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A Deep Transfer Learning Framework for the Multi-Class Classification of Vector Mosquito Species

Reshma Pise[1*], Kailas Patil[1]

[1] Department of Computer Engg., Vishwakarma University, Survey No. 2, 3, 4, Laxmi Nagar, Kondhwa Budruk, Pune, 411 048, Maharashtra, India

* Corresponding author's email: reshma.pise@vupune.ac.in

ABSTRACT

Mosquito borne diseases pose a substantial threat to public health. Vector surveillance and vector control approaches are critical to diminish the mosquito population. Quick and precise identification of mosquito species predominant in a geographic area is essential for ecological monitoring and devise effective vector control strategies in the targeted areas. There has been a growing interest in fine tuning the pretrained deep convolutional neural network models for the vision based identification of insect genera, species and gender. Transfer learning is a technique commonly applied to adapt a pre-trained model for a specific task on a different dataset especially when the new dataset has limited number of training images. In this research work, we investigate the capability of deep transfer learning to solve the multi-class classification problem of mosquito species identification. We train the pretrained deep convolutional neural networks in two transfer learning approaches: (i) Feature Extraction and (ii) Fine-tuning. Three state-of-the-art pretrained models including VGG-16, ResNet-50 and GoogLeNet were trained on a dataset of mobile captured images of three vector mosquito species: Aedes Aegypti , Anopheles Stephensi and Culex Quinquefasciatus. The results of the experiments show that GoogLeNet outperformed the other two models by achieving classification accuracy of 92.5% in feature extraction transfer learning and 96% with fine-tuning. Also, it was observed that fine-tuning the pretrained models improved the classification accuracy.

Keywords: computer vision, convolutional neural network, mosquito classification, deep transfer learning, vector control.

INTRODUCTION

According to the World Health Organization statistics, vector-borne diseases result in over one billion infections and one million deaths annually. Mosquito-borne diseases (MBD) represent a primary public health concern in tropical and subtropical nations among them. Certain species of mosquitoes are vectors of pathogens responsible for spreading life threatening diseases such as Dengue, Malaria, Yellow fever, West Nile virus, Chikungunya and Zika virus. The harmful mosquito species are found in the genera Aedes, Anopheles and Culex (WHO, 2000). Table 1 lists some of the vector mosquito genera and the diseases transmitted by them. The preventive measures for MBDs are mainly based on vector control as no effective vaccine is available to date (Benelli et al., 2016). Vector surveillance and vector control interventions are taken up by the local government and public health officials to study and control mosquito population. Vector surveillance is aimed to evaluate mosquito population distribution, density and species distribution models (SDMs) – also known as ecological niche models (i.e., species prevalent in a geographic area) Vector control strategies are implemented to contract the population of vector mosquito species and prevent the spread of MBDs (Barker & MacIsaac, 2022; Fournet et al., 2018; Wilson et al., 2020)

The commonly employed vector control methods include: Environmental hygiene, Larviciding , Biological control, Chemical control through mosquito insecticides, sprays and toxic lures and individual protection (National Center for Vector Borne Diseases Control, 2023). In

Table 1. Mosquito-borne diseases

Vector	Diseases caused
Aedes	Chikungunya Dengue Lymphatic filariasis Rift Valley fever Yellow Fever Zika
Anopheles	Lymphatic filariasis Malaria
Culex	Japanese encephalitis Lymphatic filariasis West Nile fever

spite of the developments in these approaches MBDs continue to grow. Laying mosquito traps is an effective targeted and ecofriendly alternate to the above methods. The specimens collected from these traps can provide information essential for targeted vector control interventions such as: changes in mosquito populations, species abundant in a geographical area etc. The current method involves examining the trapped specimens under microscope in laboratory by skilled taxonomists for genera, species or gender identification based on the morphological features. The process is manual and time intensive and requires significant domain expertise (Goodwin et al., 2020; Sasmita et al., 2021). Also there is a scarcity of skilled taxonomists. For these reasons, it is important to automate the task of mosquito species classification. In recent years, several Machine learning (ML) and Deep learning (DL) approaches have been developed for the rapid and precise species identification using features unique to mosquito species such as wing beat frequency, morphology of wings and whole body. Among these, computer vision techniques coupled with deep convolutional neural networks (DCNNs) have demonstrated expert-level classification accuracy in insect classification tasks. Automated mosquito identification models can be deployed to detect the species prevalent in a geographic region. The vector control efforts can be tailored to the particular region and species present, which can increase their effectiveness. In general, automated taxonomic identification is valuable not only to mosquitoes but also for insects in general as it is beneficial in many contexts such as harmful vector control, biodiversity monitoring, sorting and detecting biological specimens and preventing epidemic outbreaks. In the past decade there have been several research studies aimed to automate the task of insect genus/ species / gender classification. The review mainly focuses on the application of ML and DL approaches. In these studies, the models are built to predict the mosquito genus, species and gender based on the acoustic features: (wing beat frequency) or the morphological features extracted from body parts (wings) or whole insect body (Martineau et al., 2017; Siddiqui & Kayte, 2022).

