AUTOMATIC CLASSIFICATION OF MOSQUITO GENERA USING TRANSFER LEARNING

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ABSTRACT

Certain species of mosquitoes are the main vectors of arboviruses that cause Dengue, Yellow fever, Chikungunya, Zika and Japanese encephalitis. These species are contained in the genera Anopheles, Culex, Aedes. Mosquito-borne diseases pose significant threat to public health. Therefore, vector surveillance and vector control strategies are crucial. Automation of genera identification is essential to implement effective vector control strategies. In the past decade several machine learning and deep learning models have been investigated for image-based automatic and accurate classification of vector mosquitoes. Such applications also aid entomologists in insect identification task. In this study, a deep convolutional neural network technique to classify two genera of mosquitoes: Aedes and Culex based on the morphological features is proposed. In our work, an optimization technique i.e., transfer learning using the pretrained deep learning models has been employed. Transfer learning saves the model training time and addresses the problem of low performance due to insufficient amount of training data. This paper presents the architecture of three state of the art pretrained neural networks, including VGGNet, ResNet and GoogLeNet. The models were trained with our own dataset of images of the two genera of mosquitoes. Classification performance of the models is evaluated in terms of classification accuracy and loss during training and validation phases of model building.
Keywords: *Artificial Neural Networks, Image Classification, Machine Learning, Vector Control*

1. INTRODUCTION

In the last decade growing cases of dengue fever (DF) and dengue hemorrhagic fever (DHF) have been reported worldwide. It has resulted in high mortality rate. Currently, antiviral drug for the treatment or vaccine to protect against dengue virus is not available. According to the World Health Organization (WHO) report, mosquito-borne diseases infect millions of people throughout the nation every year causing devastating effect on health and even death [1]. Mosquito bites cause more than 1 million deaths every year. Dengue, Malaria and Zika are some of the prevalent viral infections transmitted by mosquito species. As shown in Figure 1, in the last ten years, the number of dengue cases in India has continuously increased in India according to National Vector Borne Disease Control Programme (NVBDCP) figures[2]. Therefore, the first remedial step is to control the mosquito population growth.

Aedes genus of mosquito contains the species aegypti, a main vector of arboviruses known to transmit Dengue, Yellow fever, Chikungunya, Zika which can cause irreversible central nervous system problems and death. Mosquitoes of Genus Culex are responsible for the spread of diseases such as Japanese encephalitis and West Nile fever. Malaria is a parasitic infection transmitted by Anopheline mosquitoes. These are life threatening diseases and are of great public health concern. These mosquito species are a major threat for public health. Hence there is a need of effective vector control systems as prevention is always better than cure. So far, the approaches to prevent the transmission of the vector borne diseases relied on the vector control strategies to diminish the population of dangerous mosquito species.

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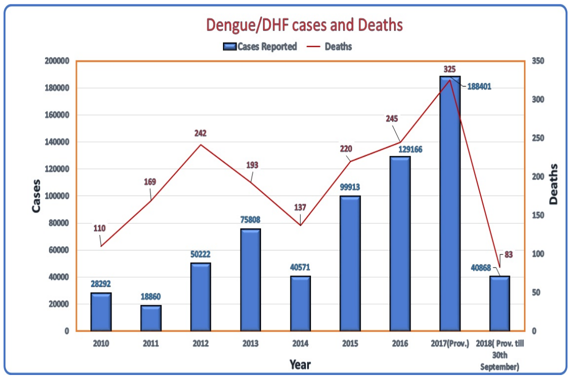

Fig 1 Dengue cases and deaths

Commonly used mosquito vector control methods include:

i) Environmental sanitation
ii) Larvicides
iii) Biological control
iv) Chemical control (using mosquito insecticides, sprays and toxic lures)
v) Personal protection

There is no evidence that any of these vector-control interventions had any significant effect on the spread of vector borne diseases. These strategies are expensive and inefficient if the exact location of mosquito habitat is not identified. Also, long term insecticide exposure can pollute the environment and can impact the health of people.

In the past decade machine learning and deep learning techniques have been successfully applied to address the challenges related to public health and environment [3,4]. Image based automatic insect classification by applying deep learning techniques has become an area of research interest. A model of input data is built by training a deep neural network. Convolutional Neural Networks (CNNs) , a class of deep neural networks are very efficient in image recognition and image classification tasks.

Another area where automatic insect classification can be applicable is in entomology for accurate insect identification, which requires in depth study and skilled entomologists. Automation of insect identification is required because there is a shortage of expert entomologists [5]. It can also provide an effective way of counting specimens to estimate their abundance.

In our work we propose a deep convolutional neural network (DCNN) solution in order to classify mosquito images at the genera level based on the visual features specific to a genus.

The key contributions of our study are:

- A dataset of images of two genera of mosquitoes: Aedes and Culex is created.
- Transfer learning is applied on the popular pretrained models using the dataset created, to classify mosquito images into correct genus.
- The performance of the pretrained models is evaluated in terms of classification accuracy and loss obtained during training the networks.

The rest of this paper is arranged as follows: Section 2 presents the literature review. Data set collection and preprocessing is described in Section 3. Section 4 gives an overview of the working of deep neural networks and architecture of the 3 state of the art pretrained convolutional neural networks followed by the technique of transfer learning. Section 5 gives the details of our experimental setup for training DCNNs. The discussion about results obtained and limitation of our work is presented in Section 6. Conclusion and future scope of our work are summarized in Section 7, followed by the list of references.

