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Dengue mosquito larvae identification using digital images

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***Abstract*: Dengue is one of the highest spreading mosquito-borne diseases in tropical and subtropical regions all over the world. This disease is mainly spread by the mosquito vector called 'Aedes'. In Sri Lanka, the number of infected patients reported is increasing, and it has become a public health problem. Health Inspectors are using different methods to reduce the spread of this viral disease and one of the main methods used is the fumigation by identifying the Aedes Larvae breeding locations. Currently, this identification is done manually by the specialized health inspectors and it is totally observer-biased and consumes a considerable amount of time, which could lead to false decision making and inefficient identification. The purpose of this research is to build an automated computational model to identify Aedes Larvae in real-time with more accuracy and convenience. Even though there are good results in previous researches done in Convolutional Neural Networks (CNN) on Aedes Larvae identification, the method of capturing Larvae Images is a bit complicated since they have used a Microscope lens of amplification capacity 60-100 times to get the magnified images. In this research, we propose the method of identifying Aedes mosquito larvae with a digital amplification of 8-12 times without using any microscope lenses attached, using ResNet50 CNN. The proposed model will identity the mosquito larvae by their genus 'Aedes' or 'non- Aedes' using a digital photo taken by a smartphone or camera in the upside of the larvae body. Hence it would help Health Inspectors, even the general public on identifying Aedes Larvae more efficiently, accurately and conveniently than the traditional method. This study shows that the trained model can identify images of Aedes and Non-Aedes Larvae separately with an accuracy of 86.65%. Furthermore, with using pre-processing techniques, the accuracy level can be enhanced to 98.76% for magnified images.**

Keywords: *Aedes larvae, Convolutional Neural Networks (CNN), Dengue, Larvae classification, Mosquito*

I. INTRODUCTION

Dengue is one of the most dangerous and rapidly spreading mosquito-borne viral diseases in the world. Sri Lanka is one of the countries that has a higher risk of this viral disease being spread. For the year 2018, 51659 and for the year 2019, 92930 suspected dengue cases were reported (Fig. 1) to the Epidemiology Unit from all over the island [1].

Dengue (DENV) is spread from a bite of the female mosquitoes (Aedes aegypti and Aedes albopictus). The Aedes mosquito becomes infected when it bites a person who is infected with the dengue virus. Aedes aegypti has evolved into an intermittent biter and prefers to bite more than multiple persons during his feeding period.

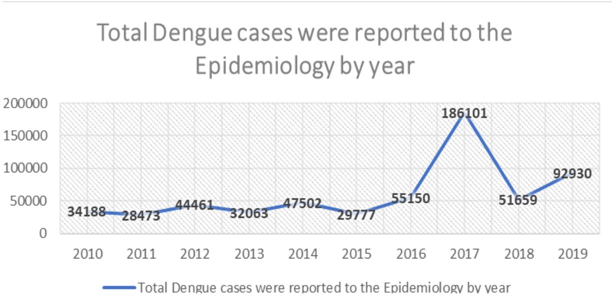

Fig. 1. Total Dengue cases reported in Sri Lanka from 2010 to 2019

This mechanism has made Aedes aegypti a very highly efficient epidemic vector mosquito. Once the mosquito is infected, it remains infected for its life span. So, it is difficult to control breeding after the mosquito starts flying. [2].

Aedes aegypti is known as a holometabolous insect. This means that the insects go through a complete metamorphosis with an egg, larvae, pupae, and adult stage. The adult life span can range from two weeks to a month depending on environmental conditions. Larval development is temperature-dependent. It can remain in the larval stage from 3 days to months, so long as the water supply is enough. [3]. So, the best stage to identify the mosquito before spreading is the larval stage since it lives as a larva for more than 4 days to months as discussed. There is a possibility to identify the larvae as Dengue-borne (Aedes) Larvae by observing the morphological key features such as the body parts, hairy or non-hairy, color etc. The easiest larvae to identify by its genus is Anopheles (Fig. 2) since it has no siphon tube in its tail. The Culex Larvae and Aedes Larvae are a bit similar from their siphon but if we observe closely, we can identify that the Aedes Larva has got a 'barrel sized' short siphon, where Culex Larva has got much longer thin siphon and has a lighter color compared with Aedes[4].

