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Aedes Mosquito Larvae Recognition with A Mobile App

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ABSTRACT

In the era of industrial revolution, mobile application becomes the heart of the intelligent system that integrates Artificial Intelligent (AI) system for autonomous and internet-of-things (IoT). Smartphone acts as an IoT and ubiquitous gadget to perform data analytics for fast detection or prediction. Therefore, the use of the technology is to overcome the problem of increasing number of dengue cases in Malaysia, which the Intelligent Mosquito Larvae Detection Mobile Application (iMOLAP) is proposed in this study. The purpose of iMOLAP is to help the community to responsive about the dengue larvae spotted in their area by using their smartphone and also can be used to classify the species of mosquito larvae. The mobile application uses one of the Convolutional Neural Network (CNN) techniques, which is the Inception V3 model. The new mobile application learns and classify the species of mosquito larvae by referring to a pre-set collection of mosquito larvae species image. The image captured is compared with pre-set image collection to measure the accuracy. As the results, the accuracy shows 92.8% after the image is captured using the mobile application. Finally, iMOLAP successfully analyze and able to classify the aedes species of mosquito larvae from the image taken and detect the affected area of location. The impact of iMOLAP performs fast response in mosquito larvae detection and an awareness tool for the community in combating dengue cases in Malaysia

Key words : Convolutional Neural Network, Inception V3Industrial Revolution 4.0, Mosquito Larvae.

1. INTRODUCTION

Mosquitoes are holometabolous insects and experience four larval and a pupal phases before they getting adult. The mosquitoes larvae stay in contact with the surface of the water and have a posterior respiratory siphon, which permit them to hang on the surface of the water and breathe in the atmospheric air [1].

Aedes Mosquito is one of the mosquito species causes dengue disease and fatal to human health. Hence, it is crucial to demolish the reproduction of the aedes mosquito at the early stages. Conversional method to exterminate the aedes mosquito dengue habitat such as fogging operation. However, this method was proved less effective and costly because the fogging place might not be the targeted habitat and it is implemented after an incidents or cases has recognized. In fact, the local community needs to play a key role in preventing the dengue cases precisely at the beginning stage of the mosquito growth.

It would be a great if the aedes mosquito larvae could be eliminated at an early stage by the community. Nevertheless, aedes mosquito larvae are difficult to be detected with the normal eye view, unless it is taken to the laboratory for further investigation. Thus, due to this reason motivates researchers to create a tool that able to detect aedes mosquito larvae.

Currently, there is no tool or platform that can be used by the community to identify the mosquito larvae either it is aedes mosquito or culex, which is important for the community to inform about the aedes larvae reproduction with the local authorities.

Therefore, this study implements the mobile app application since majority of the local community owned smart phones. In actual fact, a mobile app application development uses state-of-the-art image classification algorithm via smartphone to recognize the aedes mosquito larvae.

Additionally, the mobile app application keeps track the location of the captured mosquito larvae and spot in the map. The map is shared among community and authorities using this mobile app application. As a result, the authorities can take action immediately and help the community in preventing dengue cases.

The paper has been divided into four parts. Section 2 begins with the related work that explains about Aedes mosquito and technique used in the application. Section 3 explains the design of an architecture of aedes mosquito mobile app. Section 4 performs the result and discussion. Finally, Section 5 concludes the study.

2. RELATED WORKS

The development a mobile app application for Aedes Mosquito Larvae Detection help the community to recognize and classify the mosquito larvae by using smartphone. This application is the new way of approaching the community to increase the awareness about the mosquito larvae and provide fast response in aedes larvae detection. Thus, it is important to understand the Aedes Mosquito larvae characteristics since less effort on trying to study about it.

2.1 Mosquito

Mosquitoes belong to the huge Culicidae group and abundant family that developsduringmoderatetemperature or at tropical regions of the world. There are 3,523 types of Culicidae are presently recognized worldwide [2]. Mosquitoes are ecologically beneficial to biodiversity, food chains, pollination, and only some species are sources of threat to human and animal health due to their role as vectors of disease pathogen. In recent years, about 20 species are identified to have significantly extended their distribution range. Under the favorable condition, mosquitoes can reproduce from egg to adult in a minimum of one week. Figure 1 shows the general lifecycle of the mosquito [3].