2. RELATED WORK

The first step in effectively implementing vector control strategies in a geographic region is to track and estimate the type of mosquito species that are predominant in that region. Hence recently there are several developments in the automatic classification of mosquitoes. There are studies aimed at classifying mosquito species based on their wingbeat frequency and harmonics [6]. Prashant Ravi et al. proposed a machine learning method that can distinguish mosquito species with an accuracy of 80% accuracy, using the features extracted from the wingbeat frequency spectrum [7]. There are research studies which used pseudo-acoustic optical sensors to acquire features related to insect's flight behavior and train the machine learning model to achieve better classification accuracy [8,9]. The limitations of these approaches are:

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a) as the sensors have limited storage it is difficult to store and process the complete data in real time and filter out background noise.

b) an intelligent sensor must adapt to changes in the climate. Variations in temperature, pressure and humidity can affect the behavior of insects [9].

c) Vibrations and flashing lights may introduce noise in the data captured by sensors.

There are molecular techniques used to species identification with DNA barcoding, real time PCR (qPCR) that can be used to distinguish morphologically similar species. This approach is time consuming and expensive [10, 11].

There are research studies based on image-based classification of mosquito species and these methods focus on geometric morphological characters of body parts of mosquito such as wing shape [12]. This approach requires lab setting to remove body part and capture photograph for analysis. The difficulty with this method is capturing images of wings in a controlled pose is a tedious task and also the identification needs domain expertise to design effective feature extractors.

Few of the advanced countries, use mosquito traps for the surveillance of species in an area. The professionals lay traps and collect trapped specimens to visually inspect, count and identify the species. This gives an estimate of the harmful species prevalent in that area so that necessary actions can be taken. However, the process is manual, expensive, time consuming and requires skilled personnel.

There have been initiatives taken for the development of an imaging system within a mosquito trap to obtain the images of trapped specimen and identify the genus / species. The camera embedded in these traps captures the static images of the mosquitoes. With the recent advancement in image processing techniques coupled with deep neural network structures, researchers have attempted to automate the insect classification task.

Masataka et al. developed a vision based system that was capable of identifying mosquitoes from other insects based on the morphological and color features and support vector machine- algorithm [13]. Minakshi et al. identified seven mosquito species with an accuracy of 83.3% on a sample size of 60 images using Random Forests algorithm [14].

Diego F. Silva et al. devised an intelligent trap with a laser sensor to catch and identify insects. In this work, the authors evaluate feature sets extracted from audio analysis and machine learning algorithms in order to develop models which can accurately classify insects [15].

Vinícius M. A. de Souza designed one-class classifier for insect classification, where the training was accomplished only with the instances of target class i.e., positive examples to identify Aedes aegypti mosquitoes [16]. Maxime Martineau et al. presented an extensive survey of types of image capture techniques, feature extraction, classification methods and the tested datasets. They have also discussed the challenges faced in the image capture process to achieve a good recognition performance [17].

Recently, deep learning techniques especially the convolutional neural networks (CNNs) have been proved to perform better than the machine learning techniques in computer vision applications. In 2012, a CNN model called AlexNet outperformed all the other models in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). In this competition, there were 1.3 million images belonging to 1000 classes such as “lion,” “cup,” “car wheel,” and different animals. The model attained 37.5% and 17.0% as top-1 and top-5 error rates respectively. This was a great improvement over the previous state-of-the-art models [18]. Since then, there has been growing interest in training CNNs for automated image classification tasks.

Transfer learning is an optimization technique employed in deep learning to address the challenges in training a deep neural network from scratch. In this approach, a pretrained model i.e., the CNN trained for a generic image classification task is fine tuned for a specialized task.

Miroslav valan et al. developed an effective CNN model, based on feature transfer from VGG 16 architecture pretrained on the ImageNet data set for

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the taxonomic identification of insects. The model achieved > 92% accuracy in classifying images into Diptera and Coleoptera families and > 96% in identifying i) visually similar species of Plecoptera larvae and ii) Closely related species of Oxythyrea that are hard to distinguish even for experts [19]. The study carried out by Kazushige Okayasu et al. presents a comparative analysis of performance of conventional, manual feature-extraction based method with that of CNNs to classify images of 3 mosquito species i.e., Aedes albopictus, Anopheles stefensi, and Culex pipiens pallens. The accuracy achieved with deep learning approach (with ResNet using data augmentation) was ~ 13 % higher than the conventional method [20]. The research work conducted by Junyoung Park et al. investigated the performance of three pretrained models: VGG-16, ResNet-50 and SqueeezNet to classify mosquito species using a dataset of 3,600 images of 8 mosquito species belonging to Aedes, Culex and Anopheles genera. The highest classification accuracy obtained was 97.19 % (VGG-16 with fine tuning) and 93.45 % (ResNet-50 without fine tuning) the models [21].

Thus, it can be concluded that the approaches based on machine learning techniques as reported in the previous studies required feature extraction from the images to train the machine learning model i.e., classifier. The most commonly used features were color histogram, texture, geometrical shape etc. Those methods could entail significant domain knowledge for effective feature extraction. There were some research studies that focused on morphological structure of insect body parts like wings to classify the mosquitoes or insects. These methods were time consuming and also require lab settings with domain expertise. The performance of the classification techniques based on wingbeat frequency and harmonics were found to be dependent on atmosphere conditions and the sensors' memory capacity.