Acoustic approaches

The wing beats generated by mosquitos are unique to each species. Therefore the acoustic signal generated by their wing beats can serve as a reliable feature for discerning the species of mosquitoes. The acoustic studies for species classification are based on the audio signal recording and spectrum analysis of mosquito wing beat waveforms. The audio signal produced by the mosquito flight is recorded using optical sensors and smart phone microphone The features derived from the audio waveforms are used to train a ML or DCNN classifier for genera, species and gender identification (Chen et al., 2014; Fernandes et al., 2021; Ouyang et al., 2015; Silva et al., 2013). Identifying species through this method poses challenges as there can be overlapping frequencies and filtering the ambient noise is extensively difficult (Spitzen & Takken, 2018).

Vision based approaches

Vision based automatic classification of mosquitoes has been studied by many researchers due to the developments in image processing and machine learning techniques. These approaches involve training a ML or DL model on images dataset to predict the genera, species and gender. The algorithms examine the distinctive morphological features of mosquitoes and classify them accurately.

There have been studies for genera / species identification based on the shape and size of body parts. Important among these is the wing geometric morphometrics (geometry of wing venations, structure, shape and size of wings) (de Souza et al., 2020; Virginio et al., 2021; Wilke et al., 2016). However there are several difficulties in image acquisition process with this approach such as:

- Requirement of special laboratory setting to carry out the removal of body parts and take photographs for inspection.
- Tedious to capture images in a constrained / controlled position and

- Wings and other body parts can be damaged or deformed during the process.

Due to these challenges there are limited numbers of datasets available and the datasets have less number of images per species.

Classification based on the whole body

There have been image based ML initiatives to automatically classify insects like flies and bees, grasshoppers, beetles mosquitoes butterflies and crop insects (Martineau et al., 2017). These techniques involve extracting the hand-crafted features that are specific to a genus or species from the images data set and then training a ML classifier to predict the class of new data based on the predefined features. This approach involves identifying and selecting specific features of an image that are believed to be relevant for classification. The important features considered are: a) global properties such as: color histogram, texture and shape features (e.g., area, perimeter, eccentricity, major and minor axis length, circularity, solidity, compactness), wavelet coding b) local features (Histogram of Oriented Gradients (HOG) and Scale Invariant Feature Transforms (SIFT). The training algorithms used were mainly K-Nearest Neighbor (KNN), Naïve Bayes(NB), Kmeans and also Support Vector Machine (SVM) (Joshi & Miller, 2021; Kasinathan et al., 2021).

A SVM based binary classification model was proposed to identify Aedes aegypti mosquito from other species such as Aedes albopictus and Culex with an accuracy of 92.5% (De Los Reyes et al., 2016). The prior work by Minakshi (2018) attempted to classify mosquito images belonging to seven different species with an accuracy of 83.3% on a dataset of 60 smart-phone images by applying Random Forests (RF) algorithm. In a later study, they designed a system with unsupervised clustering and SVM algorithm for the classification of nine mosquito species. The authors constructed an images dataset of adult female mosquitoes belonging to nine species and extracted local textures, local binary patterns and spatial dependencies among textures (Haralick features) for training the classifier. The images were captured by Samsung Galaxy phone and background segmentation was applied. The system was able to achieve an overall accuracy of 77.5% for all nine species (Minakshi et al., 2018). In another study, a SVM based model was developed to identify mosquitoes from bees and flies using SIFT feature extraction with 85.2% accuracy (Fuchida et al., 2017). Mosquito images were classified at the genera level using images dataset of Aedes and Culex mosquitoes (*Image Dataset of Aedes and Culex Mosquito Species, IEEE DataPort*, n.d.; Rustam et al., 2022). They introduced a novel feature extraction technique RIFS by combining region of interest (ROI) based image filtering and forward features selection (FFS) technique. The highest accuracy obtained was 99.2% with Extra tree classifier (ETC) followed by 98.4% with RF algorithm.

