Health Science Monitor
2024; 3(2): 113-119
Published online (http://hsm.umsu.ac.ir)

Review Article

Impact of artificial intelligence on medical entomology research

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Abstract

Artificial intelligence (AI) and its techniques are a rapidly growing field and are being used in various fields, including healthcare and many others. Medical entomology is one of the important sectors in health care. Diseases transmitted through carriers impose a great economic and social burden on the health of society. Mosquito-borne diseases pose major challenges to human health, affecting more than 600 million people and killing more than 1 million people each year. In the current study, we reviewed more than 30 papers in PubMed and Google Scholar that dealt with the application of artificial intelligence techniques in medical entomology. Articles were classified based on the use of AI and its techniques in this field and show that this new tool can play an important role in predicting the risk of contracting vector-borne diseases and the accurate monitoring of insect vector species.

Keywords: Artificial intelligence, Deep learning, Machine learning, Medical entomology

Received 22 October 2023; accepted for publication 27 February 2024

Introduction

Artificial intelligence is a developed computer system that can perform a series of tasks that require human intelligence. These tasks can include image comprehension, speech recognition, decision making, and language translation (1). During productivity, AI systems use techniques such as machine learning, and deep learning to process and learn (2). Machine learning algorithms are usually trained on structured data organized in a predefined format, such as a table, enabling computers to make predictions or decisions by learning from the data (3). Deep learning is a specialized subset of machine learning and has different types, such as supervised learning, unsupervised learning, and reinforcement learning, all of which involve using data to train a model, and their algorithms use artificial neural networks modeled like the human brain (4). Machine learning is a rapidly growing field with applications in a wide variety of sectors, including healthcare and many others (5). Vector-borne diseases impose a great economic and social burden on public health (6, 7). Diseases transmitted by mosquitoes of the Culicidae family are a major challenge for human health, because they infect more than 600 million people every year and lead to more than 1 million deaths (8, 9). Machine learning can play an important role in predicting the occurrence of these diseases, providing new strategies for their control, and closely monitoring insect vector species (10). Additionally, this technique has the potential to revolutionize medical entomology by providing new tools and approaches to identify, monitor, and control disease vectors (11, 12).

This minireview focuses on the use of AI and its techniques in the field of medical entomology, which discusses new approaches and recent trends in this regard. It has also been shown that this new tool can predict vector-borne diseases and monitor insect vector species.

Identification and classification of insect species:

AI can use images, sounds, or DNA sequences to identify and classify insect species, which can help researchers quickly and accurately identify disease vectors and develop targeted control strategies, because identification methods and species monitoring are old and ineffective, necessitating new and reliable methods to study species (13, 14). In the future, molecular methods can play a role in insect monitoring as a precise identification tool, but currently, they cannot provide a reliable abundance estimate (15-18). Today, new methods can be used to identify, count, classify, and discover species for biological monitoring purposes, and deep learning techniques are one of these innovative approaches (19, 20). In a study aimed at Dacus management and its identification using deep learning methods and cameras deployed in traps, Kalamatianos et al. (2018) were able to identify Dacuses with a performance accuracy of 91.52% among the images taken of different pests (21). In these methods, the insects are caught in the McPhail trap, formula trap, or liner, and in the trap, the pest is photographed in the belly, back, and sides with a digital camera. The images are then collected by the computer and transferred to the deep learning servers and in the central system, deep learning networks identify pests based on images (22). The Biodiscover device can automatically perform the process of sorting insect samples as well as species identification (23).

Khalighifar et al. (2019) provided AI with Mexican species and Brazilian species of Triatominae species and used advanced deep learning techniques of TensorFlow to determine the difference between these two Chagas vector species. Finally, deep learning networks analyzed the images and based on the results, the identification rate was more than 98% for the Brazilian species and more than 95% for the Mexican species (24).

