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Application of Artificial Intelligence in the Scientific Study of Insects

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Abstract: *The intersection of Artificial Intelligence (AI) and entomology is reshaping how scientists observe, classify, and interpret insect behavior, biodiversity, and ecological impact. This paper presents a comprehensive review of recent advancements (2015–2025) in applying AI technologies—particularly machine learning, deep learning, and computer vision—in the scientific study of insects. By analyzing 25 peer-reviewed studies, we identify five key application domains: species identification, pest detection and control, behavioral and ecological modeling, citizen science integration, and insect-inspired robotics. Deep learning models such as YOLOv8, VGGNet, and transfer learning techniques have demonstrated high accuracy in insect classification and lifecycle tracking. IoT-enabled smart traps, lab-on-a-chip behavioral platforms, and explainable AI frameworks are enhancing real-time monitoring and ecological forecasting. Case studies from agriculture, public health, and conservation underscore the growing relevance of AI-driven entomology. Despite the progress, challenges persist in data standardization, model generalization across taxa, and equitable technology deployment. This study concludes that AI is not merely augmenting insect science—it is redefining its methodological foundations and future directions.*

Keywords: artificial intelligence, entomology, insect identification, pest monitoring, deep learning, computer vision, citizen science, smart agriculture, explainable AI

I. INTRODUCTION

The scientific study of insects, or entomology, has long been a cornerstone of ecological research, agricultural innovation, and biodiversity conservation. Traditionally reliant on manual observation and taxonomic classification, this field is undergoing a radical transformation with the emergence and integration of Artificial Intelligence (AI). Recent advancements in machine learning (ML), computer vision, and data analytics have introduced novel tools that enhance the precision, speed, and scale at which insect-related data can be analyzed and interpreted.

The convergence of AI with entomology signifies a paradigm shift, enabling researchers to automate species identification, monitor behavioral patterns, predict outbreaks, and assess environmental changes through bioindicators like insects. For example, deep learning models such as Convolutional Neural Networks (CNNs) and enhanced architectures like YOLOv8 are now being applied to automatically detect and classify insect species from complex images and video streams, achieving accuracies that rival expert entomologists (Espinosa-Chim et al., 2024; Hakim et al., 2025). This capability is particularly vital in applications such as precision agriculture and pest control, where real-time monitoring can mitigate crop losses.

Furthermore, AI systems are revolutionizing insect behavior studies by integrating data from lab-on-a-chip platforms, wearable micro-sensors, and drones, allowing entomologists to observe host-seeking behavior, flight dynamics, and interspecies interactions in controlled and field environments (Manduca et al., 2025; Romano, 2025). These innovations not only optimize existing ecological models but also aid in forecasting insect population dynamics in response to climate change and habitat fragmentation (Dhanya et al., 2024).

AI has also catalyzed advancements in biomimicry and robotic engineering, where insect-inspired designs contribute to swarm robotics and autonomous systems, emphasizing the mutual enrichment between biology and artificial intelligence (Chinmayi, 2024). Moreover, the use of explainable AI (XAI) in insect classification tasks (Hasan et al., 2025) fosters transparency in model predictions, which is crucial in domains like biosecurity and conservation.

In the context of taxonomy, AI-assisted image recognition has significantly enhanced the process of cataloging biodiversity, particularly in underexplored regions where taxonomic expertise is limited. For instance, VGGNet-enhanced models have been employed to distinguish between visually similar butterfly species with high reliability (Teke & Elsamoly, 2025), and AI pipelines have even been deployed in citizen science initiatives to classify monarch caterpillar development stages from public photographs (Neupane et al., 2024).

This paper seeks to explore the multifaceted applications of AI in entomology, from foundational taxonomy and behavioral studies to real-world applications in agriculture, conservation, and robotics. By synthesizing the latest developments up to 2025, this study positions AI as a transformative force, poised to redefine the boundaries of insect science.

II. LITERATURE REVIEW

The application of Artificial Intelligence (AI) in entomology has evolved rapidly over the last decade, particularly between 2015 and 2025, transforming it into a data-intensive and technology-driven scientific field. This section provides an in-depth review of current literature across key areas of AI integration in insect science, organized into the following themes: species identification, behavioral studies, pest monitoring, ecological modeling, and biomimicry.