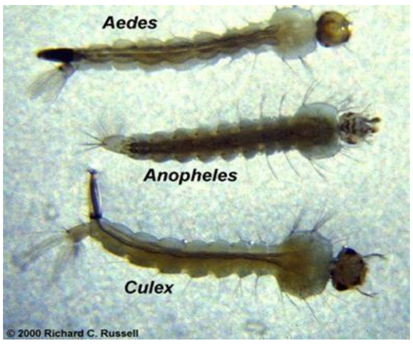

Fig. 2. Different mosquitos at larvae stage

Nowadays technology plays a vital role in almost every field but till today traditional methodologies are being used for identifying mosquitoes in both adult and larval stages in Sri Lanka.

PHI's (Public Health Inspectors) investigate Aedes Larvae breeding places, and they have the authority to fine the victims who welcome mosquitoes to breed. Those inspectors check the larvae from the naked eye and make the decision as to whether it is an Aedes Larva or not. This is totally observer biased. At some points, they take samples to their lab testing for further clarification, where they will enlarge the larvae using a microscope and identify the Genus. This is time-consuming and can be observer biased since observer inspects the siphon size of the larvae which is barrel size or longer. These inspections can make false identifications since the observer checks so many samples for a day. People get fined for the decisions taken by the observer which is totally biased for him/herself. Considering the zoological perspective, many researches try to study dengue mosquito spread by analyzing patterns and breeding places. For that purpose, they have to go to the field and collect larvae samples with the GPS location tagged. All the samples have to be tested back in a laboratory using a microscope with the guidance of an expert. This is also time-consuming and may damage the samples during transport. To eliminate these issues Information Technology can come forward to automate the identification of the larvae, in order to make it more effective and efficient. So, the main purpose of this research is to develop a model using image classification techniques such as deep learning, image processing, which will be able to identify mosquito larvae accurately and make the decisions effectively and easily. The major objective of this study is to design a model to identify Aedes Mosquito at the larval stage using image classification techniques with a smartphone camera. (using digital magnification).

II. PREVIOUS WORK

There are few researches done for identifying mosquitoes at the larval stage using Information Technology. The first study presented in [5] used texture descriptors, such as Local Binary Pattern (LBP), 2D Gabor filters and Co-Occurrence matrix, to extract characteristics and classify them using a Support Vector Machine (SVM) and K-means method using low-level features, such as Co-occurrence Matrix (CM), Local Binary Pattern (LBP), and Gabor filtered features (FG2). The results showed that SVM achieves higher accuracy, but with the research published by [6], they have shown that using AlexNet CNN they could archive better performance than SVM. In [7] they have used VGG16 CNN and with the data augmentation, they were able to archive higher performance. With the proposed system it will be able to identify the Aedes larva quickly in the fieldwork using an equipment(microscope) attached to the camera. In the study [8] they have compared different CNN architectures such as VGG16, VGG19, ResNet50, and InceptionV3) in classifying mosquito larvae images based on their classes (Aedes and Non- Aedes) as the previous studies. This study has collected enhanced images using a microscope and using image collection platforms. From the results, they have come up with the conclusion that ResNet50 is the best model to identify mosquito larvae and implement it to mobile devices or the web. The major drawback that can be seen compared with the proposed system is all those systems use a magnifier (Fig. 3) to get an enlarged system of the larvae. So, the magnifier is a must, if a person needs to get benefited through their system.

III. METHODOLOGY

Fig. 3. Previous work is done using a microscope

The methodology of this research is to implement a suitable classification model to identify mosquito larvae using digital images taken from smartphones or digital cameras without any lenses attached. This model should be accurate and efficient. Since early identification of mosquito larvae was done using 60x-100x (Fig. 3), enlarged images were taken with the help of microscope lenses. Those microscope lenses would be costly and difficult to find in the Sri Lankan market for everyone.

Therefore, this study is to identify whether it is possible to classify mosquito larvae only using digitally zoomed images. For that, a thorough comparison is done between images collected with 60x-100x enlarged images using an equipment attached to the camera, and digitally zoomed images taken without any equipment attached under the same condition.

