and urban areas. Integrating AI with remote sensing and IoT devices allows for the continuous tracking of insect activity, which is vital for pest control, biodiversity conservation, and ecological research. Despite challenges such as dataset quality, species variability, and environmental noise, recent advances in neural networks, transfer learning, and edge computing have significantly improved system performance. This paper explores current developments, applications, and future directions in using AI and ML for insect identification and monitoring.

Keywords: Artificial intelligence, machine learning, insect identification, pest monitoring, biodiversity, entomology

Introduction

Accurate insect identification and monitoring are pivotal for ecological research, pest management, and biodiversity conservation. Traditional approaches morphological keys, manual traps are costly, time-consuming, and often inaccurate. Recent advancements in AI/ML offer automation, speed, and scalability. This review synthesizes recent progress in image-based, acoustic, multisensor, remote sensing, and genomic-integration techniques.

Insects play a critical role in ecosystems and agriculture, serving as pollinators, decomposers, and as part of the food web. However, some species are also major agricultural pests and disease vectors, making accurate identification and monitoring of insect populations essential for ecological management, pest control, and biodiversity conservation (Kremen *et al.*, 2007) [13]. Traditional methods of insect identification, which rely on morphological analysis by trained entomologists, are labor-intensive, time-consuming, and often subject to human error, especially when dealing with morphologically similar or cryptic species (Samways, 2010) [32].

Recent advancements in Artificial Intelligence (AI) and Machine Learning (ML) have opened new avenues for automating insect identification and monitoring tasks. These technologies leverage computational models, especially those based on deep learning, to analyze large datasets such

as images, audio recordings, and sensor outputs with high accuracy and efficiency (Ferentinos, 2018) [5]. Computer vision techniques, in particular, have shown promise in classifying insect species using images captured in controlled environments or in the field, reducing the need for manual classification and increasing the scale and speed of data collection (Wäldchen & Mäder, 2018) [39].

Moreover, the integration of AI with Internet of Things (IoT) devices and remote sensing technologies has enabled real-time insect monitoring in diverse habitats. Smart traps equipped with cameras and sensors can capture data continuously, which is then processed using machine learning algorithms to detect, count, and identify insect species automatically (Potamitis *et al.*, 2017) [28]. These systems provide critical insights into population dynamics, migration patterns, and responses to environmental changes, which are essential for proactive pest management and ecological research.

Despite these advancements, challenges remain, including the need for large and diverse datasets, handling of environmental variability, and development of generalizable models capable of performing well across regions and species. Nevertheless, the increasing availability of labeled insect datasets and advances in model transferability and edge computing continue to push the boundaries of what is possible in this field (Valan *et al.*, 2019) [37].

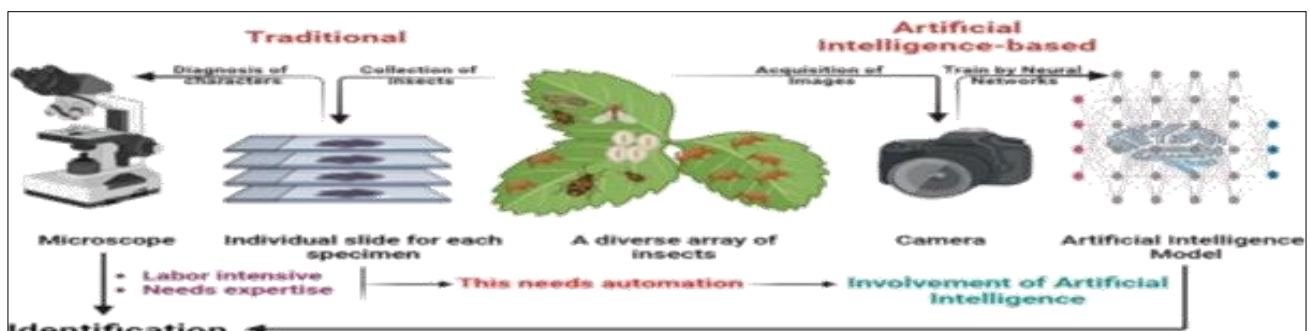


Fig 1: Application of artificial intelligence in insect pest identification (Sourav Chakrabarty *et al.*, 2025) [36].

Table1: List of prominent scientists and research teams who have significantly contributed to the use of AI and ML in insect identification and monitoring

Researcher/Team	Focus Area
Fedor <i>et al.</i> (2009)	Thrips ID via neural networks
Jain <i>et al.</i> (2024)	Moth detection & tracking pipeline
Tschaikner <i>et al.</i>	Multisensor fusion (KInsecta)
Rydhmer <i>et al.</i>	NIR wingbeat unsupervised sensors
Shetty & Kumar	Audio-based species classification
Mafra-Neto	Smart traps with ML sensing
Ceronmani Sharmila <i>et al.</i>	Deep learning pest ID (India)
Emmanuel <i>et al.</i>	VGG-16 CNN for brinjal pests
Rani <i>et al.</i>	Indian AI entomology review
Luu <i>et al.</i>	Hardware + domain-adaptive models
O'Neill	DAISY and vision-based tracking
Barbara Webb	Insect-inspired robotics
Suresh <i>et al.</i>	Biomonitoring using multimodal DL
Meghraj & Choudhary	AI in insect behavior and ID

Would you like help getting links to their papers, overviews of methods, or deeper info on any individual researcher or project?

