Transfer Learning for Mosquito Classification Using VGG16

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Abstract. A challenge in computer vision known mosquito classification hasn't gained much traction. Automatic mosquito species credentials using real-time images is a crucial feature. Mosquitoes are a serious matter of concern since they can spread diseases including dengue fever, zika, and malaria. It's important to control mosquito populations in order to effectively control mosquitoes. The World Health Organization reported that over a million people worldwide experience malaria and dengue fever each year. In this investigation, we analyze a deep learning vgg-16 network architecture for mosquito specifically chosen. On our mosquito dataset, which included six (6) species of mosquito. The pre-trained vgg-16 network architecture with transfer learning technique was studied and proved to identify distinct mosquito species, with an average accuracy rate of 97.1751 percent Loss 0.094359393954277. The results of VGG 16 and CNN are compared. The results show that CNN with multi class classifier is achieving 85.75 percent accuracy and VGG 16 with 97.1751 accuracy. It shows that the VGG 16 model is pretty good in results as compare to CNN.

Keywords: VGG16 · CNN · Mosquito · Transfer Learning · MSCMosquito Species Classification

1 Introduction

Classifying mosquito species is particularly difficult due to the tremendous degree of resemblance in appearance between various species. Because of the visual similarities between distinct species, mosquito categorization presents a wonderful chance to utilize new Deep CNN algorithms. The pre-processing of images uses image processing techniques.

The extraction and classification of visual features has long been an important and essential area of research in the science of computer vision. The Convolutional Neural Network offers a comprehensive learning model. (CNN).[1] (K., 2019).

The classification of mosquitoes is regarded as an area of computer vision that is rarely addressed. The classification of mosquitoes makes use of classifiers and a variety of machine learning techniques. Due to the existing Machine Learning (ML) algorithms' inadequacy to precisely extract the features from the mosquito image, they are still unable to reach optimal performance, making it extremely challenging to increase

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the recognition accuracy of the system. Extraction of features and classifier are the two main processes in the majority of constructed Mosquito classification systems. The difficulty in developing an accurate mosquito classification system is largely due to the longer computing time and distinct feature extraction. Deep learning methods are typically recommended for resolving these issues in a variety of image-based applications since they conduct combined feature extraction and classification tasks. As features are automatically extracted by deep learning algorithms, computation time is decreased and recognition accuracy is increased. The primary innovation of the work is the creation of a new VGG-16 algorithm with transfer learning for mosquito classification using different active layers. Additionally, it creates the Convolutional Neural Network (CNN) for classification of mosquitoes. A fresh classification scheme for mosquitoes was introduced in the proposed work. Three main steps make up the procedure: collecting databases, classifying mosquitoes to identify specific species, and assessing performance. For the first step, we created a dataset of 6 different species of total 5400 mosquito images. Second step, efficient MSC (Mosquito species classification) algorithm is then used to recognize mosquito species. Here, the MSC system is introduced to two distinct deep learning algorithms, CNN and VGG16 with Transfer Learning. Keras and TensorFlow are used to implement this proposed approach. Thirdly, precision, recall, F1-score, accuracy are used to assess how well these two classifiers perform. From results it concludes that proposed algorithm produces higher accuracy results of 97.1751%, whereas the other existing classifiers such as CNN gives the accuracy results of 85.75% values respectively. The project is implemented in Python, along with additional supporting frameworks like Keras and TensorFlow for the analysis of mosquito species image detection and classification.

2 Problem Statement

Mosquitoes are the most common disease vector, accounting for a large number of deaths in both children and adults. Disease affecting about 430,000 people each year, according to a study published in 2015[2].

Scientists have been able to pinpoint where the Zika and West Nile viruses originated because of the clear spread of diseases like dengue and yellow fever. The Zika virus is spread by mosquitoes of the Aedes genus, especially Aedes aegypti and Aedes albopictus. Figuring out whether a mosquito species that transmits disease is present in a particular community seems to be the first step towards an efficient disease prevention plan. Once a carrier mosquito is discovered in the vicinity, it is reasonable to presume that there are others because of how rapidly mosquitoes reproduce.

