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Application of artificial intelligence in insect pest identification - A review

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A B S T R A C T

The increasing danger of insect pests to agriculture and ecosystems calls for quick, and precise diagnosis. Conventional techniques that depend on human observation and taxonomic knowledge are frequently labour-intensive and time-consuming. Incorporating artificial intelligence (AI) into detection has emerged as an effective approach in agriculture, including entomology. AI-based detection methods use machine learning, deep learning algorithms, and computer vision techniques to automate and improve the identification of insects. Deep learning algorithms, such as convolutional neural networks (CNNs), are primarily used for AI-powered insect pest identification by categorizing insects based on their visual features through image-based classification methodology. These methods have revolutionized insect identification by analyzing large databases of insect images and identifying distinct patterns and features linked to different species. AI-powered systems can improve insect pest identification by utilizing other data modalities. However, there are obstacles to overcome, such as the scarcity of high-quality labelled datasets and scalability and affordability issues. Despite these challenges, there is significant potential for AI-powered insect pest identification and pest management. Cooperation among researchers, practitioners, and policymakers is necessary to utilize AI in pest management fully. AI technology is transforming the field of entomology by enabling high-precision identification of insect pests, leading to more efficient and eco-friendly pest management strategies. This can enhance food safety and reduce the need for continuous insecticide spraying, ensuring the purity and safety of the food supply chains. This review updates AI-powered insect pest identification, covering its significance, methods, challenges, and prospects.

1. Introduction

Agriculture is the backbone of many countries (Newman et al., 2020) and plays a strategic role in economic development of a nation. Among all stressors, biotic stresses, mainly weeds and insects, cause significant crop yield losses accounting for 33 % and 26 % respectively (Lal et al., 2017). With the global population estimated to reach 9.8 billion by 2050, climate change-induced insect pest outbreaks are expected to further aggravate crop losses, particularly impacting food availability in vulnerable communities (Van Huis, 2013).

Insect pests cause extensive damage to plants through various feeding mechanism. Some feed on above ground parts, while others attack below-ground portions such as roots. Sap-sucking insects like aphids, whiteflies, scales, and mealybugs feed on tender plant parts, leading to distortion, puckering, and stunted growth. Stem and shoot borers such as *Leucinodes orbonalis*, *Scirpophaga incertulus*, and *Chilo partellus* penetrate plant tissues, causing the plants to wilt. Defoliators such as *Spodoptera litura*, *Athalia* spp., and *Papillio* spp. consume green leaf matter, directly reducing crop yield. Additionally, many insect pests are vectors for plant viruses, contributing to indirect plant damage and disease outbreaks (Naveed et al., 2023). The rapid spread of plant viruses even can cause epidemics, particularly in perennial trees where losses are compounded by the time and cost associated with re-establishment (Moreno et al., 2008; Naidu et al., 2014; Rimbaud et al., 2015). These concerns underscore the need for advanced tools to manage biotic stresses, especially insect pests during the cropping season. Accurate and timely pest identification is critical for implementing sustainable pest management strategies. Traditionally pest identification relies on expert knowledge, which is labour-intensive and not easily scalable (Ding and Taylor, 2016; Sun et al., 2018; Li et al., 2021a). Many small and medium farmers believe that their empirical

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knowledge is insufficient to address contemporary farming challenges (Hillnhütter et al., 2010). Consequently, early identification of insect pests becomes crucial as this can lead to fastening the interventions with reduced impacts on food safety and security (Selvaraj et al., 2019).

To support early pest detection and forecasting, digital technologies such as artificial intelligence (AI), internet of Things (IoT), machine learning (ML), and deep learning (DL) have entered the agricultural landscape (Javaid et al., 2023). Artificial Intelligence (AI) is the field focused on developing algorithms and models to empower machines or computer systems with the capacity to execute tasks typically requiring human intelligence. From recognizing patterns in data to complex tasks like language translation and image analysis, AI spans a spectrum of applications. Its transformative potential lies in simulating human cognitive functions, revolutionizing industries, enhancing automation, and tackling intricate problems. It is challenging to pick one definition of AI because researchers have many definitions of AI in various formats (Gbadegeshin et al., 2021). One of the core parts of AI includes Artificial Neural Networks (ANN) (Mohankumar et al., 2021), and these are inspired by biological nervous networks, i.e., a neuron, and function as the "Brain" (Fig. 1) of an AI (Kumar and Ramadevi, 2022). Machine learning (ML), a subset of artificial intelligence that enables computers to learn from data and make decisions or predictions without being explicit programming (Samuel, 1959), often struggles to recognize different pests and damage symptoms due to its reliance on manual feature selection and fusion (Chakrabarty et al., 2024). Deep Learning (DL), a subset of machine learning, and an advanced form of ANN, provides a breakthrough in addressing the complex problems of traditional machine learning. Deep Learning can ascertain comprehensive features from the training dataset, eliminating the need for further image processing to meet outdoor conditions (Li et al., 2022c). This makes it essential for general object recognition tasks (Mohankumar et al., 2021), as shown in the crop research (Bheemanahalli et al., 2021).

AI-based image classification systems, coupled with machine learning and deep learning tools, are extremely helpful in identifying insect pests (Wäldchen and Mäder, 2018). These can extract the features from the images, interpret, and understand the visual information, and thus allow a system to improve its performance on a particular task (like- identification) over time (Teixeira et al., 2023). The algorithms are highly dependable on ground truth features, which imply much human knowledge and complex parameters in their development (Espinoza et al., 2016; Valan et al., 2019; Wang et al., 2012; Wen and Guyer, 2012). These technical and effective algorithms can replace the traditional way and avoid the spread of insect pests over a large area (Patel et al., 2020), thereby improving crop yield.

While AI-based tools for insect pest identification have gained attention, there is still a lack of consolidated understanding on the steps how these tools perform across different practical scenarios in agriculture. In real-world applications, the conditions may vary widely as open fields present challenges such as uneven lighting and moving backgrounds; trap-based images often involve overlapping pests or low resolution; and baseplate images require fine detection under cluttered conditions. Therefore, this review provides the comprehensive overview regarding the use of AI tools for insect pest identification under different agricultural settings. The relevant papers are scrutinized, and their methodologies, results, and datasets are analyzed thoroughly. This paper is structured as follows: Section 2 outlines the search methodology adopted for formulating this review. Section 3 presents an overview of the key areas where artificial intelligence can be integrated into basic and applied entomological research. Section 4 delves into the principles and practices of AI-based insect identification, while Section 5 provides a chronological timeline of major AI models developed for automatic insect recognition. Section 6 compiles successful applications of AI tools for insect pest detection across various contexts, and Section 7 offers a critical discussion of the reviewed works. Finally, Sections 8 and 9 elaborate on the future prospects of AI-based insect detection and provide concluding remarks, respectively.

2. Materials and methods

To ensure comprehensive coverage of relevant studies in the domain of AI-based insect pest identification, a targeted and structured literature search was conducted using Google Scholar (https://scholar.google.com/) as the primary database, supplemented by ScienceDirect (https://www.sciencedirect.com/), IEEE Xplore (https://ieeexplore.ieee.org/Xplore/home.jsp), and SpringerLink (https://link.springer.com/) to expand the scope of peer-reviewed and technically rigorous content. The search spanned publications from 2016 to 2025, reflecting the period of accelerated growth in AI applications in entomology.

The literature search employed a combination of Boolean operators and keyword strings, including using keywords such as "AI-based insect pest identification", "machine learning in entomology", "deep learning in insect pest detection", "smart pest monitoring", "automated insect

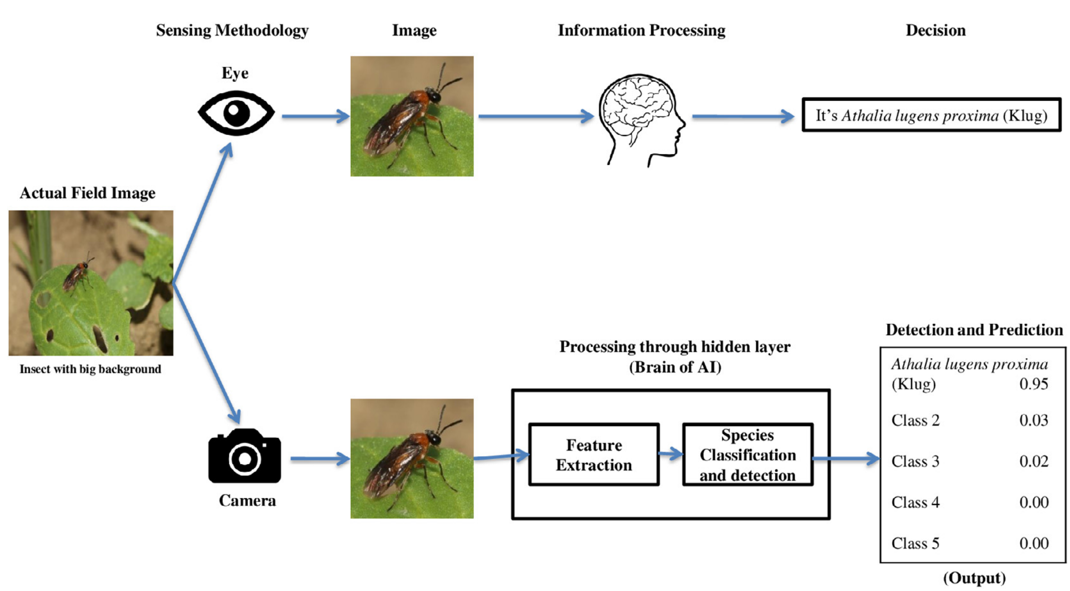

Fig. 1. Pipeline of Differences between Human Learning and Artificial Intelligence- How does a human learn, and how does a machine? Humans process information through the brain, while machines process information through the neural network.