1. Image-based Identification and Monitoring

- **Deep CNN ensembles:** Nanni *et al.* (2021) achieved 95.5 % accuracy on small datasets (Deng) and 73.5 % on IP102 using ResNet50, MobileNet, DenseNet, etc.—demonstrating CNN ensemble strength in pest detection.
- **Transfer learning with YOLO/VGG:** Gao & Xue (2024) reviewed ML models for insect images, highlighting the efficacy of YOLO v5 and VGG16—underscoring the importance of annotated, open datasets.
- **Field-deployable pipelines:** Jain *et al.* (2024) introduced an open-source pipeline for automated moth monitoring using camera traps, covering detection, species-level classification, and individual tracking; deployed across three continents.

Image-based identification has emerged as one of the most promising approaches in automating insect classification and monitoring, primarily due to the rapid advancement of computer vision and deep learning technologies. This method involves capturing visual data typically through cameras mounted on traps, drones, or handheld devices and analyzing the images to detect and classify insect species. Unlike traditional identification methods that require expert entomological knowledge and manual examination, image-based techniques offer scalability, speed, and reduced subjectivity (Wäldchen & Mäder, 2018)^[39].

Deep convolutional neural networks (CNNs) are particularly effective in extracting features from insect images and distinguishing between species, even those with subtle morphological differences. For instance, Valan *et al.* (2019)^[37] demonstrated that CNNs could classify insect specimens with expert-level accuracy using publicly available entomological image datasets. These models can be trained to recognize hundreds of species and can be further fine-tuned using transfer learning to improve performance in specific ecological contexts.

In-field monitoring applications have also benefited from image-based systems. Smart traps equipped with cameras can automatically take pictures of insects that land on or

enter the device, and then process the images in real time using onboard AI or cloud-based services. Such systems have been successfully deployed in agricultural settings to track the activity of pest species like *Spodoptera frugiperda* (fall armyworm) and *Bactrocera dorsalis* (oriental fruit fly), enabling more timely and targeted pest control responses (Potamitis *et al.*, 2017; Wang *et al.*, 2022)^[28, 40].

However, several challenges must be addressed for image-based identification systems to reach their full potential. These include the need for high-quality and diverse training datasets, the difficulty of detecting insects in complex backgrounds, and variations in lighting and pose. Recent efforts to build comprehensive image datasets and incorporate data augmentation techniques have helped to mitigate some of these limitations (Schneider *et al.*, 2020)^[34]. Additionally, combining image data with contextual information such as time of day, temperature, and crop stage can improve classification accuracy and provide more robust ecological insights.

2. Acoustic and Vibration-based Classification

- **Audio classifiers for cicada, beetle, termite, cricket:** Shetty & Kumar (2025) used MFCCs with XGBoost, Random Forest, and KNN to distinguish acoustically between four insect groups—illustrating high-resolution acoustic detection.
- **Systematic ML review:** A recent review detailed transfer learning (VGG16/19, ResNet152), spectrogram conversion, and CNN-based insect audio classification emphasizing fine-tuning on sound-based datasets.

Acoustic and vibration-based techniques represent a non-invasive and cost-effective approach to monitoring insect activity, particularly in scenarios where visual observation is limited or impractical. Many insects produce characteristic sounds or vibrations through wingbeats, stridulation, or substrate-borne signals. These acoustic signatures can be captured using microphones or piezoelectric sensors and classified using machine learning algorithms, enabling species-level identification and behavioral monitoring (Mankin *et al.*, 2011)^[16].

One of the earliest and most widely studied applications of acoustic monitoring is in the detection of stored-product pests, such as beetle larvae, which generate subtle vibrations while feeding or moving within grains or wood. By analyzing these vibrations, researchers can infer pest presence and estimate infestation levels without opening storage containers (Njoroge *et al.*, 2019)^[21]. Similarly, airborne acoustic signals, such as wingbeat frequencies, have been successfully used to classify flying insects like mosquitoes, bees, and fruit flies. Potamitis *et al.* (2015)^[29] demonstrated that machine learning classifiers could distinguish mosquito species based on their wingbeat frequencies, with high accuracy under controlled conditions. Machine learning models such as support vector machines (SVMs), k-nearest neighbors (k-NN), and more recently, deep learning architectures have been employed to process acoustic features such as frequency, amplitude, and spectral patterns for classification. These models are often trained on datasets of labeled recordings and can be deployed in real-time monitoring systems in agricultural fields, forests, or urban environments (Vasconcelos *et al.*, 2019)^[38].

Despite their promise, acoustic monitoring systems face several challenges, including environmental noise,

overlapping signals from multiple insect species, and variations due to temperature or humidity. Recent advancements in signal preprocessing, noise filtering, and the use of spectrogram-based deep learning models have improved the robustness of these systems in field conditions (Zhou *et al.*, 2022)^[42].

