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Artificial Intelligence in Entomology: Revolutionizing Insect Classification and Systematics

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Abstract
Accurate and rapid insect identification is a cornerstone of entomology, biodiversity monitoring, and integrated pest management. Traditional taxonomic approaches, reliant on expert morphological evaluation, are often time-consuming, labor-intensive, and prone to human error, especially when handling large-scale datasets. Recent advances in artificial intelligence (AI), particularly deep learning (DL) and machine learning (ML), have revolutionized insect classification and systematics by enabling automated, high-throughput, and scalable identification pipelines. Convolutional neural networks (CNNs), object detection frameworks, and hybrid approaches that integrate morphological, spectral, and acoustic data have demonstrated performance approaching human-level accuracy for several insect taxa. Despite these advancements, challenges such as limited labeled datasets, class imbalance, small-object detection, domain adaptation, and integration with classical taxonomy remain. This review synthesizes current AI approaches in insect classification, evaluates available datasets and benchmarking strategies, examines applications in biodiversity monitoring, pest management, and life-stage analysis, and outlines limitations and solutions to enhance AI-assisted entomological research.

Keywords: Artificial intelligence, deep learning, insect classification, systematics, computer vision, biodiversity monitoring

Introduction

Insects represent the largest and most diverse group of organisms on Earth, with over a million described species and estimates suggesting millions more remain undescribed [1]. Accurate identification is critical for ecological studies, pest control, conservation biology, and disease vector management. Traditional taxonomy relies heavily on morphological examination by trained experts, often using microscopes, dichotomous keys, and specialized identification manuals [2]. While accurate, these methods are labor-intensive and slow, making large-scale monitoring impractical. Moreover, morphologically similar or cryptic species such as *Anopheles gambiae* (mosquito), *Bactrocera dorsalis* (oriental fruit fly), and *Sitophilus oryzae* (rice weevil) often require molecular techniques such as DNA barcoding for accurate identification, further increasing time and cost [3].

The integration of artificial intelligence (AI) in entomology has significantly transformed traditional workflows. AI techniques, particularly deep learning (DL), have demonstrated remarkable ability to classify insects at species or genus levels using images, videos, or acoustic signals. These approaches can rapidly process vast datasets, accommodate variations in specimen appearance, and operate effectively under field conditions with minimal human intervention [4]. This review synthesizes current AI approaches applied to insect classification and systematics, discusses their applications, highlights challenges, and outlines limitations and solutions.

AI Approaches Used in Insect Classification and Systematics

1. Supervised Deep Learning (Convolutional Neural Networks)

Convolutional neural networks (CNNs) are the most widely used deep learning architecture for image-based insect identification. CNNs extract hierarchical features from input images through layers of convolutional filters, pooling, and activation functions. Early layers capture low-level features such as edges and textures, while deeper layers encode high-level patterns such as body segmentation, wing venation, and coloration patterns [5]. Transfer learning, wherein pre-trained networks such as ResNet, VGG, and EfficientNet are fine-tuned on insect-specific datasets, has shown excellent performance even when labeled data are limited [6].

Fine-grained classification is particularly relevant for insects, as species often exhibit subtle morphological differences. Multi-scale CNN architectures, attention mechanisms, and ensemble methods enhance the network's ability to discriminate visually similar species [5, 6]. Studies have demonstrated that CNNs can achieve over 90% accuracy for certain taxa such as *Lepidoptera* (butterflies and moths), *Coleoptera* (beetles), and *Hymenoptera* (bees, ants, and wasps) when trained on curated datasets [5, 6].

2. Object Detection and Instance Segmentation

Detecting insects in cluttered or natural backgrounds requires robust object detection algorithms. Frameworks such as YOLO (You Only Look Once), Faster R-CNN, and RetinaNet have been adapted to identify and localize insects in images from camera traps, light traps, and smartphone-based monitoring systems [7, 9]. Instance segmentation models, particularly Mask R-CNN, enable pixel-level delineation of individual insects, facilitating precise feature extraction and downstream classification.