The mosquitoes *Aedes and Culex* are well-known for the spread of deadly infections that can result in death the worst circumstances.[3] Blood-sucking mosquitoes include the *Aedes, Anopheles, and Culex* species, as shown in a tropical medicine expert.

3 Related Work

- **Mosquito flight Sound (Wingbeat):** Eleftherios Fanioudakis carried out experiment on based on optical recordings of mosquitoes' wingbeat and able to classify classified six species of mosquitoes [33]. D. R. Raman, R. R. Gerhardt constructed a prototype field-deployable acoustic insect flight detector has been constructed [36]

- **Mosquito Image:** Junyoung Park investigated classification of vector mosquitoes of 8 species with Morphological Analysis using deep learning [34] Daniel Motta, Alex A´ lisson Bandeira Santos, studied using CNN-based models with complex architectures, they tried to the automation of the detection and classification of adult mosquitoes [35].
- **Mosquito Genomic Data (DNA barcoding):** Based on information from the ribosomal DNA string's internal transcribed spacer 2 region, an artificial neural network method is proposed for the classification and identification of Anopheles mosquito species by Amit Kumar Banerjee, K.Kiran [31]A study by B T L H van de Vossenberg , A Ibáñez-Justicia shoes, real-time PCR tests for the identification of Ae. Aegypti and Ae. Albopictus are implemented, and two new real-time PCR tests for the identification of Ae. Atropalpus and Ae. j. japonicus are developed.Initial testing revealed that Ae. Aegypti and Ae. Albopictus test elements needed to be optimized [32].

4 Extention to Previous Research and Its Applications

In this paper we selected six species from the three main genera *Anopheles, Aedes, and Culex*. Some mosquito species of these genera are responsible for serious diseases like dengue, zika and malaria and Chikungunya. we study how cnn models can solve the issues associated with mosquito species classification tasks. We want to extend our problem to design automation system to classify and identify the mosquito species. The application will be able predict the mosquito species type. It can further be used in flood areas and in seasonal mosquito borne dieses spread as a prevalent to disease spread by mosquito.

5 Deep Learning

Deep Learning

Deep learning is a feature-based machine learning technology that allows a system to automatically understand the representations required for identification activities using training data [4].

Convolutional Neural Network

In the field of DL, the CNN is the most famous and commonly employed algorithm [5, 6]. The main benefit of CNN compared to its predecessors is that it automatically identifies the relevant features without any human supervision [7]. Numerous industries, including computer vision [8], voice processing [9], face recognition [10], and others have made substantial use of CNNs. Similar to a traditional neural network, CNNs have characteristics with neurons found in human and animal brains. In a cat's brain, the visual cortex is made up of a convoluted series of cells, and the CNN simulates this series [11]. The equal representations, sparse interactions, and parameter sharing of the CNN are its three main advantages. To fully utilize 2D input-data structures, such as image signals, the CNN makes use of shared weights and local connections, in contrast to typical fully connected (FC) networks [12].This technique uses a remarkably minimal number of parameters, which speeds up the network while also making training easier. The visual cortex cells also have this. Notably, rather than detecting the entire image, these cells only detect specific portions of it (i.e., these cells spatially extract the local correlation available in the input, like local filters over the input).[13] (Laith Alzubaidi1, 2021).

Convolutional Neural Network CNN Working

A commonly used type of CNN, which is similar to the multi-layer perceptron (MLP), consists of numerous convolution layers preceding sub-sampling (pooling) layers, while the ending layers are FC layers [13]. The original image can be utilized as input in Convolutional neural networks (CNN) without any image pre-processing. Since it was integrated with deep learning, CNN has showed highest accuracy in large-scale image classification and recognition. [14] Researchers utilize parameters to increase the accuracy of the CNN model structure. The majority of the upgraded models take more time to train and evaluate.[15] (Fig. 1).