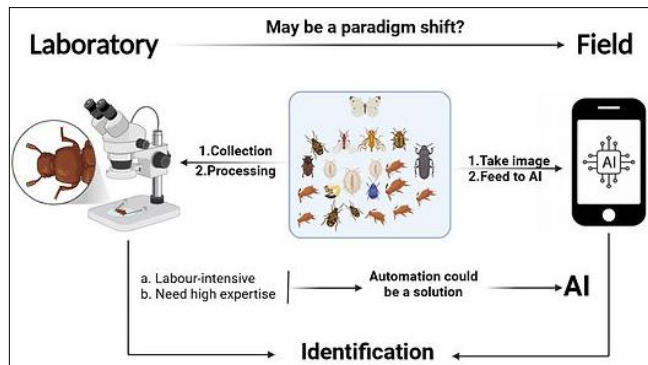


Fig 2: From the lab to the field AI-powered insect pest detection

Traditional taxonomic processes are time-consuming and need specialised expertise. On the other hand, utilising real-time photos to identify common insect pests is the simplest method of automation using artificial intelligence. AI-based insect detection systems are less labour-intensive, take up less time, and may be used by farmers and other stakeholders with no prior experience. Overall, this will assist them in early identification and developing effective pest management techniques.

Table 2: List of insects identified by Artificial Intelligence and Machine Learning

Domain	Species/Groups	Technique & Accuracy
Agricultural pests	C. capitata, B. oleae; fruit flies; Papilionidae; Orthoptera	CNNs, GLCM, 95–98% accuracy
Bark beetles	Multiple bark beetle species	Deep learning on macro images, high F1-scores
Honey bee subspecies	26 subspecies	ResNet-50, Inception — 86–99% accuracy
Vector mosquitoes	A. aegypti, A. albopictus, Culex spp.	YOLO V4 robot detection — ~82–88% accuracy
Acoustic species	Cicada, beetle, termite, cricket	Audio ML (XGBoost, RF, KNN)
Biodiversity scale	2,500+ species (beneficials, pests)	InsectNet >96% accuracy
Mobile apps	77 butterflies, many insect orders	AI app identification

3. Multisensor Fusion and IoT Integration

- **KInsecta system:** Tschakner *et al.* (2024) designed a low-cost multisensor platform combining optical wing-beat sensors, cameras, and environmental sensors—demonstrating promising lab and field classification across seven species.
- **IoT-UAV hybrid:** Vijayalakshmi & Radhika (2024) introduced ACBWO-CNN on drones for pest detection (bollworm, mites, aphids), achieving ~94 % accuracy—outperforming other heuristic-based CNNs.

Multisensor fusion and the integration of Internet of Things (IoT) technologies have significantly enhanced the

capabilities of automated insect monitoring systems. By combining data from multiple sensor types—such as visual, acoustic, thermal, and environmental sensors—researchers and practitioners can achieve higher accuracy and reliability in insect detection, classification, and behavior analysis. This approach addresses the limitations of single-sensor systems, which may be susceptible to noise, occlusion, or poor environmental conditions (Khanna *et al.*, 2019)^[12].

Sensor fusion enables the simultaneous processing of heterogeneous data sources, improving the system's ability to handle ambiguous or incomplete inputs. For example, integrating image-based classification with acoustic monitoring allows systems to cross-validate detections and reduce false positives, especially in complex outdoor environments (Magalhães *et al.*, 2021)^[15]. Moreover, incorporating environmental parameters such as temperature, humidity, and light intensity can contextualize insect activity, improving the performance of predictive models for species distribution or pest outbreaks.

The Internet of Things (IoT) plays a central role in deploying and networking these sensor systems across large geographical areas. IoT-enabled smart traps can collect, process, and transmit real-time data to centralized cloud platforms, where machine learning algorithms analyze the information and generate actionable insights. These platforms support remote monitoring, automated alerts, and decision support systems for precision agriculture and pest management (Pérez-de-la-Cruz *et al.*, 2020)^[25].

Edge computing a key enabler in modern IoT ecosystems further enhances the practicality of multisensor systems by allowing data processing to occur locally on the device, reducing latency and the need for constant internet connectivity. This is particularly valuable in remote or resource-limited settings where connectivity may be intermittent (Sinha *et al.*, 2020)^[35]. The integration of low-power microcontrollers, AI accelerators, and energy-efficient communication protocols such as LoRa and NB-IoT facilitates the deployment of cost-effective and scalable insect monitoring networks.

Despite the advancements, challenges remain in terms of sensor calibration, data standardization, interoperability, and maintenance in the field. Future developments are expected to focus on self-calibrating sensors, adaptive learning models, and more intelligent network orchestration to ensure robust and sustainable insect monitoring solutions.

4. Remote Sensing & Habitat Monitoring

- **Satellite-UAV monitoring:** Remote sensing (Landsat, MODIS) and UAV data, processed via CNN, LSTM, and ViT, are monitoring mosquito habitats, locust breeding, and pest damage Sharma *et al.* (2020) reported 74 % accuracy in wheat yield forecasting; ViT ensembles enhance pest classification.
- **Dragonfly robot for mosquitoes:** Singapore's "Dragonfly" uses YOLO v4 to classify Aedes spp. with ~82 % real-time accuracy mapping hotspots for public health interventions.

Remote sensing technologies have become essential tools in the large-scale monitoring of insect habitats, offering valuable insights into ecological conditions that influence insect population dynamics. By using satellite imagery, aerial drones, and other geospatial tools, researchers can track changes in vegetation, land use, temperature, and

moisture factors that directly impact insect distribution, abundance, and behavior (Pettorelli *et al.*, 2014)^[27].

