# Mosquito Larva Classification based on a Convolution Neural Network

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**Abstract**— *Recently in Mexico a great number of diseases has been spread by the mosquito vector, Aedes. The number of patients in some regions of the country is alarming. The spread of these diseases has become a public health problem; hence the government is applying some methods for reducing the infection rate. One of principal methods relies on the localization and fumigation of the mosquito's larvae. The localization of Aedes larvae is done manually by specialized personnel that seek to determine the areas to be fumigated. However, this task consumes a considerable amount time compared to the life cycle of a mosquito, making the task not efficient enough. Thus, a efficient algorithm, which classify whether mosquito larva is a vector or not, is required. In this paper, we propose a mosquito larva classification method based on the VGG16 pre-trained convolution neural network, where a dataset of larva is used in order to determinate two types of mosquitoes: genus Aedes and "others" genera. The proposed method would make the larva identification process more efficient, automatic and faster than the conventional methods, and thus the infection rates would be decreased. The results show a good performance on Aedes larva identification, proving that the system can be applied in the real world.*

**Keywords:** Larva, Mosquito, Aedes Classification, Convolution Neural-Network

## 1. Introduction

Nowadays several diseases such as Dengue Fever (DF), Dengue Hemorrhagic Fever (DHF), Chikungunya (CHIKV) and Zika are causing serious problems in human health. The spread of these diseases is transmitted through mosquitos of the genus Aedes, especially species Aedes Aegypti (See Fig.1). This is considered as the principal vector of the transmission of these diseases. In Mexico, an important number of patients have been reported during the years 2015, 2016 and 2017, as shown by Table 1 [1], [2], [3].

Table 1: Number of patients in Mexico 2015, 2016 and 2017

| | DF and DHF | CHIKV | Zika |
|---|---|---|---|
| Number of patients | 14,138 | 13,163 | 11,851 |
| Death | 55 | 4 | 2 |

Almost all these diseases have been detected mainly in the tropical zone of Mexico, because Aedes mosquitos are very common in these areas. However, due to the global climate change in the earth, these types of mosquitos have been observed in non-tropical zone, such as Mexico City.

These diseases transmitted by Aedes mosquitoes are observed actually in many countries. The primary strategy for stopping the disease outbreak consists on the prevention and suppression of the vector spreading. In other words, if the main carrier of these diseases, Aedes mosquitoes, is suppressed, the spread of these viruses will be radically diminished. An effective method to counter-measure the Aedes mosquitoes is to know its life cycle and apply efficient actions to interrupt it. The Aedes mosquito has four phases

Fig. 1: The Aedes Aegypti mosquito. One of its particularities is the presence of white spots in the body.

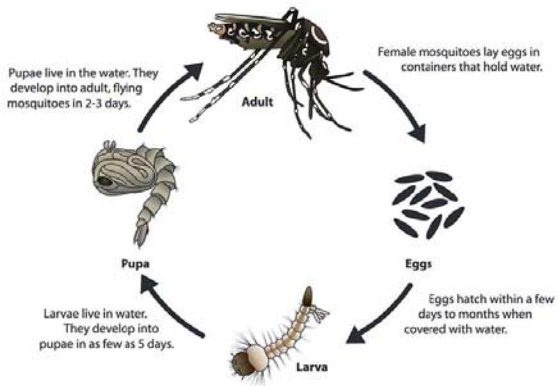


Fig. 2: The Aedes mosquito life cycle in 4 stages [4].


Fig. 3: The map of Mexico shows in red dots the places where the Aedes mosquitoes was detected and in yellow dots the places where it might be. This map provides from the national secretary in Mexico.

in its life cycle: egg, larva, pupa and mosquito as shown by Fig2. The first three phases are categorized as aquatic phases because they need water to live[4]. Under favorable conditions, the Aedes mosquitoes can reproduce in only one or two weeks.