recognition", and "image-based insect recognition". Additional manual searches of reference lists from key papers were also performed to capture relevant studies not indexed through primary queries. Only peer-reviewed journal articles and conference proceedings written in English were included for the review. The primary inclusion criteria were the studies which employed artificial intelligence (AI), machine learning (ML), or deep learning (DL) techniques for identification of insect pests using image-based and video-based inputs and also provided sufficient methodological details and performance evaluations. Articles focused solely on theoretical model development without application to insect pests and studies involving non-insect taxa unless relevant to entomological cross-application are excluded. The final set of included papers was manually screened and thematically categorized into three major application contexts viz.

1. Pest identification under open field conditions.
2. Pest detection in sticky taps.
3. Identification of insect pests on the baseplate of trap systems.

In addition to the core theme of pest identification, the search also yielded several relevant studies where AI techniques were applied in broader entomological contexts, including assessing physical attributes and growth prediction, observation of insect behaviour, sex determination, monitoring of rearing and environmental conditions, and studying pest population dynamics, severity, and pest management strategies. While these studies were not analyzed in depth, they were considered valuable to reflect the broader relevance and trajectory of AI integration in entomological research.

3. Artificial intelligence and entomology: the parallelism

AI has emerged as a powerful tool in entomology due to its ability to automatically extract relevant features from large and complex datasets. This capability makes it particularly valuable in taxonomic research, ecological studies, and pest management (Mohankumar et al., 2021). This section provides an overview of the key areas in entomology where AI technologies are making meaningful contributions and have potential to drive future innovations.

3.1. Identification and classification of insects

Correct identification of insect pests and taxonomic classification through image-based detection has several advantages, such as high efficiency, low cost, easy operation, and most importantly, this can provide necessary information to farmers to take effective measures against that pest (Gayathri and Remya Ajai, 2021). There are various methods available for detecting insect pests and diagnosis using images, such as threshold (Fan and Wang, 2019), edge (Pan et al., 2016), region testing (Zelazo et al., 2018) and graph theory (Junyan, 2020). However, these methods are only suitable for a few sample images and may not be accurate enough (Arshad et al., 2020). Deep Learning (DL) can overcome these disadvantages and is becoming increasingly popular in insect pest detection (Li et al., 2021b). The steps involved in identifying insects using AI tools and their instances have been discussed in Sections 4 and 5, respectively.

3.2. Assessing physical attributes and growth prediction

To select healthy and diseased insects, the farmers follow manual methods like checking physical body factors, size, and weight (Manoukis and Collier, 2019), especially in sericultural farms. However, these slow methods limit the sample size (Bourne et al., 2019). AI tools can be used to reduce the difficulty and invasiveness of these methods, like- computing morphometric values of various objects (like plants, livestock, or fishes) using AI tools were proposed by Zhang et al. (2020), Gebreyesus et al. (2023), and Lopez-Tejeida et al. (2022). From an entomological perspective, scientists have used computer vision and deep learning models not only to examine the physical attributes but also to prepare a growth pattern based on the correlation between the body size and weight of the insects (Rogers et al., 1976; Baur et al., 2022). Hansen et al. (2022) developed one Single Shot Detector-MobileNet-based (SSD-MobileNet) model to measure the size of Black Soldier Fly (*Hermetia illucens*) pupae to recommend the suitability for its breeding for the preparation of animal feed (Barragan-Fonseca et al., 2017). Majewski et al. (2022) also performed DL-based phenotyping of mealworms using "You Only Look Once version 5x" (YOLOv5x) and "Mask Region-Based Convolutional Neural Network" (Mask R-CNN), and they observed that Mask-RCNN achieved higher accuracy in measuring larval length, mass, curvature, and length distribution, although the inference time was longer. Deep learning enables quick and precise assessment of insect phenotypes at a wide scale, unlike traditional methods that measure insects individually or estimate individual weights by measuring batches.

3.3. Observation of insect behaviour

The ethology of insects is characterized by different phenomena such as locomotion, feeding, mating, etc. (Manoukis and Collier, 2019), and the ecologists take the corresponding observations for further studies. However, taking direct field observations is a tedious and highly constrained job (Dell et al., 2014). Insects may behave differently inside a laboratory compared to open field conditions and entomologists face huge difficulties in observing such behaviours due to a lack of proper instruments. These are the areas where artificial intelligence models can be of assistance to researchers. Technologies such as visible implant elastomer (Padget & Thompson, 2021) and miniature sensors (Abdel-Raziq et al., 2021) have been evaluated to study insect behaviours without separating them from bigger populations. However, computer vision supported by deep learning models like- DeepLabCut (Mathis et al., 2018) can increase tracking efficiency from individuals to the entire population. The behavioural outputs are represented by the trajectories of insects in each captured image or video. Fabian et al. (2024) used high-speed insect-scale motion sensors to capture the recordings of flying insects to develop a path marking when exposed to artificial lights. A YOLOv5-based computer vision system was developed to track the behavioural motifs of Black Soldier Fly and domestic cricket during their feeding and mating and mortality levels (Hansen et al., 2022). The amalgamation of AI in detecting the activities of pollinators opens a new area of research. Through AI, the number of pollinators visiting flowers at a particular time and their activities can be easily observed (Ratnayake et al., 2021), through which the foraging pattern will easily be depicted.

3.4. Sex determination of insects

Identification of male and female insects is the key component for taxonomic and entomological studies such as species delineation (Anooj et al., 2020), antennal sensilla characterization (Rani et al., 2021; Shashank et al., 2023), mating and post-mating experiments (Rupali et al., 2023). Adults of many insects possess sexually dimorphic characteristics through which we can easily identify their sex. Artificial intelligence can provide an idea to differentiate between male and female insects of a particular species using high-quality images. Even the pupal stages of both sexes may have some differences, which can be identified using AI tools (Tao et al., 2019; Proietti et al., 2022). YOLOv5 and Support Vector Machine (SVM) methods were used to determine the sex of the crickets (Hansen et al., 2022). It can be challenging to decide on the sex of insects at larval stages because they lack secondary sexual characteristics (Nawoya et al., 2024). However, using certain approaches to identify sex may not always yield accurate results due to the differences in food, habitat, and genetics. However, implementing AI in this field could result in significant advancements in biology and computer science. This technology could help researchers make well-informed decisions during insect rearing and result in better documentation.

3.5. Monitoring of rearing conditions

The rearing of insects is done in the laboratory or culture rooms, which should maintain a proper temperature and relative humidity. Artificial intelligence-based sensors and cameras may be installed to monitor every minute detail of the rearing conditions. Hansen et al. (2022) installed the device "Insecto" in the rearing room's breeding facility, which could monitor the humidity, air pressure, concentration of carbon dioxide, and volatile organic compounds for rearing crickets and altered them accordingly. Integrating deep learning with computer vision and meteorological data is essential to comprehending patterns, boosting productivity, and improving automation intelligence. Controlling the climate facilitates observing and managing insect behaviour, establishing the connection between the environment and the health, behaviour, and insect growth rate.

3.6. Studying insect population, severity, and pest management

Integrated Pest Management (IPM) has gained momentum at a different level since AI is assisting in smartly monitoring insect pests. In addition to detecting insect pests, computer vision, coupled with deep learning algorithms, has led to the development of precision agriculture (Solis-Sánchez et al., 2009; Patrício and Rieder, 2018; Habib et al., 2020). Especially from a pest management perspective, various AI-based expert systems have been developed (Boissard et al., 2008; Abu-Nasser and Abu-Naser, 2018; Alzamily, 2018). A rule-based system has been developed to diagnose insect pests like whiteflies (Shahzadi et al., 2016) which uses moisture, temperature, humidity, and leaf wetness sensors to make management decisions. In recent years, researchers have been using advanced techniques to manage pests in agriculture. For instance, a correlation between crop stage and pest population was used to determine the factors that affect *Helicoverpa armigera* abundance in cotton (Pratheepa et al., 2016). Similarly, Singh et al. (2016) developed a model map to assess the severity of mealybugs using AI-based remote sensing techniques. Furthermore, AI-powered uncrewed aerial vehicles (UAVs) have been developed to detect, monitor, and evaluate the abundance of insect pests in the field. Several studies have been conducted on this topic, including Bhoi et al. (2021), Moses-Gonzales and Brewer (2021), Syeda et al. (2021), Kanwal et al. (2022), Rustia et al. (2022), and Berger et al. (2024). All these advances have had a significant impact on smart pest management in agriculture.

