

ARTIFICIAL INTELLIGENCE IN ENTOMOLOGY: ADVANCES IN INSECT IDENTIFICATION, BEHAVIOURAL ANALYSIS, MONITORING AND PRECISION PEST MANAGEMENT

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ABSTRACT

Artificial Intelligence (AI) is revolutionizing entomology by providing automated, scalable, and data-driven methods for insect identification, behaviour, monitoring, biodiversity, pest management, and ecological interpretation. This review explores the use of AI in entomological research, focusing on machine learning, deep learning, computer vision, multimodal AI, Internet of Things (IoT), edge computing, generative AI and large language models. The use of AI-driven image analysis and deep-learning architectures, such as convolutional neural networks and object-detection models, has enhanced the ability to recognize and monitor insects, but their performance is still limited by the availability of small, geographically restricted datasets and domain shifts in the field. Computer-vision-based tracking allows quantitative measurement of insect movement and behaviour, and automated monitoring systems can be used for population estimation, biodiversity assessment, pest forecasting, invasive-pest surveillance, and biological-control applications. New multimodal and generative AI systems combine images, environmental data, sensor data, and knowledge to facilitate ecological interpretation and context-aware decision making. The IoT and edge AI enable real-time, low latency field monitoring. While significant advances have been made, there are still issues with data quality, model generalisation, field validation, computational needs, connectivity, transparency, and expert verification. Geographically diverse datasets, standardised validation, lightweight and interpretable models, and human–AI collaboration will be key to future progress. In conclusion, AI has the promise of revolutionizing entomological research by enhancing efficiency, scalability, and ecological awareness.

KEYWORDS: Artificial intelligence, Biodiversity, Computer vision, Deep learning, Insect identification

INTRODUCTION

Insects are one of the most diverse and ecologically important groups of organisms, they are involved in pollination, decomposition, nutrient cycling, biological control and food-web interactions, and are important agricultural pests and disease vectors. Therefore, correct identification, monitoring and interpretation of insect populations are essential to taxonomy, biodiversity assessment, ecological research and applied entomology.

Assessment of insect communities is often labour-intensive, time consuming and difficult to standardise, especially at large scale and over long time periods, using traditional entomological methods that involve intensive field sampling, manual identification of specimens and specialised taxonomic expertise. The volume, complexity and spatial scale of entomological observations have grown and there is a need for automated approaches that can process large numbers of observations efficiently and consistently. The limitations are being mitigated by the development of machine learning (ML), artificial intelligence (AI), computer vision and automated sensing technologies, which are revolutionizing insect identification, monitoring and research (Gao et al., 2024; Vishnoi et al., 2025).

The applications of AI in entomology go beyond species identification. AI is being used to develop automated systems for insect counting, population monitoring, body size estimation, insect behaviour tracking and biodiversity assessment. For example, the STARdbi platform integrates the imaging of insects trapped in the insect traps with machine learning-based detection and identification to deliver information on insect abundance, biomass and temporal activity, and how routine monitoring can be turned into ecological information. Likewise, deep-learning pipelines based on time-lapse imagery have been developed to automatically classify arthropods and characterise their floral environment, providing new opportunities to study pollinators, natural enemies and insect–plant interactions at high temporal and spatial resolution (Keasar et al., 2024; Bjerger et al., 2024).

AI has a special application in the monitoring of insect biodiversity and ecological change. The traditional biodiversity surveys are limited by the availability of trained taxonomists and the vast diversity and abundance of insects. Automated camera-based systems with computer vision and ML provide opportunities for continuous, standardised and scalable monitoring. AI-based pipelines have been shown to be capable of detecting, classifying and tracking insects from camera-trap images, providing information on species presence, abundance, activity and community structure that can be used for long-term biodiversity assessment (Venverloo & Duarte, 2024).

AI applications are also being applied to insect behaviour, population dynamics and applied entomology. Computer-vision-based tracking can quantify locomotion, feeding, mating, foraging and other behaviours that are difficult to measure manually, and integration of AI with environmental, climatic, acoustic and sensor-derived data can help link insect responses with changing environmental conditions. In agriculture, these technologies are expanding to pest detection, forecasting and precision management, while ecological studies can use them for automated assessment of pollinators, natural enemies and insect communities. AI is thus gradually shifting entomology from observation to automated, quantitative and predictive insect science (Chakrabarty et al., 2026; Kariyanna & Sowjanya, 2024).