These methods address challenges such as small-object detection, overlapping individuals, and variable environmental conditions (lighting, occlusion, background clutter) [7]. For example, YOLOv5 has been successfully applied to detect developmental stages of monarch caterpillars (*Danaus plexippus*) in complex field conditions, achieving high precision and recall [7]. Instance segmentation also allows automated measurement of morphological traits, such as wing area or body length, which are essential for systematics and phenotypic studies.

3. Multimodal Approaches

Beyond RGB imagery, AI pipelines increasingly integrate additional data modalities to improve identification accuracy. Acoustic analysis of wingbeat frequencies has been used to differentiate mosquito species such as *Aedes aegypti* and *Culex quinquefasciatus*, while hyperspectral imaging can capture subtle chemical or structural differences in insect cuticle [10]. Micro-CT scans and 3D morphological reconstructions enable high-resolution feature extraction for systematics and cryptic species identification [10]. Multimodal models combine these signals, often using late fusion strategies, to improve robustness under diverse field conditions.

Integrating spatial and temporal metadata (e.g., GPS coordinates, collection date, habitat type) further enhances classification, particularly for species with seasonally or geographically restricted distributions [10].

4. Semi-Supervised, Few-Shot, and Active Learning

A major limitation in insect AI is the scarcity of labeled data for many taxa. Semi-supervised learning leverages unlabeled images alongside a small number of labeled specimens to improve model performance [11]. Few-shot learning techniques enable species identification from only a handful of labeled images, mimicking human expert learning from minimal examples. Active learning frameworks allow models to identify uncertain predictions and request expert labeling, optimizing annotation efforts and improving dataset quality [11].

These approaches are particularly valuable for understudied taxa and regions, enabling scalable AI deployment in biodiversity hotspots where data scarcity is most pronounced.

5. Out-of-Distribution (OOD) Detection and Reliability Estimation

For operational applications in the field, models must recognize when they encounter unfamiliar species or low-quality images. OOD detection techniques, such as Bayesian approximations, ensembles, and specialized uncertainty estimation methods, allow AI systems to abstain or flag uncertain predictions for expert review [12]. This capability is critical in preventing misidentifications, ensuring reliability in pest monitoring, biodiversity assessment, and citizen science applications.

6. Datasets and Benchmarks

High-quality datasets are the backbone of AI-driven insect classification. Public datasets such as IP102 (pest dataset), AMI (insect monitoring images), and iNaturalist's insect collections provide diverse examples across taxa, habitats, and imaging conditions [3, 13, 14]. These datasets include millions of images from thousands of species, capturing in-the-wild conditions such as motion blur, occlusion, variable lighting, and different life stages. Representative examples include agricultural pests like *Helicoverpa armigera* (cotton bollworm) and *Spodoptera litura* (tobacco cutworm).

Curated benchmark datasets allow systematic evaluation of AI models, providing metrics for accuracy, precision, recall, and F1-score [13, 14]. They also facilitate comparison between algorithms and architectures. Dataset augmentation techniques, such as rotation, scaling, and color jittering, further enhance model robustness, particularly for rare species [13].

Citizen-science platforms like iNaturalist provide geographically diverse observations but require careful validation to account for misidentifications and class imbalance [13, 14]. Combining curated datasets with citizen-science images improves both model generalization and ecological relevance.

Key Applications

1. Biodiversity Inventories and Faunal Monitoring

Automated insect identification accelerates large-scale surveys and specimen processing from malaise traps, pitfall traps, light traps, and camera traps. AI enables near real-time monitoring of species richness, abundance trends, and phenology [9, 15]. For example, automated identification of *Bombus terrestris* (buff-tailed bumblebee) and *Papilio demoleus* (lime butterfly) has facilitated pollinator population studies.