As shown in Fig. 4 these images will be sent through pre-processing steps to find out the best suited pre-processing technique that can be used to increase the accuracy of Aedes mosquito larvae identification. The main steps of the methodology are as shown in Fig. 5.

According to the previous research findings mentioned, this study has used the ResNet50 Model of CNN for the classification of mosquito larvae since it has performed as the best in previous studies.

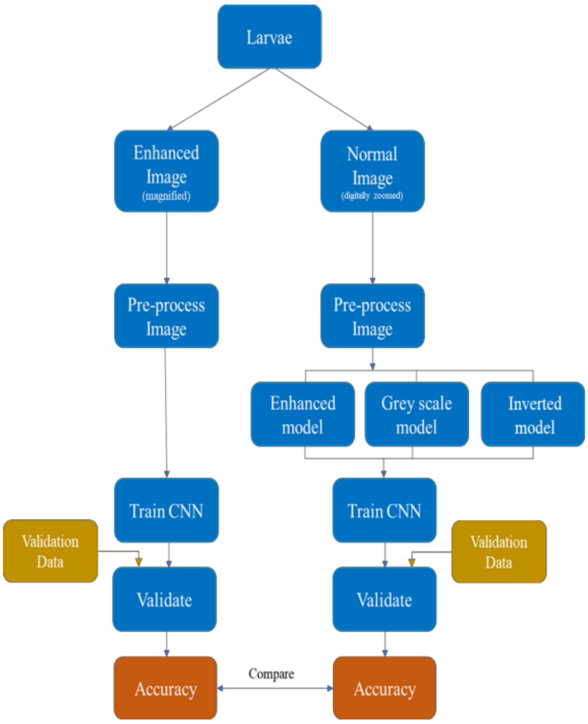

Fig. 4. Overall Methodology Process

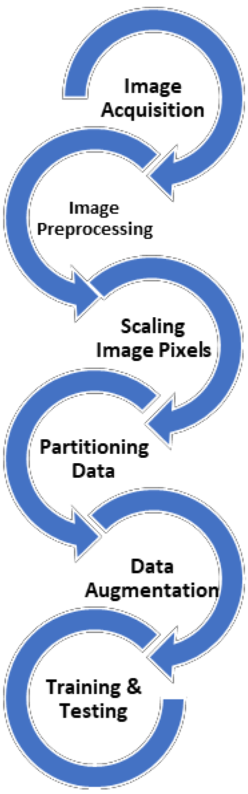

Fig. 5. Methodology Process

A. Image Acquisition

Fig. 6. Types of Images Collected

In this phase, sample larvae images were collected, which are required to train and build the classification model. There are 19 genera of mosquitos available in Sri Lanka and Aedes is a one popular genus available in Sri Lanka [9]. Out of those, the most available 3 genera were selected and categorized into Aedes and Non-Aedes. Each of the mosquito samples was selected from different regions in Sri Lanka where mosquito diseases are most populated like Gampaha, Colombo, Kalutara, since high dengue cases are reported in these districts in 2019 according to the statistical data. [1] Since the target is to identify Aedes mosquito larvae out of other larvae, these images are labelled as Aedes and Non-Aedes with the expert guidance [8]. Larvae from all 4 stages are captured in a white background. These images are taken using 12 mega-pixels mobile phone digital camera with 8x digitally zoomed and with x60 magnifier attached. We collected 90 images of Aedes and 70 of Non-Aedes images without using any microscope and 130 of Aedes and 108 of Non- Aedes Images using x60 microscope for both training and testing the classification model. 10 random images from every 4 types were chosen to validate the model (See Fig. 6). Images were taken from different angles, under different environmental and lighting conditions. The reason is, if this will be developed for a mobile application, the possibility of uploading larvae images using mobile phone will be very high. Then the mobile application should identify the larvae vector accurately. The images were saved in standard JPG format. Images shown in Fig. 6 are the categories of mosquito larvae that were collected under the data acquisition. Since the target task is a binary classification i.e. to find whether it was an Aedes Larvae or Non-Aedes Larvae, the collected data were categorized into two classes which are 'Aedes' and 'Non-Aedes'

B. Image Pre-processing

After collecting the images, image processing was done to improve the image quality. Then the images were resized into 224x224 pixels because the processing takes more time when the image size is too large.