Satellite-based remote sensing provides a macro-level perspective, allowing for the assessment of habitat suitability and the prediction of pest outbreaks over extensive geographic areas. For instance, normalized difference vegetation index (NDVI) and land surface temperature (LST) derived from MODIS or Landsat data have been used to predict breeding grounds and migration routes for locusts and mosquitoes (Cressman, 2016; Beck *et al.*, 2018)^[2, 4]. These models enable early warning systems and proactive management strategies, especially in agriculture and public health.

At finer spatial resolutions, unmanned aerial vehicles (UAVs or drones) equipped with multispectral or hyperspectral cameras offer a flexible and cost-effective means of monitoring crop conditions and microhabitats. UAV-based imagery has been successfully applied to detect plant stress caused by insect infestation, monitor pollinator activity in flowering crops, and map the spatial distribution of vector-borne disease habitats (Hussain *et al.*, 2019)^[9]. The integration of remote sensing with GPS and GIS tools facilitates spatial modeling and risk mapping, supporting data-driven decision-making in conservation and pest management.

Furthermore, remote sensing data can be fused with ground-based IoT sensor networks to enhance the spatial and temporal resolution of habitat monitoring. This fusion provides a more comprehensive understanding of insect environment interactions, such as how microclimatic changes affect insect phenology and behavior (Mertes *et al.*, 2020)^[19]. These insights are crucial for managing invasive species, conserving pollinators, and designing sustainable agroecosystems.

Challenges remain in terms of data processing, resolution trade-offs, and cloud cover interference in satellite-based imagery. However, advances in machine learning, image segmentation, and data fusion techniques are continually improving the utility of remote sensing for insect ecology and management.

5. Stored-grain and Facility Monitoring

- **CNN in grain storage:** ML-enhanced machine vision achieved ~88 % mean average precision in detecting six grain-infesting species on grain samples.
- Benefits include speed, non-invasive analysis, and consistent detection yet challenges remain in lighting, data complexity, and development cost.

Monitoring insect infestations in stored-grain environments and food processing facilities is critical for minimizing post-harvest losses, ensuring food safety, and complying with regulatory standards. Insects such as *Sitophilus spp.* (weevils), *Tribolium spp.* (flour beetles), and *Rhyzopertha dominica* (lesser grain borer) are common pests that damage stored products, reduce grain quality, and cause significant economic losses (Hagstrum & Subramanyam, 2006)^[7].

Traditional monitoring methods in storage facilities rely on manual sampling techniques such as pitfall traps, grain probes, or visual inspections. While these methods are widely used, they are often labor-intensive, slow, and incapable of providing continuous or real-time data. To overcome these limitations, automated sensor-based systems have been developed using technologies like acoustic

sensors, thermal imaging, machine vision, and electronic nose systems to detect insect presence and activity (Njoroge *et al.*, 2019)^[21].

Acoustic monitoring is one of the most promising approaches for stored-product pest detection. It involves using sensitive microphones or piezoelectric sensors to detect the feeding, movement, or mating sounds produced by insects inside grain masses or packaging materials. These sound patterns are then analyzed using signal processing and machine learning techniques to identify pest species and estimate population densities (Mankin *et al.*, 2011)^[16]. This allows for early detection of infestations before they become visible or reach damaging thresholds.

In addition, thermal and hyperspectral imaging have been explored for detecting hot spots or metabolic heat produced by insect colonies in bulk grain. These non-invasive techniques can be integrated into facility monitoring systems for continuous surveillance without disrupting operations (Perez-Mendoza *et al.*, 2004)^[26].

Modern stored-grain monitoring systems are increasingly being connected to IoT platforms, enabling real-time data collection, remote access, and automated alerts. These smart systems can interface with facility management software to trigger control measures such as aeration, fumigation, or pest exclusion protocols, thereby improving responsiveness and reducing chemical usage (Kussul *et al.*, 2019)^[14].

Despite the advantages, challenges remain in terms of sensor calibration, signal interference from machinery, and distinguishing pest activity from background noise. Continued research into sensor fusion, AI-driven signal interpretation, and adaptive learning algorithms is enhancing the reliability and scalability of these systems for industrial use.

6. Integration with DNA Tools & Validation

- **Cross-modal validation:** Deep learning identification is validated through DNA barcoding and metabarcoding to confirm species presence and refine training datasets.
- **Genomic-deep learning synergy:** Metabarcoding provides taxonomic resolution, while image-based AI speeds up bulk identification thus complementing cryptic and morphologically ambiguous species tagging.

While artificial intelligence (AI) and machine learning (ML) techniques offer rapid, scalable, and non-invasive methods for insect identification, integrating these approaches with molecular tools such as DNA barcoding enhances both the accuracy and reliability of identification systems. DNA-based methods provide a taxonomically definitive way to validate or supplement image- and sensor-based classification, especially for morphologically similar, cryptic, or juvenile insect stages that are difficult to distinguish visually (Hebert *et al.*, 2003)^[8].