4. Artificial intelligence, insects, and identification: principles and practices

Artificial intelligence (AI) has ushered in a transformative approach in the field of entomology, enabling faster, scalable, and potentially more accurate identification of insect pests. AI-powered image-based detection overcomes the problems of traditional identification methods by automating the process, offering quick results, and making the technology accessible to non-experts such as farmers. Early detection facilitated by AI enhances pest monitoring and helps in optimizing pesticide spray scheduling, minimizing crop loss, and reducing environmental footprint of chemical usage (Li et al., 2021b). In AI models, inputs are given, and the corresponding features are extracted by the model, and in return, it provides the output (Fig. 2). The entire process comprises of several critical steps that determine the final performance of the model, which are elaborated below.

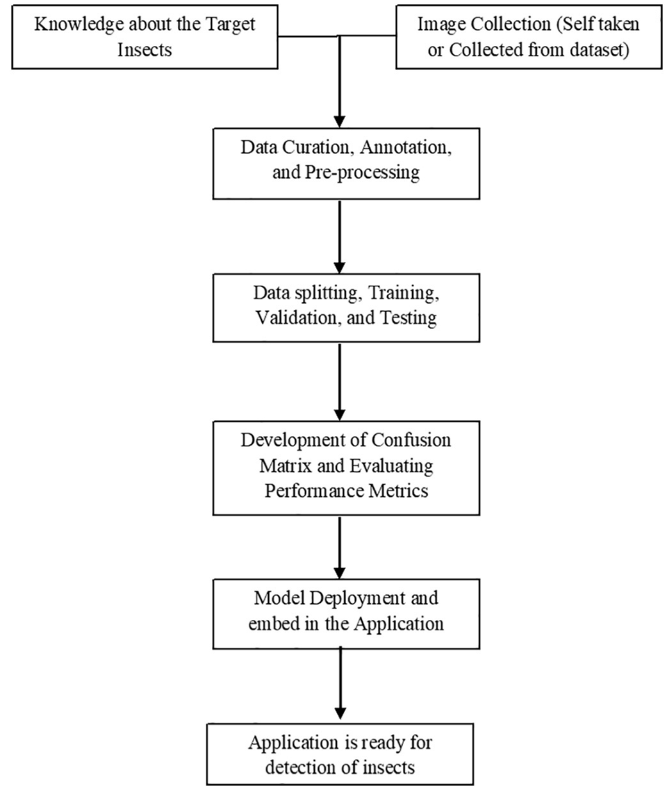

Fig. 2. A General Overview of Detection and Identification of Insect Species Using Artificial Intelligence Models.

4.1. Acquisition of images

Image acquisition is the foundational step in building an AI model for insect identification. One can get necessary images from different internet search engines (Liu et al., 2016), publicly available datasets (Wang et al., 2020b, 2020c, 2021a; Chudzik et al., 2020; Wu et al., 2019; Li et al., 2020b; Kusrini et al., 2020; Thenmozhi and Reddy, 2019; Li et al., 2021a; Xie et al., 2015, 2018) or using own images captured through mobile (Li et al., 2019b; Wang et al., 2021b), SLR cameras, or stationary cameras in a trap (Ding and Taylor, 2016).

4.2. Annotation of images

Annotation is a crucial step in supervised learning where objects of interest (e.g. insects) are labeled in the images. The bounding box annotations encode the label view and combine it with convolutional neural network feature representation for multi-label object identification (Yang et al., 2016). The annotated images generate a set of files in different formats such as XML (Pascal VOC) or TXT (YOLO), containing metadata such as image dimensions, object class, and bounding box coordinates. These annotations act as ground truth during training, allowing the model to learn spatial and categorical information about the insect instances. Annotation can be done manually using tools such as LabelImg, VoTT, or Roboflow, or semi-automatically through pretrained models. Though it is time-consuming, high-quality annotation is essential for robust model training.

4.3. Preprocessing of images

Image preprocessing is a fundamental step in preparing raw image data for training for object detection models (Nigam and Jain, 2019). In the context of insect identification, preprocessing ensures that the input data is clean, standardized, and compatible with model requirements. Unlike traditional image analysis methods, AI-based models are data-hungry and sensitive to inconsistencies in input data. Therefore, applying appropriate preprocessing techniques enhances both model accuracy and training efficiency. Different preprocessing techniques are discussed in the following subsections:

4.3.1. Image resizing

Images are often captured using various devices (e.g. smartphones, SLR/DSLR cameras, trap-based surveillance cameras), resulting in different resolutions and aspect ratios. However, the fundamental aspect of deep learning networks is homogenizing the input data (Goodfellow et al., 2016). Therefore, adjusting all the images to a consistent and convenient pixel dimension (e.g. 640 × 640) ensures uniform input to the model. While resizing, it is important to preserve the aspect ratio of the original image to prevent distortion, which could misrepresent insect morphology and impair learning. If the aspect ratio is altered too much, key identifying features may become unrecognizable to the model. Adding blank pixels around the resized image (Padding) can be used to maintain the aspect ratio during resizing.

4.3.2. Normalization

Normalization standardizes the range of pixel intensity values. Raw image pixels typically range from 0 to 255, but models perform better when pixel values are scaled to a normalized range such as [−1,1] or [1,0] etc. Normalization contributes to faster convergence during model training by reducing numerical instability, improved model performance by reducing sensitivity to brightness or colour inconsistencies, and better gradient flow reducing the chances of vanishing or exploding gradients. Mathematically, normalization is expressed as.

$$\text{Normalized Pixel} = (\text{Pixel value}–\mu)/\sigma \tag{1}$$

Where, μ is the mean of the dataset and σ is the standard deviation.

4.3.3. Data augmentation

AI modeling needs a huge quantity of training data (here images or videos of insects) to achieve robust performance. In entomology, collecting extensive datasets of insect species under varying environmental conditions can be time-consuming. Data augmentation addresses this by synthetically expanding the dataset and introducing variability, thus helping the model generalize better and preventing overfitting. It includes geometric transformations (Xing et al., 2019) such as rotation, horizontal and vertical flipping, scaling and zooming, cropping and padding (Duong and Nguyen-Thi, 2021); photometric adjustments such as brightness, contrast, and saturation changes; colour jittering (Maharana et al., 2022), gamma correction, colour space transformations (RGB to HSV) (Chen et al., 2020; Rahman et al., 2020); noise injection or reduction (Khanramaki et al., 2021) such as addition of Gaussian or salt-and-pepper noise, blurring or sharpening files, using denoising autoencoders for reconstructuring noisy inputs.

4.3.4. Image segmentation

Segmentation refers to the process of isolating the region of interest (ROI), i.e. the insect or the damage symptoms from the background. This step is particularly useful when dealing with complex, cluttered, or noisy backgrounds, which may confuse the model (Goncalves et al., 2021). Several segmentation techniques have been employed in insect detection and pest monitoring systems, ranging from classical image processing to deep learning-based methods.

Thresholding is a basic and widely used technique where pixel values are divided into foreground and background based on a fixed threshold intensity value. Though computationally simple, it fails in variable lighting or non-uniform backgrounds, which are common in field images (Bhargavi and Jyothi, 2014).

GrabCut, a semi-automated algorithm, provides better segmentation by using iterative graph-cut optimization. The user initially provides a rough bounding box around the object (i.e. insect), and the algorithm refines the foreground segmentation. This algorithm is effective for simple scenes but not suitable for automated processing of large datasets as well as overlapping objects (i.e. insects) (Malik et al., 2023).

Watershed algorithm is well suited for segmenting overlapping objects (i.e. insects). It treats the image as a topographic surface and separates objects based on watershed lines (Baur et al., 2022). In trap-based or controlled environments where the background is static, the background image can be subtracted from the frame to isolate the insect by means of Background Subtraction algorithm (Preti et al., 2021). Now-a-days, deep learning-based segmentation techniques using convolutional neural networks (CNNs) such as U-Net (Biradar and Hosalli, 2024), DeepLab (Yuan et al., 2022), or Mask R-CNN (Kasinathan and Uyyala, 2023; Wu et al., 2024) are widely used, enabling pixel-wise labeling of insects or damage symptoms. These models can generalize well across varying field conditions and backgrounds and are ideal for large scale entomological applications.