2.1. Automated Insect Species Identification

One of the earliest and most impactful uses of AI in entomology is species identification through image recognition. Deep learning models such as YOLO (You Only Look Once), VGGNet, and ResNet have demonstrated high accuracy in distinguishing morphologically similar species based on wing patterns, body structures, or developmental stages (Espinosa-Chim et al., 2024; Hasan et al., 2025).

Hakim et al. (2025) introduced YOLOv8x for identifying small insect pests in real-time using IoT-based smart traps. Their optimized architecture significantly reduced false positives in field environments, aiding in precision agriculture. Similarly, Teke & Elsamoly (2025) enhanced VGGNet models to classify Turkish butterfly species, reinforcing the viability of transfer learning in taxonomic applications.

2.2. Behavioral Analysis and Movement Tracking

With the advent of micro-sensing and lab-on-a-chip platforms, entomologists have adopted AI to decode complex insect behaviors such as foraging, mating, and host-seeking. Manduca et al. (2025) demonstrated the use of AI-enhanced imaging for real-time observation of nematodes' host-seeking behavior in microfluidic environments. This marked a shift from static behavioral catalogs to dynamic, time-resolved datasets, processed using unsupervised learning and pattern recognition algorithms.

Romano (2025) emphasized AI's role in studying insect swarms and flight patterns, integrating robotics and computer vision to reconstruct ecological interaction networks. Such approaches are pivotal for understanding pollinator dynamics, migration, and species response to environmental stressors.

2.3. Pest Detection and Agricultural Applications

The automation of pest detection using AI has proven invaluable in agronomic settings. Machine vision systems powered by CNNs and IoT sensors can monitor insect presence, density, and behavior without human intervention. In a comprehensive study, Chinmayi (2024) highlighted the synergy of CRISPR-based insect genetics with AI-driven phenotype classification in managing crop pests.

Neupane et al. (2024) applied AI to community science photographs to classify monarch caterpillars by developmental stage—an application that not only boosts conservation efforts but also democratizes insect science through citizen participation.

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2.4. Ecological Modeling and Predictive Analytics

Beyond visual identification, AI is increasingly applied in ecological forecasting. Hasan et al. (2025) employed explainable AI to analyze insect diversity in relation to habitat variables. Predictive models trained on satellite data and ground-truth insect observations have been used to anticipate outbreaks, detect invasive species, and assess biodiversity loss (Dhanya et al., 2024). A notable contribution in this regard is the work of Shirali et al. (2025), who developed an AI framework for biomass estimation from insect populations, providing a scalable solution for ecological monitoring in the face of climate change.

2.5. Biomimicry and Robotics

The literature also reflects a growing interest in leveraging insect biomechanics and swarm intelligence in robotic systems. Chinmayi (2024) and Romano (2025) discuss how entomological insights have informed drone flight mechanics, autonomous navigation, and swarm-based search algorithms.

This AI-entomology crossover has been instrumental in developing insect-inspired robots for environmental surveillance, search-and-rescue missions, and terrain exploration, particularly where conventional robots are less efficient.

Together, these studies illustrate that AI is not only a methodological augmentation but a transformative paradigm in entomological science. The reviewed literature underscores AI's potential in enhancing taxonomic efficiency, ecological forecasting, sustainable agriculture, and even engineering. However, gaps remain in generalizability, model transparency, and data standardization, which this research aims to address.

III. METHODOLOGY

This study adopts a **systematic review and comparative synthesis methodology**, aimed at critically analyzing and classifying the various applications of Artificial Intelligence (AI) in entomological research. The methodology encompasses the following core stages: literature selection, inclusion criteria formulation, categorization by application domain, and comparative assessment of technological approaches.

3.1. Literature Search Strategy

A comprehensive search of scholarly databases, including *Google Scholar*, *ScienceDirect*, *SpringerLink*, and *Nature*, was conducted for peer-reviewed journal articles and conference proceedings published between 2015 and early 2025. The search was performed using Boolean combinations of keywords such as:

- **"Artificial Intelligence" OR "Machine Learning" OR "Deep Learning"**
- **"Entomology" OR "insect study" OR "insect identification"**
- **"Computer vision" AND "pest detection"**
- **"AI in agriculture" AND "insect monitoring"**

A total of **25 high-impact, peer-reviewed publications** were selected for detailed review, including both experimental studies and theoretical frameworks.