The current work, investigates the capability of pretrained CNNs to classify mosquito genera using a dataset of images constructed by the authors. The pretrained CNNs are used without any changes in their architecture. The models can automatically extract hierarchical feature representations from the input images, during the training phase. This alleviates the requirement of designing feature extractors manually. The transfer learning technique is applied to avoid training the model from scratch. This technique not only saves model training time but also addresses the data scarcity problem faced in training CNNs. The performance of three pretrained CNNs : ResNet, VGGNet and GoogLeNet was evaluated in order to classify the mosquito images at the genera level.

3. DATASET GENERATION AND PRE-PROCESSING

The two genera of mosquitoes i.e., Aedes and Culex differ in morphological features as shown in Figure 2a and 2b. A machine learning / deep learning model can be trained to learn these features in order to identify mosquito genus.

The first step in any machine learning project is data collection and preprocessing. For accurate classification results, a large and quality dataset is required for training the CNN model. In the proposed work, classification of mosquitoes into two genera i.e., Aedes and Culex is performed. As there was no standard dataset of mosquito images available online, dataset comprising of images of the two mosquito genera was constructed by the authors. The images were obtained from online public domain platforms. Total 532 images of Aedes and 383 images of Culex genus were collected. The images were pre-processed. They were resized to 224x224 to speed up the processing. The main difficulty in training was the small size of the dataset as the deep learning networks are data hungry models. To address the data scarcity problem, a series of data augmentation techniques were applied to the original images like random rotations, zooms, shifts, shears, flips, and mean subtraction. The augmented dataset consists of 1250 of images Aedes and 950 images of Culex [22]. Table 1 summarizes these details.

Table 1 : Data set details

Genus	Original Images	Augmented dataset
Aedes	532	1250
Culex	383	950

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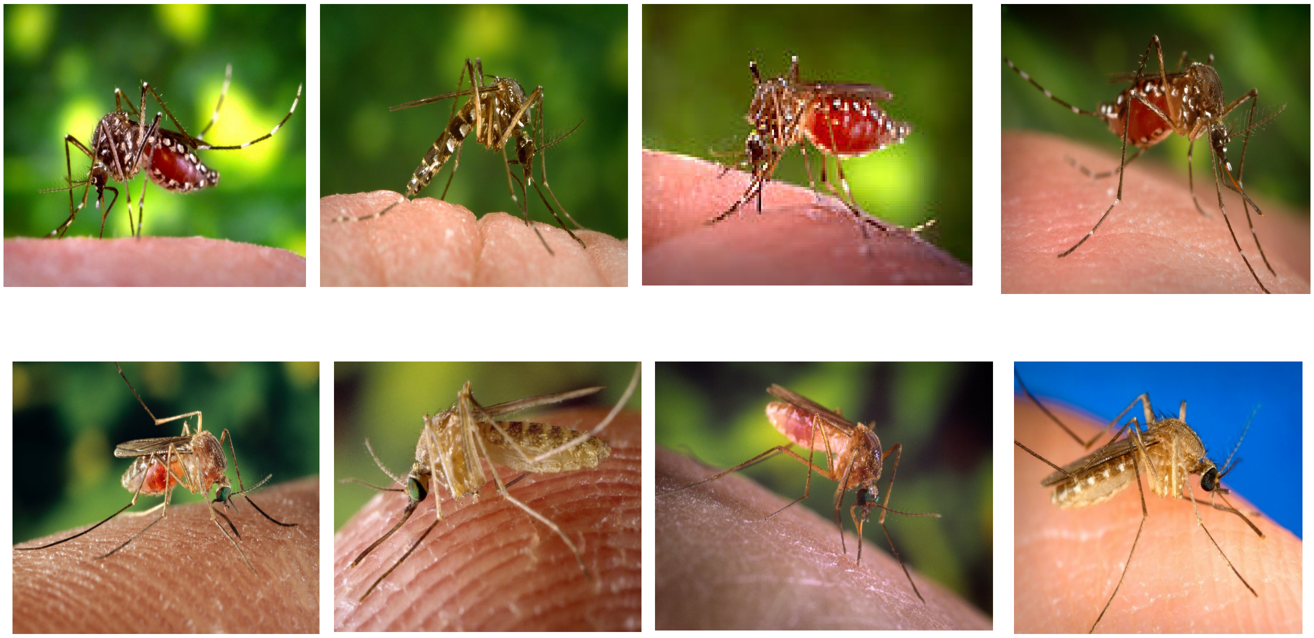

