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AI-Driven Neural Network Methods for Detecting Harmful Insects in Sustainable Agriculture

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Artificial intelligence (AI), particularly deep learning via convolutional neural networks (CNNs), is revolutionizing insect pest detection in modern agriculture. As pests threaten crop yields and food security, early, accurate identification is vital for effective integrated pest management (IPM). Traditional manual scouting is labor-intensive and costly; AI-driven systems address this by automating image acquisition through drones and high-resolution cameras, coupled with CNN models for precise pest classification and plant damage assessment (e.g., leaf damage, discoloration, tissue deterioration). Field-captured high-resolution images enable scalable monitoring and infestation severity estimation, supporting timely interventions. These scalable, efficient tools enhance precision agriculture, reduce chemical inputs, and promote sustainability. Recent studies confirm CNNs achieve high accuracy in real-world conditions, positioning AI as a cornerstone of sustainable pest management.

Introduction

Artificial intelligence (AI) is creating new opportunities for improving insect pest detection in modern agriculture. Insect pests pose a serious threat to crop productivity and global food security; therefore, early and accurate detection is essential for effective pest management. The integration of artificial intelligence with advanced computational frameworks has significantly transformed insect pest detection by providing innovative and efficient solutions to this agricultural and environmental challenge. This transformation is largely driven by rapid advancements in deep learning (DL) technologies, supported by increased computational resources and data availability, which have enabled the development of highly efficient and sustainable pest detection systems (LeCun et al., 2015).

Recent progress in deep learning, particularly convolutional neural networks (CNNs), has facilitated the development of automated and precise pest detection models. These models reduce the time, labour, and cost associated with conventional manual monitoring techniques. CNN-based approaches have become integral components of computer vision systems, as they are specifically designed to detect and learn complex patterns from image data (Khan et al., 2018). A major advantage of CNNs is their ability to automatically perform feature extraction and feature selection through deep network architectures and weight sharing mechanisms, which also help reduce the risk of overfitting (Nasiri et al., 2019).

AI- and DL-based models, particularly those relying on image processing and CNN architectures, are increasingly being applied in precision agriculture (PA) and integrated pest management (IPM) systems (Mavridou et al., 2019). These technologies enable automated monitoring of insect pest populations and facilitate more efficient management of agricultural resources. Furthermore, such models can identify plant damage symptoms caused by insect feeding, including leaf holes, discoloration, and tissue deterioration, enabling early diagnosis of pest infestations.

The use of high-resolution imaging technologies, including drones and advanced digital cameras, has further enhanced the capabilities of AI-based pest detection systems. Images captured under field conditions allow large-scale crop monitoring and more accurate estimation of pest infestation levels. Integrating automated or supervised image acquisition with CNN-based models has been shown to significantly improve detection accuracy and reliability.

Despite the promising results achieved by conventional CNN-based object detection approaches, detecting small objects such as insect pests remains a challenging task. Most general object detection models are not specifically optimized for recognizing small and complex targets, resulting in limited detection performance for insect pests (Kuzuhara et al., 2020). Therefore, further research is required to develop more robust deep learning models that can accurately detect and classify insect pests under diverse field conditions.

Automated Insect Detection and Classification in Field Crops Using Machine Learning

Step 1: Dataset Acquisition

First, insect image datasets were collected from different crop environments. These datasets contained images of multiple insect species and served as the primary input for developing the classification system (Li et al., 2020).

Step 2: Image Pre-processing

The collected images were then pre-processed to improve their quality. Image enhancement techniques were applied to remove noise and improve brightness, clarity, and sharpness so that the important structural features of insects could be clearly observed (Malek et al., 2021).

Step 3: Feature Extraction

Next, important features such as the shape and morphological characteristics of the insects were extracted from the processed images. These features represent the unique structural patterns of different insects and help the system distinguish among species (Mavridou et al., 2019).

Step 4: Classification

The extracted features were used as input for several machine learning classifiers, including Artificial Neural Network (ANN), Support Vector Machine (SVM), K-Nearest Neighbour (KNN), and Naïve Bayes (NB). These algorithms learn patterns from the data and classify the insects accordingly. In addition, a Convolutional Neural Network (CNN) model was used to automatically learn features directly from the images and perform insect classification.

Step 5: Performance Evaluation

Finally, the performance of the classification models was evaluated using standard metrics such as accuracy, precision, recall, and F1-score. These measures help determine how effectively the models can identify and classify insect pests in field crops.

