Analyzing Social Network Images with Deep Learning Models to Fight Zika Virus

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Abstract. Zika and Dengue are viral diseases transmitted by infected mosquitoes (Aedes Aegypti) often found in warm, humid environments. Mining data from social networks helps finding locations with highest density of reported cases. There are approaches that analyze text from networks such as twitter, but here we propose a new strategy using images from Instagram. For this purpose, we use two customized Deep Neural Networks trained on real images. The first detects objects commonly used for mosquito reproduction such as tires and bottles with 85% precision. The latter classifies mosquitoes as Culex (common mosquito) or Aedes Aegypti with 82.53% accuracy. Results indicate that using both networks can improve the current effectiveness of existing social network mining strategies such as the VazaZika project.

Keywords: Deep Neural Networks, Zika, Aedes Aegypti, Social Networks

1 Introduction

Over the years, Zika, Chikungunya and Dengue have become a big problem for health organizations. The main reason is the good adaptation of Aedes Aegypti mosquito to urban environments in countries with warm and humid weather, adequate conditions for reproduction. To make matters worse, Zika may cause microcephaly [13, 14], a condition characterized by babies born with abnormally small heads.

An approach to locate mosquito breeding sites is to mine data from social networks. Based on users posts in platforms such as Twitter, pest control authorities may retrieve information as geo-location, amount of reported cases, etc. For instance, the VazaZika project[1] [17, 12] provides a platform where users can report cases from which a geographical map containing the highest concentration of mosquitoes can be inferred.

To extend the amount of collected information, we process posts from image-based social networks such as Instagram. For this purpose, we use Deep Neural Networks trained for two tasks. One is more general and performs the detection of

[1] http://vazadengue.inf.puc-rio.br/

objects commonly used by mosquitoes for egg deposition, eg., tires, bottles, jars, etc. The second identifies whether a mosquito belongs to the class culex (common mosquito) or Aedes Aegypti (vector of Zika and other viruses). To the extend of our knowledge, no work has been presented where Deep Neural Networks have been used to achieve this goal. We argue that our solution, working in tandem with the VazaZika project, improves the effectiveness of health agencies actions by pinpointing main loci, reducing the number of cases among the population. To the extent of our knowledge, no work with such specific purpose has been presented so far.

Our contribution is twofold. First, we collected and annotated a database comprising images of Culex and Aedes Aegypti mosquitoes and most common mosquito breeding sites such as tires, empty bottles and plant pots. Our second contribution is the training of deep models which performed well when tested on pictures from Instagram. The models are implemented on the VazaZika project platform. All databases and source codes are publicly available for research purposes.

2 Related work

The challenge of identifying and classifying bug and mosquitoes is not new. In [7] it was proposed a prediction model for mosquito habitat using remotely sensed data with aerial photographic identification techniques. The authors used sophisticated airborne and satellite-sensor technology, often unavailable alternatives to poor nations due to high costs.

Wang et al. [18] used feature extraction, SVM and Artificial Neural Networks for classification. They analyzed features such as area, perimeter, etc, from high resolution close-up images. Jahangir et al. [1] studied insect's characteristics for species classification. In both cases, image processing and common morphology features were used.

Mahantesh et al. [3] analyze mosquitoes images and classify them as Dengue, non-Dengue, or other insects. They use a decision tree showing the work to be carried out, where the principal objective is to identify female mosquitoes.

SVM for classification of mosquitoes was used along with morphological features by [5]. Picture segmentation was utilized to separate mosquito and background, while the Sobel filter was applied for edge detection. In this paper, the authors did not consider wings and arms of mosquitoes due to the segmentation process. SVM was also used in [4] to classify species and genus of fruit flies and mosquitoes using only images of their wings. The breadth of the used dataset was remarkably (72 species of fruit flies and 76 species of mosquitoes), so they applied GAD (Greedy Adaptive Discrimination) to find and extract features within the image groups.

Recent advances in neural network researches has allowed many applications. CNN is used in [6] for face verification based on deep representation. The authors were able to reduce computational demands of CNN architectures.