Figure 2 Aedes (top) and Culex (bottom) mosquito images

4. DEEP LEARNING MODEL

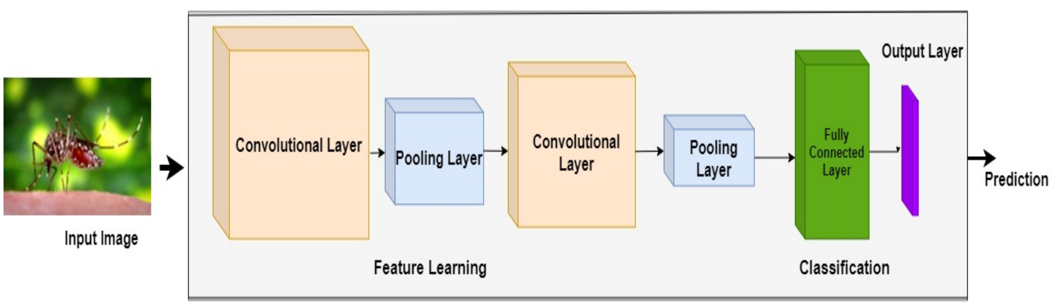

Figure 3 Convolutional Neural Network

Deep learning, a form of machine learning technique attempts to mimic the human brain behavior. In a deep learning network, the input feature representations are extracted by the network layers automatically hence feature extraction step is not required prior to training the model. A deep neural network is a multi-layer network comprising of a large number of computing units called neurons organized in multiple interconnected hidden layers. The network can be trained with a learning algorithm. A deep learning algorithm can take in an input image, assign weights and biases to connections in order to identify patterns in a way similar to nervous system does. The network uses a non-linear activation functions such as Sigmoid, TanH , ReLU (Rectified Linear Unit), Softmax. Activation function computes the output of the neuron for a given input. Convolutional neural network is a special type of deep neural network, that is efficient in computer vision tasks. CNNs have been trained to adaptively learn hierarchies of complex features from the input data using convolution layers, pooling layers and fully connected layers [23] (Figure 3).

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4.1 Transfer Learning

In training deep learning models, dataset size is a key factor to accomplish a good performance. To train a new CNN, with a good accuracy, it is necessary to have a huge set of labeled images and substantial computational resources [19]. Training a deep learning model on small dataset may lead to a modeling error called "overfitting". This occurs when the model learns exactly its training data and cannot perform precisely against new data. Transfer learning is a technique that addresses this problem. In transfer learning, we reuse the pretrained model instead of training the model from scratch. A pretrained model is a model trained for a generic image classification task using a large dataset for e.g., ImageNet. The knowledge gained for this task can be used to solve a new problem (Figure 4). It is similar to the way humans apply knowledge gained for one task to perform a new task. Transfer learning saves training time and makes it possible to develop deep learning models when the size of the data set is inadequate. It is proved that models trained with transfer learning generalize better [24,25].

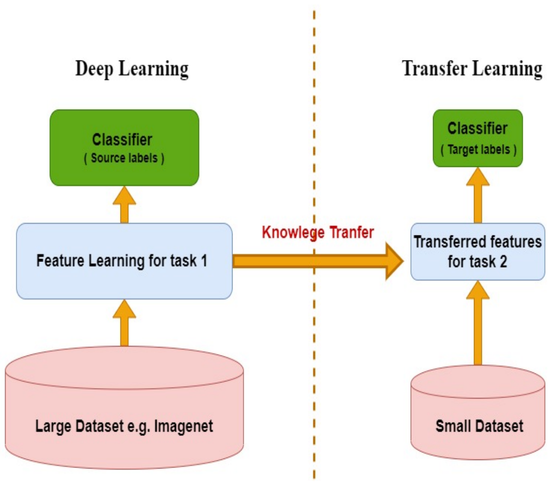

Figure 4 Transfer Learning

Deep learning models learn hierarchical representation of features at different layers. The last layer is fully connected layer which gives final output. In deep transfer learning, a large pre-trained network (trained on a large dataset) can be used as a feature extractor for our specific task. Additionally, the network can also be fine-tuned where the pre trained part (i.e., initial convolutional layers of the base model) is reused as a fixed feature extractor. The last 'n' layers (generally n=1 or n=2) are replaced with fully connected nodes and the network is trained with the new data [26]. This results in reduction in the computation time required for training the neural network. In the current work, the three pretrained models: VGGNet, ResNet, and GoogLeNet are reused for mosquito genera identification task.

4.1.1 Resnet 50

ResNet, short for Residual Network is a popular deep learning model which scored the 1st place in the ILSVRC 2015 classification competition. ResNet-50 is a widely used and smaller version of ResNet 152 CNN model, with 48 convolution layers, one max pool and one average pool layer. The pretrained model is extensively used for transfer learning. The network processes input images of dimension 224 x 224. The network was trained to classify images into 1000 object categories, such as pencil, keyboard, mouse, and animals. The CNN has been trained to extract very good feature representations from a wide array of images.

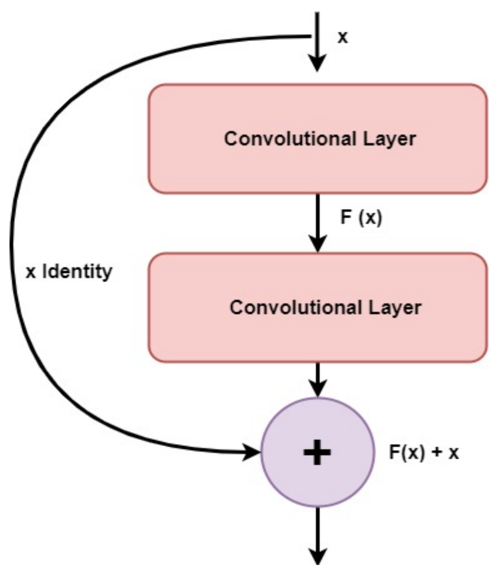

Fig 5 Residual learning: a building block

Researchers observed that just piling more layers to the deep neural network didn't improve the performance. The accuracy of the network saturated or degraded due to a phenomenon known as "Vanishing Gradient" effect. The initial layers of the network won't learn effectively and accuracy will degrade or it may saturate at a certain value. To address the above problem, ResNet applies residual learning technique, i.e., stacked layers directly fit a residual mapping function by adding the identity connection (skip / shortcut connections) between the layers [27]. Figure 5 shows the residual block used in the network. The shortcut connections simply perform identity mapping and the result of the identity mapping are added to the outputs of the stacked layers. It has been shown that it is easier to optimize residual mapping than the original mapping and does not require extra computations. ResNets have proven that a very deep neural networks can be trained with great performance.

