Chapter

Use of Artificial Intelligence on the Control of Vector-Borne Diseases

Daniel da Silva Motta, Roberto Badaró, Alex Santos and Frank Kirchner

Abstract

Artificial intelligence has many fields of application with an increasing computational processing power, and the algorithms are reaching human performance on complex tasks. Entomological characterization of insects represents an essential activity to drive actions to control the vector-borne diseases. Identification of the species and sex of insects is essential to map and organize the control measurements by the public health system in most areas where transmission is actively occurring. In many places in the world, the methodology done for identification of the mosquitos is by visual examination from human trained researchers or technicians. This activity is time-consuming and requires several years of experience to have skills to do the job. This chapter addresses the application of artificial intelligence for identification of mosquitos associated with vector-borne diseases. Benefits, limitations, and challenges of the use of artificial intelligence on the control of vector-borne diseases are discussed in this review.

Keywords: artificial intelligence, machine learning, deep learning, mosquitoes classification, vector-borne diseases

1. Introduction

For those who are not familiar with artificial intelligence (AI), imagine that some tasks that are done by humans, such as object detection, visual interpretation, and speech recognition, can be done by computers without human interference. Why is that important? There are many benefits with the use of AI that we intend to discuss in this chapter.

AI is growing in fields that require algorithms (mathematical instructions for computers) and machines to solve problems that are intellectually difficult for human beings but relatively easy for programmable computers. Nevertheless, "the true challenge of AI is to solve tasks that are easy for people to perform, but hard to be described, once it requires intuition [1]." When we look at an image, our interpretation is instantaneous: Is there a car? Is there a person? Is there a house? Computers are able to interpret as well, but not in same way that humans do. Computers translate an image in numbers, as illustratively shown in **Figure 1**.

In the early years of artificial intelligence, a rapid growth has been experienced. "The AI index—2017 annual report, created at Stanford University, presents the volume of activities that involves AI. In this report, indicators help to understand the importance of artificial intelligence technologies for academia, industry, and

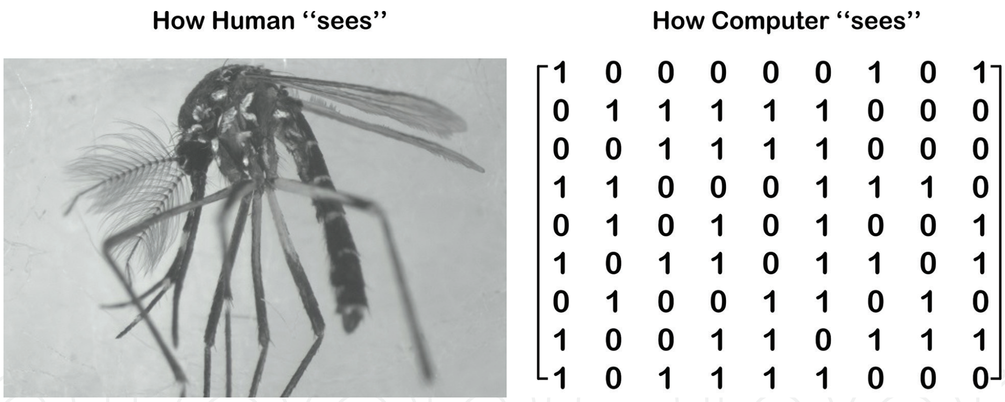

Figure 1.
Human vs. computer: how an image is recognized by each (illustrative).