Though ML algorithms have been used successfully for the vision based classification, there are certain limitations in applying them for the classification of small insects like mosquitoes. ML approaches demand manual feature extraction. The effectiveness of these models depends on the features extracted. The features used to train the model must be distinctive enough to discern between different species. Designing effective and relevant feature extractors from mosquito images requires significant domain expertise (Valan et al., 2019; Xia et al., 2018).

In recent years, deep learning methods, particularly convolutional neural networks (CNNs), have demonstrated exceptional performance in computer vision related tasks as compared to ML techniques. A deep neural network can learn complex feature representations from the input data automatically. The DCNNs learn in an end-to-end manner, starting from raw images to target class. This alleviates the necessity for manual design of feature extractors. However, training a deep learning model is time-consuming and requires sufficiently large amount of training data. Therefore, transfer learning is commonly used to overcome this problem. It involves leveraging the feature representations learned by a pretrained CNN model to train a new model on a smaller dataset (Pise et al., 2022; Xia et al., 2018)

The research by (Motta et al., 2019) leveraged three pre trained CNNs (LeNet, GoogleNet, and AlexNet) to identify three mosquito species: Aedes aegypti, Aedes albopictus and Culex quinquefasciatus. The dataset included images from ImageNet database and pictures of mosquitoes shot with camera in a lab setting. The GoogleNet attained maximum test accuracy of 76.2%. Okayasu (2019) compared the efficiency of SVM algorithm based on handcrafted features and ResNet CNN in order to discern the images of 3 mosquito species i.e., Aedes albopictus, Anopheles stefensi, and Culex pipiens pallens. They obtained an accuracy of 82.4% with ML and 95.5% with ResNet on an augmented dataset.

A transfer learning model based on Inception-ResNet V2 architecture achieved an accuracy of 80% in classifying mosquitoes images of 9 species from Aedes, Anopheles and Culex genera. The DCNN was trained on a database of 25,867 augmented pictures of 250 mosquito samples captured with different mobile cameras (Minakshi et al., 2020). A study based on fine-tuned transfer learning with three DCNNs (VGG-16, ResNet-50, SqueezeNet) and data augmentation was conducted to classify eight species of adult female mosquitoes using a database of 3,600 images taken in laboratory settings. VGG-16 exhibited the highest average test classification accuracy of 97.19% (Park et al., 2020).

A feature extraction based transfer learning approach was proposed to classify Aedes and Culex mosquito images at the genera level with 92.5% accuracy by transfer learning the GoogLeNet model (Pise et al. 2022). However, they did not include identification at the species level. The review unveils that most of the previous vision based studies included dataset of camera captured images of female mosquitoes.

The proposed study aims to classify the species based on the mobile captured images of both male and female mosquitoes in a transfer learning paradigm. The key contributions of our study are:

1) A dataset of mobile captured images of mosquitoes belonging to three species: *Aedes aegypti*, *Anopheles stephensi* and *Culex quinquefasciatus*.
2) Investigate the capability of transfer learning with pretrained DCNNs for the multi-class classification problem to classify the images in our dataset into correct species.
3) Evaluate the performance of two transfer learning approaches: (a) feature extraction transfer learning, (b) fine-tune transfer learning by unfreezing the layers of the base model.

PROPOSED METHODOLOGY

Visual transfer learning technique

Deep learning techniques have facilitated to solve complex computer vision problems such as object recognition and image classification with excellent results. However in practice, training a CNN to achieve good performance requires huge training data and a long training time. Training a DCNN on a small dataset leads to the phenomenon of "over fitting". Transfer learning is a technique commonly applied to address these limitations in deep learning. It aims to apply the knowledge extracted from a source task to solve a similar new task. A framework for transfer learning is defined in terms of domain, task and probabilities (Pan & Yang, 2010; Weiss et al., 2016).