4.1.2 VGG

VGGNet is a CNN architecture proposed by Karen Simonyan & Andrew Zisserman from Visual Geometry Group, Oxford University. This model won the 1st runner up place at ILSVRC 2014 in the image classification task [28]. The figures 16 and 19 in VGG16 and VGG19 indicate the number of weight layers in the network. The inputs to the network are images of size 224 x 224 x 3. (Figure 6).

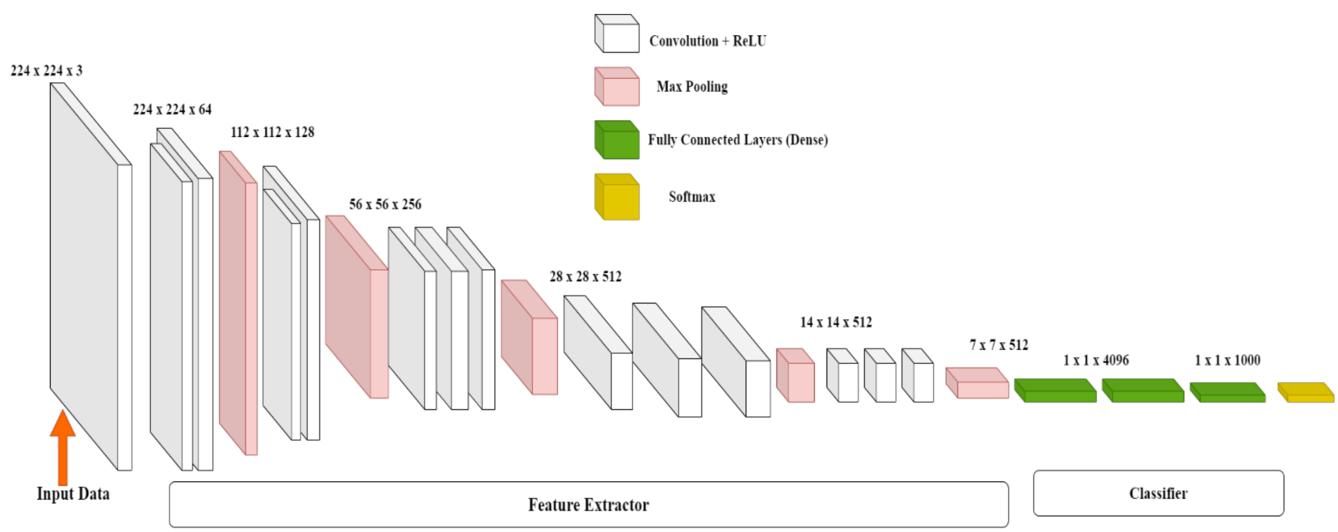

Figure 6 VGG Net Architecture

The image is processed through a sequence of convolutional layers, which apply filters with a very small receptive field: 3 × 3. Max pooling is performed to decrease the size of the input. The network has three final layers which are Fully-Connected (FC). The first two FC layers have 4096 channels each, and the last layer is a soft max classifier which performs 1000 class ILSVRC classification and thus contains 1000 channels (one for each class) [29].

4.1.3 GoogLeNet:

GoogLeNet also called as Inception v1 is a variant of Inception architecture. It was the winner at ILSRVRC 2014, with 1st place in both classification and detection task. The network has relatively lower error rate of 6.67% in classification task as compared with that of VGGNet. GoogLeNet is a DCNN architecture that is 22 layers deep (27 layers with pooling layers), including 9 inception modules. (Figure 7). The network design allows increasing the depth and width of the network, while keeping the computational burden in limit. This feature makes it possible to use on systems with limited computational resources [30].

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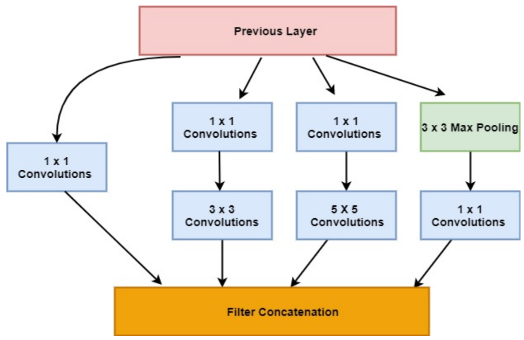

Figure 7 Inception module with dimension reduction

The inputs to the network are images of dimension 224 x 224 with RGB color channels. The convolutions in the network have Rectified Linear Units (ReLU) as activation functions.

The network design includes
i) 1×1 convolutions at the middle of the network as a dimension reduction module to reduce the computations.
ii) Instead of fully connected layers, Global average pooling is included at the end of the network. The authors found that this modification improved the top-1 accuracy by about 0.6
iii) Inception module which makes it possible to have different sizes / types of convolutions and max pooling for the same input and extract different kinds of features. The feature representations at different paths are added together as the input for the next module.
iv) Auxiliary Classifier for Training : The creators of the architecture introduced two auxiliary classifiers which are utilized only during training to address "Vanishing Gradient" problem and provide additional regularization. The auxiliary classifiers apply SoftMax function to the outputs of two of the inception modules and compute an auxiliary loss which is added to the total training loss.