2. Pest Detection and Crop Protection

Early detection of pest outbreaks is crucial for sustainable agriculture. AI-integrated traps, drones, and smartphone apps allow rapid, species-specific pest identification, enabling targeted interventions and reduced pesticide use [16, 17]. Notable cases include automatic recognition of *Nilaparvata lugens* (brown planthopper), *Locusta migratoria* (migratory locust), and *Leptinotarsa decemlineata* (Colorado potato beetle).

3. Life-Stage and Behavior Classification

Identifying insect developmental stages (larvae, pupae, adult) is essential for ecological and pest management studies. DL models have been trained to classify instars and detect behaviors such as foraging, mating, and oviposition from video and image datasets [16, 18].

4. Museum Digitization and Taxonomic Workflows

AI assists in digitization of entomological collections, pre-sorting specimens, and suggesting candidate identifications [5, 6]. Experts can then focus on validation and taxonomic research, increasing efficiency and reducing human error. Integration with taxonomic databases and specimen metadata ensures correct labeling and facilitates discovery of misidentified or novel species [6].

5. Performance, Accuracy, and Comparisons with Experts

AI models, when trained on well-curated datasets, achieve species-level classification accuracies exceeding 90% for many insect taxa [1, 5, 7]. Comparative studies show that CNN-based systems often approach expert-level performance for visually distinct species, but accuracy declines for cryptic or rare taxa such as *Culex pipiens* or *Cryptolaemus montrouzieri*. Ensemble models, multi-scale architectures, and attention-based mechanisms improve performance in such cases. AI complements rather than replaces human experts; human validation remains critical for cryptic species, synonymy resolution, and taxonomic revisions [1, 5, 7].

Major Challenges and Current Solutions

1. Data Scarcity and Class Imbalance

Many insect species are underrepresented or absent in labeled datasets, limiting model generalization. Approaches such as transfer learning, synthetic data augmentation, few-shot learning, and collaborative citizen-science labeling platforms have been used to address this challenge [6, 13].

2. Small-Object Detection and Occlusion

Insects often occupy a small portion of images or are partially occluded by vegetation or other individuals. Multi-scale object detectors, high-resolution imaging, and attention mechanisms improve detection and segmentation [7, 9].

3. Domain Shift and Out-of-Distribution Samples

Models trained on museum or laboratory images may perform poorly in field conditions due to variations in lighting, angle, or background. Domain adaptation, fine-tuning on in-the-wild datasets, and OOD detection modules mitigate misclassification risks [12, 16].

4. Explainability and Taxonomic Integration

Black-box predictions can hinder adoption by taxonomists. Explainable AI methods, such as saliency maps and class activation mapping, reveal which morphological traits influence model predictions, aiding expert interpretation and trust [6].

5. Taxonomic Resolution and Synonymy

Species concepts evolve over time, creating challenges for AI integration. Linking models to authoritative taxonomic backbones, updating synonym lists, and versioning datasets are critical to maintain accuracy and consistency in systematics [5].

Deployment, Edge Computing, and Citizen Science

Edge devices, including smart traps and mobile apps, enable real-time insect detection with low computational cost and minimal connectivity requirements [13, 15]. Citizen-science platforms contribute large volumes of labeled and unlabeled data, increasing model generalization. However, data quality control, expert validation, and noise filtering remain essential to maintain model reliability [13, 15, 17].

Conclusion

Artificial intelligence has emerged as a transformative tool in insect classification and systematics. DL and ML models enable rapid, scalable, and accurate identification, complementing traditional taxonomy. AI has proven effective for biodiversity monitoring, pest detection, life-stage analysis, and museum digitization. Despite the progress, challenges such as data scarcity, small-object detection, domain adaptation, and explainability persist. Addressing these challenges through integrative, multimodal, and community-based approaches will ensure that AI achieves its full potential, enhancing both applied and fundamental entomological research.

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