As the next step to reduce the background of the images we implemented two automatic cropping algorithms which are 'crop to fit' and 'crop to square' methods. Crop to fit method will identify the larvae body max-contour area and crop the image into it where 'crop to square' will identify the max-contour axis and crop to it by creating a square (Fig.7).

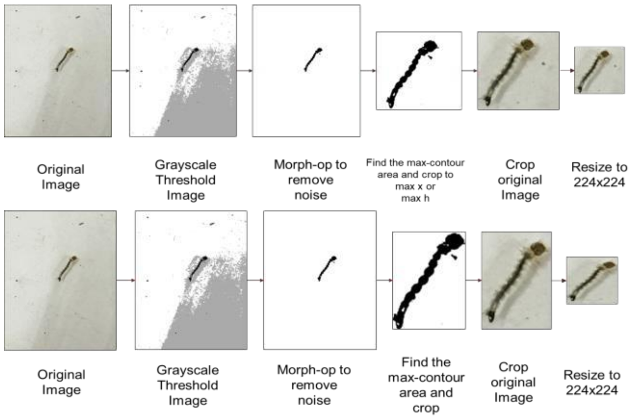

Fig. 7. Cropping Methods

CNN uses convolution layers to extract the patterns of the images in source image pixels. Therefore, enhancing image features may increase the CNN learning [10]. First, the original image is enhanced with added contrast and brightness to improve the larvae of the image from the background. Then the image is cropped for the target to avoid distraction from the background for the training. The same dataset with 3 channels (RGB) is converted to 2 channel grayscale data set and those grayscale images are bit-wise inverted as a further step. Those 3 types of pre-processed data are used to validate the accuracy and efficiency of the proposed approach because one of the research objectives is to find the most suitable pre-processing technique for identifying mosquito larvae.

I. Grey-scale model

Greyscale color pattern is a set of grey shades without apparent color. Black is the darkest shade available, and white is the lightest shade possible. This range of the models is measured from 0-1. Black is represented with 0, and white with 1.

II. Inverted Grey-scale model

Inverted Grey-scale color model is an inverted range of shades of grey without apparent color. The darkest possible shade is white, and the lightest possible shade is black. This model range is represented from 0 - 1. Black is represented by 1 and white is represented by 0.

III. Enhanced model

An Image can be enhanced by Histogram Equalization method. Histogram Equalization is a computer image processing method used to improve image contrast. This is achieved by distributing the most regularly distributed intensity values widely, i.e. stretching out the intensity range of the image. This can usually increase the global contrast of images when its usable data is represented by close contrast values. This allows for areas of lower local contrast to gain a higher contrast. which means the gap between rich intensities and poor intensities increases with this model.

C. Scaling image pixels

Data is inserted into CNN as a matrix of numeric values. Therefore, image pixel intensities are converted into numeric values in the range of 0-1. As the first step of scaling image pixels, all the pixel intensities are converted into numeric values. Then those numeric values are divided by 255 to range the intensities to 0-1.

D. Partitioning data

In this study, data is divided into training, testing and validation datasets. 10 random images from each class will be taken into the validation dataset where those will be used for validating the model trained. The remaining data will be split into training and testing datasets with 80%, 20% of percentages (Fig. 8) [11].

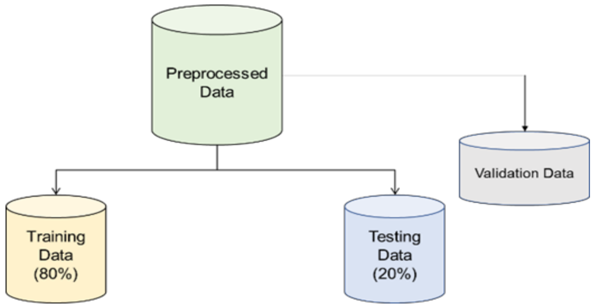

Fig. 8. Data Split Procedure

E. Data augmentation

Data augmentation is a technique to artificially produce new data for training using available data. Image data augmentation is done by applying domain-specific methods and techniques to the example from the training data that creates new and different training examples. This is one of the most well-known mechanisms in augmentation of data and involves creating transformed versions of images in the training dataset, that belong to the same class as the original image.