5. EXPERIMENTAL SETUP:

The study aims to evaluate the three pretrained models for two performance metrics: Accuracy and Loss and to find the model which performs best on our dataset.
Classification accuracy is defined as the percentage of correct predictions for the test data. It is the ratio of the number of accurate predictions to the total number of predictions.

$$\text{Accuracy} = \frac{\text{Number of Correct predictions}}{\text{Total number of predictions}}$$

Loss is another important metric to analyze the performance of the model. Loss function determines the error between the predicted output of the model and the given target value. It is a measure of how far a predicted value is from it's correct or actual value. Since our problem is a two-class classification problem, we have analyzed binary cross entropy loss also referred to as log loss, a most commonly used metric for binary classification problems. The loss function can be mathematically represented into an equation as follows:

$$Loss = -\frac{1}{N}\sum_{i=1}^{N} y_i \,.\log\left(p\left(y_i\right)\right) + \left(1 - y_i\right).\log\left(1 - p\left(y_i\right)\right)$$

where y_i represents the actual class
$p\,(y_i)$ is the probability of class 1.

$1 - p\,(y_i)$ is the probability of class 0.

The three pretrained models: VGG16, ResNet50 and GoogLeNet were trained using the dataset constructed. The images were resized to 224 x 224 x 3 dimension, as this is the default input size accepted by the pretrained models.

The implementation was carried out using Keras, an open-source library written in Python 3.7, with Tensor flow deep learning framework 2.1.0 as backend on an Nvidia GTX 1050, GPU platform. The image dataset is split into 80-20% ratio for training and validation for each of the genera. Figure 8 depicts the process of our proposed methodology.

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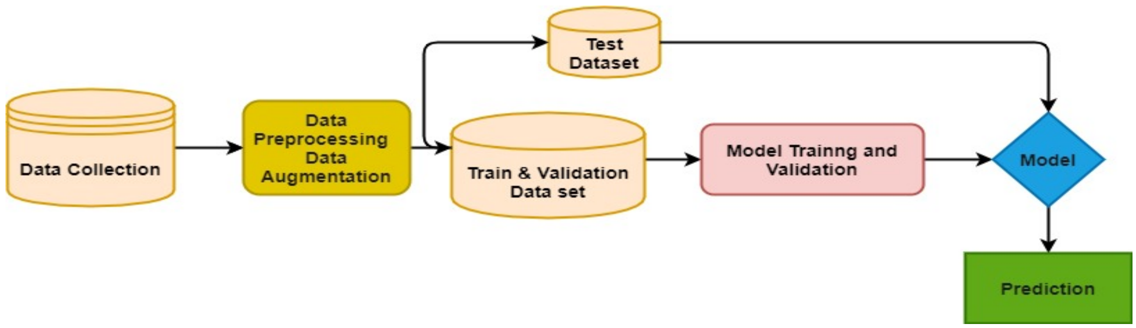

Figure 8 Process of Model Training & Testing

We need to set certain model parameters such as number of epochs, learning algorithm, loss function, batch size and learning rate etc. prior to training the DCNN. These parameters impact the performance i.e., classification results. Number of epochs for training was set to 100 and adam optimizer algorithm was used to train the DCNN model. Adam is an effective optimization algorithm used in deep learning to update the network weights iteratively based on the training data in order to minimize the loss function. Loss function was set to binary cross-entropy as this is a binary classification problem. Batch size and learning rate were initialized to a default value that is predefined for each of the networks.

6. RESULTS

Model performance evaluation is an integral part of the machine learning model development process. In the current study, we analysed the model performance in terms of loss and classification accuracy (during training and validation phases) and test accuracy. The three pretrained DCNNs were trained using the parameters specified under section 5.

Figures 9a, 9b and 9c show the accuracy and loss obtained during the validation phase for each of the pretrained CNNs. VGGNet model achieved classification accuracy of 92.5% and the loss was observed to be ~0.82 during the validation phase (Figure 9a). The surge in the validation loss shows that the model is overfitting. Figure 9b presents the results obtained with ResNet model. The model attained an accuracy of 89.0 % and the loss during validation phase was ~ 0.80.

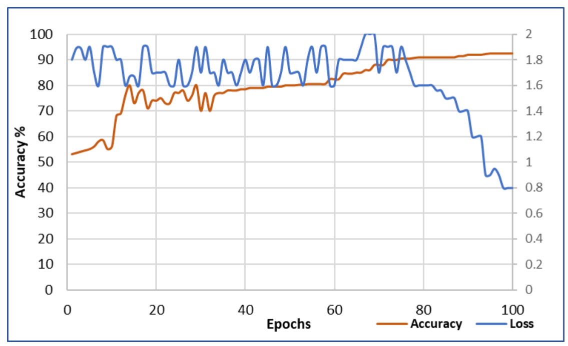

Fig 9a VGG Net Model

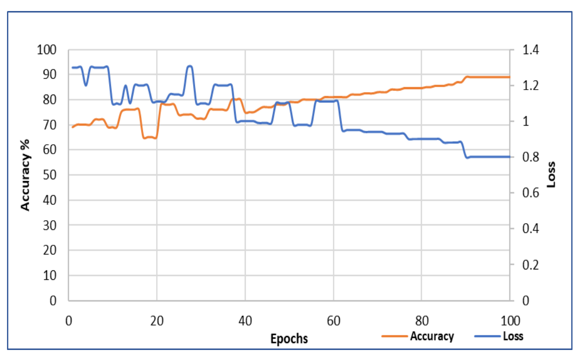

Fig 9b ResNet Model

As shown in Figure 9c, with GoogLeNet, the validation accuracy obtained was 94.3%. The loss during validation phase reduced to approximately 0.47. We can find that the performance exhibited by GoogLeNet is the best as compared with that of ResNet and VGGNet.

