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Mosquito Larvae Detection using Deep Learning

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Dengue cases has become endemic in Malaysia. The cost of operation to exterminate mosquito habitats are also high. To do effective operation, information from community are crucial. But, without knowing the characteristic of Aedes larvae it is hard to recognize the larvae without guide from the expert. The use of deep learning in image classification and recognition is crucial to tackle this problem. The purpose of this project is to conduct a study of characteristics of Aedes larvae and determine the best convolutional neural network model in classifying the mosquito larvae. 3 performance evaluation vector which is accuracy, log-loss and AUC-ROC will be used to measure the model's individual performance. Then performance category which consist of Accuracy Score, Loss Score, File Size Score and Training Time Score will be used to evaluate which model is the best to be implemented into web application or mobile application. From the score collected for each model, ResNet50 has proved to be the best model in classifying the mosquito larvae species.

***Keywords**: Aedes, dengue, convolution neural network, deep learning, performance vector, performance category.*

I. INTRODUCTION

Rrecently several diseases such as Dengue fever, Chikugunya, Malaria and Zika which are transmitted through mosquito as their vectors are causing serious problems in human health. These diseases are mostly transmitted by mosquito genus Aedes, especially species Aedes Aegypti [1]. To combat this problem, various method was implemented by the local government to control the mosquito outbreak but to no avail. One of the reasons is due to lack of effective mosquito control in areas where dengue is endemic [2]. Although there was the method of fogging which is a large-scale extermination of mosquito habitat but the cost to operate this is quite high and inefficient as dengue cases must appear in that area before the operation will be executed.

Deep learning is one of the branches in machine learning where we create a model to train our data and do some analysis, prediction or others that are suitable. The deep learning architecture has allowed a computational model that were composed of multiple processing layers to learn representations of data with multiple levels of abstraction [3]. Deep learning or artificial neural network (ANN) was modelled after human brain neural network where there are at least 3 layers of nodes. The first layer is the input layer where the data enter the neural network. Second layer usually consist of hidden nodes to do the processing of data[4]. The third layer is the output layer where output of the process is produced [5].

In deep learning there are few models that has been created using the deep learning architecture that is Convolutional Neural Network, Recurrent Neural Network and Recursive Neural Network [6], [7], [8]. In the field of image recognition and classification, CNN has created a good performance in the last decade in large scale [11] – [14]. Especially with the sprouting of image recognition competition such as ImageNet Large Scale Visual Recognition Challenge, Low Power Image Recognition Challenge and many more [17], [22]. The advancement of deep visual recognition architecture has been largely played by the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) which act as the testbed for a few generations of large-scale image classification systems [13], [22]. With image recognition model, a computer can easily identify the object using visual from camera or images.

II. RELATED WORK

The project by Sanchez-Ortiz et al [1] proposed using CNN to classify mosquito larvae species into *Aedes* and *Others*. The paper proposed to classify the larvae species by the larvae 8th segment where they can observe a comb-like figure as shown in Figure 1.

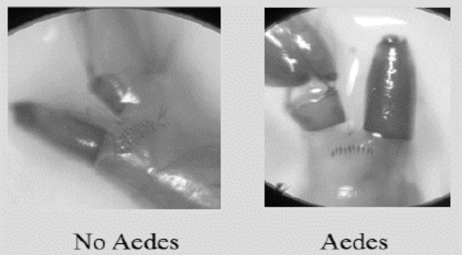

Figure 1: Classes of larva based on 8th segment [14]

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The paper proposed a rather simple methods in their project that is data acquisition, image pre-processing, training the CNN and real-time classification [1]. The result from the classification is the system is capable to recognize the larvae of *Aedes* mosquitos with an accuracy of approximately 96.88% in average while for *Others* is 64.95%.

III. CONVOLUTIONAL NEURAL NETWORK

Deep learning is a subfield of machine learning methods based on artificial neural network. This learning can be supervised, unsupervised or semi-supervised [15]. Convolution Neural Network (CNN) is a class of deep learning which is commonly applied to analysing visual imagery. It was inspired by biological processes where connectivity pattern between neurons are resembling the animal visual cortex [23]. Basically, CNN perceive the images the same as brain process visual that is in 3-dimensional.

