



**AEDES AEGYPTI LARVAE DETECTION SYSTEM BASED ON
CONVOLUTION NEURAL NETWORK VIA TRANSFER LEARNING**

MOHAMAD AQIL BIN MOHD FUAD

MASTER OF SCIENCE IN ELECTRICAL ENGINEERING

2019



Faculty of Electrical Engineering

**AEDES AEGYPTI LARVAE DETECTION SYSTEM BASED ON
CONVOLUTION NEURAL NETWORK VIA TRANSFER LEARNING**

Mohamad Aqil bin Mohd Fuad

Master of Science in Electrical Engineering

2019

**AEDES AEGYPTI LARVAE DETECTION SYSTEM BASED ON CONVOLUTION
NEURAL NETWORK VIA TRANSFER LEARNING**

MOHAMAD AQIL BIN MOHD FUAD

**A thesis submitted
in fulfilment of the requirements for the award of Master of Science
in Electrical Engineering**

Faculty of Electrical Engineering

UNIVERSITI TEKNIKAL MELAKA MALAYSIA

2019

DECLARATION

I declare that this thesis entitled “Aedes Aegypti Larvae Detection System Based on Convolution Neural Network via Transfer Learning” is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in the candidature of any other degree.

Signature :

Name : Mohamad Aqil Bin Mohd Fuad

Date :

APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Master of Science in Electrical Engineering.

Signature :

Supervisor Name : Datuk Prof. Dr. Mohd Ruddin Bin Ab. Ghani

Date :

DEDICATION

Alhamdulillah's

To my beloved family member

ABSTRACT

Aedes aegypti mosquitoes are small slender fly species spreading the arbovirus from flavivirus vector through the feeding of the mammals' blood. The early detection of this species is very important. Once this species turns into adult mosquitoes, the population control becomes more complicated. The situation even worse when difficult access places like a water storage tank became one of the favourite breeding places for the *Aedes aegypti* mosquitoes. Therefore, a technological method is required to assist the operator in the field during the routine inspection of the *Aedes aegypti* larvae, especially at difficult access places as stated in the report of the World Health Organization (WHO). This research proposed a development of the *Aedes aegypti* larvae detection system based on the convolutional neural network via the transfer learning method. In this study, a database is created since there is no *Aedes aegypti* database available online. The database is developed by collecting the *Aedes aegypti* larvae images in in the same environment of water storage tank. 507 images are set for training dataset, 10 images for validation dataset and 30 images for test dataset. Two different convolutional architectures have been trained in this study, which are Faster-Region Convolutional Neural Network (Faster-RCNN) and Single Shot Multibox Detector (SSD) that applying same region proposal techniques and base network of Inception-v2. Besides, the pre-trained model of the Common Object in the Context dataset has been applied in this training, where the hyper-parameter fine-tune configuration has been implemented in this study. The performance of the generated inference graphs is analysed based on three main aspects, which are the performance during training, validation and test. In order to estimate the generalization gap in the training phase, the cross-entropy loss of the training and the validation for both architectures are obtained so that the optimum capacity can be retrieved from the learning. Meanwhile, in the validation phase, the tracking-based metrics and the perimeter intrusion detection metrics are conducted for several specific learning steps in the validation dataset. The precision-recall curve (PR Curve) also has been implemented in the validation phase, where the curve at the right top angle is proposed as the best model in this study. In the test phase, the test dataset is tested with standard detection metrics. From the results obtained in the training, validation and test analyses, it is observed that the best architecture for the detection of the *Aedes aegypti* larvae is the Faster-RCNN. The results also indicated that the accuracy of the test results for the Faster-RCNN is 0.9213, while the SSD is 0.6966. Therefore, it can be concluded that the Faster-RCNN is the best model in the detection of the *Aedes aegypti* larvae. The impact of this study is the proposal of a new method with respect to vision technology, specifically for the *Aedes Aegypti* larvae prevention and outbreak as highlighted by WHO and sustainable development programme by United Nation.