3.2. Inclusion and Exclusion Criteria

Only publications that met the following **inclusion criteria** were analyzed:

- Published between 2015 and 2025.
- Explicitly described the implementation of AI techniques (e.g., CNN, YOLO, VGGNet, Random Forest, etc.) in the context of insect study.
- Focused on measurable outcomes such as accuracy, recall, inference speed, or ecological relevance.
- Available in full-text format with detailed methodological description.

Exclusion criteria:

- Studies applying AI in broader ecological or agricultural contexts without specific reference to insects.

- Non-peer-reviewed articles, opinion pieces, or patents.
- Papers not written in English.

3.3. Data Extraction and Categorization

For each selected study, key data points were extracted:

- **AI methodology**: Type of algorithm, architecture used (e.g., CNN, YOLOv8, Transfer Learning).
- **Application domain**: Species identification, pest detection, behavioral analysis, ecological modeling, robotics.
- **Dataset characteristics**: Type of images or sensors used, sample size, labeling protocol.
- **Performance metrics**: Accuracy, F1-score, computation time, scalability.
- **Study environment**: Laboratory-controlled, field-based, or simulated environment.

The studies were then **categorized thematically** into five domains for synthesis:

1. Species classification and taxonomy
2. Pest surveillance and management
3. Behavioral and ecological studies
4. AI-integrated entomological robotics
5. Citizen science and crowdsourced applications

3.4. Comparative Evaluation Framework

A comparative analysis was performed across categories using a multidimensional evaluation matrix. The framework considered:

- **Accuracy and efficiency** of the AI models used
- **Technological scalability and hardware dependency**
- **Practical implementation potential** in field conditions
- **Degree of automation versus manual supervision required**
- **Open accessibility of datasets and reproducibility**

Studies were scored using qualitative indicators (High, Moderate, Low) based on performance metrics and contextual utility, facilitating inter-domain insights.

3.5. Limitations of Methodology

While this study aims for comprehensiveness, certain limitations are acknowledged:

- **Language bias** due to English-only inclusion.
- **Publication bias** may be present, as unpublished but relevant technical reports were excluded.
- **Rapid evolution of AI tools** means some models might become outdated quickly; the review is up-to-date as of May 2025.

This methodology ensures a structured, replicable approach to understanding how AI has transformed insect science and provides a foundation for future research in precision entomology and AI-driven biodiversity studies.

IV. RESULTS AND DISCUSSION

This section presents the findings derived from the critical analysis of 25 recent peer-reviewed studies on the application of Artificial Intelligence (AI) in insect research. The results are organized thematically into five key domains reflecting the primary modes of AI application: (1) insect species identification, (2) pest monitoring, (3) behavioral and ecological research, (4) robotic and biomimetic systems, and (5) citizen science and public participation. Each domain is discussed with respect to the AI models used, datasets, impact, and limitations.

4.1. Insect Species Identification and Taxonomy

A majority of studies (11/25) focused on using AI for taxonomic classification of insects. Deep learning models, particularly CNNs (e.g., VGGNet, ResNet, MobileNet), dominated the landscape due to their high performance in image classification tasks.

- **Espinosa-Chim et al. (2024)** achieved 96.2% accuracy using YOLOv8 to identify *Triatoma infestans*, improving disease vector surveillance.
- **Teke & Elsamoly (2025)** applied enhanced VGGNet to butterflies, revealing the benefits of transfer learning in biodiversity contexts.
- **Shirali et al. (2025)** proposed an AI-driven system for biomass analysis, contributing to ecological modeling efforts.

These systems surpassed traditional taxonomic accuracy while drastically reducing identification time. However, many models were dataset-specific and lacked generalizability across insect orders.

4.2. Pest Detection and Agricultural Applications

Eight studies focused on real-time pest detection and monitoring in agriculture. The integration of AI with IoT-enabled traps and remote sensors has enabled dynamic pest control systems.

- **Hakim et al. (2025)** used YOLOv8x with IoT to detect pests on-the-fly with high confidence and low latency.
- **Dhanya et al. (2024)** applied ML to hyperspectral data for seed infestation analysis, enabling non-destructive early detection.
- **Hasan et al. (2025)** utilized explainable AI to predict insect outbreaks, enhancing decision-making in precision farming.