There are two main parts to a CNN architecture

- A convolution tool that separates and identifies the distinctive characteristics of an image for investigation using a technique called Feature Extraction.
- A fully connected layer that uses the convolution process output to predict the image's class based on the features extracted in previous steps.

CNN is made up of three types of layers: convolutional layers, pooling layers, and fully-connected (FC) layers. A CNN architecture is formed when these layers are stacked. In addition to these three layers, the dropout layer and the activation function are critical parameters [17] (Gurucharan, 2020).

Transfer Learning

When a model is used as the base for one task but not another, this process is known as "transfer learning." TL is a fantastic technique in which models with identical weights that have been sent on a big amount of data are utilised as a starting point for processing another problem with fewer data and improving the task's predictions. It provides a methodology where a model is first trained on a problem that is similar to the one being solved and then applied to a different task. Even before the emergence of current deep learning, the concept of knowledge sharing amongst machine learning models was well known. [29] (Fig. 2).

VGG16

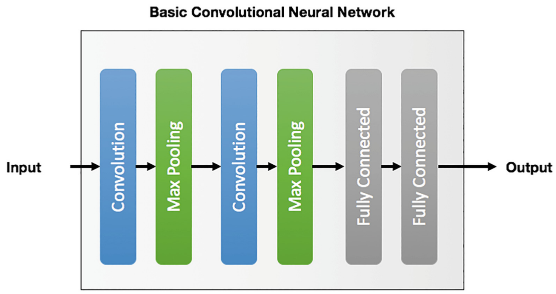


Fig. 1. Convolutional Neural Network CNN architecture [16] (Building a simple CNN, 2022)

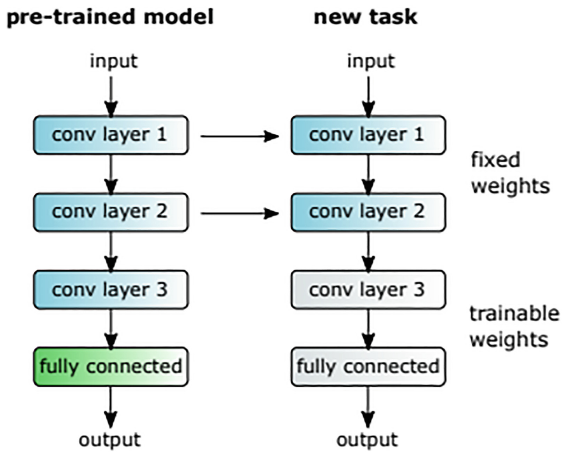


Fig. 2. Schematic View of trasfer learning idea Image source [30]

A ConvNet is a type of artificial neural network that is also known as a convolution neural network. An input layer, an output layer, and various hidden layers comprise a convolution neural network. VGG16 is a CNN (Convolution Neural Network) that is commonly acknowledged as one of the best computer vision models available today.

VGG16 Architecture

The Visual Geometry Group at the University of Oxford and Google DeepMind jointly developed VGGNet, a CNN whose architecture can be thought of as an extended AlexNet and is characterized by 3×3 convolutional kernels and 2×2 pooling layers. To improve feature learning, the network architecture can be further developed by using smaller convolutional layers. VGGNet-16 and VGGNet-19 are the two most popular versions of the VGG Net at the present. [28].

The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is an annual computer vision competition. Each year, teams compete on two tasks. The first is to detect objects within an image coming from *200* classes, which is called object localization. The second is to classify images, each labeled with one of *1000* categories, which is called image classification. VGG 16 was proposed by Karen Simonyan and Andrew Zisserman of the Visual Geometry Group Lab of Oxford University in 2014 in the paper "VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION". This model won the 1st and 2nd place on the above categories in 2014 ILSVRC challenge (Fig. 3).