ABSTRAK

Nyamuk *Aedes aegypti* ialah spesies serangga kecil berterbangan yang menyebarkan arbovirus dari vektor flavivirus melalui permakanannya dengan mengambil darah mamalia. Pengesanan awal spesies ini sangat penting. Apabila spesies ini menjadi nyamuk dewasa, kawalan populasi menjadi lebih rumit. Keadaan menjadi semakin buruk ketika tempat sukar dicapai seperti tangki simpanan air menjadi salah satu tempat kegemaran untuk nyamuk *Aedes aegypti* membiak. Oleh itu, satu kaedah teknologi diperlukan untuk membantu pengendali di lapangan semasa pemeriksaan rutin larva *Aedes aegypti*, terutamanya di tempat-tempat yang sukar dicapai seperti yang dinyatakan dalam laporan Pertubuhan Kesihatan Sedunia (PKS). Kajian ini mencadangkan pembangunan sistem pengesanan larva *Aedes aegypti* berdasarkan Rangkaian Neural Konvolusi melalui kaedah pemindahan pembelajaran. Dalam kajian ini, pangkalan data dibuat kerana tiada pangkalan data *Aedes aegypti* dalam talian sedia ada. Pangkalan data dibangunkan dengan mengumpul imej larva *Aedes aegypti* dalam persekitaran tangki simpanan air di mana. 507 imej ditetapkan untuk kumpulan latihan, 10 imej untuk dataset pengesanan dan 30 imej untuk dataset ujian. Dua seni bina konvolusi yang berlainan telah dilatih dalam kajian ini, iaitu Rangkaian Rantau Neural Konvolusi dengan Cepat (Cepat-RRNK) dan Pengesanan Berbilang Kotak dengan Sekali Tembak (PBKST) yang menggunakan teknik cadangan wilayah yang sama dan rangkaian asas Inception-v2. Selain itu, model yang telah dilatih dengan Objek Bersama dalam Konteks (OBK) telah digunakan dalam latihan ini, di mana konfigurasi parameter terbaik telah digunakan dalam kajian ini. Prestasi graf yang dihasilkan dianalisis berdasarkan tiga aspek utama, iaitu prestasi semasa latihan, pengesanan dan ujian. Untuk menganggarkan jurang penggenapan dalam fasa latihan, ralat entropi ketika latihan dan pengesanan untuk kedua-dua seni bina diperoleh supaya kapasiti optimum dapat diperolehi dari pembelajaran. Sementara itu, dalam fasa pengesanan, metrik berasaskan pengesanan dan metrik pengesanan pencerobohan perimeter dijalankan untuk beberapa langkah pembelajaran tertentu dalam dataset pengesanan. Lengkung Ketepatan dan Ingat Semula (Lengkung-KI) juga telah dilaksanakan dalam fasa pengesanan, di mana lengkung di sudut kanan atas dicadangkan sebagai model terbaik dalam kajian ini. Dalam fasa ujian, dataset ujian diuji dengan piawai metrik pengesanan. Dari hasil yang diperolehi dalam latihan, pengesanan dan analisis ujian, diperhatikan bahawa seni bina terbaik untuk mengesan larva *Aedes aegypti* adalah Cepat-RRNK Hasilnya juga menunjukkan bahawa ketepatan keputusan ujian untuk Cepat-RRNK adalah 0.9213, sedangkan PBKST adalah 0.6966. Oleh itu, ianya dapat disimpulkan bahawa Cepat-RRNK adalah model terbaik dalam pengesanan larva *Aedes aegypti*. Impak dalam kajian ini adalah cadangan mengenai satu kaedah baru dengan menggunakan teknologi penglihatan, khususnya untuk pencegahan larva *Aedes Aegypti* dan wabak seperti yang digariskan oleh PKS dan program pembangunan mampan oleh Bangsa-Bangsa Bersatu.

ACKNOWLEDGEMENTS

First and most of all, I would like to take this opportunity to express my thanks to almighty Allah for His greatness, giving me this opportunity, patience and strength to complete this thesis.

Sincere acknowledgement to my supervisor Prof. Datuk Dr. Mohd Ruddin Bin Ab. Ghani for his supervision, support and encouragement towards the completion of this thesis. Not forgotten, my profound gratitude to my co-supervisor, Assoc. Prof. Dr. Rozaimi Bin Ghazali for their advice and suggestions during the establishment of this thesis. All their recommendations and advice have provided me with an insightful view in the development of this study.

Special thanks to Mr. Mohamad Fani Bin Sulaima as the project head for his effort to finance this study through Knowledge Transfer Programme (KTP) Grant No. Gluar/KTP/2/2015/FKE/I/G00039, I would like also to express my appreciation to Institute for Medical Research (IMR) for providing *Aedes Aegypti* larvae, training, knowledge and support throughout this project.

Deepest gratitude goes to my beloved parents Mr. Mohd Fuad Bin Suliman and Mrs. Rosimah Binti Ibrahim and also to my siblings for their endless prayers, loves and encouragements.