A domain D is defined as a 2-element tuple:

$$D = \{X, P(X)\} \tag{1}$$

where: X – feature space, $P(X)$ – marginal probability distribution where:

$$X = \{x_1, x_2, x_3,.. x_n\}, x_i \in X \tag{2}$$

A task T is defined as a two element tuple in the domain D:

$$T = \{Y, f(.)\}$$

where: Y – a label space and $f(.)$ – a predictive function that can be learned from the training samples (i.e. feature vector, label) pairs $\{(x_i, y_i) \mid \mathrm{i} \in \{1, 2, 3, \ldots, N\}\}$, where $x_i \in X$ and $y_i \in Y$.

From a probabilistic viewpoint, for each feature vector x_i in the domain D, f ($\mathrm{x_i}$) calculates its corresponding label.

$$f(x_i) = p(\mathrm{y_i} \mid \mathrm{x_i}) \tag{3}$$

Task T can be represented as:

$$T = \{X, P(Y \mid X)\} \tag{4}$$

Given a source domain D_s and a corresponding learning task T_s, a target domain D_t and learning task T_t, transfer learning is a technique that aims to refine the learning of conditional probability distribution $P(Y_t \mid X_t)$ in D_t by utilizing the information gained from D_s and T_s, where $D_t \neq D_s$ or $T_t \neq T_s$. There can be multiple source domains.

In visual transfer learning paradigm, feature representations learned by the CNN on a very large dataset (source domain) task can be repurposed by a new CNN for a new related task on a different dataset. There are many state-of-the-art deep learning models developed for computer vision and natural language processing (NLP) problems. These CNNs are trained on a huge generic dataset (e.g., ImageNet, which consists of 1.2 million images across 1000 classes) for a large scale image-classification task (*ImageNet*, n.d.). The performance of these networks is better than human experts. In deep transfer learning, a pretrained network is reused as a fixed feature extractor for a different problem with small changes. The target network is trained on a new dataset D_t for a similar task T_t. The advantage is that the new network is trained without having to start from scratch. It speeds up the process of training a new CNN and solves the problem of small size dataset in the target domain. Also it is demonstrated that generalization capability of transfer learned models is superior (Krizhevsky et al., 2017).

Data collection

A key challenge in training a deep learning model is the availability of a sufficiently large quality dataset for accurate results. To this end, the authors prepared a dataset consisting of images of adult mosquitoes of both genders belonging to three species: *Aedes aegypti*, *Anopheles stephensi* and *Culex quinquefasciatus*. The mosquito samples were collected from the mosquito colony maintained by Ross Life lab, India. The specimens were imaged using a handheld One Plus mobile RGB camera of 48 Mpx under day light conditions. The photographs were shot at various directions to capture morphological features unique to each of the species. The description of the dataset and a sample image of each of the species from the dataset are presented in Table 2. We performed a series of data augmentation to the original images to expand the size of the dataset and to address the inadequate number of samples available. The original pictures were resized to 256×256 pixels and image augmentation transformations: random rotations, zooms, shifts, shears, flips, and Gaussian blur etc. were applied to all the resized original images. As a result of this we obtained 2640 images (Pise et al., 2022).

The dataset was split randomly into 70–20% partitions for model training and validation. Remaining 10% portion of the data was set aside for testing. A 5-fold cross validation technique was employed to train the models and the validation dataset was used to check the progress of training.

Experimental design

The objective of this study was to leverage transfer learning for the classification of vector mosquito species having morphological resemblance. To this end, we investigated pre-trained DCNN models in two transfer learning approaches: Feature extraction and Fine-tuning. We imported three pretrained DCNN models: VGG-16, ResNet-50 and GoogLeNet. In order to train and test our models, we employed Keras, an open-source Python 3.7 library, along with the Tensorflow 2.1.0 deep learning framework, and executed on an Nvidia GTX 1050 GPU platform.

As shown in Figure 1, a DCNN consists of a series of convolution (Conv.) layers followed by dense layers i.e., Fully Connected (FC) layers. The Conv. layers learn different features of the input images in consecutive iterations of back propagation algorithm. The initial layers capture generic features, while the higher layers learn features relevant to the specific task. The FC layers predict the image class based on the feature maps extracted in the preceding layers. We can leverage the knowledge gained by a DCNN, from a large dataset and adapt it to a new task.

Hyper parameter configuration

Prior to training a CNN, we need to define and optimize several key parameters to attain better classification accuracy. The parameters were finalized by iteratively training the networks and analyzing statistically to find the optimal value.