The precise structure of the VGG-16 networks shown in Fig. 7 is as follows:

- The first and second convolutional layers are comprised of 64 feature kernel filters and size of the filter is 3×3. As input image (RGB image with depth 3) passed into first and second convolutional layer, dimensions changes to $224 \times 224 \times 64$. Then the resulting output is passed to max pooling layer with a stride of 2.
- The third and fourth convolutional layers are of 124 feature kernel filters and size of filter is 3×3. These two layers are followed by a max pooling layer with stride 2 and the resulting output will be reduced to $56 \times 56 \times 128$.

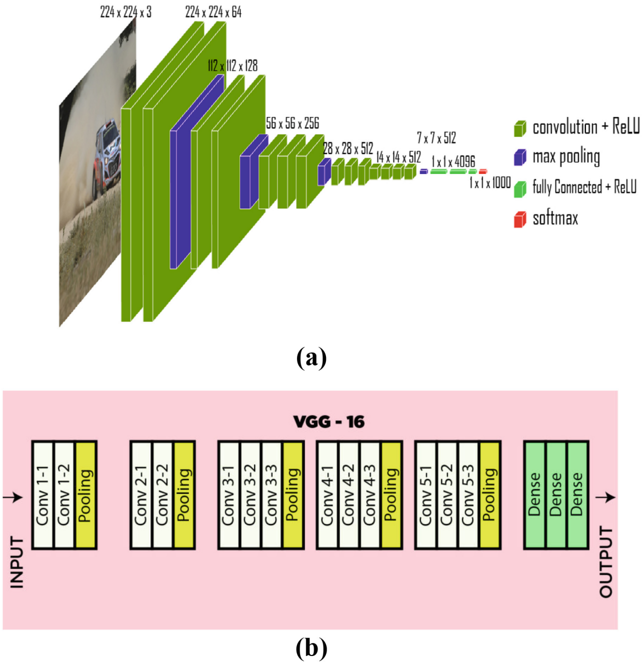


Fig. 3. **(a)** VGG16 architecture **(b)** VGG16 architecture [18] (pawangfg, 2020)

- The fifth, sixth and seventh layers are convolutional layers with kernel size 3 × 3. All three use 256 feature maps. These layers are followed by a max pooling layer with stride 2.
- Eighth to thirteen are two sets of convolutional layers with kernel size 3 × 3. All these sets of convolutional layers have 512 kernel filters. These layers are followed by max pooling layer with stride of 1.
- Fourteen and fifteen layers are fully connected hidden layers of 4096 units followed by a softmax output layer (Sixteenth layer) of 1000 units. [19] (Tammina, October 2019)

Transfer Learning with VGG-16

Transfer learning is simply a machine learning technique where the knowledge obtained from the previous task can be applied to another related task and at the same time improves the learning operation [27]. The CNN network architecture like ResNet, VGG, AlexNet and so on, are already trained on a huge image dataset of ImageNet comprising more than one million labelled high-resolution images belonging to one thousand (1000) categories. Thus, the knowledge obtained already from a particular task is assigned to learn a new different task. It is especially used where the training data is relatively small. In addition, it shows good performance, especially during classification tasks and the computational complexity is significantly minimized to some extent as the entire operation need not start from the scratch.

6 Proposed System

The mosquito classification system is shown in Fig. 4. The main process is composed of image collection, image pre-processing, feature extraction, train pattern, mosquito species classification (Figs. 5 and 6).