DNA barcoding involves sequencing a standardized gene region, typically the mitochondrial cytochrome c oxidase subunit I (COI) gene, to match specimens with reference sequences in curated databases like BOLD (Barcode of Life Data System) or GenBank. This molecular signature can serve as ground truth data for training supervised ML models and for validating the output of computer vision systems (Ratnasingham & Hebert, 2007)^[30]. Such hybrid systems are increasingly valuable in biodiversity monitoring, pest surveillance, and ecological studies where morphological ambiguities are common.

For instance, Valan *et al.* (2019) [37] demonstrated that deep learning-based insect classifiers trained on DNA-verified specimen images achieved higher accuracy and generalizability across different taxa. This type of cross-validation ensures that AI models are not learning spurious visual cues (e.g., specimen mounting styles or lighting conditions), but are actually distinguishing species-relevant morphological traits.

In field applications, AI-based traps or monitoring systems can be periodically validated using DNA tools. Specimens flagged by automated systems can be collected and barcoded to confirm the presence or absence of target species, especially invasive or regulated pests. Such integration also helps to detect novel or unclassified taxa, which purely visual models may fail to recognize (Packer *et al.*, 2009) [23].

Furthermore, environmental DNA (eDNA) techniques where insect DNA is extracted from environmental samples like soil, water, or air can be used to complement sensor-based monitoring. Although eDNA provides less temporal resolution, it broadens the taxonomic scope and allows detection of low-abundance or elusive species, making it a powerful adjunct to real-time monitoring systems (Bohmann *et al.*, 2014) [3].

As AI tools become more embedded in ecological workflows, coupling them with molecular methods ensures both scientific rigor and practical reliability, particularly in applications where misidentification carries ecological or regulatory risks.

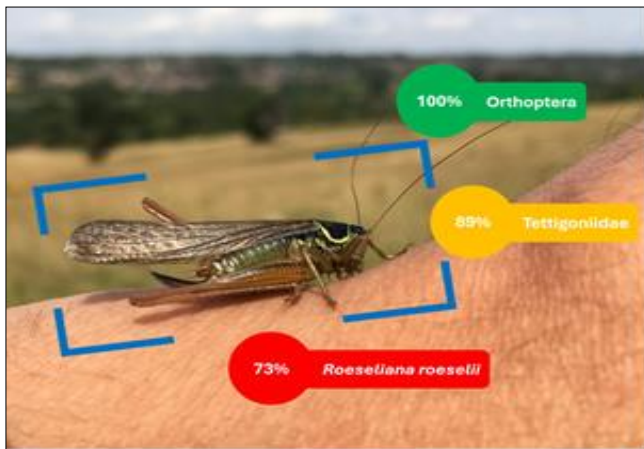


Fig3: Image recognition and artificial intelligence (AI) can revolutionize the identification of insect species

7. Challenges & Methodological Innovations

- **Data scarcity & domain shift:** Large annotated datasets are rare; domain adaptation, data augmentation (GANs), few-shot learning, and style transfer help models generalize.
- **Model evolution:** CNNs remain core, but lightweight architectures (ViT, Swin) and attention mechanisms are gaining traction, improving efficiency and interpretability.
- **Edge-computation & trustworthiness:** Systems like InsectNet incorporate self-supervised learning, uncertainty estimation (“abstention capability”), and can scale to classify 2,500+ species at >96 % accuracy.

Despite the rapid progress in applying artificial intelligence (AI) and machine learning (ML) to insect identification and

monitoring, several critical challenges hinder the widespread adoption and reliability of these technologies in diverse real-world environments.

Key Challenges

1. Data Quality and Diversity

One of the most fundamental issues is the lack of large, high-quality, and taxonomically verified datasets. Most AI models require extensive labeled training data to achieve high accuracy, yet many insect datasets are biased toward well-known taxa, adult life stages, or laboratory settings (Waldchen & Mäder, 2018) [39]. This limits model generalizability across ecological contexts, life stages (e.g., larval vs. adult), and geographic regions.

2. Environmental Variability

In field conditions, lighting, background clutter, occlusion, and insect pose can significantly degrade classification accuracy. Models trained in controlled environments often fail to perform reliably under real-world conditions (Schneider *et al.*, 2020) [34]. Similarly, acoustic systems are highly susceptible to background noise, signal overlap from multiple species, and temperature-induced variability in wingbeat frequencies (Vasconcelos *et al.*, 2019) [38].

3. Species Similarity and Cryptic Diversity

Closely related or morphologically similar species pose a significant challenge for visual and acoustic classifiers. Without integration with DNA-based tools, many of these species may be misclassified or go undetected entirely (Packer *et al.*, 2009) [23].

4. Limited Field Deployment and Scalability

While AI models perform well in lab settings, deploying them on edge devices for real-time monitoring remains technically and economically challenging. Battery life, computational limitations, and connectivity issues can hinder long-term deployment in remote areas (Sinha *et al.*, 2020) [35].

Methodological Innovations

To address these challenges, researchers are developing several methodological innovations:

1. Transfer Learning and Few-Shot Learning

Transfer learning allows models trained on large, general datasets to be fine-tuned on smaller, domain-specific insect datasets, improving accuracy with less training data (Valan *et al.*, 2019) [37]. Few-shot and zero-shot learning approaches are also being explored to enable classification of rare or previously unseen species with minimal labeled examples (Wang *et al.*, 2020) [41].