Table 2. Dataset description

Species	Number of images	Sample Image
Aedes aegypti	900	
Anopheles stephensi	540	
Culex guinquefasciatus	1208	

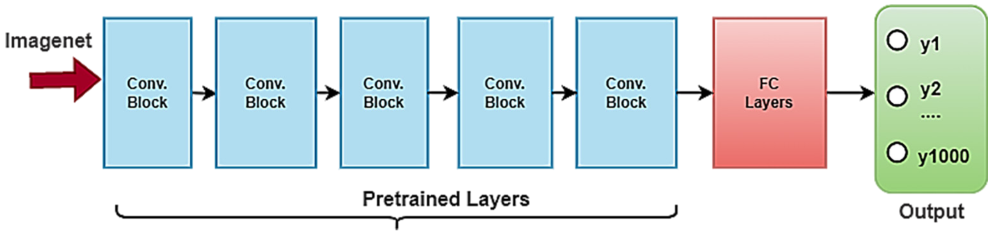

Figure 1. Pretrained DCNN model

Training Algorithm: Adam (Adaptive Moment Estimation) optimizer is the default choice to train most of the deep learning applications. Networks trained using this algorithm reveal faster training times and require tuning of fewer parameters in order to decrease the loss function. All the three models were trained in a 5-fold cross validation approach using ADAM optimizer algorithm with the parameters β1 and β2 set to 0.9 and 0.999 respectively.

Loss Function: In terms of ML, the problem being solved is a multi-class classification task and cross-entropy is the preferred loss function for multiclass classification. The function minimizes the error i.e., the average difference between the actual and predicted probability distributions for all the target classes. We have chosen 'categorical cross – entropy' function from Keras library to train the models.

Learning Rate: The learning rates were initialized ranging from 3×10^{-5} to 5×10^{-3} for different models. The training was performed for 50 epochs.

Feature extraction transfer learning

This is the most commonly used method for implementing deep transfer learning. The pre trained model is utilized to extract the features from the images of new dataset as it has previously learnt feature maps on a large generic dataset. To implement this, the convolutional layers of the pre trained CNNs were freezed, with their 'imagenet' weights by setting models' trainable attribute to false. That is the weights of these layers are prevented from being updated during training process. The last FC layer of the pretrained models was replaced with a new FC layer and initialized with random weights. Then the networks were trained with our dataset to update the weights of the new FC layers and predict the three new class labels i.e., mosquito species (Fig. 2).

Fine-tuned transfer learning

The second group of experiments was carried out to test the impact of fine- tuning the models converged in the first experiment. It is observed that fine- tuning the pretrained models by unfreezing all or last few layers of the network can improve the performance further (Fig. 3).

In the proposed work, weights of all the layers of the models trained in the first experiment were rendered trainable (unfrozen) by setting the trainable attribute to true. Then the entire model is recompiled and retrained end-to-end with a very small learning rate 0.00001. This permits the models to incrementally update higher-order feature maps that are more specific to the new dataset.

RESULTS AND DISCUSSION

The three pretrained DCNNs were trained in two transfer learning approaches with the settings specified for 50 epochs. The performance of the models was assessed in terms of classification