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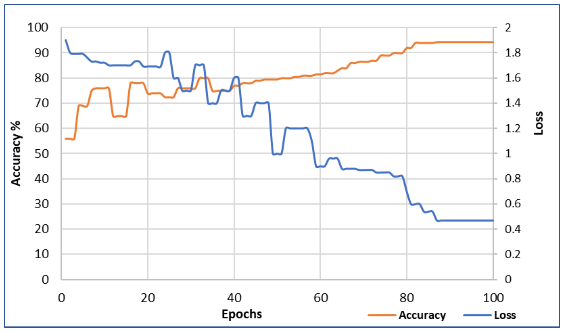

Fig 9c Google Net Model

To evaluate the classification performance of the models on the unseen input i.e., test data, we used 200 images including 120 images of Aedes and 80 images of Culex genus. These images were new i.e., they were not part of the training / validation set. Table 2 summarizes the accuracies of the three models observed, during training and testing phases. Figures 10 shows the confusion matrix for each of the models.

Table 2: Train and Test accuracies

Architecture	Accuracy (Train)	Accuracy (Test)
VGGNet	92.5%	90.0%
ResNet	89.0%	86.5%
GoogLeNet	94.3%	92.5%

Predicted		
Aedes	112 93.3%	12 15%
Culex	8 6.7%	68 85%
	Aedes	Culex
	True class	

Predicted		
Aedes	100 83.3%	7 8.7%
Culex	20 16.7%	73 91.3%
	Aedes	Culex
	True class	

Predicted		
Aedes	115 95.8%	10 12.5%
Culex	5 4.2%	70 87.5%
	Aedes	Culex
	True class	

Figure 10 Confusion Matrix for VGG-16, ResNet-50 and GoogleNet

Overall, the performance of the GoogleNet is found to be better than ResNet and VGGNet.

The main limitation in training CNNs was the non-availability of large dataset of mosquito images of different genera. To address this problem different image augmentation functions were applied on the original images to increase the training dataset size.

7. CONCLUSION AND FUTURE WORK

The study demonstrates the application of pretrained DCNN for the automatic and accurate classification of mosquito genera. The three models VGGNet, ResNet and GoogLeNet were trained to classify the mosquito images into Aedes and Culex genus. The classification performance of the models was evaluated with the metrics: accuracy and loss during training and validation phases and test accuracy. In spite of having considerably small dataset, GoogLeNet demonstrated the best performance with classification accuracy of 94.3% during training and 92.5% on test data.

As a future work, we can apply transfer learning with fine tuning. The process of fine tuning can lead to higher classification accuracy. We could also create a large standard dataset of images of mosquito specimen belonging different genera / species captured in the lab setting. The DCNNs can be trained on this dataset for multiple genera or species identification and achieve better classification results.
The work presented in our study can be beneficial for controlling vector borne diseases and can assist in the area of entomology for other similar image classification tasks.

REFERENCES:

[1] World Health Organization, https://www.who.int/news-room/fact-sheets/detail/dengue-and-severe-dengue

[2] National Vector Borne Disease Control Programme (NVBDCP), www.nvbdcp.com

[3] Bharati S Ainapure, Reshma Pise, Aniket Wagh, Jitesh Tejnani, Kaushal Oza, “Prognosis of COVID- 19 Patients with Machine Learning Techniques”, Annals of RSCB, vol. 25, no. 6, pp. 20183–20200, Sep. 2021

[4] Nan He, Guanghao Li,Urban neighbourhood environment assessment based on street view image processing: A review of research trends, Environmental Challenges,Volume 4, 2021,100090,
ISSN 2667-0100, https://doi.org/10.1016/j.envc.2021.100090

[5] Hassan, Siti & Rahman, Nur & Zaw, Zaw & Win, Shoon. (2014). Vision Based Entomology: A Survey. International Journal of Computer Science & Engineering Survey. 5. 19-32. DOI:10.5121/ijcses.2014.5103

[6] Silva DF, De Souza VMA, Batista GEAPA, Keogh E, Ellis DPW. “Applying machine learning and audio analysis techniques to insect recognition in intelligent traps”, Proceedings—2013 12th International Conference on Machine Learning and Applications, ICMLA 2013. 2013. pp. 99–104. https://doi.org/10.1109/ICMLA.2013.24

[7] Prashant Ravi , Uma Syam, Nachiket Kapre “Preventive Detection of Mosquito Populations using Embedded Machine Learning on Low Power IoT Platforms”, ACM DEV ’16, November 17 - 22, 2016, Nairobi, Kenya.

[8] Chen, Yanping et al. “Flying insect detection and classification with inexpensive sensors.”, Journal of visualized experiments : JoVE , 92 e52111. 15 Oct. 2014, doi:10.3791/52111.