CNN are widely used architecture in detecting, recognizing, or classifying images. The most popular CNN for object detection and object category classification from images are AlexNet, GoogLeNet, and ResNet50 [6]. CNN constitute many classes of models such as generic object recognition, convolutional deep belief network, handwritten digit recognition and many more related to images [9], [16], [19]. CNN learns the filters that in traditional image processing algorithm which make it independence from prior knowledge and human effort in feature design.

CNN has many applications in the field of computer learning, which is image and video recognition, recommender system, image classification, medical image analysis and natural language processing [9], [10], [20].

A. VGG16

VGG16 is a CNN model that was proposed by K. Simonyan and A. Zisserman from the University of Oxford. It was one of the famous models that was submitted to ILSVRC-2014 which has achieved 92.7% top-5 accuracy test in ImageNet which has a dataset of over 14 million images that belong to 1000 classes [13].

B. VGG19

VGG19 is a CNN model which was also proposed by K. Simonyan and A. Zisserman from the University of Oxford to compete in ILSVR-2014 along with VGG16. The differences of VGG16 and VGG19 is only on their number of weight layers which is 16 layers for VGG16 and 19 layers for VGG19. VGG19 also has achieved results of Top-5 Error Rate with value of 9.0% [13].

C. InceptionV3

InceptionV1 or GoogLeNet was developed by Google to compete in ILSVRC 2014 and become the winner. It achieved a top-5 error rate of 6.67% which was very close to human level performance. The network used the architecture of LeNet but implemented a novel element which is the inception module. It used batch normalization, image distortions and RMSprop in the architecture.

This architecture allows for increasing the number of units at each stage significantly without an uncontrolled blow-up in computational complexity [21]. The inception architecture is based on finding out how an optimal local sparse structure in a convolutional vision network can be approximated and covered by readily available dense components [21]. InceptionV3 is an upgrade of InceptionV1 architecture where there is an addition of batch normalization of InceptionV2 and additional factorization ideas in third iteration of InceptionV3 [21].

D. ResNet50

ResNet50 is a 50 layers Residual Network where Residual Network is a type of residual learning where its purposes are to solve the difficulty of network training and saturating of network accuracy. It is explicitly letting these layers fit a residual mapping. Formally, we let the stacked nonlinear layers fit another mapping of $F(x) := H(x) - x$ where $H(x)$ is the desired underlying mapping. The original mapping is recast into $F(x)+x$. It is hypothesized that it is easier to optimize the residual mapping than to optimize the original, unreferenced mapping. If an identity mapping were optimal, it would be easier to push the residual to zero than to fit an identity mapping by a stack of nonlinear layers [18].

IV. METHODOLOGY

The methodology used in this project is as follow. First, we acquire the dataset to train the models. Then, we pre-processed the acquired dataset to perform the functionality of data mining and train the model. Then, the classification task will be performed using the 4 selected models; VGG16, VGG19, InceptionV3 and ResNet50. The individual model will be evaluated using performance vector; Accuracy, Log-Loss and AUC-ROC graph and using this performance vector each model will be scored using the Performance Category Score; Accuracy Score, Loss Score, File Size Score, and Training Time Score. This scoring is using tournament rule where we rank the Performance Category of each model.

A. Data Collection

The data collected was from various image collection platform such as Flickr.com and Shutterstock.com while some of the images are captured in Pusat Kesihatan Melaka Tengah using live Aedes larvae sample.

B. Data Pre-Processing

The acquired data will be separated into different folders named ‘test_set’, ‘training_set’ and ‘validation_set’. Each folder set has 2 subfolders called *Aedes* and *Non-Aedes* containing their respective images. All the data will be standardized by converting the size to 244×244×3 for all images with RGB color channel. Data augmentation will be applied to the images before being fed to the model. The augmentation technique is very important to increase the training dataset as each augmented image has 20 random orientations of images.