While these developments are promising, there are significant challenges to be addressed in bringing AI-driven solutions to fruition in the field. The performance of the models can be significantly influenced by limited availability of large, well labelled and well taxonomized datasets, as well as by variation in illumination, background, insect orientation, developmental stage and field conditions. Current research is also not evenly distributed, with a significant amount of focus on Lepidoptera, Diptera, Hemiptera and Coleoptera, and a need for more taxonomic diversity and field validation (Høye et al., 2021; Cheerkoot-Jalim et al., 2026).

While machine learning and computer vision and automated insect identification have been explored in the past, the current surge in AI applications has now moved beyond recognition to include behavioural analysis, automated monitoring, pest forecasting, biodiversity assessment, ecological interpretation and multimodal decision support. A comprehensive evaluation of these changes is therefore required to grasp the impact of AI on entomological research and to pinpoint biological, technical and operational challenges that hinder its use in practice. In this review, the authors discuss recent advancements in AI applications in various entomological fields such as insect identification and taxonomy, behaviour analysis, automated monitoring, biodiversity assessment, pest management and ecological inference, and critically explore the emerging technologies, current challenges, research gaps, and future directions. The major applications of AI in entomological research, along with the approaches, data sources, potential benefits, and key limitations are summarized in Table 1, and the overall AI-enabled workflow from data acquisition, computational analysis, to entomological applications and human expert validation is illustrated in Figure 1.

Table 1. Major applications of AI across entomological research

Entomological domain	AI approach	Data source	Major application	Potential benefit	Key limitation
Insect identification	CNN, YOLO, transformers, self-supervised learning	Images	Species/taxon identification	Rapid, scalable recognition	Taxonomic similarity; domain shift
Behaviour analysis	Object tracking, deep learning	Video	Movement and behavioural phenotyping	High-throughput quantitative analysis	Occlusion; annotation burden
Monitoring & biodiversity	Computer vision, automated detection	Trap/camera images	Counting, abundance, activity, community monitoring	Continuous scalable surveillance	Taxonomic and geographic bias
Pest forecasting	ML/DL, explainable AI	Pest + weather + crop data	Forecasting and early warning	Earlier risk assessment	Data quality; external validation
Biological control	CV/ML	Images/video	Natural-enemy identification and quality assessment	Automation of monitoring/QC	Limited validated datasets
Precision management	AI + IoT + UAV	Multimodal field data	Targeted interventions	Spatial/temporal targeting	Field robustness and connectivity
Decision support	LLM, RAG, multimodal AI	Text + sensor + image data	Context-aware recommendations	Integration of heterogeneous evidence	Hallucination; expert validation