Considering the serious situation in public health caused by the Aedes mosquitoes, some Mexican local governments apply a methodology to reduce the infection rate of the viruses mentioned above. The methodology relies on the localization of larvae of the Aedes mosquitoes, which is based on capturing mosquito larvae in several regions of the country that have a considerable number of confirmed patients. As it can be observed in the map of Fig. 3, according to the Secretary of Health in Mexico, the map shows the location confirmed of the people infected and possible location of Aedes mosquito. After this samples are captured and sent to the State central laboratory where a few specialists classify each one of the great amount of larvae captured. After the identification of the Aedes larvae captured, a group of exterminators go to fumigate Aedes larvae using insecticides.

However, this method is not efficient due to short life cycle of Aedes mosquitoes, being the case that the larvae have already converted into mosquitoes and also have reproduced in other pools. It makes the process of fumigation not efficient enough.

Additionally, this methodology is very time consuming and tedious. Taking in account the actual problems that Mexico and many Latin American countries are confronting, in this paper, we propose an efficient method to identify larva of Aedes mosquitoes using the pre-trained VGG16 Convolution Neural Network (CNN) with a modification in the las layer using bottleneck features applied to the larva's images captured by mobile device. In the proposed scheme, the identification process of larvae can be more efficient, automatic and faster learning time than the conventional methods, such like using AlexNet CNN[7], Support Vector Machine (SVM) and K-means method. These conventional method assumes full-scratch build only from given training set, so the increasing of the dataset size requires computational costs. On the contrary, we adopt pre-trained method, which utilize the other domain knowledge such like general object recognition task[12][13].

The rest of the paper is organized as following. In section 2, we explain the previous works related to the mosquitoes larva classification. In section 3, we explain the data acquisition method. In section 4, we show our proposed method for larva image classification using VGG16. In section 5, we show a experimental results and comparison with the other works. And the we make a discussion. Finally in section 7, we make a conclusion.

## 2. Previous Works

Due to the outbreak of the diseases in Latin America, this project started around three years ago in the Polytecnical National Institute in Mexico City in collaboration with a Public Health Laboratory of Hidalgo State in Mexico that is the provider of the larva samples to obtain the dataset. This dataset is commonly used in this work and previous ones. The target task is a binary classification whether the Aedes larva is a vector or not. In the previous works, this binary classification was based on the computational tools such as image processing, pattern recognition and deep learning. In [5] the larva classification was made using Support Vector Machines (SVM) and K-means method using low-level features, such as Co-occurrence Matrix (CM), Local Binary Pattern (LBP), and Gabor filtered features (FG2). It was used 308 images for both cases "Aedes" and "Others". The classification was made extracting the features of every image obtained by the texture descriptors and the image pre-processing.

Table 2: Accuracy results 2 conventional classifiers

| | CM | LBP | FG2 |
|---|---|---|---|
| K-means | 59% | 55% | 60% |
| SVM | 67% | 72% | 79% |

The table 2 shows the accuracy performances for these 2 classifiers using conventional image descriptors. In [6] the classification was made using the AlexNet CNN [7] with 310 images trained from scratch. It was necessary to do a great number of iterations in order to increase the accuracy. Using 200 epochs the network could achieve 96.8%. It took a long time for the network to converge unlike the method proposed in the work.

Suzuki *et al.* applied the AlexNet to classify medical image classification using transfer style learning[13]. In their report, using the transfer learning makes convergence speed faster than that of the full scratch version. So, we apply this transfer style method into the CNN learning.

## 3. Data Acquisition

There exist more than 15,000 species of mosquitoes evolved to feed on blood from warm vertebrate animals. But in particular the most abundant urban mosquitoes in South America that preferentially feed on humans is the Aedes mosquito which is an important genus because it is a principal vector of several diseases [8]. There exists several ways to classify mosquitoes. In this work, we adopt image classification based method since it is a very convenient way to acquire and evaluation. In the larva images, the Aedes larva has specific feature in its eighth (VIII) segment, where we can observe a comb-like feature. The Figure 4 shows the image of complete larva and its eighth segment of different types. The form of the comb-like figure can be used to discriminate larvae of the genus Aedes from larvae of other genera. For example any larva of Aedes has a single row in its comb, while the other genera of mosquitoes have several rows in their comb.