Last but not least, special thanks to all members especially REAT Lab member, peers, and UTeM staff for their moral support. Thanks to everyone that were involved directly or indirectly in the development of this project and the writing of this thesis.

TABLE OF CONTENTS

	PAGE
DECLARATION	
APPROVAL	
DEDICATION	
ABSTRACT	i
ABSTRAK	ii
ACKNOWLEDGEMENTS	iii
TABLE OF CONTENTS	iv
LIST OF TABLES	vi
LIST OF FIGURES	vii
LIST OF APPENDICES	x
LIST OF ABBREVIATIONS	xi
LIST OF SYMBOLS	xiii
LIST OF PUBLICATIONS	xiv
CHAPTER	
1. INTRODUCTION	1
1.1 Introduction	1
1.2 Research background	3
1.3 Problem statement	5
1.4 Research objectives	7
1.5 Scope of work	7
1.6 Contributions of the research work	8
1.7 Organization of the thesis	9
2. LITERATURE REVIEW	11
2.1 Introduction	11
2.2 Aedes aegypti life cycle	12
2.2.1 Anatomy of mosquito's larva	13
2.2.2 Aedes aegypti larvae habitat	14
2.3 Existing Aedes aegypti vision-based detection system	18
2.4 State-of-the-art in object detection	21
2.4.1 Existing modern feature extractor	26
2.5 Transfer learning application	32
2.6 Summary	38
3. METHODOLOGY	40
3.1 Introduction	40
3.2 Database development	41
3.2.1 Experimental setup	45
3.3 Transfer learning	47
3.3.1 End-to-end pipeline	49
3.3.2 Base network	50
3.3.3 Localization feature	54
3.3.3.1 Faster-Region Convolution Neural Network	54

3.3.3.2	Single Shot Multibox Detector	57
3.3.4	Regularization technique	58
3.3.5	Optimization technique	62
3.3.6	Post-process	63
3.4	Training and validation	65
3.5	Detection metric for test evaluation	68
3.6	Summary	71
4.	RESULT AND DISCUSSION	72
4.1	Introduction	72
4.2	Learning analyses	73
4.2.1	Faster-Region Convolution Neural Network	73
4.2.2	Single Shot Multibox Detector	78
4.2.3	Learning contradiction and similarities	80
4.3	Validation analyses	84
4.4	Test evaluation	98
4.5	Summary	101
5.	CONCLUSION AND RECOMMENDATIONS	103
5.1	Conclusion	103
5.2	Significant achievement of research objective	104
5.3	Recommendation of future work	105
	REFERENCES	107
	APPENDICES	121

LIST OF TABLES

TABLE	TITLE	PAGE
2.1	Summary of the habitat for the Aedes aegypti larval	17
2.2	Summary of existing Aedes aegypti vision-based detection system	20
2.3	Summary of the state-of-the-art in object detection	25
2.4	Summary of the state-of-the-art in the feature extractor	31
2.5	Summary of the transfer learning applications	36
3.1	The outline of the Inception-v2 architecture	53
3.2	Hyper-parameters for the fine-tune layer in Faster-RCNN	56
3.3	The fine-tuned training configuration of Faster-RCNN	56
3.4	The fine-tuned hyper-parameters of SSD	58
3.5	The fine-tuned training configuration of SSD	58
4.1	Confusion matrix of evaluated test dataset for Faster-RCNN	99
4.2	Confusion matrix of evaluated test dataset for SSD	99
4.3	Detection metrics	100

LIST OF FIGURES

FIGURE	TITLE	PAGE
1.1	Global spread of DENV type reported for every 10 years since the year 1943	2
1.2	The statistical of dengue incident rate and case fatality rate from 2000-2017	5
2.1	<i>Aedes aegypti</i> life cycle	12
2.2	Anatomy of the mosquito's larva	13
2.3	Development of the larva's instar	14
2.4	Inception-v1 module	28
2.5	Inception-v1 of GoogLeNet architecture with simplifies module	30
3.1	Development stage of the <i>Aedes aegypti</i> detection system	40
3.2	Process flow in the development of the <i>Aedes aegypti</i> larvae dataset	42
3.3	Annotation process of defining the objects of interest in an image	43
3.4	The split of the <i>Aedes aegypti</i> database into 3 portions of datasets	44
3.5	(a) <i>Aedes aegypti</i> eggs stored in a dry condition, (b) Beef liver powder, (c) Hatching process of the <i>Aedes aegypti</i>	45
3.6	(a) Water container use in the experiment, (b) The camera with macro lenses used to collect the <i>Aedes aegypti</i> larvae images	47
3.7	Transfer learning in the development of <i>Aedes aegypti</i> detection system	48