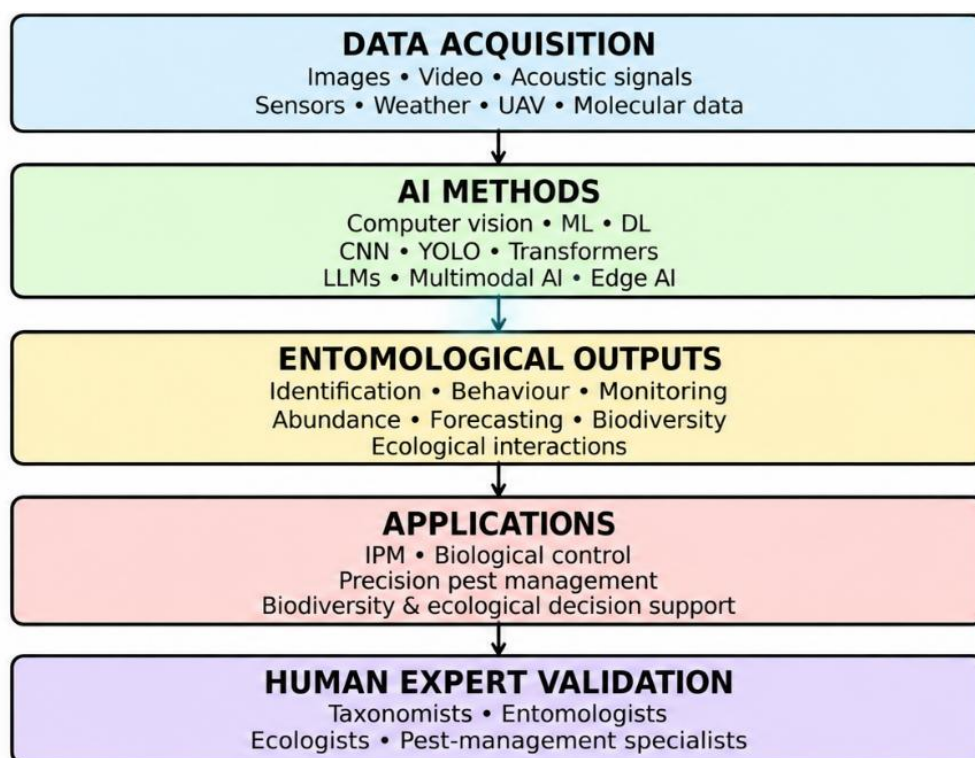


Figure 1. AI-enabled transformation of entomology: from data acquisition to ecological decision-making

2. Artificial Intelligence (AI) for Insect Identification and Taxonomy

Correct identification of insects is essential for taxonomy, biodiversity studies, ecological monitoring, biological control and pest management. Traditional identification is based mainly on morphological characters, taxonomic keys and expert knowledge, and can be time consuming when many specimens, morphologically similar taxa or immature stages are involved. Such restrictions have encouraged the development of automatic image-based identification systems based on machine learning (ML) and deep learning (DL). Based on a systematic review of insect image-based identification studies, it has been found that the use of DL-based methods has increased compared to traditional image-processing and shallow-learning methods, but the application is still limited to agricultural pests and a relatively small number of insect orders (Høye et al., 2021).

The development of computer vision and deep neural networks, especially convolutional neural networks (CNNs), has significantly enhanced the capacity of computational systems to extract discriminative morphological features from insect images. The general steps in AI-based identification are: image acquisition, image preprocessing, segmentation or object detection, feature extraction, and taxonomic classification. DL models can learn discriminative features directly from images, as opposed to manually defined morphological features. A recent review by Gao et al. (2024) highlighted the increasing application of ML and DL in automated identification for Coleoptera, Lepidoptera, Hymenoptera, Diptera and Orthoptera and the importance of having accurate and diverse image databases.

In recent years, the focus has been on simultaneous detection and classification of insects under complex conditions, rather than just image classification. Object-detection architectures such as YOLO can detect individual insects within an image and assign taxonomic labels. If insects are already separated from their backgrounds, then classification architectures like ResNet, EfficientNet, and MobileNet are typically employed. In recent years, YOLO-based detectors and CNN-based classifiers have been the most popular in computer vision studies, and transformer-based and self-supervised approaches are emerging as alternatives, especially when insect images are scarce (Souifi et al., 2022; Cheerkoot-Jalim et al., 2026).

A major advancement is the increasing capacity of AI systems to make finer taxonomic discriminations. It is much more difficult to automatically recognize closely related species than to classify them in a broad taxonomic group as closely related species may only differ in subtle colour patterns, wing venation, body shape or other diagnostic characters. In addition, there is significant intraspecific variation that may be due to sex, developmental stage, geographic origin and environmental conditions. In the absence of large expertly labelled datasets, research has turned to transfer learning, ensemble neural networks, and self-supervised learning to enhance performance (Valan et al., 2019; Sadia & Alam, 2025). For instance, InsectNet employed a large global image set for self-supervised learning and fine-tuned with smaller expert-labelled regional datasets. These methods are especially applicable to entomology as many insect species have few labelled images.

However, high classification accuracy in laboratory or controlled imaging conditions does not guarantee similar performance in field conditions. Illumination, image quality, background complexity, insect orientation, occlusion, camouflage and life stage can significantly impact model performance (Jain et al., 2024a). Moreover, there are still limited insect datasets that are publicly available, well labelled, and geographically representative.

The current literature suggests that computer-vision research has focused on a limited number of insect orders and geographic areas, and that field testing is less prevalent than laboratory testing. These constraints are particularly important in taxonomy, where misidentification of closely related species may have ecological or management implications.