In order to obtain the images, an image acquisition system shown in Fig 5 is used. In the acquisition system, a microscope lens is attached to a smart-phone, so that it is a very simple and portable system to acquire data. The microscope has amplification capacity of 60-100 times.

Using image acquisition system shown in Fig. 5, we acquire several raw data. In order to construct and evaluate a classification system with machine learning, The Aedes dataset is configured as following: The larvae image dataset has 1,118 items of larvae 8th segment, in which there are 559 images for each type of “Aedes” and “Others”. All larvae used to make the datasets are previously identified in the Public Health Laboratory of Hidalgo State in Mexico. The Figure 6 shows two images of eighth segment of tow larvae: the left image belongs to “Others” and the right image belongs to the Aedes genus.

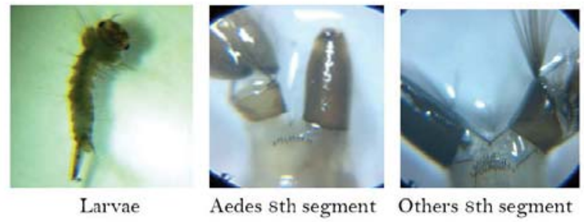


Fig. 4: Typical mosquito larva examples

Fig. 5: Data acquisition system using smart phone.

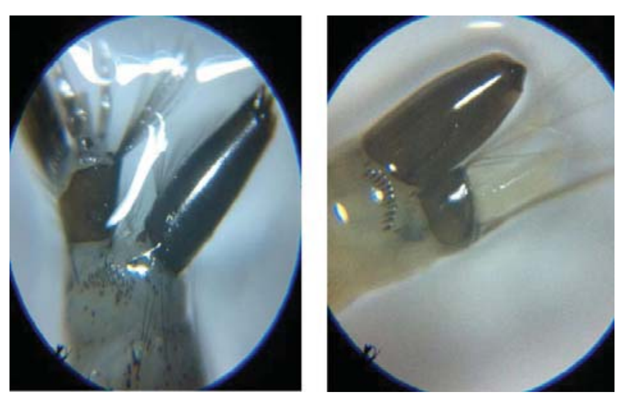

Fig. 6: Example image of larva and its 8th segment.

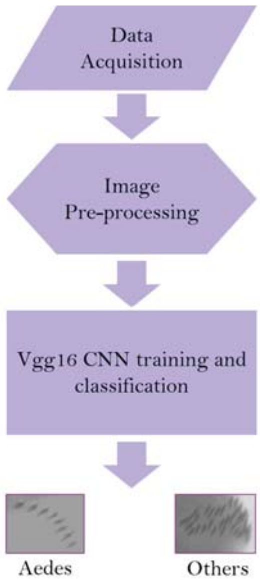


Fig. 7: . Block Diagram of the proposed scheme

# 4. Proposed Method

In this work, it is proposed a novel manner to classify mosquito's larva images making use of Convolution Neural Networks based on the VGG16 model to classify the larva images, which consist in the following steps: 1) Data acquisition, 2) Image pre-processing, 3) Training of the CNN and 4) Classification. The block diagram of the proposed scheme is shown in the Figure 7. In this section, we describe last three steps: Image pre-processing, Training of the CNN and real Time Classification.

## 4.1 Image pre-processing

The raw images are not suitable for the training and evaluation, so it was necessary to carry out pre-processing. Due to the images are taken using a microscope lens, there are some regions that are not relevant for the classification purpose. In the Figure 8, we can observe the pre-processing applied to the dataset.

For the elimination of noise, the total validation method is applied. The technique of total variation is used to decompose an $I$ image into two images: texture image $I_t$ and caricature image $I_c$ , where $I = I_t + I_c$ . Since the cartoon image $I_c$ is a noiseless image, feature vector is extracted from the $I_c$ [8]. After applying this technique, it can be noticed that the image still have withe spots that may interfere in the classification hence it was applied a method by finding the highest value of the histogram of the image. To finish with the pre-processing was applied the image normalization process in order to make the image suitable for the network.