Transforms are done with a pool of operations from the field of image manipulation, such as width-shift, height-shift, flips, zooms, rotate and many more.

The intention is to expand the training dataset with new augmented images which means, variations of the training set will be high that is likely to be seen by the model. For example, a vertical flip of a picture of a larva may make sense, because the image could have been taken when the larvae was in its upside-down position (See Fig.9).

As per the study [12], they have shown that using a different variety of algorithms for data augmentation can bring huge potential to improve training data-hungry deep learning algorithms such as CNN.

Fig. 9. Data Augmentation

F. Training and Testing

Training testing dataset size and the method of training classification have to be determined. There are many different approaches for supervised learning, such as SVM, ANN and CNN. Out of them, literature has shown that the CNN method performs best when it comes to image classification. Therefore, CNN is used as the classification method in this study. Basically, CNN trains its network by feeding its nodes with images' intensities and identifying their highly specific features. In the training phase, we used the CNN with the architecture called ResNet50. It was decided to use this architecture because of the network configurations and because this model has scored best in terms of performance, lower size, training time and accuracy [8]. Furthermore, ResNet50 has been ranked as the best model to be employed into a mobile application or a web application. As mentioned earlier, out of 160 images 128 were added to the training, and for the zoomed image collection out of 238 images, 190 images were added. After the training and testing using CNN, each model's accuracy is calculated according to the following formula, with the validation dataset.

$$Accuracy\ (\%) = \frac{\text{avg Aedes(p)} + \text{avg Non-Aedes(p)}}{200} * 100\% \tag{1}$$

Aedes(p) : - accuracy of Aedes larvae identification
Non-Aedes(p) : - accuracy of non-Aedes larvae identification

The equation (1) is chosen to finally test and validate the data models using validation data, verifying the trained model in Aedes and Non-Aedes identification accurately. Here, the accuracies of both Aedes and Non-Aedes Larvae is summed and divided by 200 since both accuracies will be given in percentages. Finally, the total will be multiplied by 100% to get the total accuracy percentage of the model.

According to those accuracies, the study will show whether it is possible to identify mosquito larvae by their genus using deep learning with accurate results.

IV. EXPERIMENTAL RESULTS

Images of larvae were collected using an attached microscope to the camera and using digital zooming without any microscope in the same condition. As mentioned in previous literature, we were able to archive the mentioned accuracy level of 97% using the collected dataset for the magnified images when the model was trained. The collected data without using a microscope was trained using CNN without using any pre-processing techniques and we were able to archive 77.13% accuracy from the trained model. As in Fig. 10 it can be identified that the model learns by reducing the training loss and increasing the training accuracy.

Next, the same dataset was sent through two cropping algorithms which are 'crop to fit' and 'crop to square'. The trained models showed 62.8% and 67.5% accuracy respectively for both cropping methods, where it was observed that the accuracy is falling after cropping. After that, the dataset was sent through pre-processing methods such as the Enhanced model, Grey model, Inverted Model.

Out of those 3 models, the best identification was archived using Enhanced Model for the pre-processing which is **86.65%** (See Table 1). Grayscale and Inverted Grayscale models archived 53.6% and 58.08% of accuracy respectively.

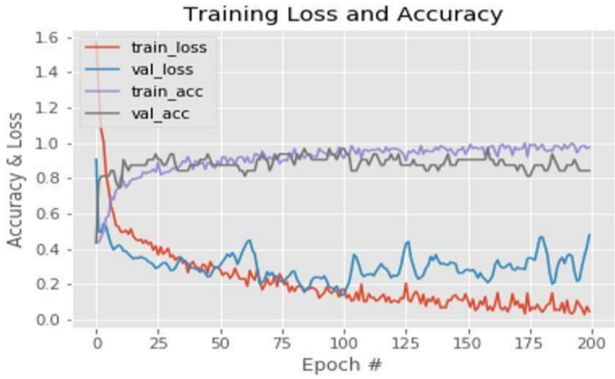

Fig. 10. Training Loss and Accuracy Graph for Model trained without cropping and pre-processing