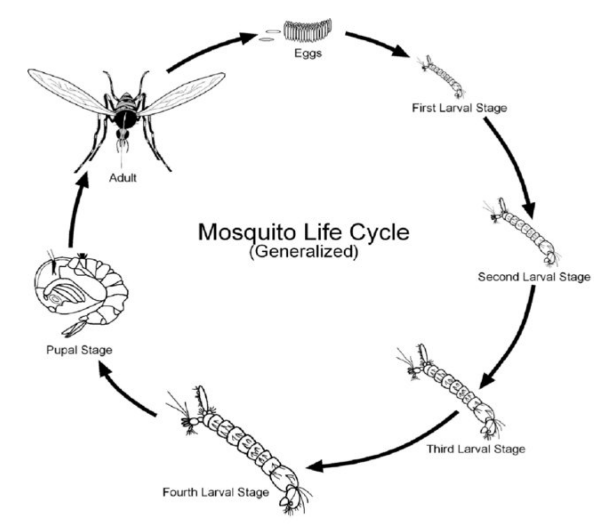


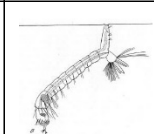
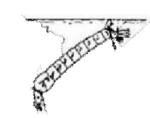
Figure 1 : Life Cycle of Mosquito

2.2 Aedes Mosquito

The dengue virus is carried and spread by mosquitoes in the genus of Aedes. The dengue virus isspread to humans through the bites of infected Aedes mosquitoes, primarily by Aedes Aegypti [4]. The dengue infection is influenced by the age and genetic family of the host, the strain and categorize of the infecting virus and the prior history of dengue infections of the host [5]. This mosquito is widely distributed around the world especially in a hot and humid weather conditions[4].

Aedes mosquitoes usually can lay their eggs larvae inside still water or the inner wall of still container. Aedes mosquitoes is capable to breed in both clean and contaminated water [1][6]. Other species like Culex is also has aquatic environment similarity [6]. The larvae will emerge from the egg only when the water levels rise to cover the egg. Mosquito larvae's characteristic can be differentiated by their behavior and the body segmentation as shown in Table 1 and Figure 2.

Table 1: Anopheles vs Culex vs Aedes [7]

Anopheles	Culex	Aedes
		
Rest parallel to water surface. Has rudimentary breathing tube	Rest at angle to the water surface Long, slender air tube with several pairs of hair tufts	Rest at angle to the water surface Has short, stout breathing tube with one pair ofhair tufts.

Among all the mosquito larvae, anopheles are the easiest to identify as they have no siphon and stay parallel to the water surface while Aedes and Culex are almost similar but Culex has a hairier body and longer body length and lighter color.

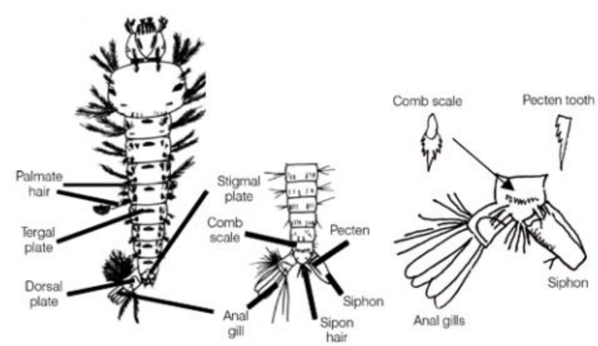


Figure 2 :Aedes aegypti larval morphology

2.3. Convolutional Neural Network (CNN)

Image classification using deep learning has become more and more advanced as of late because of the booming of data in the recent year. Also, the existence of competition to classify images such as ImageNet has attracted many bright minds in Artificial Intelligence to create new algorithm to classify images. Deep learning naturally integrates low/mid/high level features and classifiers in an end-to-end multilayer fashion, and the levels of features can be enriched by the number of stacked layers(depth) [8]

Convolutional Neural Networks (CNNs) is one of deep learning models that is a widely in detecting, recognizing, classifying images[9]. The further most famous CNNs architectures for image detection and classification are AlexNet, GoogLeNet, and ResNet50[10]. CNNs found many classes of models such as generic object recognition, convolutional deep belief network, Handwritten digit recognition and many more related to images[11].

In general, CNNs architecture comprises of three types of layers, which convolutional, pooling, and fully-connected layers. The convolutional layer aims to learn feature representations of the inputs and generate different new feature maps. The pooling layer aims to achieve shift-invariance by reducing the resolution of the feature maps [12]. By stacking several convolutional and pooling layers, it will gradually extract higher-level feature representations [13]. By taking and connecting all neurons from the previous layers in fully connected layers, it will generate global semantic information in the output layer[14]. The general architecture of CNN is described in Figure 3.