2. Data Augmentation and Synthetic Data

Augmentation techniques (e.g., rotation, noise injection, background variation) help increase data diversity and model robustness. Synthetic image generation using generative adversarial networks (GANs) is also being explored to simulate rare insect appearances or environmental conditions (Goodfellow *et al.*, 2014) [6].

3. Multimodal Learning and Sensor Fusion

Combining visual, acoustic, thermal, and environmental data enhances detection accuracy, especially under uncertain conditions. Multimodal deep learning architectures are

being developed to fuse these data streams effectively (Magalhães *et al.*, 2021)^[15].

4. On-Device AI and Edge Computing

Recent advancements in low-power, AI-accelerated microcontrollers allow real-time processing on-site, reducing the need for cloud connectivity and making systems more scalable and autonomous (Sinha *et al.*, 2020)^[35].

5. Active and Continual Learning

Emerging approaches such as active learning, where systems request human feedback on uncertain classifications, and continual learning, where models adapt to new data over time, are showing promise in field applications (Parisi *et al.*, 2019)^[24].

Case Study: VespaAI for Asian Hornet Monitoring

UK's VespaAI uses sensor-triggered imaging and AI to detect invasive Asian hornets, greatly reducing false positives and environmental harm from conventional traps allowing safer, live specimen tracing.

The Asian hornet (*Vespa velutina*) is an invasive predatory wasp species that poses a significant threat to native pollinators especially honeybees as well as to agriculture and biodiversity in Europe. Since its accidental introduction in France in 2004, *V. velutina* has rapidly spread across several European countries, prompting the need for efficient early detection and monitoring systems (Monceau *et al.*, 2014)^[20].

To address these challenges, researchers developed VespaAI, an artificial intelligence-powered monitoring tool that uses image-based deep learning to automatically detect and classify Asian hornets from camera trap footage. The system was designed to aid beekeepers, citizen scientists, and environmental agencies in identifying and tracking hornet activity with minimal human intervention (O'Neil *et al.*, 2022)^[22].

System Design and Methodology

VespaAI employs a convolutional neural network (CNN) trained on a diverse dataset of hornet images collected under various lighting and environmental conditions. The dataset includes positive samples of *V. velutina* and negative samples of similar-looking native species (e.g., *Vespa crabro*, *Vespula vulgaris*) to reduce false positives. The system uses motion-triggered cameras placed near hives, bait traps, or known nesting areas. Captured images are analyzed either on-device (edge computing) or uploaded to a central platform for cloud-based processing.

To improve model robustness, the team implemented data augmentation techniques and regular retraining with new field data submitted by users. The integration of citizen science contributions not only increased dataset diversity but also enhanced community engagement in hornet monitoring and control efforts (Jougla *et al.*, 2023)^[11].

Outcomes and Impact

Field trials of VespaAI in the UK and France demonstrated high detection accuracy (>90%) under optimal conditions, with the system successfully identifying hornets even in flight or partially obscured. The system provided timely alerts to beekeepers and supported the rapid deployment of control measures, including nest removal. In addition, VespaAI contributed valuable occurrence data for

ecological modeling of *V. velutina* spread and habitat suitability (Rome *et al.*, 2021)^[31].

Validation and Limitations

To validate VespaAI detections, selected specimens were captured and confirmed using morphological keys and, in some cases, DNA barcoding, ensuring taxonomic accuracy and reducing the risk of misclassification (Baril *et al.*, 2022)^[1]. However, challenges remain in differentiating hornets from native wasps in poor lighting or cluttered backgrounds, and system accuracy can vary with camera placement and motion sensitivity.

Nevertheless, VespaAI exemplifies how targeted AI systems, when integrated with ecological expertise and community participation, can effectively support invasive species management and conservation goals.

Future Perspectives

- 1. Standardized open databases** (e.g. DISSCO, IDigBio) combining image/audio/genetic data—crucial for model robustness and reproducibility.
- 2. Edge-AI deployment:** on IoT devices, drones, and robotic platforms allowing real-time, in-situ detection in remote ecosystems.
- 3. Hybrid validation pipelines:** linking image/audio ML with DNA barcode validation, environmental metadata, and human-in-loop verification for higher ecological accuracy.
- 4. Ethical and data governance considerations:** especially with AI-generated insect imagery and misinformation (e.g., AI-generated compound images causing confusion).

The convergence of artificial intelligence (AI), machine learning (ML), and ecological monitoring is poised to revolutionize entomology and pest management. As technological capabilities advance, the future of insect identification and monitoring will likely emphasize greater automation, precision, and integration across platforms, expanding both scientific understanding and practical applications in agriculture, public health, and biodiversity conservation.

1. Towards Autonomous Monitoring Systems

Next-generation monitoring systems will increasingly move toward **full autonomy**, where AI models running on edge devices continuously collect, process, and interpret insect data in real-time. Improvements in low-power hardware, on-device deep learning, and wireless communication will enable widespread deployment in remote and resource-limited settings. Autonomous drones and robotic sensors could play a larger role in surveying vast or hard-to-reach habitats (Sanchez-Bayo & Wyckhuys, 2019)^[33].