Redmon et al. (2018) proposed a You-Only-Look-Once (YOLO), model which can classify an image using CNN in a short time (25). Kitty Chai et al. (2021) aimed to compare the performance of YOLO networks in detecting and classifying some of the caught colecid mosquitoes, which were photographed in the dorsal and ventral planes. In the identification and classification process, six combined models of the YOLO network, including one and two-stage methods, were evaluated, and finally, the evaluation of the models showed that the performance of the YOLOv3 two-stage learning model is more accurate in identifying mosquitoes and has a very low misclassification rate (26).

Balla et al. (2020) used an IRSR infrared electronic optical sensor ring consisting of a photodiode and infrared light emitting diodes to identify pests, with the help of which arthropods of very different sizes and shapes can be recognized (27).

Gebru et al. (2018), in a study used machine learning in controlled laboratory conditions using backscattered light as a measurement criterion, a focus lens, a polar beam splitter, and two two-channel sandwich detectors for mosquito gender and species detection. The sampling frequency was 20 kHz with a bandwidth of 5 kHz, and the spectra were different from each other (28). Kirkeby et al. (2021) tested three different methods for the automatic classification of insects. Based on their observations, the NN method was better than the Tefeatures and WBF methods and had the best performance with an accuracy of more than 80%. The results show that machine learning can be used to process optical signals and differentiate between insect taxa (29).

New methods have been developed to identify pest insect sounds and distinguish them from each other using background noise. However, the most powerful new method is machine learning that includes neural networks and contrast limit adaptive histogram equalization (CLAHE) as a new system for detecting insect sounds using an advanced spectrograph, where a convolutional neural network (CNN) as a classifier extracts the deep feature by machine learning (30). Kiskin et al. (2020) used deep learning and CNN to detect the presence of mosquitoes by identifying the sound signal of wing beats (31).

Genoud et al. (2018) implemented a distant lidar system with an elliptical approach to distinguish between mosquito species solely based on their wing beat frequency, obtained from the scattered light of mosquitoes passing through a laser beam (32). This technique allowed for the identification and differentiation of mosquito species solely based on their wing beat frequency, with an accuracy of 62.3% for species/genus classification and 96.5% for gender classification, using wing beat frequency as the only predictor variable for two classification categories: gender alone (two classes) and species/genus (six classes). The authors suggest that this method could serve as an efficient tool for identifying insect families (32). With the aim of identifying insect species based on wing beat frequency, Potamitis et al. (2017) used common and low-cost plastic traps for various grain pest beetles and placed optoelectronic sensors inside them. Among the signals generated from the insects caught in the trap, adult cockroaches were identified with 98-99% accuracy (33). The summary of insect identification methods using new tools and machine learning techniques has been included in Table 1.

Table 1. Insect identification methods using new tools and machine learning techniques

Identification method		**Name of the tools**	**Identified species**	**Reference**
Imaging		YOLO	Mosquitoes	(26)
		Biodiscover	Beetles, Crab spiders	(23)
		TensorFlow	Triatomines	(24)
		RetinaNet	Red Turpentine Beetle	(22)
		DIRT	Dacuses	(21)
Optical sensor (Infrared)	**Wing beat frequency**	NN	Brassica napus pests	(29)
		SVM	Mosquitoes	(31)
		IR beam-stop	Vector mosquitoes	(32)
		CLAHE	47 types of insect	(30)
		IoT	Various stored grain beetle pests	(33)
	Without/ Wing beat frequency	IRSR	Arthropods	(27)

In the context of entomology research and insect species identification, the use of deep learning techniques introduces new technical challenges, as these models generally require a large number, around 200 samples, of a specific species to learn how to detect its presence in the background. This is known as the training sample requirement for deep learning models (34).

Diagnosis of Disease:

One of the applications of AI is to use it to diagnose diseases among human and animal populations, which can help researchers predict disease outbreaks by identifying patients (35). Malaria is a dangerous disease caused by the Plasmodium parasite. This parasite is transmitted by the female Anopheles mosquito (36). To diagnose malaria, blood samples are usually examined with a microscope, which is cheaper compared to molecular methods, but again, this method requires laboratory and specialist equipment, and access to such facilities is limited in poor malaria-endemic areas (37).