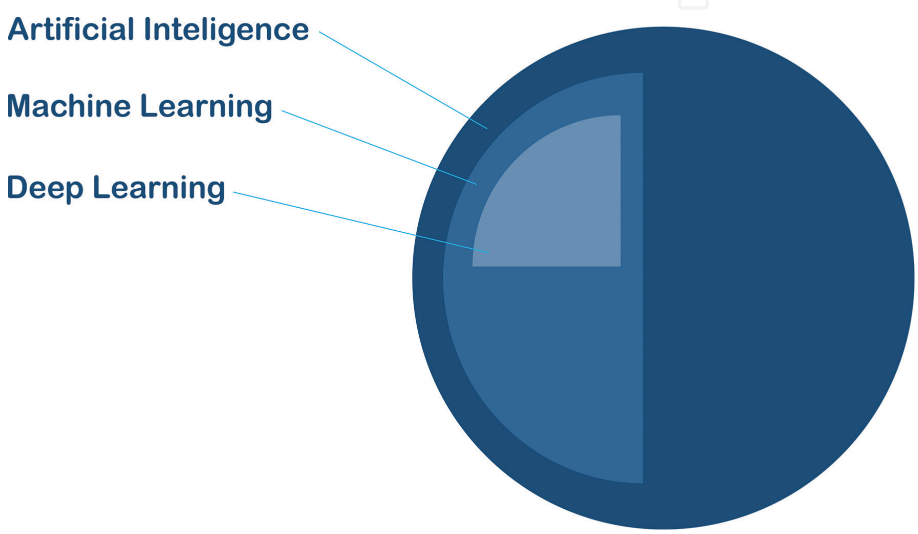

Figure 2.
Relationship between artificial intelligence, machine learning, and deep learning.

public sector. The number of AI published papers produced each year has increased by more than nine times since 1996. For industry, the number of active US startups developing AI systems has increased 14 times since 2000 [2]."

Machine learning (ML) is a subarea of artificial intelligence that is able to learn from previous experience. "ML algorithms are design to solve problems extracting features from existing data, learn from these features and predict the outcomes" [3]. For example, intelligent mosquito's trap can be designed with the functionality to classify harmful from beneficial insects, release the nontarget insects, and kill the target ones. The classifying process can previously learn from wingbeat frequency data of different species of insects, and whenever a new insect approaches the trap, it will automatically classify and take the decision—release it or kill it. That was exactly what "De Souza and Silva proposed using machine learning techniques" [4, 5].

Recently, "Deep Learning (DL) methods—a subarea of Machine Learning—are considered essential for general object recognition" [6]. "Tasks that consist of mapping an input to an output and that are easy for a person to do rapidly, can be accomplished via Deep Learning, given sufficiently large models and dataset of labeled training examples" [1]. "In the largest contest for object recognition, ImageNet Large Scale Visual Recognition Challenge (ILSVRC), a breakthrough for deep learning occurred in 2012 when a Deep Learning network won the competition, bringing the state-of-art top-5 error rate from 26.1% to 15.3%" [1]. **Figure 2** illustrates how artificial intelligence, machine learning, and deep learning are related.

An important field for application of artificial intelligence is health care. Based on the knowledge of medicine and historical data, AI can be used to support medical doctors to take better and faster decisions. For instance, AI can support medical doctors with robotics systems for some special tasks such as surgery, to increase the life expectancy of human beings, to increase the quality of life for people with some physical disability, and also to increase the community participation to improve the performance of a human care system.

In medicine, arboviruses have received a global attention, since "vector borne diseases are responsible for 17% of the estimated global burden of communicable diseases. It causes more than 700,000 deaths yearly and at least 80% of the global population lives in areas at risk" [7]. Entomology research is considered priority by the World Health Organization for the development of tools that can be applied to reduce incidence and mortality and prevent epidemics due to vector-borne diseases globally.

Identification of the species and sex of mosquitoes is essential to map and organize the control measurements by the public health system in most areas where transmission is actively occurring. In many places in the world, the methodology for identification of the mosquitos is done by visual examination from human trained technician. "This activity is time consuming and requires several years of experience to have skillful to do the job" [8].

This chapter addresses the application of artificial intelligence to help on the control of vector-borne diseases. Research trends and technologies connecting AI to vector-borne diseases are presented for a better understanding on how much researchers and institutions are becoming interested on both topics together. The use of machine learning and deep learning techniques, as a subarea of AI, is discussed for classification of mosquitos in their different life cycle—eggs, larval, pupal, and adult. Benefits and limitations are also presented to help the reader to understand the potential and challenges of artificial intelligence applied to entomology.

2. Research and technological trends on AI and vector-borne diseases

Since 2000, a continuous growth on published research (papers) and patents granted relating artificial intelligence with vector-borne diseases has been noticed. **Figure 3** represents the number of papers published yearly using the keywords: (insect OR mosquito OR culicid OR vector-borne OR zoonotic disease) AND (artificial intelligence OR machine learning OR deep learning). This review considered the following sources: IEEE, PlosOne, Capes, PubMed Web of Science, Current Contents Connect, Conference Proceedings, and Inspec.

It is interesting to notice that in 2017 the number of papers is almost six times it was in 2000. This result demonstrates that artificial intelligence has several possible applications on the control of vector-borne diseases as an important interest topic for many researchers around the world.

Figure 4 shows the number of patents granted in the world with the same keywords as the ones used for review papers. For the patents research, the platform Derwent Innovation was used.