It's important to note that accurate identification of adult mosquito species is essential for identifying disease vectors and designing disease control strategies. [20]. Due to their outstanding capacity to detect patterns from images, CNNs are one of the most prominent deep learning network architectures used in computer vision [21]. New models for the

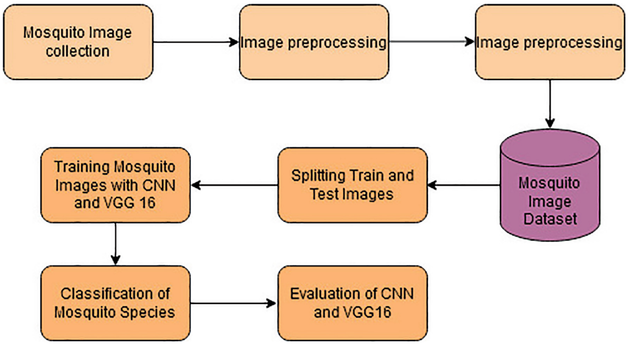


Fig. 4. Overview of Proposed system

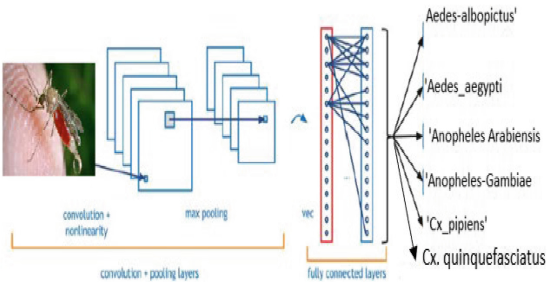


Fig. 5. Mosquito classification system using CNN

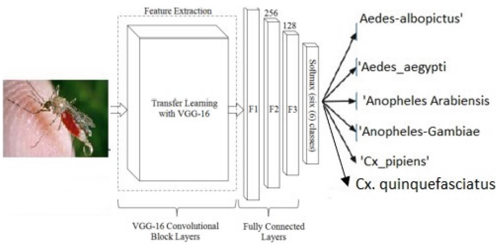


Fig. 6. Mosquito species classification with VGG 16 model

automatic classification of mosquitoes have recently been proposed. The frequency and harmonics of mosquito wingbeats have been used in several studies to classify mosquito species [22]. Techniques based on image feature analysis have also been used as a classification method. In addition, Machine Learning and Deep Learning techniques have been used for mosquito classification [23]. A feature extractor and a classifier that are trained end-to-end can describe the architecture of such networks. Many convolutional and pooling layers make up the feature extractor. Between their inputs and their learnable weights, convolutional layers perform weighted convolutions. As a result, they identify local patterns in the data. Non-trainable pooling layers reduce the dimensionality of their input by mapping a single layer in the input to a single number locally. One or more fully connected layers and a SoftMax function are commonly used to create the classifier [24]. Deep learning methods are essential for the processes underlying general object recognition.[25].

7 Dataset Preparation

Dataset used in this study is created by collecting images from different websites. We use Chrome extension downloads all images for collecting images of different mosquito species. It cannot filter images based on their sizes therefore preprocessing of images is required.

Image Sources

Images were collected from websites/blogs using chrome extension.

Data: Dataset of 5400 images is created. Images of three different genera of mosquito species are collected. Dataset consists of Images of *Aedes, Anopheles* and *Culex*. There are six types of mosquito species included in dataset. The mosquito species images included in dataset are *Aedes-albopictus, Aedes_aegypti, Anopheles Arabiensis, Anopheles-Gambiae and Culex quinquefasciatus and Culex _pippins.*

Pre-processing. Images were converted to uniform format of jpeg. All image size is also changed to uniform size images. Images of each type of mosquito species collected from Google. Then images were rescaled to uniform size. The insect images were rescaled for achieving improved accuracy and eliminate the problems of overtraining. All images are converted into.jpg format.

Data Augmentation for Generating Image Dataset. Image data augmentation techniques such as rotation, flipping, gray scale operators are used to increase the training set for achieving improved accuracy and eliminate the problems of. As shown in Fig. Downloaded image dataset of 6 types of mosquitoes is converted into multiple images by using augmentation by applying different operators. After using augmentation on the training set, datasets contain 5400 augmented mosquito species images. The details are given in supporting information Tables 1.