4.4. Dataset splitting, training, and feature extraction

The dataset after preprocessing, is randomly split into training, validation, and testing subsets generally in 80:10:10 ratio. The training subset is utilized for training the models, and the validation subset has been used to adjust the values of hyperparameters so that the best model can be achieved. Finally, the testing subset measures the model's effectiveness on unseen insect images. The model is trained with the given data and extracts useful information or features from the raw data that can be fed into an AI-model.

4.5. Performance evaluation

Based on the training and validation outcomes, a confusion matrix (CM) will be constructed to evaluate the performance of the model. In the CM, column elements indicate “predicted values”, while row elements represent “actual values”. The diagonal entities correspond to the correctly predicted values; whereas the off-diagonal elements represent misclassifications. From a CM, the following variables are derived:

True positive (TP): Elements predicted positive, and it is true.
True negative (TN): Elements predicted negative, and it is true.
False positive (FP): Elements predicted positive, and it is false.
False negative (FN): Elements predicted negative, and it is false.

Using these values, key performance metrics are calculated to assess and compare model effectiveness:

a. Precision: It measures the proportion of correctly predicted positive observations to the total predicted positives.

$$\text{Precision} = \frac{\text{True positives (TP)}}{\text{True positives (TP)} + \text{False positives (FP)}} \tag{1}$$

b. Recall: It measures the proportion of correctly predicted positive observations to all actual positives.

$$\text{Recall} = \frac{\text{True positives (TP)}}{\text{True positives (TP)} + \text{False negatives (FN)}} \tag{2}$$

c. Accuracy: It represents the overall correctness of the model across all the classes.

$$\text{Accuracy} = \frac{\text{True positives(TP)} + \text{True negatives(TN)}}{\text{True positives(TP)} + \text{False positives(FP)} + \text{True negatives(TN)} + \text{False negatives(FN)}} \quad (3)$$

d. F1-score: It represents the harmonic mean of precision and recall which is especially useful when class distribution is imbalanced.

$$\text{F1} - \text{score} = 2 \text{ x } \frac{\text{Precision x Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

e. Intersection over Union (IoU): It measures the overlap between the predicted bounding box and the ground truth bounding box of an object. IoU is calculated as the ratio of the area of intersection between the predicted and the ground truth bounding boxes to the area of their union. It is formulated as shown in Eq. (5).

$$\text{Intersection over Union (IoU)} = \frac{\text{Area of intersection}}{\text{Area of union}} \quad (5)$$

Where,

Area of Intersection refers to the region where the predicted bounding box and the ground truth bounding box overlap, representing the correctly localized portion of the object by the model.

Area of Union is the total region encompassed by both the predicted bounding box and the ground truth bounding box, combining the area of both boxes while excluding their overlapping region only once.

IoU ranges from 0 to 1, where.

IoU = 0 indicates no overlap between the two boxes.

IoU = 1 indicates a perfect overlap, meaning the predicted box exactly matches the ground truth.

In object detection tasks, it is standard practice to set a threshold IoU value (commonly 0.5) to classify a detection as a true positive. If the IoU between the predicted and the ground truth boxes exceeds the threshold, the detection is considered as correct, otherwise, it is classified as a false positive or a missed detection.

f. Mean Average Precision (mAP): It evaluates the balance between precision and recall by calculating the average precision (AP) for each class and then averaging across all the classes (Zhu et al., 2020). Average Precision (AP) quantifies precision at various recall levels by calculating the area under the precision-recall curve (Mekhalfi et al., 2021) as depicted mathematically in Eq. (6), where "precision (r)" indicates the precision at a given recall level r. A higher mAP indicates better model performance, reflecting an optimal balance between correctly identified instances and the ability.

$$\text{Average Precision (AP)} = \int_0^1 \text{precision (r) dr} \quad (6)$$

There are two commonly used types of mAP based on IoU thresholds:

mAP@0.5: It indicates the mean average precision at an IoU threshold of 0.5.

mAP @0.5:0.95: It represents the mean average precision across a range of IoU thresholds from 0.5 to 0.95.

Both of these metrics are used to assess and compare the performance of object detection models. Additionally, several loss functions are computed during training and validation phases, including,

Box loss: It measures the error in the predicted bounding box coordinates.

Class loss: It measures the error in class prediction.

Object loss: It measures how well the model identifies the presence or absence of an object.

Apart from these, computational complexity is also an important consideration and can be assessed through factors such as the number of trainable parameters and the time taken per epoch during training. While training and validation results provide a preliminary understanding of model performances, real-world applicability must be evaluated using unseen (test) images. For this, same performance metrics, along with inference speed can be calculated on the test dataset. The model that demonstrates the best balance of detection accuracy, computational efficiency, and inference speed can be considered optimal for practical deployment.

5. Artificial intelligence models for identification of insect pests: a chronology

Before the advent of deep learning technology, traditional computer vision methods and machine learning were often employed for image-processing tasks to identify insects (Salvi et al., 2021). Several machine learning models viz., SVM (Le-Qing and Zhen, 2012), KNN (Liantoni and Hermanto, 2017), Decision Trees and Random Forests (Yuan and Hu, 2016; Hu et al., 2018) were employed for quick detection of insects. These systems use handcrafted features from an image that help in characterizing important aspects of that image for identifying pests (Liu and Wang, 2021). Expert systems are also developed here to perform quality control, measurement, and online detection using computational intelligence algorithms (Wu and Banzhaf, 2010).

However, developing convolutional neural networks (CNNs) is a breakthrough in AI-based insect identification (Anwar and Masood, 2023), especially in deep learning research (Gu et al., 2017). This can give a more precise performance in image classification (Khan et al., 2020), feature learning (Zhiqiang and Jun, 2017), and spatial hierarchies (Zhao et al., 2017; Zhiqiang and Jun, 2017; Chen et al., 2021b), object localization (Zhao et al., 2017) and real-time image processing (Li et al., 2019c). These CNN architectures can be adapted and optimized for specific pest detection challenges (Xia et al., 2018). Different CNN models have been developed with other specifications that make insect identification easier. GoogleNet (Christian et al., 2014) introduced the concept of Inception Modules (Kim et al., 2019), which consist of repeating blocks where the output of a block acts as an input to the next block. Its architecture is highly reliable in recognizing pests amidst the diverse visual information in field images (Ali et al., 2023). "Visual Geometry Group Network"- VGGNet (Simonyan & Zisserman, 2014), having simpler and more uniform architecture than GoogleNet, is used by several scientists for correct identification of pests like- fruit flies (Hadipour-Rokni et al., 2023), pests of tomato (Huang et al., 2022) and brinjal (Saikumar et al., 2023). The major advancement of deep learning in the identification of insects occurred when models like- "You Only Look Once"-YOLO (Redmon et al., 2016), "Retina Neural Network"-RetinaNet (Lin et al., 2017), and "Single Shot Detector"- SSD (Liu et al., 2016) were introduced. YOLO has already upgraded to its twelve different versions viz. YOLOv2 (Redmon and Farhadi, 2017), YOLOv3 (Redmon and Farhadi, 2018), YOLOv4 (Bochkovskiy et al., 2020), YOLOv5 (Jocher, 2020), YOLOv6 (Li et al., 2022a), YOLOv7 (Wang et al., 2023), YOLOv8 (Jocher et al., 2023), YOLOv9 (Wang et al., 2024b), YOLOv10 (Wang et al., 2024a), YOLOv11 (Khanam and Hussain, 2024), YOLOv12 (Tian et al., 2025). However, due to inability of capturing comprehensive global spatial features and dependencies by CNN-based models, different advanced deep learning techniques viz. Transformer-based models like- DETR (Qi et al., 2022), Pyramid Vision Transformer (Chen et al., 2025); Swin-Transformers (Zhao et al., 2022; Liu et al., 2025), ViTs (Li et al., 2022b; Akhtar et al., 2025); Multi-modal Fusion and Hybrid Models (Linfeng et al., 2023); Multi-head attention mechanisms (Qian et al., 2025) are introduced for rapid detection of insects. But, due to an increased number of matrix operations in the attention mechanism, the computational cost becomes higher in these models (Yu et al., 2022). This has created an extensive