In 2017, the number of patents granted is relevantly almost 10 times the average it was in the previous years. This result demonstrates that not only researchers but also companies have interest in intellectual property assets applying AI on the control of vector-borne diseases.

Figure 5 presents the top countries' and regions' intellectual properties' ownership. China, Korea, and Japan are the countries with more granted patents.

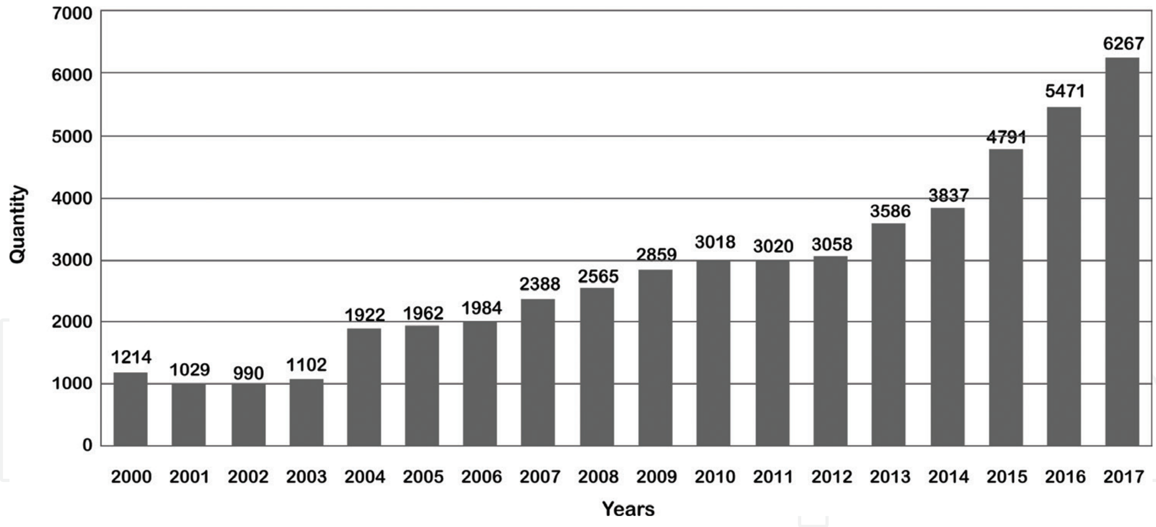

Figure 3.
The number of papers published from 2000 to 2017 relating AI to vector-borne diseases.

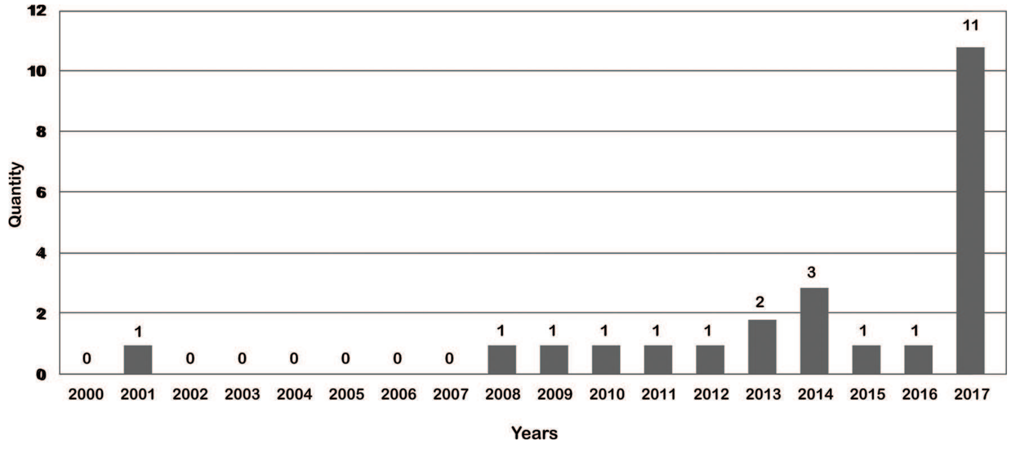

Figure 4.
The number of patents granted from 2000 to 2017 relating AI to vector-borne diseases.