In [10], the authors utilized Artificial Neural Network for automated identification of mosquito. They applied Fourier Transform to wing-beat sound waveform, generating the input signals for the ANN. On the other hand, [9] generate a Wavelet representation of the mosquitoes sound, passing it as input to a CNN classifier. A comparison to well-established classifiers is also provided.

The authors in [16] propose a novel method based on Convolution Neural Networks (CNN) for mosquito larva classification, using Alexnet architecture for the deep model.

Dong et al. [2] Citation

Mehra et al. [11] collected data from from multiples sources, combining RGB and thermal images in order to detect the presence of poodles in them. They used an ensemble of Bayesian classifiers in order to provide the binary output.

3 Methodology

We developed two deep learning models. The first performs *detection of objects* commonly used for Aedes reproduction, like recipients capable of retaining stagnat water for egg deposition such as tires[2], empty bottles and flower pots. The second executes mosquito *classification*, i. e., it tells whether a mosquito is a Culex (most common mosquito) or belongs to class Aedes Aegypti (Zika vector). In the last case only, authorities are alarmed.

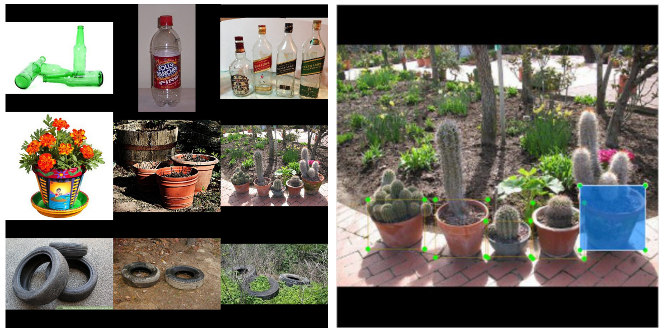
To accomplish the aforementioned objectives, we collected images from different sources with three approaches. First we downloaded files from unbroken URLs available on ImageNet[3] for the following keyword searches; (i) `aedes aegypti`; (ii) `culex`; (iii) `soda bottle`; (iv) `car tire`; (v) `flowerpot`. Secondly, we downloaded files from Google Images. Thirdly, we collected real pictures from Instagram for testing the models and obtaining real performance metrics.

3.1 Aedes Aegypti Egg Laying Objects Database – AedesEgg

For the object detection database, we collected a total of 519 images, of which: 169 containing tires, 167 containing bottles and 183 containing flower pots. Samples from the gathered images are shown in Fig. 1. Object's Bounding Boxes (BBs) were manually annotated and saved to XML files.

Since this model deals with object detection, we used TensorFlow Object Detection API. It includes a set of customizable models, allowing the user to modify a CNN model depending on the desired application [8]. We tested the Faster RCNN Resnet[15] model, using the following augmentation options: (i) `random horizontal flip`; (ii) `random vertical flip`; (iii) `random 90 deg rotation`. The training and evaluation process were executed in a dedicated GPU, using a total number of 10.000 training steps. The split rate for training and evaluation was 9:1.

[2] Particularly convenient for mosquitoes for providing black camouflage.
[3] www.image-net.org



(a) (b)

Fig. 1. Samples of the object detection dataset. (a) Examples of bottles (top), recipient (middle) and tires (bottom). (b) Illustration of the manual annotation procedure.

The accuracy metric was based on Intersection Over Union (IOU) definition. Let A be the detected BB, and B be the ground-truth BB. We denote $IoU(A, B) = \frac{A \cap B}{A \cup B}$. For IoU @ 0.5, it means a "hit" if the ratio is larger than 0.5, meaning a "miss" otherwise. For each detection d related to one specific class c, we calculate the BBs number of true positives $TP(c, d)$ and false positives $FP(c, d)$. The average precision for all classes C in one detection is given by $AP(d) = \frac{1}{\|C\|} \sum\limits_{c\ in\ C} \frac{TP(c,d)}{TP(c,d)+FP(c,d)}$, being the metric used in the object detections evaluation.