AI-based insect taxonomy is thus progressing towards more flexible and ecologically representative identification systems. New techniques involve self-supervised learning, vision transformers, multimodal models, hyperspectral imaging, and techniques to tackle under-represented taxa (Chiranjeevi et al., 2025). It is especially crucial to incorporate the expertise of taxonomists with AI, not to replace them. AI can be used as a fast screening and identification tool, and expert validation is required for difficult specimens, newly emerging taxa and taxonomic revision. Future systems could then be expanded to include the discovery of biodiversity and taxonomic organisation.

3. Artificial Intelligence (AI)-Assisted Analysis of Insect Behaviour

Ecological interactions, host selection, foraging, mating, locomotion and responses to environmental conditions are all based on insect behaviour. Traditional behavioural studies usually rely on direct observation or manual analysis of video recordings, which are time-consuming, labour-intensive and subjective. AI, specifically computer vision and deep learning, is allowing for behavioural observations to be made at larger temporal and spatial scales, and with more automated quantitative analysis. Recent advances have allowed for the automatic detection, tracking and classification of insect movements, providing behavioural information that is hard to consistently gather manually (Li et al., 2026).

The automatic tracking of insect movement and trajectory is one of the most important applications of AI. Computer vision algorithms can detect individual insects in each frame of the video and measure parameters like distance travelled, velocity, acceleration and turning behaviour. Machine learning-based tracking systems have been created for insects like honey bees, enabling quantitative analysis of individual movement and activity patterns (Rozenbaum et al., 2024). AI has also been applied to the study of mosquito flight patterns and movement, with the use of deep-learning algorithms to analyse their flight paths and movement patterns, which has the potential to help understand the behaviour of mosquitoes and how they transmit diseases (Javed & López-Denman, 2024). These quantitative measurements are variables that are hard to get manually for behaviour.

AI can also be used to measure behavioural states and activity patterns. Deep-learning models can process temporal sequences and classify activities like walking, resting and feeding, which helps to minimize the subjectivity and workload of manual observations. Recent advances in automated behavioural phenotyping indicate a trend towards high-throughput and non-invasive analysis of insect behaviour with computer vision and deep learning. For instance, an infrared multi-object tracking system was designed using YOLO11 and OCSORT to track adult *Tuta absoluta* continuously and quantify the circadian activity (Cui et al., 2025).

4. AI for Automated Insect Monitoring and Biodiversity Assessment

Automated insect monitoring is a link between individual identification and population/community-level ecological assessment. Images captured by camera traps, sticky traps and time-lapse cameras can be used to identify, classify and count insects using AI-based systems over a long period of time. These methods can provide data on abundance, activity, biomass and community composition and can save on the amount of labor required for manual trap checks. The STARdbi platform and other automated monitoring pipelines demonstrate the potential of image-based AI to transform mundane surveillance into structured ecological data (Keasar et al., 2024; Bjerger et al., 2024).

5. Applications in Applied Entomology and Pest Management

In entomology, AI is being used more and more to aid in the early detection of pests, automated monitoring, population estimation, forecasting, and precision management. Traditional pest monitoring relies on field scouting and manual trap checks, which can be time consuming and may not detect developing infestations. Images captured by field cameras, sticky traps and other monitoring methods can be analysed using computer vision and deep-learning algorithms to identify, classify and quantify pest populations. Recent automated insect-monitoring pipelines integrate object detection, species classification and individual tracking, providing scalable solutions for continuous monitoring (Jain et al., 2024b).

AI-powered predictive modelling is also being used more and more for pest forecasting and early-warning systems. Machine-learning algorithms can integrate past pest observations with meteorological, crop and environmental data to detect intricate relationships linked to pest occurrence and population growth. These models can be used to predict when and where pest pressure may rise, which can help to better time pest management. Crop-pest forecasting has been recently evaluated, and machine-learning methods are increasingly being used to convert complex environmental and surveillance data into information for pest-management decisions (Yang et al., 2026). To account for the nonlinear relationship between weather and pest dynamics, explainable deep-learning models have been developed by combining historical pest observations with multivariate meteorological data (Wang & Zhang, 2024).

6. AI for Invasive and Emerging Pest Surveillance

AI-powered surveillance can also help with early detection and monitoring of invasive and emerging insect pests. Computer vision, UAV imagery, smart traps and machine-learning based sensor systems can aid in the detection of pest presence and spatial distribution prior to widespread establishment. Recent studies on the use of UAS, computer vision and AI in invasive insect management show the potential of integrating remote observations with

targeted management strategies (Chiabrando et al., 2025). However, the performance of models needs to be tested at different locations and environmental conditions for invasive pests, as false negatives are especially problematic in early-detection systems.