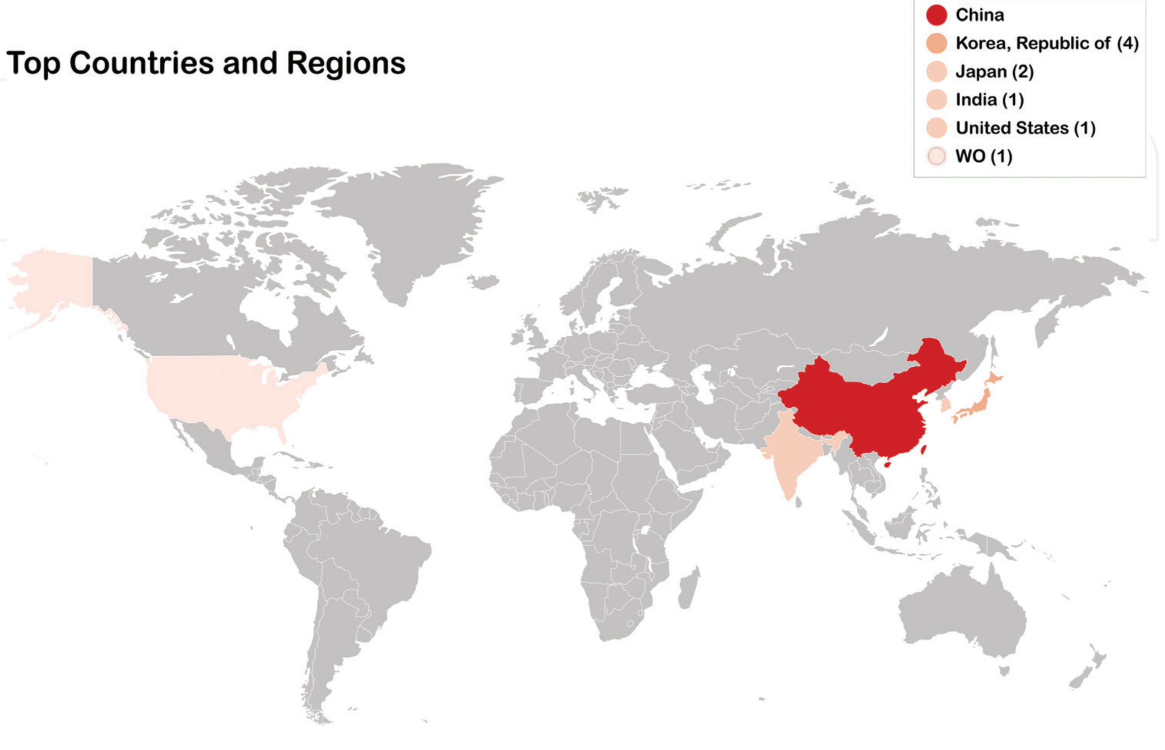

Figure 5.
Countries with more patents from 2000 to 2017 relating AI to vector-borne diseases.