Kumari et al. (2020) conducted research on automated methods to differentiate between parasitic and non-parasitic cells using image processing and machine learning algorithms (38). They followed the waterfall methodology or linear sequential life cycle model (39) and used a set of images of parasitic and non-parasitic cells to train the recognition system. The system takes an image as input, and then all pre-processing operations are performed (40). Then, by converting the images to DWT format and extracting the system feature, it distinguishes between parasitic and non-parasitic images (41).

Holmström et al. (2020) conducted a study with the aim of detecting the Plasmodium falciparum parasite with a fluorescence digital microscope which was based on deep learning methods. The parasite and red blood cell samples were imaged using a digital microscope scanner and then evaluated by two researchers. The red blood cells and the parasite merged into one image were trained to two deep learning systems called DLS to identify and quantify the malaria parasite, and after analysis, the results showed that this method can diagnose malaria and monitor the treatment response through the automatic quantification of parasites (42).

In a study to predict malaria using an artificial neural network called Multi-Layered Progesterone (MLP) with three learning rules, including back propagation, forward propagation with movement, and elastic propagation, Parveen et al. (2017) first stored patients' symptoms and history as input in a database. In the neural network database, in one layer, eight different neurons were used to investigate each of the symptoms of malaria, such as chills, headache, fever, and fatigue as the four main symptoms, and four other minor symptoms of malaria, including vomiting, enlarged spleen, dry cough, and back pain. According to doctors, if the two main symptoms appear at the same time, the person has malaria, and based on the results of elastic diffusion learning, a system was more efficient and predicted the patient with malaria with an accuracy of 0.927 (43).

Predicting the age of insects:

In a study to predict the age of mosquitoes using AI and near-infrared spectroscopy (NIRS) as a predictive model, Ong et al. (2020) scanned the head and chest of mosquitoes using a spectrometer and used a Spectralon plate to collect the spectral background. The results showed that the resulting NIRS spectra can determine the age of laboratory-reared mosquitoes (44). However, there are many challenges in developing and implementing NIRS as an age classification tool, and more information is needed in this area.

Carrier presence warning system:

Južnič et al. (2022) conducted a study aimed at investigating and managing disease-carrying mosquitoes with the help of a citizen science system, in which a citizen observes live or dead adult mosquito and sends the photo to the team members through the mosquito alert program on the smart phone. The photos are converted into data after being checked and validated by entomologists, and each one gets an identification label separately. This system can also be used as an early warning system to identify invasive species at different scales, and related images can help to train machine learning models to recognize and classify mosquitoes (45).

Conclusions and Future Work

Machine learning is becoming the preferred approach for solving more complex real-world problems. Scientific advances in deep learning methods, computer vision, and image and audio processing have reached a stage where they can support or replace manual observations in species identification and routine laboratory sample processing tasks in entomological research. So far, recent advances in the use of AI techniques in the field of medical entomology have been mentioned, and some important studies that have been conducted in this field have been reviewed. AI can also be used in other fields of medical entomology, and it can be used to analyze environmental and weather data to predict the occurrence and distribution of disease vectors. Machine learning algorithms can also be used to analyze satellite images to predict the spread of mosquitoes which carry diseases such as malaria or dengue fever. Timely detection of insects and diseases transmitted by them, monitoring pest abundance to determine whether the pest population threshold has been exceeded is an important process, and AI can be used to develop and optimize control strategies for disease carriers.

However, the complexity of deep learning models and the challenges of entomological data require large-scale investment in interdisciplinary efforts to unlock the potential of deep learning in entomology. We hope that more research will be done in this area, that these techniques will be used more widely, and that we will see progress in this area.

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Acknowledgments

The authors express their gratitude to the Health and Biomedical Informatics Research Center, Urmia University of Medical Sciences in Iran.

Conflict of interest

The authors have no conflict of interest in this study.

Ethical Statement

Considering that this study is a review article, there is no need for a code of ethics.

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