C. CNN Model Training

During this step, the log-loss, training time and model file size after training will be recorded for score evaluation using Performance Category.

D. Classification using Selected Model

In this step, the trained model will be tested using 'testing_set' and validated using 'validation_set'.

The accuracy of 15 random images of *Aedes* and *Non-Aedes* will be feed into the trained model where their classification accuracy and AUC-ROC graph will be evaluated and recorded.

The model needed to be fine-tuned before training as we currently have only very small dataset with low computational power and the augmentation technique was not enough as to avoid the overfitting problem.

- To fine-tuned VGG16 and VGG19, all the layers except for the last 4 layers will be freeze (untrainable) as the initial layers learned the general features.
- To fine-tuned ResNet50, I freeze all the layers except the fully connected SoftMax layers in the last layers.
- For fine-tuning InceptionV3, all convolutional InceptionV3 layer will be trained except for top layers.

E. Model Performance Evaluation Vector Scoring

The performance evaluation vector was used to measure the performance of each individual models in terms of classifying the mosquito larvae. Three elements that was used are accuracy, log loss and the value of AUC-ROC where all these results derived from the graph. Description is shown in Table 1.

Table 1:Performance Evaluation Vector

Performance Evaluation Vector	Description
Accuracy	Epochs in which prediction accuracy and validation accuracy differences is ±0.01.
Log Loss	Epochs in which prediction loss and validation loss differences is ±0.01
AUC-ROC	Value of AUC-ROC of tested model

F. Tournament Selection using Performance Category

Using the recorded result of Performance Vector of each model, the models Performance Category (Accuracy Score, Loss Score, File Size Score and Training Time Score) will be ranked between 1 (the best) and 4 (the worst) for each model. Table 2 shows the description for Performance Category. The scoring for each model based on the Performance Category will be added as shown in (1) and the best model has the lowest ∑Score among them.

$$\sum \text{Score}=\text{score}(a)+\text{score}(l)+\text{score}(f)+\text{score}(t) \qquad (1)$$

Where, a = Accuracy
l = loss
f = file size
t = training time

Table 2:Performance Category

Performance Category	Description
Accuracy, *a*	Average classification accuracy of 10 images testing, $TP+TNTP+TN+FP+FN$
Loss, l	Average Loss
File Size, f	Size of trained model in Megabyte
Training Time, t	Time taken to train the model in hour and minute

V. RESULTS AND DISCUSSION

The result will be divided into few parts. The first one is the individual model comparison which compare the model's individual accuracy, loss, and AUC-ROC. Next will be the result for 20 images testing (10 images of *Aedes* class and 10 images of *Non-Aedes* class). The last part is the scoring result to evaluate which model is the best to be implemented into web or mobile application.

A. Individual Model Comparison

Each model will be evaluated according to accuracy graph, log loss graph, the value of AUC-ROC and loss during training. The training dataset was imported into the system and the training result will be analysed. Their individual performance will be evaluated using the performance evaluation vector.

From the results in Table 5, in terms of log-loss during training VGG16 yield the best results compared to other models where the loss is 0.3128 which is lower than other models. ResNet50 has the highest value of AUC-ROC compared to VGG16, VGG19, and InceptionV3. The high value of AUC-ROC indicates its capability to perform better for classification task. In terms of high accuracy achieved per epoch, ResNet50 performs the best as it achieved high training and validation accuracy in less than 40 epochs.

B. 20 Images Testing Results

Table 3 record the confidence of classification in classifying 10 images of *Aedes* larva while Table 4 record the confidence of classifying 10 images of *Non-Aedes* class. According to the result in Table 4, VGG19 has the highest average accuracy with 87.26% for classifying Aedes larvae followed by VGG16 at 81.29% accuracy. As shown in the Table 5 ResNet50 has the highest accuracy in classifying non-Aedes class with 86.38% classification confidence followed by VGG16.