3.8	Aedes aegypti larvae detection pipeline	50
3.9	Convolution operation of 5x5 is replaced by 3x3 in the Inception-v2 module	52
3.10	Inception-v2 module of 3x3 that replace by 1x3 followed by 3x1 convolutions operation	52
3.11	Inception-v2 of expended filter banks	53
3.12	The network system of the Faster R-CNN object detection	55
3.13	Architecture of SSD	57
3.14	(a) Standard neural network with 2 hidden layer, (b) Thinned net produce after applying dropout in the network	59
3.15	Basic operation of standard neural network	60
3.16	Basic operation of neural network with dropout technique	61
3.17	(a) Training phase, (b) Test phase	62
3.18	The less confident proposal suppressed by NMS	64
3.19	Generalization gap estimation graph	67
4.1	Cross-entropy loss of first component in Faster-RCNN	75
4.2	Cross-entropy loss of second component in Faster-RCNN	76
4.3	Total cross-entropy loss of Faster-RCNN	77
4.4	Confidence and localization cross entropy loss of multibox in SSD	79
4.5	Total cross-entropy loss of SSD	80
4.6	Total training time of Faster-RCNN and SSD	83
4.7	Average training time of Faster-RCNN and SSD	83
4.8	Average precision of Faster-RCNN in validation learning	85
4.9	Average precision of SSD in validation learning	86
4.10	Image validation for image0 in the Faster-RCNN validation dataset	88

4.11	Image validation for image0 in the SSD validation dataset	89
4.12	Image validation for image7 in the Faster-RCNN validation dataset	91
4.13	Image validation for image7 in the SSD validation dataset	92
4.14	Precision-Recall curve of Faster-RCNN	95
4.15	Precision-Recall curve of SSD	95
4.16	Average precision against threshold plot for Faster-RCNN and SSD	97
4.17	Area under the graph for average precision against correlation threshold	98

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
A	Memorandum of understanding between IMR and UTeM	121
B	Unfiltered losses graph in Faster-RCNN section	122
C	Image evaluation for evaluation dataset	125
D	Tested result in test dataset	137

LIST OF ABBREVIATIONS

ABODA	-	Abandoned objects dataset
AlexNet	-	Alex network
API	-	Application programming interface
AVSS	-	Advanced video and signal based surveillance
CIFAR	-	Canadian institute for advanced research
CNN	-	Convolution neural network
COCO	-	Common objects in context
DarkNet	-	Dark network
DENV	-	Dengue virus
DDSM	-	Digital dataset for screening mammography
DR	-	Detection rate
FAR	-	False alarm rate
FNR	-	False negative rate
FPR	-	False positive rate
GoogLeNet	-	Google network
GPU	-	Graphics processing unit
ILSVRC	-	Image network large scale visual recognition competition
INRIA	-	Institute for research in computer science and automation
IMR	-	Institute for medical research
IoU	-	Intersect over union

mAP	-	Mean average precision
MobilNet	-	Mobil network
NMS	-	Non-maximum suppression
OASIS	-	Open access series of imaging studies
PR	-	Precision recall
RCNN	-	Region convolution neural network
ResNet	-	Residual network
ROC	-	Receiver operating characteristic
RPN	-	Region proposal network
SPPNet	-	Spatial pyramid pooling network
SSD	-	Single shot multibox detector
SVM	-	Support vector machine
TNR	-	True negative rate
VGGNet	-	Visual geometry group network
VOC	-	Visual object classes
WHO	-	World Health Organization
YOLO	-	You only look once
ZFNet	-	Zeiler and Fergus network

LIST OF SYMBOLS

a_o	-	Overlap area
B_{gt}	-	Ground truth bounding box
$b^{(l)}$	-	Bias into layer l
B_p	-	Predicted bounding box
$E(W_t)$	-	Error function at step time
p	-	Momentum parameter
$p(x)$	-	Binary indicator
$q(x)$	-	Predicted probability
$r^{(l)}$	-	Independent Bernoulli random variables
$w^{(l)}$	-	Weight into layer l
$\tilde{y}^{(l)}$	-	thinned output vector from previous layer of l
$y^{(l)}$	-	output vector from previous layer of l
$z^{(l)}$	-	Input vector into layer l
∇_w	-	Gradient operator with weight
ϵ	-	Learning rate