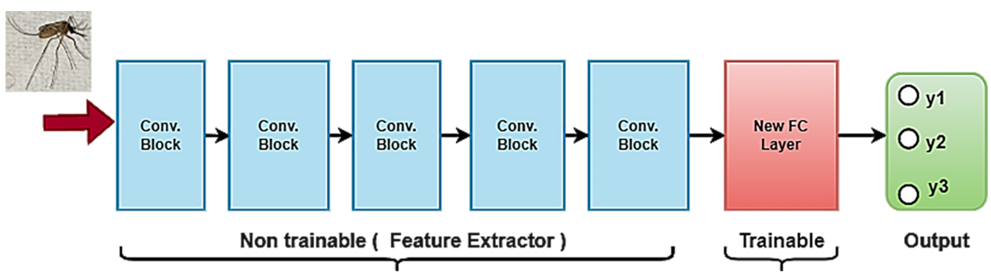

Figure 2. Feature extraction transfer learning

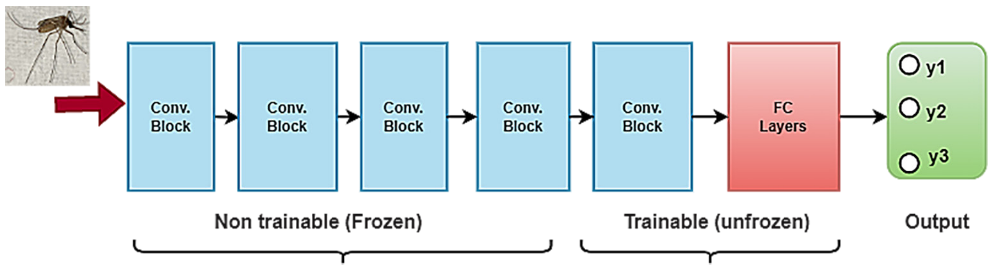

Figure 3. Fine-tuned transfer learning

accuracy and loss. Accuracy is computed as the fraction of predicted class labels that precisely match the actual class labels. The loss function gives a measure of the error made by the model. The validation accuracy and validation loss after each epoch is visualized for both experimental setups as plotted in Figure 4 and Figure 5. The validation accuracy of all the models got stabilized after 30 epochs and attained an optimal value within 50 epochs. It can be observed from the graphs that all the models exhibited remarkably higher validation accuracy when they were fine-tuned by unfreezing the layers. GoogLenet model outperformed the other two models with the highest validation accuracy of 96.2% in feature extraction and 98.5% in fine-tuned transfer learning. The performance of the models was evaluated on the test dataset which included the images that were not used for

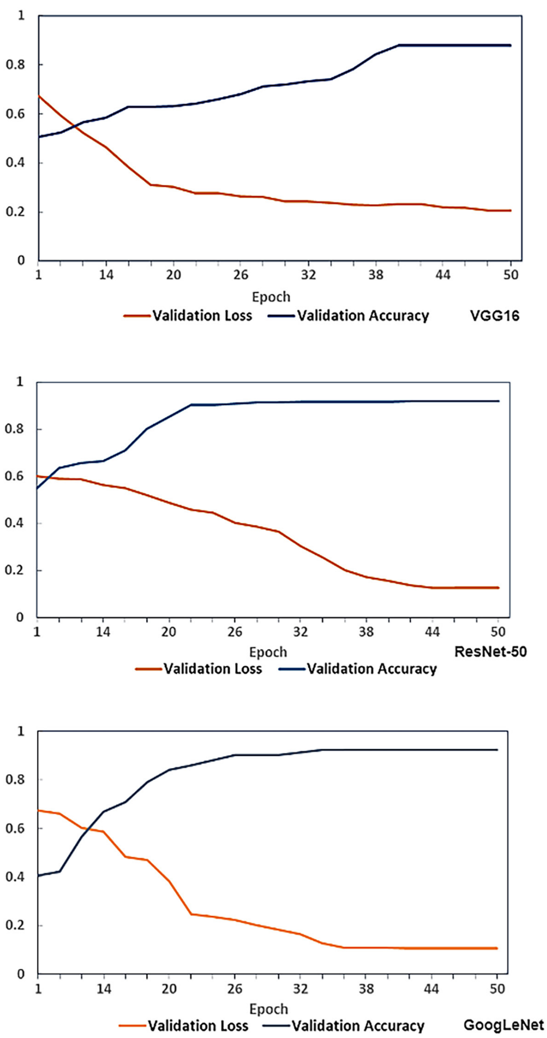

Figure 4. Validation accuracy and validation loss in feature extraction transfer learning