C. Performance Tournament Results

In Table 6, the value to be used in the performance criteria are taken from Table 3 until Table 5. To get *a* value, we use (2) to get the value for each model. Then we will rank their performance category from 1 until 4, from best to worst.

$$Accuracy, a = \frac{avg\ Aedes(p) + avg\ Non - Aedes(p)}{200} \times 100 \qquad (2)$$

Where, avg Aedes(p) = Avg. accuracy Aedes class
avg Non-Aedes(p) = Avg. accuracy Non-Aedes class

From Table 7, we can see the respective ranking of each models according to the performance category. From Table 8 we can conclude that ResNet50 is the best model to be employed into mobile application or web application.

The accuracy for this model is quite high with little loses. In terms of deployment into application its file size is still quite small compare to VGG models with training time that's only second to InceptionV3.

Table 3 : 10 Aedes Images Test Result (%)

Aedes Img	VGG16		VGG19		ResNet50		InceptionV3	
	Aedes	Non-Aedes	Aedes	Non-Aedes	Aedes	Non-Aedes	Aedes	Non-Aedes
Img 1	22.45	77.55	79.90	20.10	25.86	74.14	22.20	77.80
Img 2	99.99	0.01	100.00	0.00	100.00	0.00	95.04	4.96
Img 3	90.47	9.53	93.60	6.40	76.81	23.19	48.19	51.81
Img 4	0.38	99.62	0.99	99.01	1.68	98.32	21.72	78.28
Img 5	99.99	0.01	98.12	1.88	100.00	0.00	24.68	75.32
Img 6	99.99	0.01	99.99	0.01	100.00	0.00	99.74	0.26
Img 7	99.70	0.30	99.99	0.01	100.00	0.00	99.82	0.18
Img 8	99.99	0.01	99.99	0.01	100.00	0.00	99.99	0.01
Img 9	99.99	0.01	99.99	0.01	100.00	0.00	99.98	0.02
Img 10	99.99	0.01	99.99	0.01	100.00	0.00	99.90	0.10
Avg Accuracy	81.29	18.71	87.26	12.74	80.44	19.56	71.13	28.87

Table 4 : 10 Non-Aedes Images Test Result (%)

Non-Aedes Img	VGG16		VGG19		ResNet50		InceptionV3	
	Aedes	Non-Aedes	Aedes	Non-Aedes	Aedes	Non-Aedes	Aedes	Non-Aedes
Img 1	5.19	94.81	12.34	87.66	0.46	99.54	5.12	94.88
Img 2	99.51	0.49	99.23	0.76	99.99	0.01	97.47	2.53
Img 3	96.77	3.23	51.96	48.04	99.93	0.07	99.52	0.48
Img 4	99.70	0.30	99.66	0.34	99.99	0.01	85.61	14.39
Img 5	61.49	38.51	68.85	31.15	63.46	36.54	49.58	50.42
Img 6	99.99	0.01	99.96	0.04	100.00	0.00	99.96	0.04
Img 7	99.59	0.41	99.97	0.03	100.00	0.00	99.83	0.17
Img 8	92.61	7.39	99.98	0.02	100.00	0.00	99.98	0.02
Img 9	99.94	0.06	97.61	2.39	100.00	0.00	98.19	1.81
Img 10	99.99	0.01	99.98	0.02	99.99	0.01	99.69	0.31
Avg Accuracy	85.48	14.52	82.95	17.05	86.38	13.62	83.50	16.50