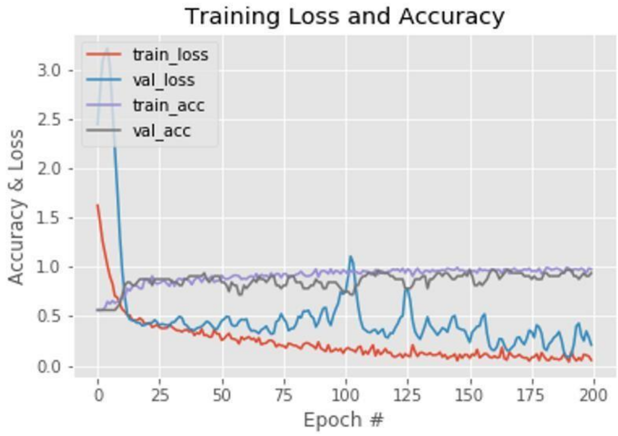

Fig. 11. Training loss and accuracy graph for model trained after using an enhanced model

TABLE I. MODEL ACCURACIES FOR THE VALIDATION OF IMAGES WITHOUT USING MICROSCOPE

	Aedes	**Non-Aedes**
Sample1	100	99.97
Sample2	100	99.99
Sample3	99.90	99.91
Sample4	100	53.74
Sample5	100	False-Prediction
Sample6	100	100
Sample7	100	60.4
Sample8	100	69.4
Sample9	100	53.44
Sample10	99.8	96.54
Average Accuracy (%)	**99.97**	**73.34**

Furthermore, the enhanced pre-processing technique used, tested the dataset of enlarged images of larvae which were taken with a camera attached to the microscope. The trained model showed that the accuracy was increased to 98.76% from 97.62%. The training loss, accuracy for the model and the and the experimental results are shown in Fig. 12 in Table II respectively.

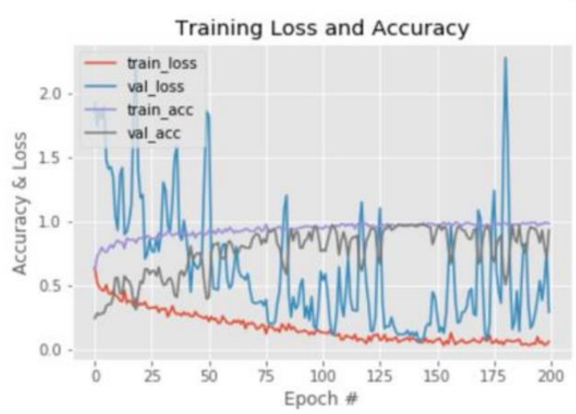

Fig. 12. Training Loss and Accuracy Graph for the Model trained after using enhanced model for a dataset with magnified images (using a microscope).

TABLE II. MODEL ACCURACIES FOR THE VALIDATION OF IMAGES USING MICROSCOPE AND ENHANCED PRE-PROCESSING MODEL

	Aede	**Non-Aedes**
Sample1	99.87	96.86
Sample2	99.99	99.85
Sample3	96.59	99.22
Sample4	99.72	98.99
Sample5	99.95	99.72
Sample6	99.99	92.07
Sample7	99.96	99.98
Sample8	99.92	99.98
Sample9	94.15	99.41
Sample10	99.21	99.28
Average Accuracy (%)	**98.93**	**98.53**

V. CONCLUSION AND FUTURE WORK

In this study, the ResNet50 CNN was used to create the models, which were built according to Aedes and Non-Aedes Larvae in their different stages using a 60X microscope and digitally zoomed images. The trained model shows that this can identify a Dengue carrying mosquito larvae (Aedes) with 77.13% of accuracy using only digitally zoomed images without any magnifier attached to the camera. Furthermore, we found that using pre-processing techniques such as enhancing the image, the accuracy level is raised for both datasets of mosquito larvae images.

Since this identification does not need any third-party equipment, this can be implemented in a mobile app for crowdsourcing from people to identify dengue breeding places in the country and use it for predictions.

This research can be extended to identify multiple larvae using only a single image. Therefore, the user can identify the larvae in the same breeding place and can be applied to identify other tiny insects in there in small stages as well.

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