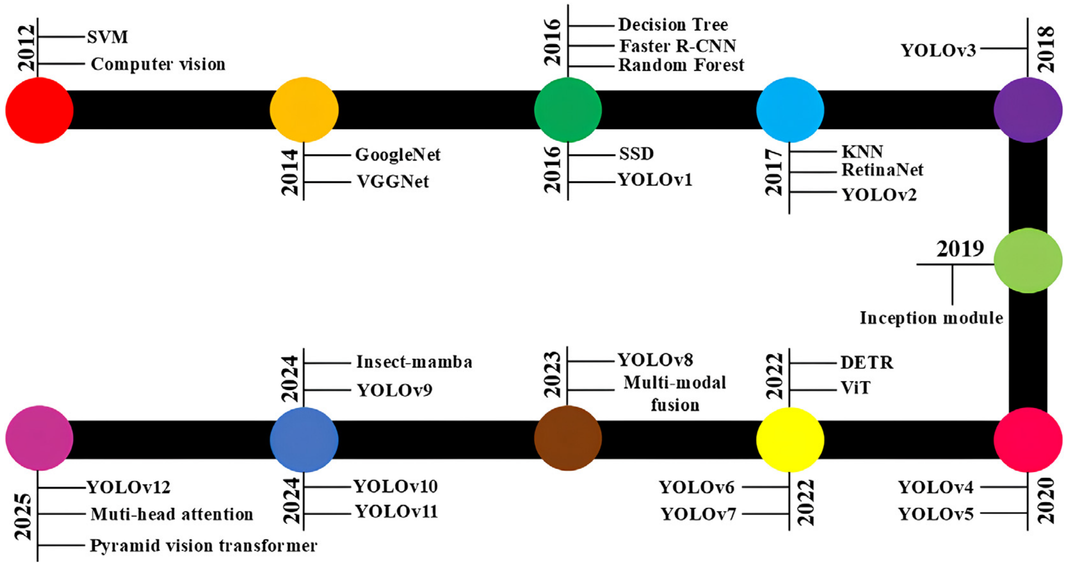

Fig. 3. A timeline of AI-based object detection models used for the identification of insects. (Abbreviations: DETR- Detection Transformer, KNN- K-Nearest Neighbour, R-CNN- Region-based Convolutional Neural Network, SSD- Single Shot Detector, SVM- Support Vector Machine, VGG- Visual Geometry Group, ViT- Vision Transformer, YOLO- You Only Look Once).

interest of using State-spaced Models (SSMs) like- Mamba among the researchers, which not only have powerful context modeling abilities but also have linear complexity (Gu and Dao, 2023; Liu et al., 2024). In recent years, scientists have developed several Mamba-based models for efficient detection of insects and plant diseases (Wang et al., 2024c; Zhang and Mu, 2024). A timeline of artificial intelligence models for the detection of insects is provided in Fig. 3.

6. Identification of insect pests using artificial intelligence tools-successful instances

6.1. Pest identification through field images

The most common AI-based detection system is identifying insect pests on the plant surface. However, detecting insect pests in fields as well as plants is a bit problematic because of the complex background (Wang et al., 2021b) and dense distributions of insects (Wang et al., 2021a). Moreover, small pest detection is more difficult as the size weakens the features in the convolutional map, leading to a loss of information (Li et al., 2021b). However, a two-stage pest detector, named coarse-to-fine network, had been designed to address the detection of small insects like aphids in the field (Li et al., 2019a). Cropping the image is a very easy solution for detection as it reduces unnecessary background and focuses on the object only. Table 1 indicates some successful instances of pest identification by field images using artificial intelligence.

6.2. Pest identification through sticky trap images

Sticky traps are installed in the fields and greenhouses to entrap the insects, making it easy to monitor and predict their population (Böckmann et al., 2021). Generally, insects are attracted to the colour and get trapped in the sticky materials of the trap (Dearden et al., 2024). Yellow sticky traps are used in the fields to manage small sucking insects like- whiteflies, aphids, and thrips (Maharlooei et al., 2017; Sun et al., 2017). However, insect detection in sticky trap photos is severely hampered by the sticky paper's light reflection, the trap's movement, and the insect's deterioration or destruction in the field (Rustia et al., 2021). To overcome these challenges, numerous researchers looked into automatic techniques for identifying tiny insects in photos of sticky traps (Xia et al., 2015; Ebrahimi et al., 2017; Gutierrez et al., 2019). Lists of a few successful cases of artificial intelligence-based pest identification using sticky trap images are depicted in Table 2.

6.3. Identification of insect pests on baseplate of a trap

Different types of light-based and pheromone-based traps have been used in the field to scout pests like- moths, beetles, etc. in the past few years (Sun et al., 2018). Due to their positive phototaxis, many categories of pests are trapped on the baseplate of light traps. However, only a few insects are attracted to pheromone traps, responding to the cocktail as pheromones are specific. In these cases, images can be acquired by embedding a camera in the trap, and based on the images, identification can be done using artificial intelligence models (Fig. 4). Table 3 summarizes successful applications of AI-based insect identification on the baseplate of traps.

7. Discussion

The integration of AI, particularly deep learning techniques into entomological research has shown remarkable progress in the identification and monitoring of insects. The rapid advances in neural network architectures have enabled a diverse array of models to achieve impressive accuracy in classifying and detecting insects. In this study, the performances of several AI models used in open fields, traps, and trap baseplates are analyzed, and it is evident that AI is no longer limited to experimental conditions but is gradually moving towards practical field applications.

One of the most striking observations is the growing preference for single-stage object detection models, particularly YOLO variants, probably due to their ability to balance speed and accuracy in real-time settings. Models such as YOLOv5, YOLOv7, and YOLOv8 have shown promising results in detecting multiple insect species simultaneously in complex backgrounds (Ahmad et al., 2022; Wen et al., 2022; Chakrabarty et al., 2024). These models are often especially relevant in open-field and trap scenarios where insects are not isolated but appear in cluttered environments, overlapping with other insects or plant parts or soil debris.

Our analysis also reveals a significant evolution in AI-based application strategies- from single species identification under controlled laboratory settings to multi-species detection in-situ. While early models, such as VGGNet-based CNNs were mainly used for binary classification

Table 1
List of some successful insect pest detection applications in the field using Artificial Intelligence.

Crop/Pest	Categories	Dataset Size	Models used	Best model	Correctness	Inference time	Limitations	References
Diseases & pests of Tomato	10	5000	Faster R-CNN, R-FCN, SSD	R-FCN	85.98 %	–	Limited dataset diversity	Fuentes et al. (2017)
Pests of Rice, Soybean, and other field crops	24	4800	SSD, Fast R-CNN, RPN-VGG 199	RPN VGG-19	89.22 %	0.083 s	a. High computational complexity b. Limited evaluations in diverse backgrounds	Xia et al. (2018)
Pests of Tomato	2	4331	KNN, MLP, Faster R-CNN, SSD	Faster R-CNN	82.51 %	571 s	High computational complexity, followed by increased inference time	Gutierrez et al. (2019)
Pests of Rapeseed	12	3022	Faster R-CNN, R-FCN, SSD	SSD	77.14 %	0.045 s	a. Dataset may not be the representative of real-world scenario b. Testing on unseen images had not done comprehensively	He et al. (2019)
Pests of Wheat	4	4400	DAG-CNN, HR, FPN, Improved CNN	Improved CNN	83.23 %	–	High computational complexity may hinder the model's incorporation in smartphone applications	Li et al. (2019b)
Banana Corm Weevil	1	701	Faster RCNN (ResNet 50, InceptionV2), SSD (MobileNetV1)	Faster R-CNN (Inception V2)	99.94 %	–	Since certain diseases can produce symptoms similar to those caused by insect pests, the study does not clearly explain how it distinguishes between disease-related and insect-induced damage	Selvaraj et al. (2019)
Pests of Cotton and Soybean	8	985	DCNN, HD-CNN, SegNet	SegNet	93.30 %	–	Limited dataset availability	Tenório et al. (2019)
Pests of Cotton	16	11,520	Modified ResNet34 and other State-of-the-art CNNs	Modified ResNet34	98 %	–	It's not clear how the farmers will use this technology in open field situations	Alves et al. (2020)
Litchi Stink Bug	1	687	RNN, Faster R-CNN, YOLOv3	YOLOv3	90 %	–	While the single-stage detection module reduces computational complexity, its application is limited to the identification of a single insect species. Expanding the system to include multiple pest species would enhance its practical utility	Chen et al. (2020)
Pests of Rice	1	4600	Faster R-CNN, YOLOv3	Faster R-CNN (in terms of recall)	87.67 % (detection) 81.92 % (counting)	–	The study does not clearly explain how the proposed technology can be adopted by farmers under open-field conditions	He et al. (2020)
Insect pests	24	20,000	Faster R-CNN, YOLO, AF-RCNN	AF-RCNN	85.1 %	0.07 s	Given the inclusion of numerous insect classes with varying morphological features and body sizes, this study requires more extensive open-field testing to validate its effectiveness	Jiao et al. (2020)
Butterflies	11	5695	Faster R-CNN + ZF, Faster R-CNN + CGG CNN M 1024, Faster R-CNN + VGG 16, YOLOv3, Integrated YOLO	Integrated YOLO	98.35 %	–	a. Dataset may not be representative, as many other common butterfly species are missed. b. Many other YOLO models (viz. YOLOv4 and YOLOv5) could be tested.	Liang et al. (2020)
Pests of Tomato	2	2381	SSD, Faster R-CNN, YOLOv3, Improved YOLOv3	Improved YOLOv3	92.39 %	20.39 s	More YOLO-based models could be tested	Liu and Wang (2020)
Pests of stored grains	8	1716	VGG16, ResNet-101, GoogleNet, Faster R-CNN, R-FCN with improved DenseNet-121	R-FCN with improved DenseNet-121	88.06 %	0.118 s	The study utilizes images containing only a single insect per frame; scenarios with multiple insects in a single image have not been explored	Shi et al. (2020)
Pests of Rice and Wheat	3	17,192	Scale-specific detection, DeepPest, VGG 16 + FPN, ResNet 50 + FPN	DeepPest	73.9 %	0.076 s	It's not clear whether the dataset is representative of the real-world scenario or not	Wang et al. (2020a)
Scale and Mealybug	3	600	Faster R-CNN, SSD, YOLOv4	YOLOv4	100 %	–	a. It's unclear how robust the dataset is. b. The study considers only three insect species, and it remains unclear how these selected individuals are representative of the entire insect family	Chen et al. (2021a)
Aphid, Flea Beetle, Jassid, Flax Budworm, Red Spider	5	500	BPNN, SSD (MobileNet), Proposed Faster R-CNN	Proposed Faster R-CNN	98 %	–	Computational complexity may be high along with lesser inference speed	Karar et al. (2021).