3.2 Aedes Aegypti vs Culex Database – AedesCulex

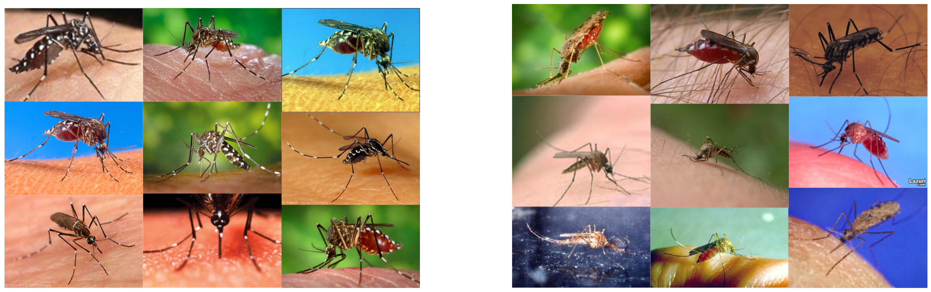
Similarly, we gathered 548 images of mosquitoes, from which 226 are Aedes and 322 are culex, as can be seen in Fig. 2. All images in the Dataset are manually verified by experts from local Zoonoses Control Center (ZCC). In addition, the dataset was enlarged by data augmentation: Rotation in 3 directions (90°, 180° and 270°) and flip for each image. The final dataset is based on 80 original images for validation and were increased to 3804 by data augmentation for the training stage. For this stage, we used TensorFlow, Python and Keras library.

Finally, we collected 60 pictures actually posted on Instagram, as presented in Fig. 4. Some of them were present in the database used for training/validation and were, therefore, excluded on our testing experiments, totaling 120 images for testing.

4 Results

We conducted experiments aiming at answering the following research questions:

– (**RQ1**): How effective is our deep learning model for detecting objects commonly associated with mosquito proliferation?



(a) (b)

Fig. 2. Example images belonging to (a) Aedes class, and (b) Culex category.

- (**RQ2**): How accurate is our mosquito classification model?
- (**RQ3**): What is the performance of the classification model applied to pictures posted on Instagram.

4.1 Object detection effectiveness (RQ1)

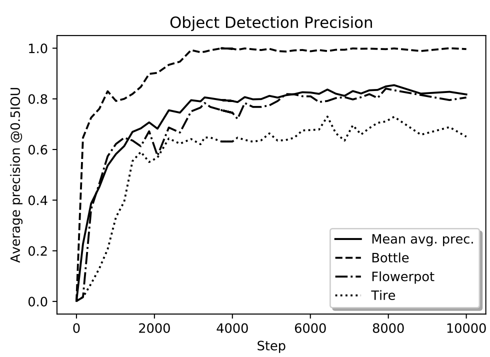


Fig. 3. Average Precision per step at 0.5 Intersection Over Union area.

Training and evaluation were executed in two parallel processes in GPU. The evaluated precision archived by the model is presented at figure 3. On the best checkpoint, we were able to obtain APs of 99%, 84% and 73%, for bottle, flowerpot and tire, respectively, resulting in a mean AP of 85% for the three classes.

Table 1. CNN architecture of the proposed classification model

CNN layer	Kernel	Channels	Dimension	Parameters
Input		1	225 x 225	
conv2d_1	3 x 3	64	225 x 225	640
conv2d_2	3 x 3	64	223 x 223	36,928
max_pooling2d_1	2 x 2		111 x 111	0
conv2d_3	3 x 3	128	111 x 111	73,856
conv2d_4	3 x 3	128	109 x 109	147,584
max_pooling2d_2	2 x 2		54 x 54	0
conv2d_5	3 x 3	256	52 x 52	295,168
conv2d_6	3 x 3	256	50 x 50	590,080
conv2d_7	3 x 3	256	48 x 48	590,080
max_pooling2d_3	2 x 2		24 x 24	0
conv2d_8	3 x 3	256	22 x 22	590,080
conv2d_9	3 x 3	256	20 x 20	590,080
max_pooling2d_4	2 x 2	256	10 x 10	0
flatten_1			25,600	0
dense_1 (dropout)		512	1 x 512	13,107,712
dense_2		1	1	513
Total				16,022,715

4.2 Mosquito classification model (RQ2)

The design model shown in Table 1 was used in this experiments. All images was reduced for 225 x 225 dimension.