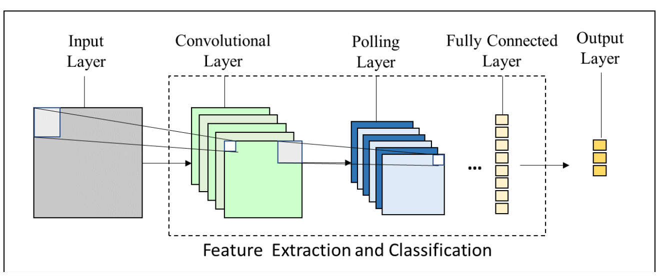


Figure 3 : A General Convolutional Neural Network (CNN)

CNNs avoids the complex preprocessing of the image which the original image inputs the original image directly to the network. It uses local receptive field, weights sharing and pooling technology that creates the training parameters greatly reduced compared to the neural networks [15].

2.4 Inception V3 Model

Inception V3 model is widely implemented CNN architecture as transfer learning method [14]. This transfer learning is used to learn current knowledge from one atmosphere and solve the other new problem, which is different but has some correlation with the existing problem[15]. In Image classification, Inception V3 work well as image classifier compared others neural network architecture as it uses a small amount of data to train the model, and accomplish high accuracy with a short training time[13].

Currently Inception V3 is available in the Python Tensorflow library. It was originally trained to classify 1000 classes using millions of images but it can also be easily retrained for custom image classification problems [18]. This model achieves high classification accuracy for many image classification applications. Resources, including tutorials and a python script, are readily available online in retraining the last layer of Inception v3 making it more readily accessible for experimentation compared to other existing CNN image classifiers [18].

Nonetheless, with the architecture of CNN, a good classifier on the Inception V3 and information stored in firebase database will not be fully functioned if there is no platform to display or view the data. Thus, the platform is developed as a mobile app application since most people have owned the smartphone.

A mobile app application is a great way to implement image classification model because of the current advancement of technology today [19]. It is possible for a user to get benefits of CNN from just the tip of their finger. Smartphone, which has advance in terms of memory, processor and camera make it possible for mobile app application of detecting mosquito larvae using CNN and Inception V3. Hence, the paper presents the development of a mobile application app that able to be used with smartphone to recognize Aedes mosquito larvae and localize the data in the map. Section III addresses the proposed method for the development based on convolution neural work with Inception V3 model.

3. THE PROPOSED METHOD

The application was developed using TensorFlow, Firebase Database and Android Studio. The application used an image taken from the built-in camera in smartphone to classify the species of mosquito larvae. While the application use Python Machine Learning Method to build a model, analyze and make decision based on large data fields, Firebase Database use as system database and Android Studio as Integrated Development Environment (IDE) to develop the application. As illustrated in Figure 4, firstly, spot a mosquito larvae nest, secondly, capture the mosquito larvae nest image by using smartphone camera that already integrated with the Intelligence Mosquito Larvae Detection Apps. The application already loads with Inception V3 model which the pretrained model. Thirdly, from the mobile app application, the image taken before is processed to produce the classification result. Fourthly, from the classification result also with the current location, all the information is stored in database. The information data are in structured data. The information from the database can be retrieve and visualize the data in map.

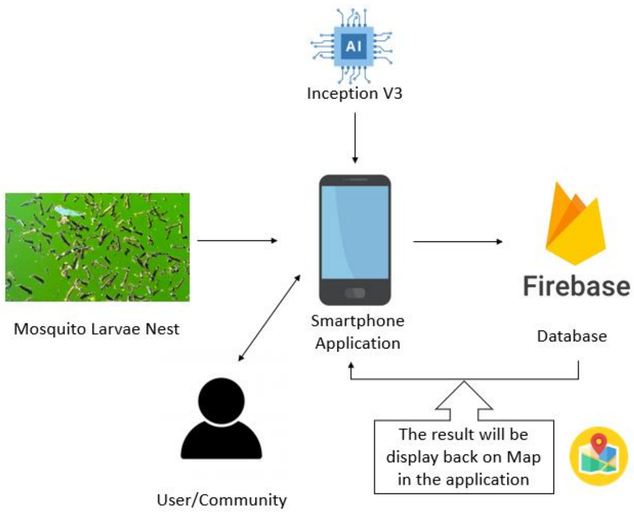


Figure 4: System Architecture

The details explanation of the proposed method is described in following subsection of phase 1 until 4 as illustrated in Figure 5.