(continued on next page)

Table 1 (*continued*)

Crop/Pest	Categories	Dataset Size	Models used	Best model	Correctness	Inference time	Limitations	References
Mite								
Pests of Field crops	24	785	ANN, SVM, KNN, NB, CNN	CNN	90 %	–	The study lacks information regarding real-time field validation, which could enhance understanding of the model's performance under actual field conditions	Kasinathan et al. (2021)
Fall Armyworm infested Maize	12	11,000	CNN	–	87 %	–	More deep learning models should be considered to find out the best model	Prabha et al. (2021)
Pests of Soybean	–	–	YOLO v3, YOLOv4, YOLOv5	YOLOv5	99.5 %	–	Computational complexity and inference speed should be checked	Verma et al. (2021)
Pests of four Field Crops	14	49,700	SSD512, RetinaNet, FCOS, Faster R-CNN, FPN, Cascade R-CNN	Cascade R-CNN	70.83 %	–	a. Unbalanced data structure. b. Employing existing generic object detection approaches in wild tiny pest detection task is not a qualified solution	Wang et al. (2021a)
Pests of Tomato	9	10,696	HOG+SVM, Faster R-CNN, SSD, YOLOv3, Improved YOLOv3	Improved YOLOv3	91.81 %	0.055 s	a. More number of pests could be added. b. Multi-locational trial is needed.	Wang et al. (2021b)
Pests and Diseases of Apple	18	819	Artificial Neural Network (ANN)	–	67–100 %	0.175 sec	a. Limited dataset diversity b. Lack of comprehensive comparison with other existing models	Abbaspour-Gilandeh et al. (2022)
Insect pests	23	7046	YOLO-Lite, YOLOv3, YOLOR, YOLOv5 (all variants)	YOLOv5x	97.8 %	–	a. The study having some false negative detections, is primarily due to challenges related to insect shape variability, complex backgrounds, and occlusions. These issues could be mitigated by expanding the dataset to include a wider range of images captured under diverse environmental conditions, including complex orchard scenarios b. Deployment of the trained model on mobile platforms (e.g., Android and iOS) remains unexplored, despite its potential to greatly enhance accessibility and adoption among farmers, thereby supporting real-time pest monitoring and agricultural productivity	Ahmad et al. (2022)
Pests of vegetable	10	1000	CNN Inception V3	–	99 %	–	The study lacks on-field validation, which is essential for assessing practical applicability	Lestari and Nurriski (2022)
Tiny insect pests	24	25,378	YOLOv4, YOLOv5 (s and m), YOLOX, DETR, TOOD, YOLOv3-W, AF-RCNN, Pest-YOLO	Pest-YOLO	77.71 %	–	This study has only been implemented in a server environment; integrating it into a hardware device would impose stringent constraints on the model's parameter size and computational requirements.	Wen et al. (2022)
Pests and diseases of cotton	–	7500	Faster R-CNN, SSD, YOLOv3, YOLOv4, YOLOv5, Improved YOLOX	Improved YOLOX	94.60 %	–	Limited dataset availability	Zhang et al. (2022)
Insect pests	10	1309	YOLOv3, YOLOv4, YOLOv5m, YOLOv5m + SWinTR+ C3TR	YOLOv5m + SWinTR +C3TR	95.70 %	–	a. MobileNet network can be integrated with improved YOLOv5m to improve accuracy b. The dataset used in the study appears to be limited in size and diversity, which may affect the model's generalizability and robustness in real-world scenarios	Dai et al. (2023)
Pests of Citrus	1	1519	ResNet-50, GoogleNet, VGG-16, AlexNet	AlexNet	99.33 %	323 s	Inclusion of additional fruit fly species could enhance the model's practical utility and broader applicability	Hadipour-Rokni et al. (2023)
Pests of Brinjal	4	204	SVM, KNN, NB, VGG 16	VGG 16	95–98 %	–	a. Many other pests as well as their life stages might be added b. Analysis with many other newer models should also be considered.	Saikumar et al. (2023)
Pests of Jute	17	6460	ResNet50, VGG 19, InceptionV3, MobileNetV2, DenseNet201	DenseNet201	99 %	–	a. 2types of pests are excluded. b. Professional pilot test is lacking c. Dataset is limited	Talukder et al. (2023a)
Pests of Potato	8	2268	CTMobileNetV2, CTNASNetLarge, CTXception,	CTInception V3	91 %	–	a. Limitations in dataset availability b. Only 8 types of potato pests are considered	Talukder et al. (2023b)

Table 1 (*continued*)

Crop/Pest	Categories	Dataset Size	Models used	Best model	Correctness	Inference time	Limitations	References
			CTDenseNet201, CTInception V3				c. Different phases of life cycle of pests are not taken into account. d. Only 5 pre-trained models are examined.	
Pests of Maize	13	4533	RetinaNet, Faster R-CNN, YOLOv3, YOLOv3-SPP, Scaled-YOLOv4, YOLOv5, YOLO-Lite, YOLOR, YOLOv7, Maize-YOLO	Maize-YOLO	76.3 %	–	a. Some types of pests have a large difference in appearance between the larval and adult stages, which can lead to poor recognition of such types of pests by the model. b. Pest types according to their growth period and morphological differences could be considered.	Yang et al. (2023)
Agriculturally important insects of crucifers	21	6403	5 variants of YOLOv5 (i.e. YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, YOLOv5x)	YOLOv5l	99.5 %	0.078 s	a. Tiny parasitoids could also be considered. b. More damage symptoms of pests might be taken	Chakrabarty et al. (2024)
Neotropical Brown Stink Bug	1	4607	YOLOv8n, YOLOv8n + C2f2, YOLOv8n + P2, Improved YOLOv8	Improved YOLOv8	71.1 %	–	Models should be further tested in more varied weather, lighting, and crop conditions to be fully tuned before deploying in an integrated platform	de Melo Lima et al. (2024)
Pests of tomato	8	1655	VGG16, ResNet50, EfficientNetB0, Xception, MobileNetV2, InceptionV3, XM-Net, SE + XM-Net, CBAM+Xm-Net, ECA + Xm-Net	ECA + Xm-Net	98.86 %	–	a. Several key model parameters have not been considered or analyzed in this study, which may affect overall model optimization and performance assessment b. The study could be strengthened by including a broader range of pest species to enhance its practical applicability and robustness	Huang and Chen (2024)
Pests of Tomato	5	11,424	CNN, CNN + RF, CNN + SVM, CNN + KNN	CNN	95.49 %	–	More number of pests might be included	Polin et al. (2024)
Stored grain pests	1	16,358	Faster R-CNN, RT-DETR, YOLOv5s, YOLOv6s, YOLOv7-tiny, YOLOv8s, YOLO-SGInsects	YOLO-SGInsects	94.20 %	–	A key limitation of this study is the lack of clear documentation regarding the specific stored grain insect species used in the dataset, which restricts its applicability for species-specific pest management research	Zhu et al. (2025)

or identifying one pest at a time, more recent frameworks have adopted multi-class classification and detection approaches that can process natural field images with multiple insects (Shi et al., 2020; Kasinathan et al., 2021).

Moreover, several studies have expanded the scope of detection beyond adult pests to include developmental stages (i.e. larvae, nymphs etc.) and even pest-induced symptoms (Yang et al., 2023). This holistic approach is crucial because early-stage identification of pests or symptoms can enable timely intervention, thereby supporting more sustainable agricultural practices.