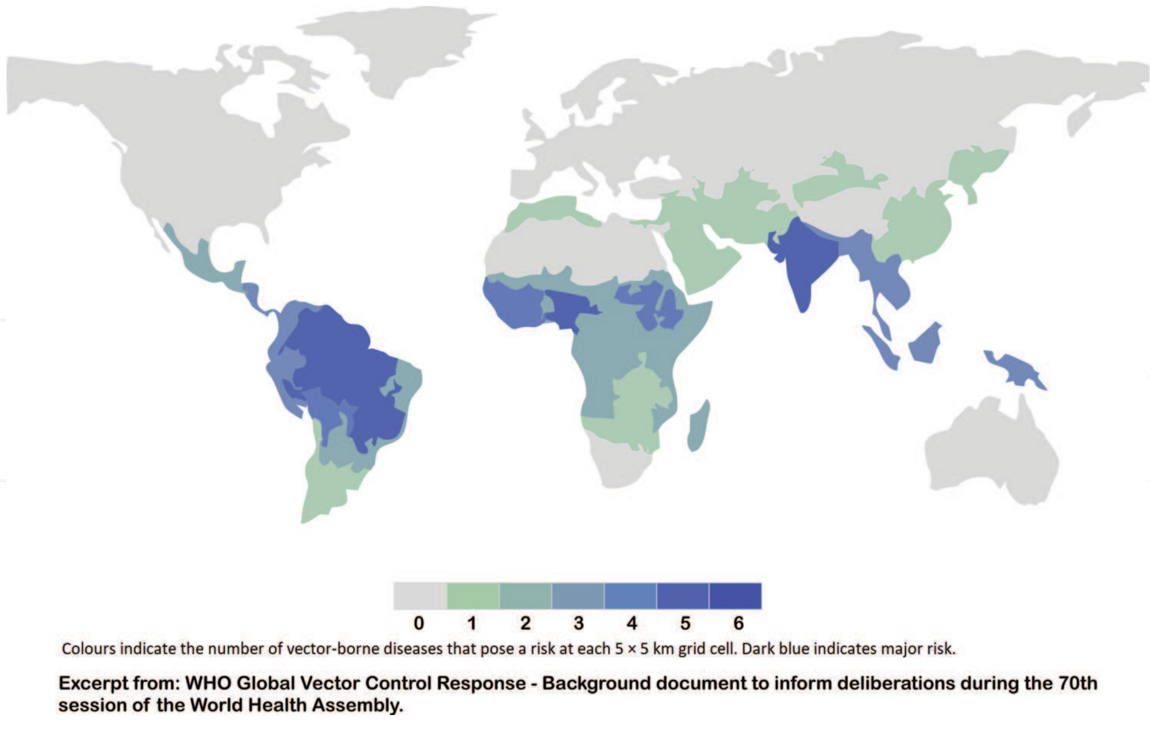

Figure 6.
Combined global distribution of seven major vector-borne diseases: malaria, lymphatic filariasis, leishmaniasis, dengue, Japanese encephalitis, yellow fever, and Chagas disease transmission [7].

Figure 6 presents the combined global distribution of seven major vector-borne diseases. Correlating **Figures 5** and **6,** some countries that own IP relating AI to vector-borne diseases are not among the main ones that appear in "the global distribution of seven major vector-borne diseases for which integration of vector control programs may be beneficial—malaria, lymphatic filariasis, leishmaniasis, dengue, Japanese encephalitis, yellow fever and Chagas disease transmission—which evidences that vector borne is everyone's problem [7]."

3. How AI can benefit entomology

In this section, we present some benefits on applying artificial intelligence techniques in areas that are of high importance on the control of vector-borne diseases. Over the last year, much attention is being dedicated to capture and kill harmful mosquitoes using different kinds of mosquito's traps. Also, several methods have been developed to help mosquito's species classification process.

A major benefit on the application of AI is to increase the community participation in the control of vector-borne diseases and therefore successfully decrease the burden of arboviruses' recurrent epidemics.

3.1 Mosquito's trap

There are many mosquitos' traps available to capture and kill mosquitoes. Some of them are dedicated to attract females to deposit its eggs in the trap. Others are designed to capture and kill larva or adult mosquitoes.

Among the studies analyzed, some were dedicated to evaluate the performance of traps of capture of adult mosquitoes. "In [9], an approach is presented to remotely collect and identify field mosquitoes captured by two traps, "BG-trap" and "CDC light." The motivation of the work is justified considering that the activity of capture and classification requires the presence of entomological specialists and, therefore, faces constraints of budget and logistic feasibility."

Entomologists recognize that monitoring the traps is crucial to accomplishing its goal. Once the traps attract mosquito's female, if not periodically monitored, it might increase the density of mosquitos in the area the trap is located.

Another issue is the damage caused in the mosquito's body during the capture process. Some samples have its parts destroyed and also dried, what makes difficult the taxonomist's job to evaluate the morphological characteristics of the mosquito's species. **Figure 7** presents an image of *Culex quinquefasciatus* from Fiocruz—Oswaldo Cruz Foundation in Brazil. Some of the morphological characteristics are no longer presented in the sample.

Artificial intelligence can help the design of mosquito's traps by incorporating new important functions. For instance, it helps identify the targeted mosquitoes and separate from the nontargeted ones. Also, using AI, it is possible to acquire and store important information that can help to understand the mosquito's behavior and correlate data such as date and time of capture, species captured, and environmental data (humidity and temperature).

The application of machine learning techniques to design intelligent traps, using a laser sensor, and audio analysis techniques have been used to help insect recognition [5]. The device developed by the authors is able to attract and distinguish harmful from beneficial insects. Also let free the nontarget insects and kill the target ones, which can provide information to estimate the density of the target insect population. Different feature sets from audio analysis and machine learning algorithms achieved 98% accuracy in the insect classification.

Another example was the development of an automatic mosquito classification system consisted of an infrared recording device for profiling the wingbeat of the in-flight mosquito species. Also, a machine learning model was used for classifying the gender, genus, and species of the incoming mosquitoes by the signatures of their wingbeats [10]. To assess the performance of the system, the authors used living male and female *Aedes albopictus*, *Aedes aegypti*, and *Culex quinquefasciatus*. The results show that the accuracies of the proposed system are above 80% on identifying the gender and genus of the mosquitoes.