Figure 5: Project Phase

3.1 Phase 1 – Data Discover, Preparation and Design

In this phase, all data (images of mosquito larvae and its label) are used to train the model. We design a model to recognize and classify the mosquito larvae according to 3 processes. Firstly, we must collect training images that already labelled larvae stages from available sources. Secondly, the system performs data augmentation and image processing processes on the gathered images with the goal of increasing variation and size of the training data. Thirdly, the processed images are given as input to the Inception V3 model. Inception V3 model approaches require an immense amount of training data. Using this labeled training images, the model learns to recognize and classify the images, changing its internal organization while waiting for it produces acceptable outcomes on a test dataset.

The images data are divided by training and testing datasets. Mosquito larvae images which collected from public health department are used as training dataset. This department provides the sample species of mosquito larvaes. There are 2 types of mosquito larvae species; Aedes mosquito larvae and Culex mosquito larvae. The dataset collection is 110 images for each type of mosquito larvae. The images are labelled to 3 classifieds which Aedes, Culex and other. For testing dataset, this study usesmosquito larvae imageswhich collected by the developed application. The mosquito larvae imagesare labelled by the application to 3 classifieds which Aedes, Culex and other.Table 2 shows the dataset volume has been use for this study.

Table 2: Dataset Volume

Dataset	Aedes	Culex	Other
Training	110	110	200
Testing	40	40	40

3.2 Phase 2 – Development of the Aedes Mosquito Larvae Recognition

To develop an aedes mosquito larvae recognition mobile app application, the most important functionality of the application is able to recognize and classify the mosquito larvae image. By using CNN with Inception V3 model, each features of the larvae image are refined iteratively and to generate high representation features. Inception V3 model learns from the features in images and classifies the correct image of mosquito larvae. This pertained Inception V3 model is embedded into a mobile application app that developed using the Android Studio development environment.

3.3 Phase 3 – Testing Recognition Module

The Train & Test phase is performing functional user acceptance and parallel testing. Functional user acceptance is important to ensure that the developed mosquito larvae detection application can support the user expectation. This functional user acceptance is mainly focus on the effectiveness and efficiency of the developed application. The testing of the module is carried out by experimenting the accuracy of the classification using test data that has been collected. The performance is then observed to see if the technique can recognize acceptably. This process is tested until it achieved the required performance threshold. This phase is important to ensure the whole process are able to perform.

3.4 Phase 4 – Deploy Phases

In the deploy phase, the developed application is encapsulated to the user execution packages for industrial demonstration. At the end of this project, all the findings, processes, result and conclusion are documented. Figure 6 illustrates the flow chart of image classification in mosquito larvae detection system.

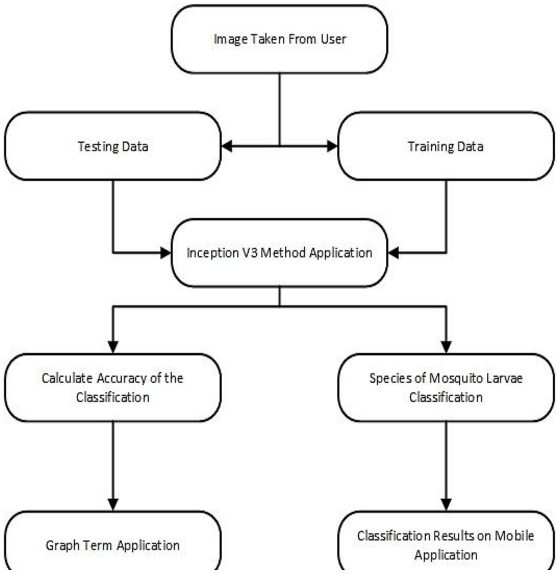


Figure 6 : Flow Chart of Mosquito Larvae Classification

4. RESULTS AND DISCUSSION

The experiment has been conducted to evaluate the performance and discuss on the accuracy of the proposed application. The chosen hardware specification for testing phase was shown in Table 3.

Table 3: Hardware Specification

Hardware	Acer Aspire E15	Asus P01Y
CPU	Intel® Core™ i5 6200U	Intel®
Ram	4 GB	1 GB
Camera	-	5MP

Table 4 provides the experiment results of accuracy based on the type of mosquito. It shows that the percentage error of classification results from the image taken were the result show the classification are above 80%. That result can be reliable to be use. However, there were some issues that need to pay attention when using the mobile app application. The first issue was the distance between the smartphone and the mosquito larvae nest. The image of the mosquito larvae needs to be clear to increasing the accuracy of the classification. The mobile app application could produce poor accuracy if the image taken are too far or not clear. From the image taken can produce the classification on the spot but the performance is depending on the processor, if the processor is high-end then it can produce result much faster than a mid-end processor.