However, while the technical capabilities of AI systems have improved considerably, their practical implementation in real-world agricultural contexts remains limited. Most of the models are trained on high-resolution, well-lit images collected under semi-controlled or controlled environments. When deployed in open fields or on trap baseplates, performance may degrade due to natural variability in lighting, insect posture, occlusions and background complexity. For example, sticky trap images often contain multiple, overlapping insects of varying sizes and orientations causing the advanced models to struggle to maintain high precision or recall too.

Another emerging consideration is the practicality of deploying these models in edge devices such as smartphones, drones, or automated monitoring devices. While some models achieve high accuracy, they demand considerable computational power and memory, limiting their feasibility for real-time, on field deployment without access to cloud infrastructure (Karar et al., 2021; Ahmad et al., 2022). Lightweight models such as YOLO-series are therefore gaining traction as ways to reduce computational burden while preserving detection accuracy.

Also noteworthy is the lack of standardized evaluation metrics and benchmark datasets in this field. Many studies report accuracy or precision or recall or mean average precision, but the absence of common test datasets many hinder meaningful cross-study comparisons. Certain studies also show the self-developed datasets, which may be small or imbalanced leading to potential biases and reduced model robustness. Moreover, real-time validation under varying agro-climatic zones and cropping systems is rarely conducted, which may raise questions about model generalizability and integrity (Wang et al., 2021a, 2021b).

Finally, interdisciplinary collaboration is the key to advancing this field. Close cooperation between entomologists, computer vision experts, agronomists, and farmers is essential for developing context-aware systems that are not only technically sound, but also user-friendly and agriculturally relevant.

8. Future prospects in AI-based insect pest detection

With the advent of new technologies in smart pest monitoring, the use of artificial intelligence-based pest detection is popularizing daily. However, various challenges hamper large-scale applications of these techniques in the field (Li et al., 2021b).

8.1. Construction of large-scale datasets

Insects have a huge diversity, with more than 1.02 million species (Valan et al., 2019), and it isn't easy to construct a large-scale image dataset. The lack of such labeled image data inhibits the progress of deep learning-based pest detection systems (Li et al., 2021b). Because

Table 2
List of some successful insect pest detection applications in traps using Artificial Intelligence.

Crop/Pest	Categories	Dataset Size	Models used	Best model	Correctness	Inference time	Limitations	References
Pest of orchards	2	177	ConvNet	–	93.1 %	–	Several other available models could have been considered to enhance comparative analysis and potentially improve performance.	Ding and Taylor (2016)
Brown Planthopper	1	687	VGG16 (transfer learning & scratch)	VGG16 (transfer learning)	95 %	–	a. The study lacks clarity regarding real-time field validation, making it difficult to assess the model's effectiveness under actual field conditions b. The study does not address how the model performs when traps contain both brown planthopper (BPH) and other morphologically similar small insect species, which may affect detection accuracy in real-world scenarios	Nazri et al. (2018)
Asian Citrus Psyllid	1	8000	Faster-RCNN	–	95 %	–	The technology could also be extended against other important viral and bacterial diseases transmitted by similar kind of insects.	Partel et al. (2019)
Fruit Fly	1	4753	ResNet-18	–	66.9 %	–	Including other related insect species could enhance the model's generalizability and practical utility in diverse field conditions	Roosjen et al. (2020)
Pests of Greenhouse	4	5173	Cascaded CNN	–	91 %	–	The dataset used may not adequately represent real-world field conditions, potentially limiting the model's generalization and robustness	Rustia et al. (2021)
Pests of Greenhouse	2	84	Faster R-CNN, *TPest*-RCNN	*TPest*-RCNN	95.2 %	–	a. The study could be enhanced by including additional small pest species alongside whitefly and thrips to improve the model's applicability and practical utility b. The study lacks analysis of computational complexity, which is crucial for assessing the model's efficiency and feasibility for real-time applications	Li et al. (2021a)
Black Pine Scale	1	50	Faster R-CNN ResNet-101, EfficientDet D4, EfficientDet D0, RetinaNet 50, SSD Mobilenet	SSD Mobilenet	95.3–97.89 %	0.012 s	The study could be strengthened by incorporating additional pest species enhancing the model's applicability and real-world utility.	Hong et al. (2021)
African Citrus Psyllid and Others	2	–	R50FPN, R101-DC5, R101FPN	R101FPN	85.7 %	–	a. The dataset used in this study is limited in diversity. b. The computational complexity should be evaluated	da Cunha et al. (2022)
Whitefly	1	120	Faster R-CNN, YOLOv4	Faster R-CNN	95.08 %	23.72 s	a. The dataset used in the study is limited in size and diversity. b. The inference time of the model could have been reduced to improve its efficiency, especially for real-time applications	Parab et al. (2022)
Pests of witloof chicory field	12	731	YOLOv5	–	76 %	–	The dataset may not adequately represent real-world field conditions, potentially limiting the model's effectiveness in diverse agricultural environments	Kalfas et al. (2023)
Aphid alates in Sorghum	1	2527	YOLOv5 variants (YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, YOLOv5x)	YOLOv5l	85.60 %	0.013 s	a. The model exhibits detection errors, including failure to identify all alates, misidentification of alates due to their similarity in shape with wingless aphids, and inaccuracies when images are blurry b. The training dataset lacks sufficient diversity; incorporating more images with varying alate densities captured using different devices such as smartphones and drones could enhance the validation and robustness of the models c. The system requires users to follow specific image capturing instructions and maintain a good internet connection for proper operation, which may limit its usability in areas with poor or no internet access	Grijalva et al. (2024)
Tomato pinworm	1	307	YOLOv3, TinyYOLOv3	YOLOv3	84.90 %	–	Employing other versions of YOLO models could potentially enhance detection accuracy and better handle clustered insects, owing to improvements in architectural design and feature extraction capabilities	de Souza et al. (2025)
Sugarcane borer	1	1415	YOLOv8x	–	96.2 %	–	Some other newer YOLO-based models could have been tested to potentially improve detection performance and evaluate the robustness of the system across different architectures	Pantoni and Dias (2025)
Hematophagous flies	3	479	YOLOv8s	–	98 %	–	a. Some other newer YOLO-based models could have been studied to provide a more comprehensive comparison and assess potential improvements in detection accuracy and efficiency b. The dataset used in the study appears to be limited, which may affect the model's ability to generalize across diverse real-world scenarios	Santaera et al. (2025)

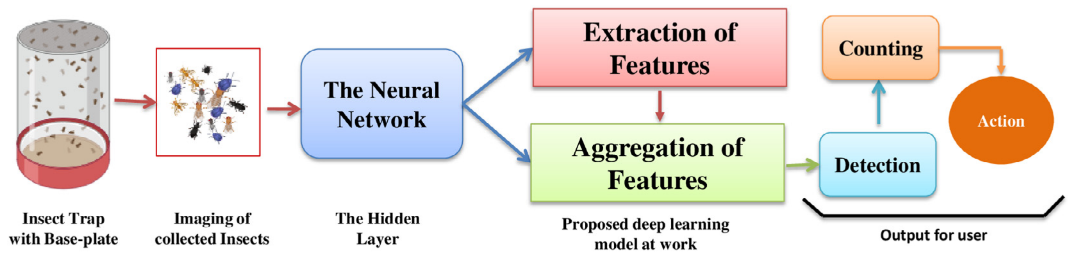

Fig. 4. Detection of insect pests in the base plate of a trap. The model will detect and identify the insect and count subsequently. The counted number will be crosschecked against the Action Threshold, and based on that, the next action plan will be decided.

insufficient data can lead to overfitting where the model can learn the training data too well while fails to generalize the unseen data. This is because the model may memorize the limited data rather than learning the generalizable patterns. Therefore, developing large-scale, diverse, and well annotated datasets remains the major goal for improving AI-based pest detection. These datasets should contain images from various geographic locations, crop types, life stages of pests, and environmental conditions to ensure model generalizability. Integrating data from multiple sources including field images, and trap-based systems can help in creating robust training datasets that better represent real-world complexities. Several datasets like- IP 102 (Wu et al., 2019); GrassHopper deteCtIon Dataset (GHCID) (Chudzik et al., 2020), Pest24 (Wang et al., 2020c), TPest (Li et al., 2021a), AgriPest (Wang et al., 2021a), Bioscan-5 m (Gharaee et al., 2024), Insect detect (Sittinger et al., 2024), Insect-foundation (Nguyen et al., 2024) etc. are already established where one can get different classes of images of insects (Please see Supplementary Table 1, ST1 for more details). The users can take the help of several citizen science platforms such as GBIF (https://www.gbif.org/), iNaturalist (https://www.inaturalist.org/), or Moths of India (Sondhi et al., 2025), where labeled data of different geographical locations can be found. Special national and international projects and organizations should be expected that allow data collection, annotation, and modeling ideas sharing worldwide to construct such database, through which sophisticated models can be prepared (Li et al., 2021b).