Its was transformed for gray-scale because we designed the CNN such that an input the size of typical image produces output of size 1x1 when the output correspond to the image probability be a aedes mosquito.

We normalized the images by subtracting mean and dividing by the standard deviation in our training sets and used the ReLU activation for the convolution layers and apply 40% dropout to layer dense_1. We trained the model with a batch size of 32 and used a k-fold cross validation was employed with k = 6.

With this model, we can see the results of train set and we obtained 82.53% accuracy.

4.3 Classification model tested on Instagram pictures (RQ3)

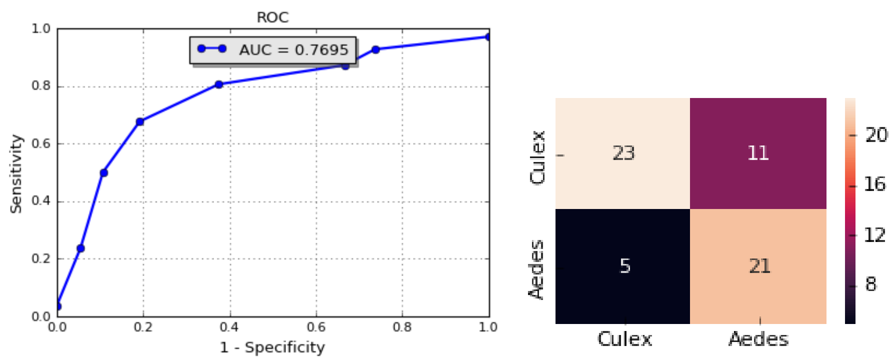
Figure 5 shows the ROC curves and confusion matrix of our approach with the images posted Instagram. With this model, we obtained 73.33% accuracy for the validation images.

5 Discussion

As figure 3 stated, the class "bottle" had the best outcomes, since the training images were well-behaved and with least or no occlusion at all. The "flowerpot"

(a) (b)

Fig. 4. Example images belonging to (a) Aedes class, and (b) Culex category posted on Instagram.



(a) (b)

Fig. 5. Results from applying the mosquito classification model to real images collected from Instagram. (a) Receiver Operating Characteristic curve showing an Area Under Curve of 0.77 . (b) Confusion matrix.

class had the second best detection success, explained by the partial occlusion provided by leaves, flowers and garden objects. On the other hand, ”tires” training images consisted mostly of big stocks of tires, each one in a different position. Besides, they were often hiding one another when only chunks of them were visible.

For the mosquito classification problem, our results show that a large deep convolutional neural network is capable of achieving good results on a highly challenging dataset using purely supervised learning. We can see in the result a decrease of accuracy for the Instagram image dataset (73.33%) in relation with train dataset (82.53%). For the authors, this is due to the Instagram images is very problematic because the Instagram users posted many diferentes images, how can see in Figure 4. The authors believe that adding an unsupervised learning, for example autoencoders, this results will be better significantly.

6 Conclusion

Our work, although using different techniques, can be considered as a complement of Mehra et. al [11]. They concerned about classifying images as either "having a puddle" or "not having a puddle", once stagnant portions of water can lead to mosquito eggs deposition. On the other hand, this paper shows an approach to detect objects that may contain stagnant water, leading to the same danger of mosquito breeding. Also, Mehra et. al [11] used thermal images in combination with RGB ones, which can be difficult in a low expenses solution. Our work aims to use ordinary RGB images collected from crowd-sourced networks, so it can not rely on expensive apparatus.

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