Table 4: Experiment Result

Image Taken	Expected Output	Testing Accuracy	Error	Testing Result
Aedes	Aedes	**Aedes: 86.4%** Culex: 11.8% Other: 1.8%	13.6%	Success
Culex	Culex	**Culex: 91.5%** Aedes: 5.6% Other: 2.9%	8.5%	Success
Pencil	Other	**Other: 89.6%** Aedes: 5.1% Culex: 5.3%	10.4%	Success
Aedes	Aedes	**Aedes: 92.8%** Culex: 4.5% Other: 2.7%	7.2%	Success
Culex	Culex	**Culex: 91.6%** Aedes: 6.9% Other: 1.5%	8.4%	Success

Figure 7: Classification Result in the Application

Figure7 shows the classification result from the image taken. The result shows the top 3 classification description with the percentage for every description. The higher percentage indicate the accuracy of the classification description from the image taken. After getting the result from the classification user can submit the information about the classification by click the save button. The information that will be save are location, username, classification description and percentage of the classification description.

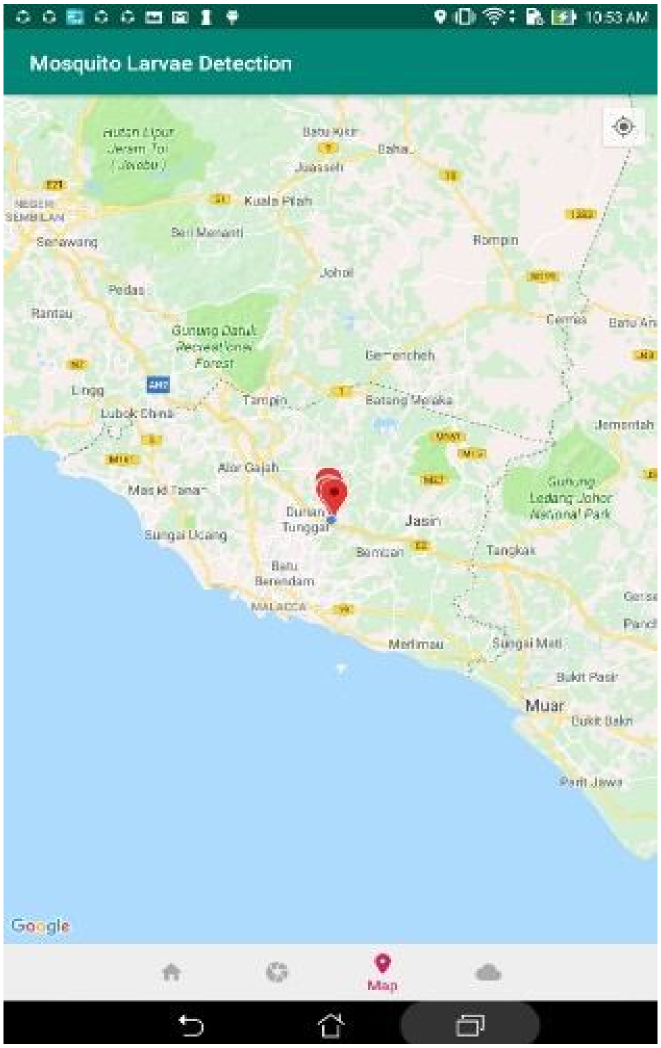


Figure 8: Information from Community in Map Visualization

As shown in Figure 8, the information that has be saved from community is visualized in the application's map. With this mapping users can view and send alert about their surrounding and take action about the information displayed. This feature very useful for user and community to be alert about Aedes breeding spot.

The details of the information also can be views as shown in in Figure 9. With this feature, it shows the latest breeding spot information according to date.

Figure 9: Latest update information on the breeding spot detected

5. CONCLUSION

As a conclusion, this proposed system has proven to be an effective in identify the mosquito larvae species and advanced image classification algorithms are employed to ensure high accuracy. The system learns and classify the species of mosquito larvae and needs by referring system dataset and image taken with neural network technique. Then this application shows the accuracy of the species mosquito larvae image taken and community can visualize the details in map.

However, the accuracy might vary in different due to camera quality, the distance of the image taken, and the environment of the image taken. The advantage of this application all smartphone that executed on android operating system 5.1.2 and above, able to use this application. Therefore, it easy for user to download and use this mobile app application. This application can be informative, which user can check the hotspot location on mosquito larvae breeding spot reported. This application helps as the education app for kid to learn by download this mobile app application and capture an image and use for education purposes.

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