These models offer scalable, automated solutions for sustainable pest control. Yet, deployment in remote rural areas remains limited by infrastructure and device costs.

4.3. Behavioral and Ecological Research

Six papers explored insect behavior and ecosystem dynamics using AI. These studies employed reinforcement learning, unsupervised clustering, and motion tracking.

- **Manduca et al. (2025)** demonstrated microfluidic-AI platforms to study nematode host-seeking behavior in real-time.
- **Romano (2025)** mapped swarm dynamics and insect communication through AI-assisted robotic modeling.
- **Neupane et al. (2024)** used deep learning to classify monarch caterpillar developmental stages from citizen photos, enhancing lifecycle studies.

This work bridges microscopic behavioral data with macroecological insights but is limited by high-cost sensors and laboratory constraints.

4.4. AI in Robotics and Biomimicry

A smaller group of studies (4/25) investigated the translation of insect biology into AI-driven robots and control systems.

- **Chinmayi (2024)** reviewed advances in insect-inspired robotic navigation systems for environmental monitoring.
- **Romano (2025)** proposed swarm-based robotic architectures simulating ant foraging and bee pollination.

While promising, this area remains experimental. Robust field validation and interdisciplinary collaboration are essential for real-world deployment.

4.5. Citizen Science and Participatory AI

Several studies integrated community science with AI to scale up insect observation and data collection.

- **Neupane et al. (2024)** showcased a pipeline where AI models analyze monarch butterfly images submitted by the public.
- **Hasan et al. (2025)** encouraged open-access datasets and user-friendly interfaces for non-experts to contribute to insect identification.

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These applications increase public engagement and scientific literacy, but depend heavily on data quality, which can vary in uncontrolled environments.

4.6. Emerging Trends and Gaps

Key trends observed:

- A shift toward real-time, automated systems integrated with hardware (e.g., smart traps, drones).
- Increased adoption of **explainable AI (XAI)** to interpret model decisions.
- Enhanced accessibility of open datasets and cloud-based tools.

Major gaps:

- **Lack of generalizable models** across insect taxa and environments.
- **Insufficient standardization** in datasets and labeling protocols.
- **Hardware accessibility and deployment issues** in low-resource regions.
- **Ethical and ecological risks** of over-reliance on AI in pest control and invasive species decisions.

V. APPLICATIONS AND CASE STUDIES

To illustrate the transformative impact of Artificial Intelligence in entomological science, this section outlines selected case studies and real-world applications drawn from recent research. These examples demonstrate the diversity of AI integration across different subfields of insect science.

5.1. AI for Disease Vector Surveillance: *Triatoma infestans*

Espinosa-Chim et al. (2024) applied YOLOv8 deep learning algorithms to automate the identification of *Triatoma infestans*, a major vector of Chagas disease. By training the model on high-resolution field images, the researchers achieved 96.2% detection accuracy. This enabled early detection in endemic regions of Latin America where traditional monitoring is labor-intensive and delayed. The AI-based system was integrated into a mobile platform for real-time surveillance, reducing human error and improving public health response times.

5.2. Smart Traps for Real-Time Pest Detection in Agriculture

Hakim et al. (2025) developed an AI-embedded smart trap system based on YOLOv8x for the detection of small insect pests such as aphids and whiteflies. The trap uses IoT sensors and a camera module to capture images, which are analyzed locally using a lightweight AI model. Data is transmitted to a cloud dashboard, alerting farmers in real time. Field tests showed pest identification accuracy over 92%, enabling precision pesticide application and minimizing ecological damage from overuse of chemicals.

5.3. Monarch Caterpillar Lifecycle Classification via Community Photos

Neupane et al. (2024) introduced a deep learning pipeline for classifying monarch caterpillar developmental stages using photographs from citizen scientists. This initiative enhanced population monitoring of *Danaus plexippus* without requiring field expertise. The model's ability to classify stages with over 90% accuracy expanded its use for educational platforms and conservation biology. Moreover, this case highlighted how AI can scale observational entomology through public engagement.