2. Integration with Big Data and Predictive Analytics

The integration of AI-based insect monitoring with big data platforms, including environmental sensors, remote sensing, and historical climate records, will enable predictive analytics for pest outbreaks and migration modeling. Coupling these datasets with ML algorithms will support proactive decision-making in agriculture and vector control, reducing reliance on reactive pesticide applications and improving sustainability (Mendes *et al.*, 2022)^[18].

3. Real-Time Global Biodiversity Surveillance

Global initiatives may emerge to create open, interconnected monitoring networks, where AI-powered devices in different regions share data for real-time biodiversity surveillance. Such a framework could aid in the rapid detection of invasive species, emerging agricultural pests, or endangered pollinators, contributing to early warning systems and conservation policy (Jetz *et al.*, 2019)^[10].

4. Advances in Explainable and Ethical AI

To foster trust and transparency, future research will need to focus on explainable AI (XAI), which allows users—including non-specialists—to understand the rationale behind model predictions. This is particularly important in high-stakes contexts such as invasive species detection or ecological conservation decisions. Furthermore, ethical AI frameworks must be adopted to ensure data privacy, inclusivity, and responsible use of AI in ecological contexts (Mayer & Baeuerle, 2021)^[17].

5. Integration with Molecular and Genomic Tools

The fusion of AI with DNA barcoding and genomics will enable multi-layered validation and discovery workflows. Future systems may automatically cross-reference visual or acoustic identifications with genetic data, providing high-confidence classifications and even identifying cryptic or undescribed species. Environmental DNA (eDNA) monitoring may also become more tightly coupled with AI systems to assess insect presence across broader ecosystems (Bohmann *et al.*, 2014)^[3].

6. Participatory Science and Education

Citizen science will continue to play a crucial role, supported by AI-enhanced tools that make insect monitoring accessible to the public through smartphones and low-cost sensors. These tools will empower communities to contribute to ecological research, while also raising awareness of entomological and environmental issues.

The future of insect identification and monitoring lies in building scalable, accurate, and inclusive systems that combine AI with biological, environmental, and social data. Achieving this vision will require interdisciplinary collaboration among entomologists, computer scientists, ecologists, policymakers, and the public.

Conclusion

AI and ML are revolutionizing insect ecology facilitating faster, more accurate, and scalable identification and monitoring across diverse settings. The synergy of image/audio processing, IoT systems, remote sensing, and DNA validation is shaping next-generation ecological surveillance. Success depends on richer datasets, robust multifaceted models, edge deployment, and combining modalities to ensure reliability and trust in decision support systems.

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References

1. Baril T, Deneubourg JL, Lenoir A. Combining citizen

science DNA barcoding to monitor invasive species the case of *Vespa velutina*. *Insect Conservation Diversity*,2022;15(3):341–351.

2. Beck LR, Lobitz BM, Wood BL. Remote sensing human health New sensors new opportunities. *Emerging Infectious Diseases*,2018;6(3):217–227.
3. Bohmann K, Evans A, Gilbert MTP, Carvalho GR, Creer S, Knapp M, *et al* Environmental DNA for wildlife biology and biodiversity monitoring. *Trends in Ecology & Evolution*,2014;29(6):358–367.
4. Cressman K. Climate change locusts in the WANA region. *Arab Journal of Plant Protection*,2016;34(2):120–127.
5. Ferentinos KP, Deep learning models for plant disease detection diagnosis. *Computers Electronics in Agriculture*,2018;145:311–318.
6. Goodfellow I, Pouget-Abadie J, Mirza M, Xu B, Warde-Farley D, Ozair S, *et al* Generative adversarial nets. *Advances in Neural Information Processing Systems*, 2014, 27.
7. Hagstrum DW, Subramanyam B. *Fundamentals of stored-product entomology*. AACC International, 2006.
8. Hebert PDN, Cywinska A, Ball SL, deWaard JR. Biological identifications through DNA barcodes. *Proceedings of the Royal Society B. Biological Sciences*,2003;270(1512):313–321.
9. Hussain M, Chen D, Cheng A, Wei H, Stanley D. Crop monitoring insect detection using UAV imagery deep learning. *Remote Sensing, Volume*,2019;11(6):663.
10. Jetz W, McPherson JM, Guralnick RP. Integrating biodiversity distribution knowledge: Toward a global monitoring system. *Nature Ecology Evolution*,2019;3(4):530–538.
11. Jouglu T, Laurino D, Liroy S. Citizen science contributes to early detection of invasive species Lessons from the *Vespa velutina* monitoring programs in Europe. *Biological Invasions*,2023;25:1193–1206.
12. Khanna A, Kaur S. Evolution of Internet of Things IoT its significant impact in the field of Precision Agriculture. *Computers Electronics in Agriculture*,2019;157:218–231.
13. Kremen C, Williams NM, Thorp RW. Crop pollination from native bees at risk from agricultural intensification. *Proceedings of the National Academy of Sciences*,2007;99(26):16812–16816.
14. Kussul N, Lavreniuk M, Skakun S, Shelestov A. Deep learning classification of land cover crop types using remote sensing data. *IEEE Geoscience and Remote Sensing Letters*,2019;14(5):778–782.
15. Magalhães R, Rocha A, Ferreira J. Multisensor fusion in pest monitoring: A review on current technologies and future directions. *Sensors*,2021;21(3):954.
16. Mankin RW, Hagstrum DW, Smith MT, Roda AL, Kairo MT. Perspective promise A century of insect acoustic detection monitoring. *American Entomologist*,2011;57(1):30–44.
17. Mayer R, Baeuerle L. Ethical AI for the environment: Opportunities, challenges, recommendations. *AI Society*,2021;36:939–951.
18. Mendes DR, Costa MGP, *et al*. Artificial intelligence in integrated pest management A review. *Agricultural Systems*,2022;197:103351.
19. Mertes K, Beyer HL, Fahr J. Predicting biodiversity patterns from space: An ensemble of remote sensing