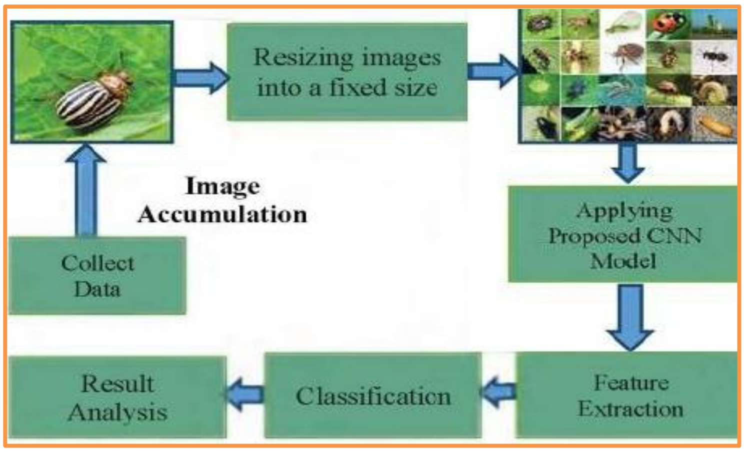

Fig 1. Methodology Flow (Malek *et al.*,2021)

Artificial Neural Network-Based Approaches in Entomological Research

AI Methods for Species Identification

AI techniques, particularly computer vision approaches based on CNNs, have been widely applied for insect species identification and classification. These models are trained using large image datasets to recognize distinctive morphological features of insects. CNN-based systems can automatically extract relevant visual characteristics from high-resolution images and compare them with reference databases for accurate species identification. Such approaches often achieve higher accuracy than traditional morphology- or behaviour-based identification methods (Apasrawirote et al., 2022).

Modelling Insect Acoustic Behaviour

Artificial intelligence techniques can also identify insect species by analysing their unique acoustic signals. This method enables accurate classification even in the presence of moderate background noise (Ashurov et al., 2022). In this approach, waveform audio data are typically converted into spectrograms or sonagrams. Important acoustic features such as Short-Time Fourier Transform (STFT) and Mel-Frequency Cepstral Coefficients (MFCCs) are then extracted to improve classification performance.

Modelling Insect Behaviour

Artificial intelligence enables the modelling and simulation of insect behaviour in silico, providing valuable insights into insect ecology and their responses to environmental changes (Singh et al., 2023). For instance, Ratnayake et al. (2021) proposed a video analysis method that combines background subtraction with deep learning-based object detection to accurately track insect movements. This approach facilitates the study of honeybee foraging behaviour in complex outdoor environments.

Predicting Habitat Suitability and Species Distribution

Artificial intelligence and machine learning techniques are increasingly used to analyse and predict habitat suitability and potential shifts in species distribution under different climate change scenarios. These models help researchers understand how environmental variables influence species distribution patterns and support conservation planning and ecological studies (Choudhary et al., 2019).

Remote Sensing and Imagery Analysis

Remote sensing technologies, particularly satellite imagery, have become important data sources for monitoring temporal changes in vegetation, land use, and land cover (Alqurashi & Kumar, 2013). Variations in the reflectance ratio between near-infrared and red spectral bands are commonly used to assess vegetation abundance through the Normalized Difference Vegetation Index (NDVI) (Meraj et al., 2022). Such information can indirectly support insect pest monitoring by identifying crop stress and habitat changes.

Pest Management in Agriculture

Artificial intelligence systems are increasingly applied to detect and monitor the spread of insect pests that can cause substantial damage to agricultural crops and ecosystems. These AI-based tools help improve early detection, monitoring, and decision-making processes in pest management, thereby supporting sustainable agricultural practices (Aigner et al., 2016).

Conclusion

Artificial intelligence (AI)–driven neural network methods are transforming the detection of harmful insects in sustainable agriculture. By combining advanced image acquisition technologies with deep learning models such as Convolutional Neural Networks (CNNs), pest identification and crop damage assessment can be performed quickly and accurately. These automated approaches reduce the dependence on time-consuming manual monitoring and improve the efficiency of pest detection. Furthermore, AI-based systems support sustainable pest management by enabling early warning, precise monitoring, and informed decision-making. Overall, these technologies strengthen integrated pest management strategies, reduce excessive pesticide use, and contribute to improved crop protection, higher agricultural productivity, and long-term food security.

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