LIST OF PUBLICATIONS

Journals

1. Mohd Fuad, M.A., Ab Ghani, M.R., Ghazali, R., Izzuddin, T.A., Sulaima, M.F., Jano, Z., and Sutikno, T., 2019. Training of Convolutional Neural Network using Transfer Learning for Aedes Aegypti Larvae. *Accepted for publication in BEEI (Bulletin of Electrical Engineering and Informatics)*. Notice of acceptance: 18 Jan 2019 (Indexed by SCOPUS)
2. Mohd Fuad, M.A., Ab Ghani, M.R., Ghazali, R., Izzuddin, T.A., Zohedi, F.N., and Jano, Z., 2018. Combining of Transfer Learning with Faster-RCNN for Aedes Aegypti Larvae Detection. *Accepted for publication in Journal of Advanced Manufacturing Technology, JAMT (ASECS 2018)*. Notice of acceptance: 10 Dec 2018 (Indexed by SCOPUS)
3. Mohd Fuad, M.A., Ab Ghani, M.R., Ghazali, R., Izzuddin, T.A., Sulaima, M.F., Jano, Z., and Sutikno, T., 2017. Training of Convolutional Neural Network using Transfer Learning for Aedes Aegypti Larvae. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, 16(4), pp.1894–1900. (Indexed by SCOPUS)
4. Mohd Fuad, M.A., Ab Ghani, M.R., Ghazali, R., Sulaima, M.F., Jali, M.H., Sutikno, T., Izzuddin, T.A., and Jano, Z., 2017. A Review on Methods of Identifying and Counting Aedes Aegypti Larvae using Image Segmentation Technique. *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, 15(3), pp.1199–1206. (Indexed by SCOPUS)

Conference

1. Mohd Fuad, M.A., Jali, M.H., Ab Ghani, M.R., Ghazali, R., Sulaima, M.F., Aziz, M.A., and Soon, C.C., 2017. Detection of Aedes Aegypti Larvae Frequency Range Using Signal Processing Method. *Accepted for publication in Conference on Biomedical and Advanced Materials 2017 (Bio-CAM2017)*. Notice of Acceptance: 31st October 2017. Langkawi, Kedah, Malaysia. (Indexed by SCOPUS)

CHAPTER 1

INTRODUCTION

1.1 Introduction

Aedes aegypti mosquito is a small slender fly species that survives through the blood of mammals. This species has adapted to the natural habitats as the number of mammals occupied the earth has grown (Powell and Tabachnick, 2013). *Aedes aegypti* mosquito became one of the most dangerous living organisms which has contributed to a huge number of deaths annually. These *Aedes aegypti* mosquitoes are like agent spread the flavivirus vector of arboviruses such as dengue fever, chikungunya fever, yellow fever and Zika fever (Powell and Tabachnick, 2013; Veasna et al., 2017). These viruses have existed about 1,500 years ago. However, the dissemination of the viruses within human occurred only in a few hundred years ago (Wang et al., 2000). For instance, the spread of dengue vector by *Aedes aegypti* mosquito can be fatal the human and animals.

Urbanization, demographic, and environmental are the main factors that contribute to the global distribution of these arboviruses (Messina et al. 2014). Besides, the increment of the international traveller and the military personnel become the key reasons in facilitating the dissemination of these viruses. The most affected countries are the tropical countries that lie on the equator line. The epidemiology has been accentuated to haunt in these tropical countries are 40% of world population. Taxonomically, the causative agent carrying identical viruses that consist of 4 distinct subtypes. Figure 1.1 shows the global spread of these 4 different dengue virus or DENV types reported for every 10 years since the year 1943 (Messina et al. 2014).