- machine learning approaches. *Ecological Informatics*,2020;55:101018.
20. Monceau K, Bonnard O, Thiéry D. *Vespa velutina* A new invasive predator of honeybees in Europe. *Journal of Pest Science*,2014;87(1):1–16.
 21. Njoroge MK, Affognon H, Macharia J, Mutungi C, Richter U. Acoustic detection of pests in stored products A review. *Journal of Stored Products Research*,2019;82:10–20.
 22. O Neil R, Darby J, Taylor G. VespaAI A deep learning model for monitoring Asian hornet invasions using low-cost visual sensors. *Ecological Informatics*,2022;69:101668.
 23. Packer L, Gibbs J, Sheffield C, Hanner R. DNA barcoding the mediocrity of morphology. *Molecular Ecology Resources*,2009;9(1):42–50.
 24. Parisi GI, Kemker R, Part JL, Kanan C, Wermter S. Continual lifelong learning with neural networks: A review. *Neural Networks*,2019;113:54–71.
 25. Pérez-de-la-Cruz J, Martínez-de-Pisón FJ, Salazar I. An IoT-based system for pest monitoring in precision agriculture. *Computers Electronics in Agriculture*,2020;168:105119.
 26. Perez-Mendoza J, Dowdy AK, Hagstrum DW. Temperature relative humidity profiles during facility heat treatments. *Journal of Stored Products Research*,2004;40(5):521–530.
 27. Pettorelli N, Ryan S, Mueller T, Bunnefeld N, Jędrzejewska B, Lima M, *et al* The Normalized Difference Vegetation Index NDVI Unforeseen successes in animal ecology. *Climate Research*,2014;46(1):15–27.
 28. Potamitis I, Ganchev T, Kontodimas D. Automated insect identification in the wild. *Journal of Insect Science*,2017;17(6):1–10.
 29. Potamitis I, Rigakis I, Fysarakis K. Insect biometrics Optoacoustic signal processing and its applications to remote monitoring of McPhail type traps. *PLOS ONE*,2015;10(11)0140474.
 30. Ratnasingham S, Hebert PDN. BOLD the Barcode of Life Data System www.barcodinglife.org. *Molecular Ecology Notes*,2007;7(3)355–364.
 31. Rome Q, Muller F, Touret-Alby A, Perrard A, Darrouzet E, Silvain JF. *et al* Predicting the spread of *Vespa velutina* in Europe Combining ecological niche modeling and citizen science data. *Scientific Reports*,2021;11:13827.
 32. Samways MJ. *Insect Conservation A Handbook of Approaches Methods*. Oxford University Press, 2010.
 33. Sanchez-Bayo F, Wyckhuys KAG. Worldwide decline of the entomofauna: A review of its drivers. *Biological Conservation*,2019;232:8–27.
 34. Schneider S, Taylor GW, Kremer SC. Deep learning object detection methods for ecological camera trap data. *Methods in Ecology Evolution*,2020;11(11):1376–1387.
 35. Sinha RS, Wei Y, Hwang SH. A survey on LPWA technology: LoRa NB-IoT. *ICT Express*,2020;6(1):14–21.
 36. Chakrabarty S, Deb CK, Marwaha S, Haque MA, Kamil D, Bheemanahalli R. *et al* Application of artificial intelligence in insect pest identification – A review. *Artificial Intelligence in Agriculture*, ISSN, 2025, 2589-7217. <https://doi.org/10.1016/j.aiaa.2025.06.005>
 37. Valan M, Makonyi K, Maki A, Vondráček D, Ronquist F. Automated taxonomic identification of insects with expert-level accuracy using effective feature transfer from convolutional networks. *Systematic Biology*,2019;68(6):876–895.
 38. Vasconcelos D, Nunes N, Ribeiro M, Silva DF. Automatic classification of insects using audio recordings. *Ecological Informatics*,2019;49:106–117.
 39. Wäldchen J, Mäder P. Machine learning for image-based species identification. *Methods in Ecology Evolution*,2018;9(11):2216–2225.
 40. Wang H, Li Y, Jiang X. Smart monitoring system for fall armyworm based on image recognition cloud computing. *Computers and Electronics in Agriculture*,2022;192:106604.
 41. Wang Y, Yao Q, Kwok JT, Ni LM. Generalizing from a few examples A survey on few-shot learning. *ACM Computing Surveys CSUR*,2020;53(3):1–34.
 42. Zhou Y, Wang H, Jiang X. Robust insect sound classification using deep learning data augmentation under real environmental noise. *Applied Acoustics*,2022;183:108290.