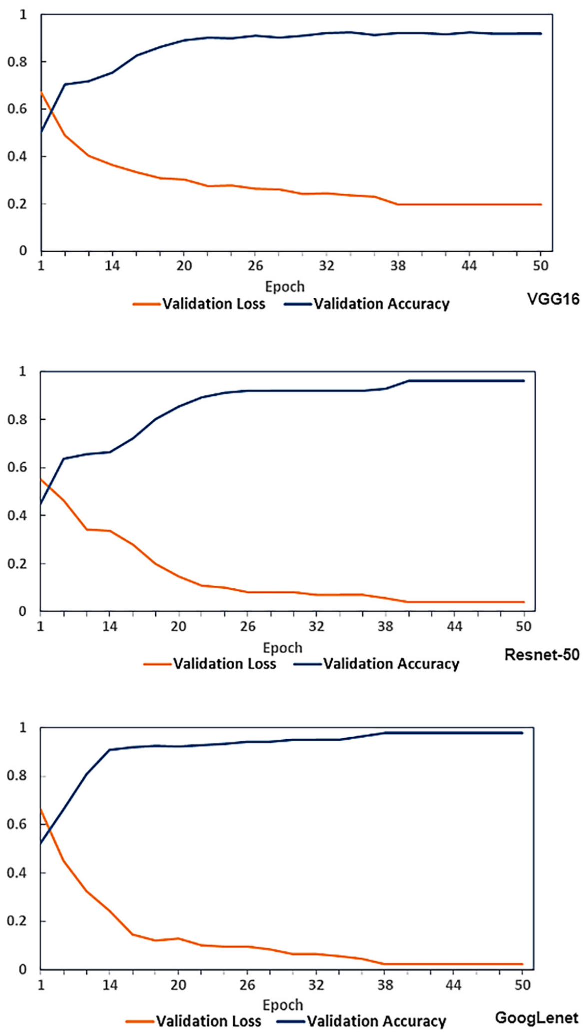

Figure 5. Validation accuracy and validation loss in fine-tuned transfer learning

Table 3. Test accuracies of the models

Model	Feature extraction, %	Fine-tuning, %
VGG-16	86	93
ResNet-50	88	92
GoogLeNet	92.5	96

model training or validation. Table 3 presents the test accuracies of the models in the two experimental settings. It can be seen that fine-tuning resulted in higher classification accuracy than feature extraction transfer learning regardless of the model. Google net turned out be the best classification model in both transfer learning approaches.

CONCLUSION

The study demonstrates the capability of visual transfer learning with pretrained CNNs to accurately classify three vector mosquito species. The results reveal that fine tuning with unfreezing layers of the base models improved the classification accuracy as compared to the feature extraction transfer learning. There is a prospective utility of deploying such automated models on a device or mosquito trap to track the harmful species circulating in geographic areas. Such findings can be used by public health agencies for targeted and effective vector control interventions. This could alleviate the prevalence of mosquito-borne diseases. The technique could potentially replace the manual time intensive task of taxonomic identification of mosquitoes.

REFERENCES

1. Barker, J.R., & MacIsaac, H.J. (2022). Species distribution models applied to mosquitoes: Use, quality assessment, and recommendations for best practice. Ecological Modelling, 472(June), 110073. https://doi.org/10.1016/j.ecolmodel.2022.110073
2. Benelli, G., Jeffries, C.L., & Walker, T. (2016). Biological control of mosquito vectors: Past, present, and future. Insects, 7(4), 1–18. https://doi.org/10.3390/insects7040052
3. Chen, Y., Why, A., Batista, G., Mafra-Neto, A., & Keogh, E. (2014). Flying insect detection and classification with inexpensive sensors. Journal of Visualized Experiments, 92, 1–9. https://doi.org/10.3791/52111
4. De Los Reyes, A.M.M., Reyes, A.C.A., Torres, J.L., Padilla, D.A., & Villaverde, J. (2016). Detection of Aedes Aegypti mosquito by digital image processing techniques and support vector machine. 2016 IEEE Region 10 Conference (TENCON), 2342–2345. https://doi.org/10.1109/TENCON.2016.7848448
5. de Souza, A.L. da S., Multini, L.C., Marrelli, M.T., & Wilke, A.B.B. (2020). Wing geometric morphometrics for identification of mosquito species (Diptera: Culicidae) of neglected epidemiological importance. Acta Tropica, 211(June), 105593. https://doi.org/10.1016/j.actatropica.2020.105593
6. National Center for Vector Borne Diseases Control (2023). Retrieved June 3, 2023, from https://ncvbdc.mohfw.gov.in/index1.php?lang=1&level=1&sublinkid=5776&lid=3690
7. Fernandes, M.S., Cordeiro, W., & Recamonde-Mendoza, M. (2021). Detecting Aedes aegypti mosquitoes through audio classification with convolutional neural networks. Computers in Biology and Medicine, 129(November 2020), 104152. https://doi.org/10.1016/j.compbiomed.2020.104152
8. Fournet, F., Jourdain, F., Bonnet, E., Degroote, S., & Ridde, V. (2018). Effective surveillance systems for vector-borne diseases in urban settings and translation of the data into action: A scoping review Frédéric Simard. Infectious Diseases of Poverty, 7(1), 1–14. https://doi.org/10.1186/s40249-018-0473-9
9. Fuchida, M., Pathmakumar, T., Mohan, R.E., Tan, N., & Nakamura, A. (2017). Vision-based perception and classification of mosquitoes using support vector machine. Applied Sciences (Switzerland), 7(1). https://doi.org/10.3390/app7010051
10. Goodwin, A., Glancey, M., Ford, T., Scavo, L., Brey, J., Heier, C., Durr, N.J., & Acharya, S. (2020). Development of a low-cost imaging system for remote mosquito surveillance. Biomedical Optics Express, 11(5), 2560. https://doi.org/10.1364/boe.382391
11. Image Dataset of Aedes and Culex Mosquito Species | IEEE DataPort. (n.d.). Retrieved June 3, 2023, from https://ieee-dataport.org/open-access/image-dataset-aedes-and-culex-mosquito-species
12. ImageNet. (n.d.). Retrieved June 3, 2023, from https://www.image-net.org/challenges/LSVRC/
13. Joshi, A., & Miller, C. (2021). Review of machine learning techniques for mosquito control in urban environments. Ecological Informatics, 61. https://doi.org/10.1016/j.ecoinf.2021.101241
14. Kasinathan, T., Singaraju, D., & Uyyala, S.R. (2021). Insect classification and detection in field crops using modern machine learning techniques. Information Processing in Agriculture, 8(3), 446–457. https://doi.org/10.1016/j.inpa.2020.09.006
15. Krizhevsky, A., Sutskever, I., & Hinton, G.E. (2017). ImageNet classification with deep convolutional neural networks. Communications of the ACM, 60(6), 84–90. https://doi.org/10.1145/3065386
16. Martineau, M., Conte, D., Raveaux, R., Arnault, I., Munier, D., Venturini, G., Martineau, M., Conte, D., Raveaux, R., Arnault, I., & Munier, D. (2017). A survey on image-based insect classification To cite