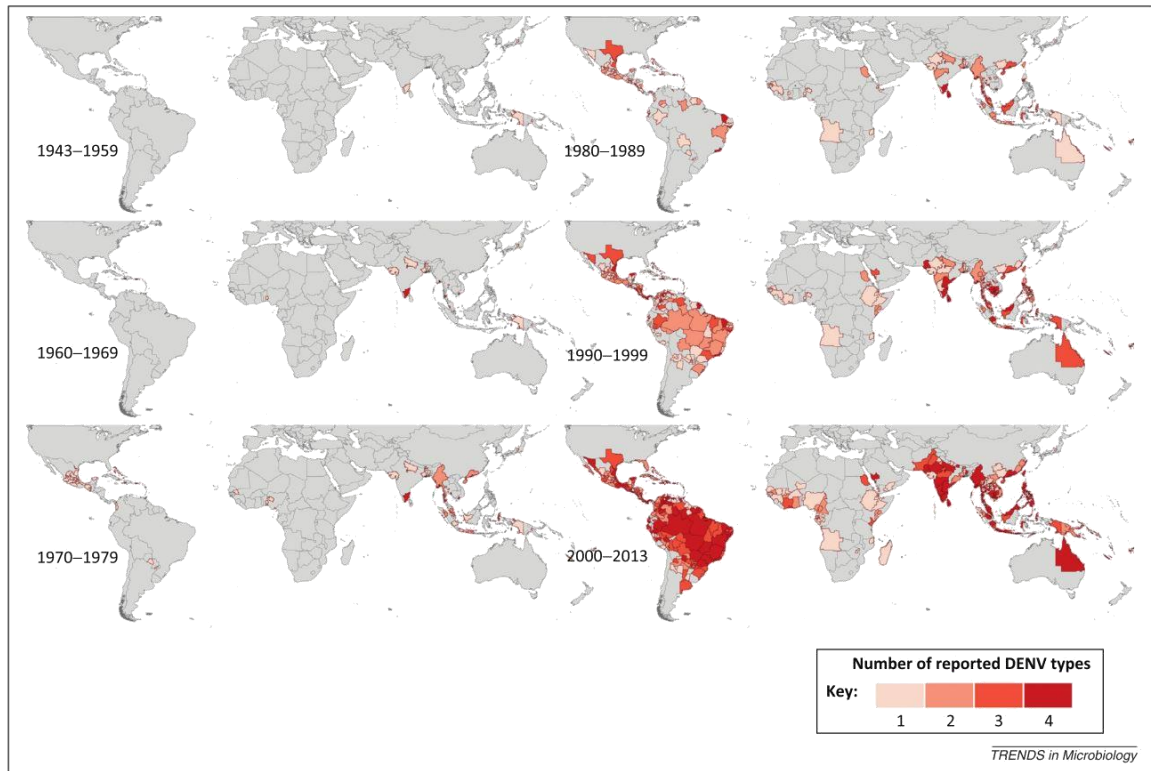


Figure 1.1: Global spread of DENV type reported for every 10 years since the year 1943

In Malaysia, the first dengue diseases was detected in 1901, while the first epidemic outbreak was raised in 1973, where the number of total cases are 969 with 54 deaths (Pang and Loh, 2016). In 2013, it is discovered that the majority of the affected community is between the age of 13 to 35 years old (Sam et al., 2013). It is a predictable trend of arbovirus of flavivirus epidemiology, especially in the spell of the wet weather during the monsoon season. Based on a survey that has been made by Shepard et al. (2013), Malaysia is estimated to be borne with US\$ 102.25 million per year, which is only due to the dengue illness. Presume that the existing of the under-reported cases, the cost would be even higher since Malaysia has a passive surveillance system (Shepard et al., 2013). The contagious of flavivirus episode has caused impacts on most health domains. A country's developments and financial are affected due to the epidemic which simultaneously reducing the quality of

life. Therefore, a significant action is required to eliminating the agent of the *Aedes aegypti* mosquitoes as an effective method to control the distribution of the virus.

1.2 Research background

In the classification of the mosquitoes, there are hundreds of different species that even the scientist does not have a common point of view on how it should be classified. Researchers have even spent so much time in exploring into their genus and species. Every species of mosquito has its own characteristics, behaviour, and the way of survival. In Malaysia, there are three common mosquitoes' species can be mostly found which are *Anopheles*, *Culex* and *Aedes*. The elimination during the larvae early stage is very important because when it turns into adult mosquitoes, the population control becomes more complicated since it can fly.

Anopheles is commonly found in America and known as the malaria carrier agent. However, due to Malaysia located within the equatorial zone with high temperature and humidity, *Anopheles* also can be found in Malaysia (William and Menon, 2014). *Anopheles* adult females lay their eggs in the shallow, clear water of swamps and ponds which are not too acidic and stagnant. The *Anopheles* larvae are tending to rest in parallel on the surface of the water rather than hanging down. It also floats fast from one point to another point (Sum et al., 2014).

Culex species were typically related with the Japanese Encephalitis, West Nile Virus and St. Louis encephalitis carrier agent. Malaysian have mostly infected with Japanese Encephalitis from the *Culex* species as the pathogen transfer through the pig whenever there are swine nearby. They lay eggs connected to each other in group, which is the so-called raft. The eggs usually float in quite drain, in pool as small as bucket or big as lakes, or as stinky