3.2 Mosquito classification

The correct identification of mosquito species is an essential step in the development of effective control strategies for vector-borne diseases. Ten years prior to

Figure 7.
Image of Culex quinquefasciatus from Fiocruz.

the occurrence of Zika virus, dengue, and chikungunya epidemic in Brazil, *Aedes aegypti* mosquito density increased almost 600 times.

Entomological characterization is fundamental to acquire information about mosquito's behavior. This activity requires trained and experienced personnel. "While the general interest in documenting species diversity has grown exponentially over the years, the number of taxonomists and other professionals trained in species identification has steadily declined [11, 12]."

According to Fiocruz, "the traditional method of classifying mosquitoes uses dichotomous keys [13]." These keys consist in analyzing morphological characteristics of the insect. "The dichotomous keys are mostly used to classify species beyond the 4th stage of larval phase" [14]. **Figure 8** represents the classification process using dichotomous keys for three different species—*Aedes aegypti*, *Aedes albopictus*, and *Culex quinquefasciatus*. The dichotomous keys are used to classify any species, not only the represented in **Figure 8** and uses images/figures/drawings to support the taxonomist during classification.

In order to use the dichotomous keys, the taxonomist needs to prepare the sample—if it is an adult, assemble the mosquito on entomological pin and observe the specimen under the microscope to evaluate the morphological characters. **Figure 9** represents the process of entomological characterization of an adult mosquito.

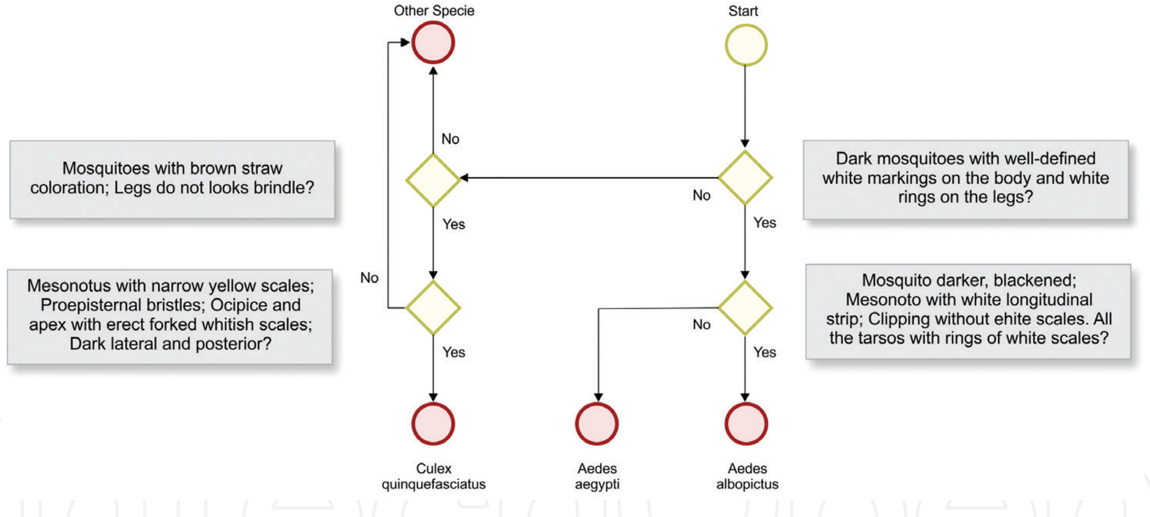

Figure 8.
Representation of the process using dichotomous keys for the classification of mosquitoes.