8.2. Multi-scale pest detection

As most of the object detection methods based on deep learning focus on the targets of a certain size, multi-scale pest detection of different sizes results in a decline in overall performance. For small insects, shallow features with small receptive fields contain some details. As it goes deep, geometric information in the extracted features disappears, and it looks extremely difficult to detect them through deep features (Li et al., 2021b). Therefore, future AI-based models must incorporate multi-scale feature extraction techniques to accurately detect pests of varying sizes and shapes, especially in cluttered backgrounds. Advanced architectures such as feature maps considering different layers in a CNN (Li et al., 2020a) or feature pyramid networks (Li et al., 2021b) or transformer-based models can enhance the ability of detecting small or partially occluded pests across different image resolutions.

8.3. Detection of insect-specific characters

Beyond general detection, there is a growing need for AI systems to recognize insect-specific morphological characters such as wing venation, antennae structure, body segmentation, or colouration patterns. However, it is a great challenge for AI-based model to identify such cases. Even the minute feature differences in similar-looking insects make the detection process more challenging. For example, three moth species viz. *Spodoptera frugiperda*, *Mamestra brassicae*, and *Hadula trifolii* look almost the same if seen by the naked eye. Leveraging fine-grained classification (Flores et al., 2019; Valan et al., 2019) and attention mechanisms (Guan et al., 2025) may enable the models to differentiate between morphologically similar species or life stages, which is crucial for pest management decisions and ecological studies.

8.4. Getting real-time requirements

To support timely pest control measures, future AI models should focus on real-time detection capabilities with low inference latency. Achieving this requires the development of lightweight yet accurate model architectures that can be effectively deployed on mobile phones, drones, or edge-computing platforms in field conditions (Gao et al., 2024a). A notable example from India is the development of an AI-based mobile application titled “BIPM on tomato pinworm *Phthorimaea absoluta*” designed for identification and bio-intensive management of tomato pinworm which is available online in https://mobileapptuta.nbair.res.in (Pratheepa et al., 2023) The integration of AI with Internet of Things (IoT) devices and remote sensing technologies holds great potential to advance real-time pest monitoring, establish early warning systems, and offer automated decision-support tools for farmers and agricultural stakeholders.

9. Conclusion

The application of AI, particularly deep learning, has revolutionized insect pest detection by offering high-throughput, and scalable solutions for pest monitoring in agricultural systems. The review synthesizes the landscape of AI-based insect pest identification, covering both field-level detection and trap-based monitoring approaches. Models such as YOLO, Faster R-CNN, and SSD have demonstrated significant progress in accurately identifying pests and damage symptoms, with some achieving detection accuracies above 90 %. However, these advancements are often constrained to controlled experimental settings and fail to fully translate into robust field applications. A major barrier is the limited availability of large, diverse, and annotated datasets, which restricts the model's ability to generalize across different crop types, geographic regions, and environmental conditions.

Furthermore, the high intra- and inter-class variability among pest species, overlapping morphologies, and multiple developmental stages introduce additional layers of complexity that current models struggle to address. Lighting variations, background noise, occlusion, and small object sizes in field images further degrade detection accuracy. While some models have begun incorporating multi-class detection and fine-grained classification, they often remain computationally heavy, making them unsuitable for real-time use in field environments with limited hardware resources. Another critical limitation is the lack of focus on biologically important features such as insect-specific morphological traits, behaviours, and damage patterns which are vital for effective pest management decisions.

Despite these challenges, the integration of AI into pest surveillance and decision-support systems marks a significant shift in agricultural entomology. The development of mobile apps, edge-based AI devices, and cloud-based platforms signals a move towards practical and

Table 3
Summary of some successful identification of pests on the baseplate of the traps.

Crop/Pest	Categories	Dataset Size	Models used	Best model	Correctness	Inference time	Limitations	References
Pests of Pine	6	2183	RetinaNet1, RetinaNet2, RTBnet1, RTBnet2, RTBnet3, RTBnet4	RTBnet4	74.6 %	0.448 s	Some other state-of-the-art models could also be evaluated to benchmark performance and enhance the robustness of the study	Sun et al. (2018)
Insect pests	3	22,479	ResNext, ResNet18, Inception, SqueezeNet	ResNet18	91.28 %–93.55 %	–	Computational complexity analysis should be conducted to ensure the model's feasibility for integration into mobile applications	Martins et al. (2019)
Moths	16	88,760	SSD300, SSD512, ZF + Faster R-CNN, ZF + PestNet, VGG16 + Faster R-CNN, VGG16 + PestNet, ResNet50 + Faster R-CNN, ResNet50 + PestNet, ResNet101 + Faster R-CNN, ResNet101 + PestNet	ResNet101 + PestNet	75.46 %	0.441 s	There is no mention of on-field validation, which is essential to assess the model's effectiveness under real-world conditions	Liu et al. (2019)
Pests in farm	8	1200	YOLOv2, SSD MobileNet, SSD Inception, Faster R-CNN + ResNet50	Faster R-CNN + ResNet50	95.98 %	31.66 s	The inference speed could have been optimized further to improve compatibility and performance in mobile-based applications	Ramalingam et al. (2020)
Codling Moth and other insects	2	4400	Modified LeNet-5, VGG16, MobileNetV2,	VGG16	97.4 %	–	Some additional pestiferous species could be included, which would enhance the practical relevance and applicability of the study	Albanese et al. (2021)
Olive fruit fly	1	11,872	VGG19 + RPN, Faster R-CNN (InceptionV2), YOLOv2, YOLOv4, Improved YOLOv4	Improved YOLOv4	97 %	–	Incorporating multi-species detection would significantly enhance the practical applicability of the study	Mamdouh and Khattab (2021)
Six-toothed Bark Beetle	1	2468	DNN-1, DNN-2, DNN-3	DNN-1	97.86 %	–	a. The proposed approach lacks a clear specification of the model architecture b. The models should be benchmarked against other state-of-the-art approaches to better evaluate their relative performance and robustness	Özcan et al. (2022)
Cucurbit Fruit Fly	1	–	YOLO v5 + SE, YOLOv5 + CBAM, YOLOv5 + CA, YOLOv5 + ECA, YOLOv5 + HC	YOLOv5 + HC	94.3 %	–	The inclusion of multiple insect species in the detection model could improve its real-world relevance and usability	She et al. (2022)
Black Pine Bast Scale	1	4134	Fast R-CNN, Faster R-CNN, RetinaNet, YOLOv3, YOLOv4, YOLOv5l	YOLOv5l	94.7 %	–	a. Incorporating multi-species detection would enhance the practical applicability and real-world relevance of the study b. The inference speed of the models has not been evaluated, which is essential for assessing real-time applicability	Yun et al. (2022)
Mediterranean and olive fruit fly	2	912	YOLOv5 (4 variants such as YOLOv5s, YOLOv5m, YOLOv5l, YOLOv5x)	YOLOv5s	93 %	0.002 s	a. The proposed approach could have the potential to be extended to include other pests, pollinators, and hematophagous species, requiring minimal data preprocessing b. Future research will focus on developing and validating testing protocols for broader applicability	Tannous et al. (2023)
Aphid	1	412	Faster R-CNN, Cascade R-CNN, RetinaNet, YOLOv5s, YOLOv7, YOLOv8s, Improved YOLOv5s	Improved YOLOv5s	65 %	–	The study does not clearly specify which aphid species were used to develop and evaluate the model	Gao et al. (2024b)
Cucurbit Fruit Fly	1	70 (videos)	Faster R-CNN, YOLOv5 + ECA, YOLOv5Ghost, YOLOv7Tiny, YOLO_MRC	YOLO_MRC	99.3 %	0.005 s	a. Limited availability of diverse and comprehensive datasets b. YOLO_MRC exhibits errors in specific scenarios, particularly under conditions of overlapping occlusions	Wei and Zhan (2024)
Fruit fly and Fall armyworm	4	36,822	YOLOv7, YOLOv8, Optimized YOLOv8x	Optimized YOLOv8x	94 %	–	Some newer YOLO-based models could have been evaluated to benchmark performance and enhance the robustness of the study	Hakim et al. (2025)

accessible pest detection tools for farmers and agricultural stakeholders. However, for these technologies to have lasting impact, future research must address the existing methodological gaps, enhance dataset diversity, improve interpretability and explainability of models, and ensure broader field validation across varied agroecological zones, Collaborative efforts among AI developers, entomologists, data scientists, and policymakers will be essential to build systems that are not only technically sound but also agriculturally and ecologically relevant.

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Declaration of competing interest

The authors declare that they don't have any known competing financial interests or personal relationships that could have appeared to influence the works presented in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.aiia.2025.06.005.

Data availability

All data are given here in the text.

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