AI can also be used to enhance biological control in integrated pest management (IPM). Computer-vision and machine-learning systems can aid in predator and parasitoid identification and monitoring, and automated image and video analysis can help determine developmental stages, survival, behaviour and reproductive performance in mass rearing. These applications could help in quality control and scalability in biological-control programmes. Successful deployment, however, will need to be validated across crops, pest densities, geographical regions and environmental conditions. AI-based detection should therefore be used in conjunction with biological information, such as pest density, crop growth stage, economic thresholds, natural-enemy abundance and potential crop losses, rather than as a replacement for existing IPM decision-making.

7. Emerging Frontiers: Generative AI, Multimodal AI, IoT and Edge AI

Next-generation AI-enabled entomology is moving beyond conventional image classification towards generative AI, multimodal learning, Internet of Things (IoT) and edge computing. These technologies can link insect observations to environmental data, domain knowledge and decision making processes in near real time. Emerging systems are not just about the presence of an insect, but also information about its presence, environmental conditions and the management or ecological response. Table 2 provides a summary of the emerging AI technologies and their applications in entomology.

Table 2. Emerging AI technologies and their applications in entomology

Technology	Primary function	Entomological application
CNN / deep learning	Feature learning and classification	Identification, monitoring, behavioural analysis
YOLO / object detection	Detection and localisation of individual insects	Smart traps, field surveillance, pest counting
Vision transformers	Image representation and classification	Fine-grained and complex insect recognition
Self-supervised learning	Learning from large unlabelled image sets	Under-represented taxa and limited labelled datasets
Explainable AI	Interpreting model predictions	Pest forecasting and decision support
LLMs / RAG	Knowledge retrieval and language-based reasoning	Pest-management information and decision support
Multimodal AI	Fusion of image, text and environmental data	Ecological interpretation and precision management
IoT	Continuous data acquisition and communication	Smart traps and environmental monitoring
Edge AI	Local inference with low latency	Remote and resource-limited field monitoring

7.1. Generative AI and Large Language Models

The advent of generative AI and large language models (LLMs) is opening up new avenues for entomological research, allowing for the extraction, synthesis and interpretation of vast amounts of scientific and management information. For instance, Scheepens et al. (2024) demonstrated that GPT-4 could accurately identify species, geographical data and ecological functions of pests and natural enemies from biological-control literature, albeit with some fabricated data found and the need for expert verification was highlighted. This is an important difference between information extraction and biological interpretation: good performance on the structured extraction tasks does not necessarily lead to reliable ecological conclusions or management recommendations.

LLMs are also being explored for their potential in supporting pest management decisions. The PestGPT framework combines IoT data on the environment, an explicit expert knowledge base, and an LLM to provide tailored pest-management recommendations, and has been tested in a real farm-management environment (Yuan et al., 2025a). The TARAG framework also incorporates time-aware retrieval-augmented generation to consider the crop phenology and pest life stages when retrieving evidence and generating pest- and disease-management suggestions (Liu et al., 2026). These developments represent a shift from information retrieval to context-aware agricultural decision support, and the need for expert supervision and validation.

7.2. Multimodal AI

The relevance of multimodal AI to entomology is especially important because decisions regarding insects are not always made from images. Images of insects, weather, crop stage, geographic location, trap counts, environmental sensors and textual knowledge can be combined to create a more comprehensive picture of insect populations and their ecological context. PEZEGO, for example, combines multimodal environmental data, an open-vocabulary pest detector and an LLM to generate pest-management recommendations (Yuan et al., 2025b). The approach is relevant because the ecological or management importance of an insect is not just a function of species, but also of abundance, life stage, host availability, environmental conditions, and interactions with other organisms.

Multimodal AI could thus contribute to the transition from individual recognition to ecological interpretation in entomology.

7.3. IoT-Enabled Entomological Monitoring

IoT is the backbone for constant monitoring of insects, connecting cameras, smart traps and environmental sensors to analytical platforms. Wang et al. (2024) designed an IoT-based pest and disease prevention system incorporating light traps, environmental sensors, wireless communication and remote-control capabilities. The system was tested in the greenhouse and field conditions with cucumber, tomato and rice crops, which showed the feasibility of the system for real-time environmental monitoring and automatic pest-management equipment. Similarly, smart-trap systems based on YOLO have been developed to incorporate pheromone traps, cameras and IoT sensors for automated monitoring of fruit flies and fall armyworm, which demonstrates how IoT can transform traditional traps into digital observatories of insect populations.