8 Results and Discussions

Mosquito classification is done with the help of convolution neural network. The dataset of mosquito images were created by downloading images from Google. Then all images were rescaled in uniform size and type. Using augmentation dataset of 5400 images was created. Details of images in dataset are given in Table 1.

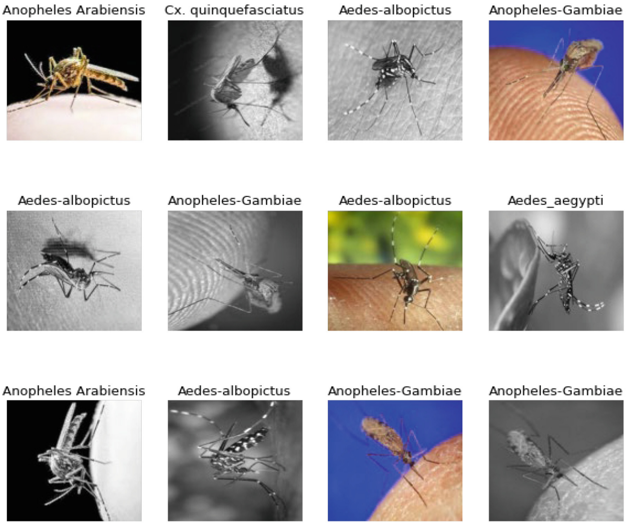


Fig. 7. Images from dataset [26]

Table 1. Types of Mosquito & Sample Count

Mosquito species	Number of mosquitoes
Aedes-albopictus	900
Aedes_aegypti	900
Anopheles Arabiensis	900
Anopheles-Gambiae	900
Culex. Quinquefasciatus	900
Culex_pipiens	900
Total images in dataset	5400

Convolution neural network is applied to dataset and compared the result. Epoch size is 50 for both the CNN and VGG16 module (Fig. 8).

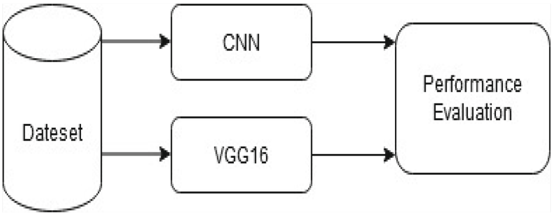


Fig. 8. Performance Evaluation of CNN and VGG 16

The first layer's feature is carried on to the next layer, and the result is sent on to CNN's hidden layers. The process is repeated until the final output in the last layer is obtained.

The screenshot in the fig. Shows the different layers used along with the output shapes and learnable.

The accuracy of this convolution neural network is evaluated by creating predictions and comparing them to test values, then calculating the accuracy based on the mean. The maximum number of epochs considered for experimentation is set to 50, so that the number of iterations required for completing the process increases and the image accuracy improves with each epoch. Table 2 shows the hyper parameter settings used for training the network and.

The input image with the labels are given as a input to the training network in the form of jpg image. The input data which is been labelled as a jpg file and it is been given for the testing purpose. The testing data is taken as the reference and the predicted data is compared to measure the accuracy level.

Figure 9 and 10 shows the plot of accuracy and loss Vs number of epochs. The accuracy plot shows that the accuracy increases when the no. of epochs increases and the maximum accuracy of 85.76% is reached in CNN Model. Similarly, the loss is found to be decreasing from 1.7 to less than 0.2 as number of iterations increases.

The accuracy obtained from this convolution neural network is calculated by making predictions and comparing it with the test values and the accuracy is calculated based on the mean obtained. The maximum epochs considered for experimentation is set to 50 so that the number of iterations taken to execute the process increases and the features was taken more from the signal so that the accuracy of the image gets improved at each epoch. Table 2 shows the hyper parameter settings used for training the network. The accuracy obtained by VGG 16 module is 97.1751 and loss decreased up to 0.094. The results shows that the pre trained model VGG 16 with CNN gives better results than CNN module (Table 3).