Table 5 : Individual Model Comparison

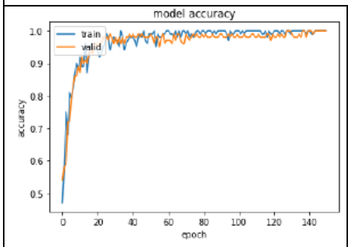
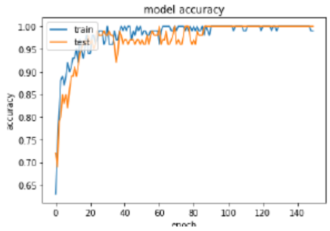
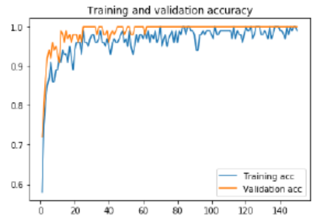
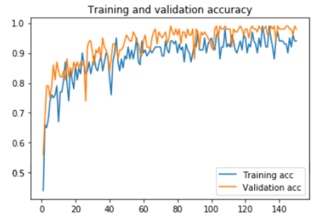
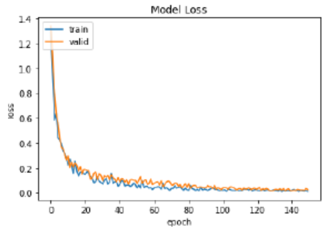
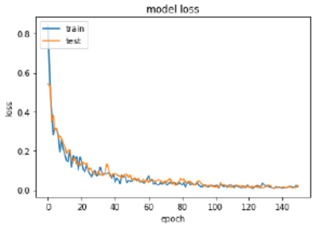
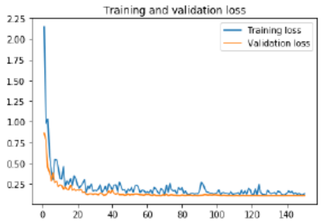
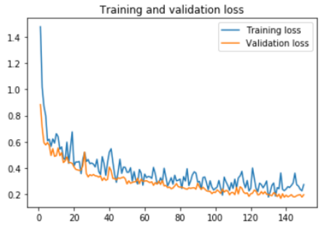
Model			
VGG16	VGG19	ResNet50	InceptionV3
Model Size (After Train)			
513 MB	533 MB	115 MB	122 MB
Training Time (150 epochs)			
5 hour 33 minutes	6 hours 55 minutes	3 hours	2 hours
Accuracy Graph			
 Converge = Epochs 137 (Accuracy Difference ±0.01	 Converge = Epochs 88 (Accuracy Difference ±0.01)	 Converge = Epochs 25 (Accuracy Difference ±0.01)	 Converge = Epochs 123 (Accuracy Difference ±0.01)
Log-Loss Graph			
 Converge = Epochs 123 (Loss Difference ±0.01)	 Converge = Epochs 130 (Loss Difference ±0.01)	 Converge = Epochs 44 (Loss Difference ±0.01)	 Converge = Epochs 123 (Loss Difference ±0.01)
AUC-ROC Value for 15 Images Testing (Batch Testing)			
0.8036	0.8611	0.9333	0.6667
Loss			
0.3128	0.5219	0.4327	0.6623

Table 6 : Performance Category Comparison

Model	Accuracy, a	Loss, l	File Size, f	Training Time, t
VGG16	83.3850	0.3128	513 MB	5 hours 33 minutes
VGG19	85.1050	0.5219	533 MB	6 hours 55 minutes
ResNet50	83.4100	0.4327	115 MB	3 hours
InceptionV3	77.3150	0.6623	122 MB	2 hours

Table 7 : Score of Performance Category

Model	Accuracy, a	Loss, l	File Size, f	Training Time, t
VGG16	3	1	3	3
VGG19	1	3	4	4
ResNet50	2	2	1	2
InceptionV3	4	4	2	1

Table 8 : Performance Category Scoring

Performance Criteria	VGG16	VGG19	ResNet50	InceptionV3
Accuracy, a	3	1	2	4
Loss, l	1	3	2	4
File Size, f	3	4	1	2
Training Time, t	3	4	2	1
Total Score, ∑Score	10	12	7	11

VI. CONCLUSION

This study empirically evaluates the performance of four CNN models (VGG16, VGG19, ResNet50, and InceptionV3) in classifying mosquito larvae images based on their class (*Aedes* and *Non-Aedes*). From the results we can conclude that ResNet50 is the best model to be implemented into web app or mobile app. For future improvement we hope that we can improve the accuracy of each models by increasing the dataset and adding algorithm to increase the performance of models.

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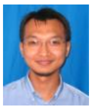

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