[9] De Souza VMA, Silva DF, Batista GEAPA “Classification of data streams applied to insect recognition: Initial results.”, Proc—2013 Brazilian Conf Intell Syst BRACIS 2013. 2013; 76–81. https://doi.org/10.1109/BRACIS.2013.2

[10] Batovska, J., Blacket, M. J., Brown, K., & Lynch, S. E. (2016). “Molecular identification of mosquitoes (Diptera: Culicidae) in southeastern Australia. Ecology and evolution”, 6(9), 3001–3011. https://doi.org/10.1002/ece3.2095

[11] Vossenberg BTLH Van De, Iba´ñez-Justicia A, Metz-Verschure E, Veen EJ Van, Bruil-Dieters ML,Scholte EJ. Real-Time PCR Tests in Dutch Exotic Mosquito Surveys; “Implementation of Aedes aegypti and Aedes albopictus Identification Tests, and the Development of Tests for the Identification of Aedes atropalpus and Aedes japonicus japonicus (Diptera: Culicidae)”, J Med Entomol. Entomological Society of America; 2015; 52: 336–350. https://doi.org/10.1093/jme/tjv020
PMID: 26334807

[12] Wilke ABB, Christe RdO, Multini LC, Vidal PO, Wilk-da-Silva R, de Carvalho GC, et al. (2016)
“Morphometric Wing Characters as a Tool for Mosquito Identification” PLoS ONE 11(8): e0161643. doi:10.1371/journal.pone.0161643

[13] Masataka Fuchida et al. “Vision-Based Perception and Classification of Mosquitoes Using Support Vector Machine”, Applied Sciences, 2017,7,51 doi : 10.3390/app7010051.

[14] Minakshi, M.; Bharti, P.; Chellappan, S. Identifying mosquito species using smart-phone camera.In Proceedings of the 2017 European Conference on Networks and Communications (EuCNC), Oulu, Finland, 12–15 June 2017

[15] Diego F. Silva, Vinícius M. A. de Souza Eamonn Keogh, Daniel P. W. Ellis “Applying Machine Learning and Audio Analysis Techniques to Insect Recognition in Intelligent Traps”, 12th International Conference on Machine Learning and Applications , 2013.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[16] Vinícius Mourão Alves de Souza "Identifying Aedes aegypti Mosquitoes by Sensors and One-Class Classifiers", Chapter from book Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications: 21st Iberoamerican Congress, CIARP 2016, Lima, Peru, November 8–11, 2016, Proceedings (pp.10-18).

[17] Maxime Martineau, Donatello Conte, Romain Raveaux, Ingrid Arnault, Damien Munier, et al.. "A survey on image-based insect classification", Pattern Recognition, Elsevier, 2017, 65, pp.273 - 284. 10.1016/j.patcog.2016.12.020. hal-01441203

[18] Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton "Imagenet Classification with Deep Convolution Neural Network", Communications of the ACM, Volume 60, Issue 6, June 2017 pp 84–90, https://doi.org/10.1145/3065386.

[19] Miroslav Valan, Karoly Makonyi, Atsuto Maki, Dominik Vondráček, Fredrik Ronquist "Automated Taxonomic Identification of Insects with Expert-Level Accuracy Using Effective Feature Transfer from Convolutional Networks", Systematic Biology, Volume 68, Issue 6, November 2019, Pages 876–895, https://doi.org/10.1093/sysbio/syz014

[20] Kazushige Okayasu, Kota Yoshida, Masataka Fuchida and Akio Nakamura "Vision-Based Classification of Mosquito Species: Comparison of Conventional and Deep Learning Methods" , Appl. Sci. 2019, 9, 3935; doi:10.3390/app9183935

[21] Park, J., Kim, D.I., Choi, B. et al. Classification and Morphological Analysis of Vector Mosquitoes using Deep Convolutional Neural Networks. Sci Rep 10, 1012 (2020). https://doi.org/10.1038/s41598-020-57875-1

[22] Reshma Pise, Mayawadee Aungmaneeporn, Kailas Patil, Prawit Chumchu, July 12, 2020, " Image Dataset of Aedes and Culex Mosquito Species", IEEE Dataport, doi: https://dx.doi.org/10.21227/m05g-mq78

[23] Aurélien Géron "Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems " , O'Reilly ,2nd Edition

[24] Weiss, K., Khoshgoftaar, T.M. & Wang, D. "A survey of transfer learning", J Big Data 3, 9 (2016). https://doi.org/10.1186/s40537-016-0043-6

[25] Meshram, V.A., Patil, K., Ramteke, S.D. (2021). MNet: A framework to reduce fruit image misclassification. Ingénierie des Systèmes d'Information, Vol. 26, No. 2, pp. 159-170.
https://doi.org/10.18280/isi.260203

[26] Transfer learning and fine-tuning https://www.tensorflow.org/guide/keras/transfer_learning

[27] He, K., Zhang, X., Ren, S., Sun, J. "Deep residual learning for image recognition".
https://arxiv.org/abs/1512.03385

[28] Simonyan, K.; Zisserman, A. Very deep convolutional networks for large-scale image recognition. In Proceedings of the International Conference on Learning Representations (ICLR), San Diego, CA, USA, 7–9 May 2015 https://arxiv.org/pdf/1409.1556.pdf

[29] ImageNet Large Scale Visual Recognition Challenge (ILSVRC)
http://www.image-net.org/challenges/LSVRC

[30] Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, et al. "Going Deeper with Convolutions", arXiv:14094842. 2014; https://doi.org/10.1109/CVPR.2015.7298594