Table 2. Parameters and values

Parameter	**CNN**	**VGG16**
No of Epoch	50	50
Batch size	100	100
Training sample	4233	4233
Testing sample	1063	1063

Table 3. Accuracy and Loss

Model	Optimizer	Accuracy	Loss	Average time per epoch
CNN	Adam	85.75%	0.280	221s
VGG16	SGD	97.17%	0.094	884s

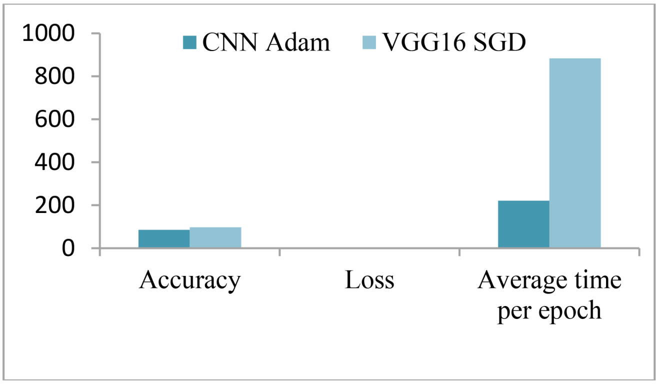
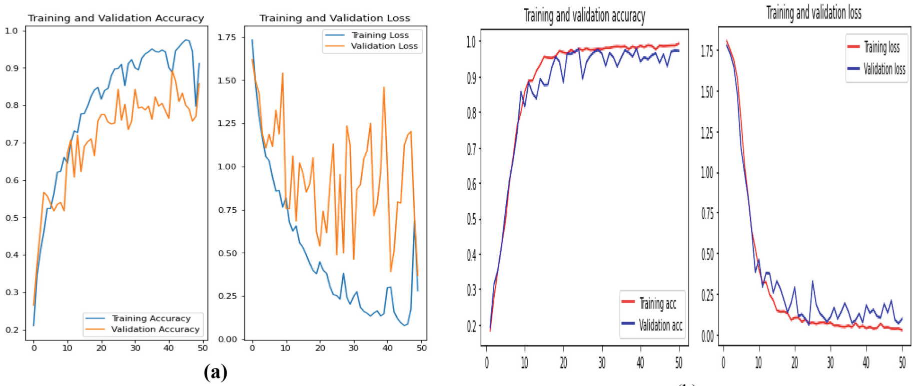


Fig. 9. Graph Accuracy and Loss of CNN



(a)

(b)

Fig. 10. **(a) & (b)** Graph Accuracy and Loss of VGG 16

9 Future Research Directions

Outcome of the study suggest us following suggestions:

I. In this study we used dataset of mosquitoes at resting position. Images are collected from internet.
II. In the next phase we will use the mosquito image captured dataset.
III. Further we want to deploy the mosquito identification system to predict the mosquito species.

10 Conclusion

In this paper, a CNN-based deep learning model is suggested that uses a multi-classifier network to classify six types of mosquito species images. The dataset consists of images of *Aedes-albopictus, Aedes_aegypti, Anopheles Arabiensis, Anopheles-Gambiae and Culex quinquefasciatus and Culex _pippins*. We used Convolution neural network and

VGG16 network to classify the mosquito species images. The confusion matrix is used by the deep learning classifier to classify the number of classes and give the class of the input image to which the class belongs. The human error in data prediction is minimized since the deep learning model does not require any human labeling to extract the features. The results of the classification are compared to those obtained with CNN and VGG 16. The results show that CNN with multi class classifier is achieving 85.75 percent accuracy and VGG 16 with 97.1751 accuracy. It shows that the VGG 16 model is pretty good in results as compare to CNN. In future the research can be incorporating alternative architectures of deep learning models.

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