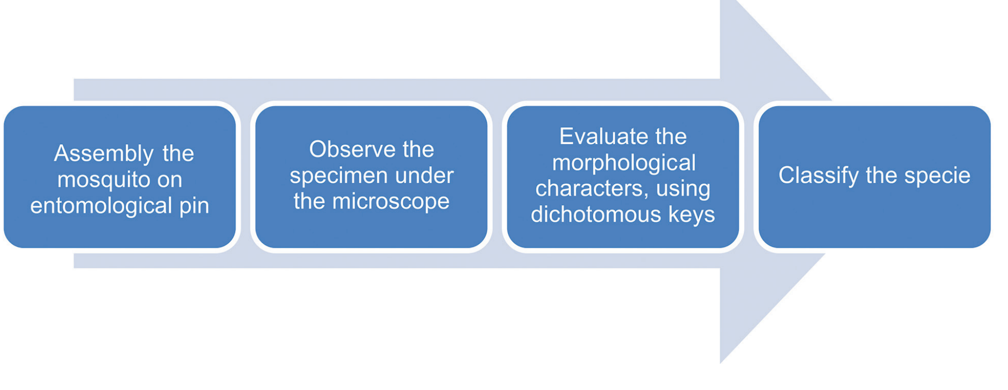

Figure 9.
Process of entomological characterization of an adult mosquito.

As already mentioned, some of the mosquito's samples are damaged and lose morphological characteristics during the capture in the field and the transport to a laboratory. Besides that, the waiting time during capture and transportation is also an issue and might dry the mosquito's body, which affect some characteristics such as color.

Another possibility for the "identification of species can be made through the use of molecular techniques that have been shown in different studies such DNA barcodes" [15]. Furthermore, molecular identification of mosquito remains a slow and expensive process for most laboratories.

Artificial intelligence can be applied to automatize the mosquito's classification process. It can be used to classify in field by entomologists or even nontaxonomists and health workers. By doing that, AI can avoid the major issues presented previously, like the need of trained and experienced personnel and lose of the morphological characteristics. Artificial intelligence application also allows increasing the number of mosquito's data, obtaining online information of population density, and the correlation with cases of incidence and mortality of vector-borne diseases.

In one AI application, deep learning was used to recognize *Aedes*-utilized wings morphology. "In [16], 17 species of the genera *Anopheles*, *Aedes*, and *Culex* were classified based on wing shape characteristics to test the hypothesis that classification using Artificial Intelligence was better than traditional classification method by discriminant analysis. The results demonstrated the AI correctly classified species more efficiently with an accuracy of 86%–100%."

Some authors study support vector machine (SVM) techniques. "In [17], the authors use digital image processing and support vector machine (SVM) to detect *Aedes aegypti* mosquito. It is suggested for a method of identification as binary key of mosquitoes from the visual identification of their morphology. A camera is integrated with a circuit board, where images are fed to a support vector machine, corresponding to body characteristics of the insect. Photos of insects are taken and then delivered to the machine for data comparison, where photo properties are valued and then matched. By the construction of the equipment, the system only responds if the identified mosquito is *Aedes aegypti* or not, to which it has an accuracy of 90% in the data."

In other applications, mosquito's larva digital images were used in a machine learning algorithm for *Aedes* larva identification. "The authors proposed a method to identify larvae of *Aedes* mosquitoes using convolutional neural networks (CNN), a new method in multilayer neural network technology that has proven its performance especially in image analysis. Larva's images were captured by cell phones. The classification method is divided into the following steps: 1) acquisition of images; 2) preprocessing the images; 3) CNN training; 4) Real-time classification. The results shown a good performance with 100% accuracy for identification of *Aedes* larva, however, for other mosquitoes the misclassification rate was 30% [18]." Although the sample size in this study was very small, it shows that artificial intelligence can be used for the mosquito's species classification.

4. Limitations and challenges on the application of ML and DL

Applications of machine learning and deep learning techniques in many areas are rapidly growing, due to the flexibility of their algorithms and also because it is not required to model previously the scenario using a mathematical function. Prototypes and computer systems are being developed, but there are still some bottlenecks to overcome. Although machine learning and deep learning algorithms are capable of capturing the complexity of several problems, in some cases the effective use of it depends on further research and development to increase the level of reliability before it can be used in the real world.

In this section, we present some limitation and challenges on the application of artificial intelligence, especially machine learning and deep learning techniques, which should be addressed in future researches.

4.1 Generic approach

An algorithm does not interpret a problem the same way that humans do. It needs a mathematical equation to build a scenario that represents the reality. The mathematical equation is a representation of the reality and usually simplifies the problem to be solved, due to that incorporates mistakes and has limitations to be generalized. Because of it, the application of machine learning and deep learning techniques to control vector-borne diseases must be designed and/or trained for this specific purpose. There is no such generic approach: each problem has its own specificity and therefore must be treated with exclusivity.

4.2 Robust dataset

Another important limitation of machine learning and deep learning is the need of historical data to be used for algorithm training, learn from these data, and predict a reliable outcome. The availability, disposal, and variability of these existing data are crucial for the computer learning process. "Objects in realistic settings exhibit considerable variability, so to learn to recognize them, it is necessary to use much larger training sets [6]."