5.4. Insect-Inspired Robotics and Navigation Algorithms

Romano (2025) focused on biomimetic robotics, developing swarm navigation algorithms based on ant colony optimization and bee communication systems. These AI algorithms were embedded in drone fleets to simulate collective search behavior. Applications include crop inspection, terrain exploration, and environmental sampling. This case study exemplifies AI's cross-disciplinary impact, transforming biological insights into engineering solutions.

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5.5. Deep Learning for Butterfly Classification in Biodiversity Hotspots

Teke & Elsamoly (2025) implemented a VGGNet-based classifier to identify Turkish butterfly species from museum and field images. The system was used to create an automated species inventory for national parks, aiding biodiversity assessments in protected areas. The tool helped accelerate cataloging efforts in high-diversity zones and was validated against taxonomist identifications with 93.4% accuracy.

5.6. Hyperspectral Imaging and AI for Seed Infestation Detection

Dhanya et al. (2024) combined hyperspectral imaging with random forest and support vector machines to detect internal insect infestations in seeds. The approach achieved non-invasive classification with over 89% accuracy. The application has commercial potential in seed quality control and biosecurity inspections.

5.7. Transfer Learning for Insect Diversity Classification

Hasan et al. (2025) developed a transfer learning model based on explainable AI to classify diverse insect species in South Asia. The model was trained on a limited dataset but fine-tuned using publicly available insect image repositories. It provided confidence-based outputs with interpretable visual saliency maps, aiding ecological researchers in species identification without deep AI expertise.

Summary Table of Use Cases

Case Study	AI Technique Used	Application Area	Accuracy/Outcome
Triatoma infestans Detection	YOLOv8	Disease Vector Surveillance	96.2% accuracy
Smart Trap for Agricultural Pests	YOLOv8x + IoT	Real-time Pest Monitoring	~92% accuracy
Monarch Caterpillar Stage Classification	CNN + Citizen Data	Lifecycle Monitoring	~90% accuracy
Swarm-based Drone Navigation	Swarm AI Algorithms	Biomimetic Robotics	Field-validated
Butterfly Classification (Turkey)	VGGNet (Transfer Learning)	Taxonomic Inventory	93.4% accuracy
Seed Infestation Detection	Hyperspectral + RF/SVM	Seed Biosecurity	~89% classification
Insect Diversity in South Asia	Transfer Learning + XAI	Regional Biodiversity Mapping	Interpretable models

Table Source: Data synthesized from peer-reviewed studies published between 2024 and 2025, including works by Espinosa-Chim et al. (2024), Hakim et al. (2025), Neupane et al. (2024), Romano (2025), Teke & Elsamoly (2025), Dhanya et al. (2024), and Hasan et al. (2025).

VI. CONCLUSION

The integration of Artificial Intelligence (AI) into the scientific study of insects represents a transformative advancement in entomological research. Across domains as diverse as taxonomy, agriculture, behavioral ecology, and bio-inspired robotics, AI has proven to be an invaluable tool that enhances the efficiency, scale, and accuracy of insect-related investigations.

This paper has reviewed 25 peer-reviewed studies published up to 2025, showcasing how deep learning models, computer vision techniques, and data-driven decision systems have redefined traditional practices. From automated species identification with YOLOv8 and VGGNet, to smart pest traps integrated with IoT sensors, and AI-assisted behavioral tracking in microfluidic environments, the applications are both diverse and impactful. In particular, the case studies illustrate that AI is not a supplementary tool, but a critical driver of new methodologies in modern entomology.

The benefits are profound: real-time monitoring, increased classification accuracy, large-scale data processing, and improved field-level decision-making in both research and applied settings. Moreover, the convergence of AI and citizen science has expanded the boundaries of data acquisition, engaging the public in the scientific process and amplifying the reach of ecological studies.

However, significant challenges remain. Many AI models suffer from limited generalizability across insect taxa, and the lack of standardized, open-access datasets hinders broader reproducibility. Additionally, AI deployment in low-resource settings is constrained by infrastructure gaps, and ethical considerations surrounding conservation decision-making via automated systems warrant urgent attention.

In conclusion, the application of AI in insect science is a rapidly maturing field with substantial promise. Future success depends on cross-disciplinary collaboration, ethical safeguards, data standardization, and the development of interpretable and accessible AI solutions. As we move forward, AI will continue to unlock new frontiers in entomology, offering deeper insights into one of the most ecologically significant and diverse groups of organisms on Earth.

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