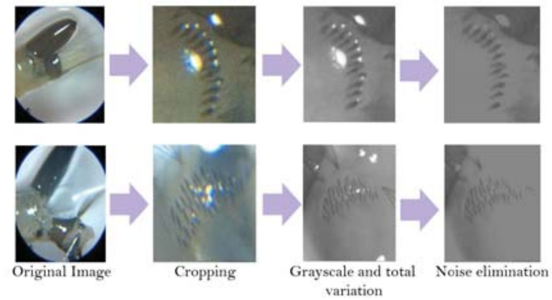


Fig. 8: Pre-process for acquired images.

Subsection can be added.

## 4.2 Training of the CNN

In this work, we propose a classification method based on the deep learning. The deep learning is a kind of machine learning algorithms which try to simulate the human brain behavior. Unlike other machine learning techniques, such as Gaussian Mixture Model (GMM) and Support Vector Machine (SVM), in the deep learning, the feature extraction task are performed in layers close to the input layer. So in the deep learning system, the feature extraction process is not required. In this paper, we used this technique in order to identify the larva of the Aedes mosquitoes. In training stage, we used the convolution neural network called VGG16[9], it was decided to use this model because of the Network configurations, this model was released in 2014 so is one of the modern models and the main contribution is a thorough evaluation of networks of increasing depth using an architecture with very small (3×3) convolution filters, which shows that a significant improvement on the prior art configurations (AlexNet), can be achieved by pushing the depth to 16 weight layers [9].

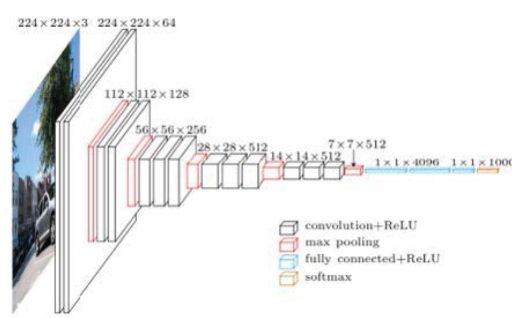


Fig. 9: The VGG16 architecture.

The network was pre-trained with the ImageNet [10] database in order to get the weights and thus obtain an accurate classification. In order to increase the number of images, we apply data augmentation method that artificially creates training images through different ways of processing or combination of multiple processing.

The figure 10 shows the block-diagram of the VGG16 in this experiment. In the figure top shows the input and bottom shows the output. The VGG16 network has 5 blocks, in which the first 4 blocks are called convolution block, and the last block is called fully-connected classifier block. In the VGG16 network, the output representation before the fully-connected layer is called the "bottleneck" features[11]. This penultimate layer has been trained to output a set of values that is suitable for the classifier to use to distinguish between all the classes to recognize. That means the bottle-neck feature representation might has a meaningful and compact summary for the input image, since it has to contain enough information for the classifier to make a good choice in a very small set of values.