Entomology, for instance, has small dataset size available open source, which turns to be difficult to adapt the model and solve the problem with proper accuracy and reliability. Researchers should be aware that the application of machine learning and deep learning for zoonotic diseases must consider the building of a robust dataset.

4.3 Underfitting and overfitting

Underfitting and overfitting also need to be addressed during the use of machine learning and deep learning techniques. The first one relies when small data are presented in the training or the training does not run a sufficient number of epochs (learning cycles). In this case, the mathematical model is unable to capture the features complexity of the input provided and present a high error level in the output—too many wrong predictions when new data are presented.

Overfitting relies when the data presented have small variability or the training learning cycles are too much, and instead of reducing the error after each epoch, it starts to increase. To clarify the understanding, imagine a student who, among the elementary arithmetic operations (addition, subtraction, division, and multiplication), only dominates multiplication. If a test is presented only with questions to multiply numbers, probably the student will have a good grade, but you cannot measure his/her knowledge with this test. That exactly what happens with the computer if the variability of data is low. The training result might present a high accuracy, but in the real world, it is not reliable.

Figure 10 graphically shows underfitting and overfitting—validation error represents the predicting error when new data are presented.

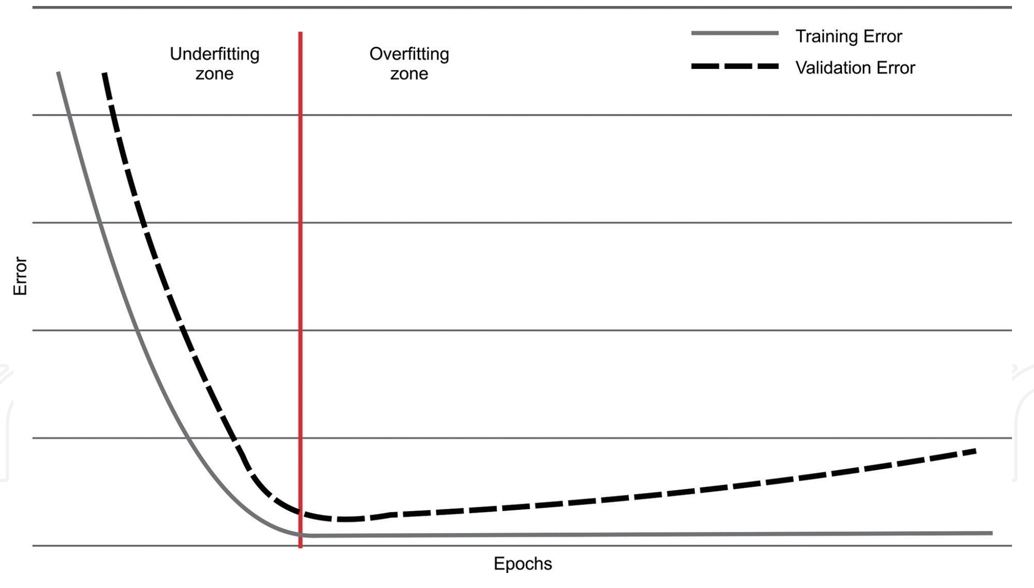

Figure 10.
Representation of underfitting and overfitting. "Adapted from [1]".

There are some methods to reduce overfitting. "The easiest and most common method is to artificially enlarge the dataset [6]."

5. Conclusions

Novel and important applications are available with the development of data mining methods. Artificial intelligence techniques are an important field to be applied on the control of vector-borne diseases. A complete and accurate identification of the 5000 mosquito's species that were already identified should be tested in this model as well as other species groups, such as complex or cryptic species, and in different populations of the same species.

Artificial intelligence could help to develop a system that anyone, who capture larvae or adult's mosquitos in several regions, can identify the *Aedes* mosquito. In the near future, a complete identification of any insect or new nonclassified ones that exist in this world could be automatically classified by anyone using a smartphone. AI will never replace mankind but will help to keep memories and activities that humans have discovered in our millenarian existence.

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Conflict of interest

We have no "conflict of interest."

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Appendices and nomenclature

AI	artificial intelligence
ML	machine learning
DL	deep learning
ILSVRC	ImageNet large scale visual recognition challenge
WO	PCI patents (world)
CNN	convolutional neural networks
SVM	support vector machine

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