7.4. Edge AI: Bringing Intelligence to the Field

Cloud-based AI involves sending large image datasets to remote servers, while edge AI is when the inference is done on or near the monitoring device. This can help to lower communication needs and latency, and can be helpful in areas with limited internet access. Kargar et al. (2024) showed that sticky traps with cameras can be used to detect *Halyomorpha halys* in an Italian orchard at low power. The system's high accuracy (over 90%) and low memory and energy consumption demonstrate the potential for autonomous insect monitoring in resource-constrained environments.

New advancements also show that AI-driven monitoring systems can be made more compact and deployable in the field. Nyakuri et al. (2025) designed an AI-IoT device called Tiny-LiteNet, which uses a Raspberry Pi 5, camera, and lightweight CNN and GSM/GPRS communication to detect crop pests and diseases in real time. The system achieved 98.6% accuracy, a 98.4% F1-score and an 80-ms inference time with 1.2 MB of model storage. Edge AI is not just about cutting down on compute needs, it's about processing data in real time near the point of observation, especially when continuous connectivity to cloud-based systems is challenging, from an entomological point of view.

8. Challenges, Research Gaps and Future Research Priorities

While AI is making significant strides in the field of entomology, the process of moving from experimental methods to practical and effective field applications is still a hurdle. Insect data is scarce and of poor quality. Although there is a vast range of insect diversity in terms of morphology, colour, developmental stage and behaviour, the available data are generally limited in size, geographical scope and taxonomic breadth. The literature is also not uniform, and there is relatively little field validation. In natural conditions, the performance of the model can be further degraded by variation in illumination, background, insect orientation and occlusion. Model generalisation and transferability is another significant challenge. AI models can be very accurate in a controlled laboratory setting, but may be less accurate when used on other crops, geographic regions, imaging devices or environmental conditions. The resulting “domain shift” is especially significant in entomology, where insects may look and act differently at various stages of their development and in different environments. Future studies should thus be directed towards geographically diverse datasets, standardised image-acquisition protocols, cross-location validation and models that can adapt to previously unseen conditions.

Although methods have been rapidly developed, evidence from actual field deployment is still relatively scarce. Computationally intensive large deep-learning models can be difficult to implement, and frequent image acquisition, data storage and data transmission can be difficult in field conditions. Low cost edge devices, light weight models and IoT-enabled sensors provide potential solutions, but these systems need to be tested in the field for accuracy, durability, energy consumption, connectivity and interoperability. AI systems should also be cost-effective, user-friendly, and reliable in diverse environmental and connectivity scenarios for farmers and field technicians.

Another significant future trajectory is the creation of human–AI collaborative entomology. AI should be used as a supplement to, rather than a substitute for, taxonomists, ecologists and pest-management specialists. Expert validation is still necessary for rare specimens, for predictions that are uncertain, for new pests and for ecological interpretation. With the advent of generative AI, concerns regarding hallucinations and misinformation are particularly important when AI-generated content is incorporated into scientific or management decisions. In recent years, the entomological and scientific communities have also highlighted the need for validation, transparency and responsible use of AI in research, teaching and scientific communication.

9. CONCLUSION

AI is an emerging enabling technology in contemporary entomology, and is increasing the ability to gather, process and interpret complex biological data. It has evolved from automated insect identification to behavioural analysis, population monitoring, biodiversity assessment, ecological research and pest management. The convergence of AI and IoT, edge computing, multimodal data and generative models is also opening up new possibilities for more continuous, interconnected and context-aware approaches to insect research.

The successful application of AI in entomology will require access to accurate data, field testing, interpretable and transparent models, and the inclusion of more taxonomically and geographically diverse insect groups. AI should be used in conjunction with, not in place of, the skills of taxonomists, ecologists and applied entomologists. The impact of AI in entomology will not just be about automation of recognition or prediction, but also about the

ability to combine computational analysis with biological and ecological knowledge. This integration can enhance the efficiency, scalability, and data-driven nature of entomological research while maintaining the ecological context essential for understanding insects and their interactions with crops and ecosystems.

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