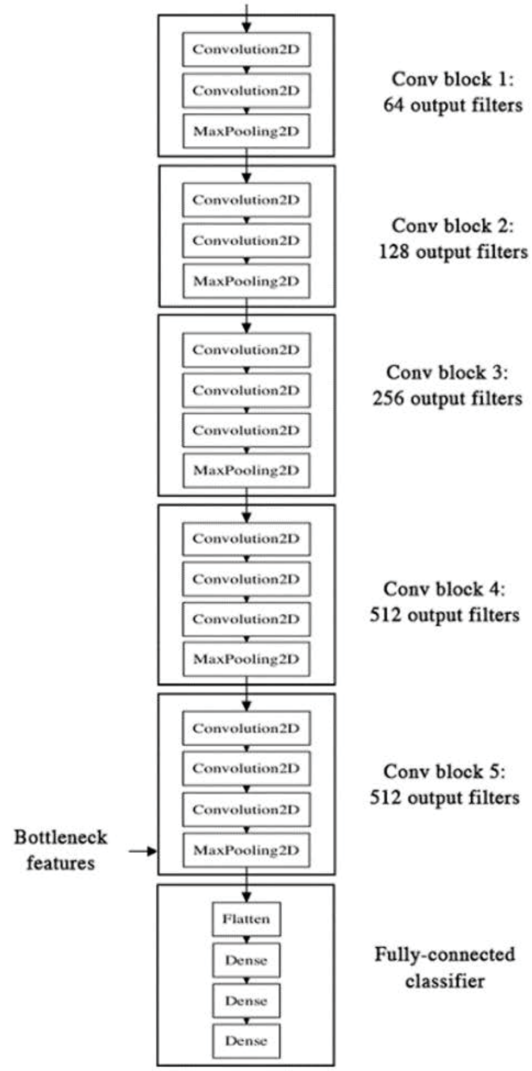


Fig. 10: The block diagram of VGG16 in this experiments

### 4.3 Classification

After the training step, for both classes it was used 740 images for training and 378 images for testing. Figure 11 shows the two types of images. It was trained a small fully-connected model on top of the stored features and thus the difference between the previous work with the AlexNet is remarkable. It was used different number of epoch to try the network but it can be seen in Figure 12 that by epoch 4 that the network achieve the maximum accuracy It can observe that the system is capable to recognize the larvae of Aedes mosquitoes with an accuracy of approximately 97% in average.

## 5. Results

In this section, it is presented the image classification results achieved by the described CNN, the shown in the Figure 12. It was not used different numbers of epochs for training. Due to the pre-train and the bottleneck features the network could achieved 97% of accuracy showing that show that it is suitable to implement this system in a mobile device, equipped with a microscope camera for Aedes larva classification in field works, and thus, the localization of this vector could be more accurate and the process of fumigation would be more efficient, and then as a result, the infection rate would be decreased.

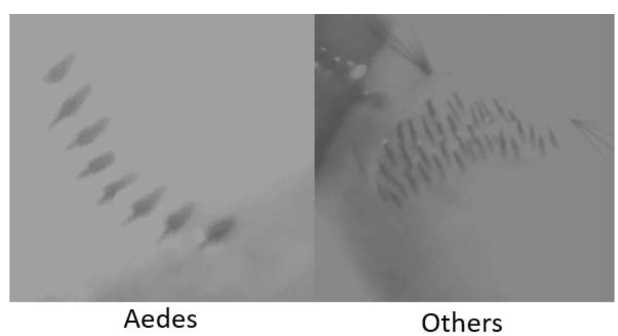


Fig. 11: Typical example images of 2 classes.

## 6. Discussion and comparison

In the previous works of the mosquito larva classification, it has been used 3 different methods out of 2 without using deep learning and with less amount of images, and the last one using the AlexNet CNN. In the Figure 13, the comparison of each classifier performance is shown. The left 6 results show the conventional methods, and the right

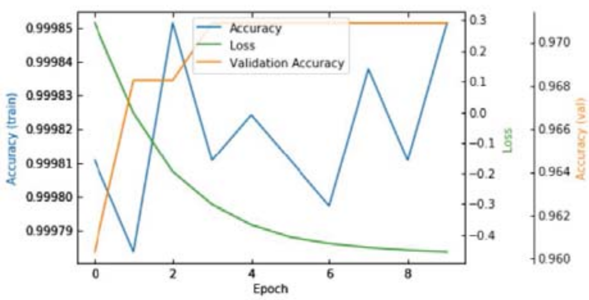


Fig. 12: convergence of accuracy performance in epochs

2 show the ones using CNNs.


Fig. 13: Comparison of classification accuracy performances

## 7. Conclusions

The result show that the network is working better that the previous Works due to the dataset augmentation and pre-training, with the help of the bottleneck features the accuracy increase a lot and it is not necessary for the network to take long time and epoch to achieve a good accuracy.

The proposed system is suitable for fast identification of the Aedes larva in the field work. It makes efficient elimination of Aedes mosquitoes which are considered as an important vector of several diseases. Using the proposed system, the persons who capture larvae of mosquitoes in several regions, can identify the larvae of the Aedes mosquito in this moment and eliminate them before the larvae become into mosquitoes.

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