this version : HAL Id : hal-01441203.

17. Minakshi, M. (2018a). A Machine Learning Framework to Classify Mosquito Species from Smartphone Images.
18. Minakshi, M., Bharti, P., & Chellappan, S. (2018b). Leveraging smart-phone cameras and image processing techniques to classify mosquito species. ACM International Conference Proceeding Series, 77–86. https://doi.org/10.1145/3286978.3286998
19. Minakshi, M., Bharti, P., McClinton, W.B., Mirzakhalov, J., Carney, R.M., & Chellappan, S. (2020). Automating the Surveillance of Mosquito Vectors from Trapped Specimens Using Computer Vision Techniques. COMPASS 2020 - Proceedings of the 2020 3rd ACM SIGCAS Conference on Computing and Sustainable Societies, 105–115. https://doi.org/10.1145/3378393.3402260
20. Motta, D., Santos, A.Á.B., Winkler, I., Machado, B.A.S., Pereira, D.A.D.I., Cavalcanti, A.M., Fonseca, E.O.L., Kirchner, F., & Badaró, R. (2019). Application of convolutional neural networks for classification of adult mosquitoes in the field. PLoS ONE, 14(1), 1–18. https://doi.org/10.1371/journal.pone.0210829
21. Okayasu, K., Yoshida, K., Fuchida, M., & Nakamura, A. (2019). Vision-based classification of mosquito species: Comparison of conventional and deep learning methods. Applied Sciences (Switzerland), 9(18). https://doi.org/10.3390/app9183935
22. Ouyang, T.H., Yang, E.C., Jiang, J.A., & Lin, T.Te. (2015). Mosquito vector monitoring system based on optical wingbeat classification. Computers and Electronics in Agriculture, 118, 47–55. https://doi.org/10.1016/J.COMPAG.2015.08.021
23. Pan, S.J., & Yang, Q. (2010). A survey on transfer learning. IEEE Transactions on Knowledge and Data Engineering, 22(10), 1345–1359. https://doi.org/10.1109/TKDE.2009.191
24. Park, J., Kim, D.I., Choi, B., Kang, W., & Kwon, H.W. (2020). Classification and Morphological Analysis of Vector Mosquitoes using Deep Convolutional Neural Networks. Scientific Reports, 10(1), 1–12. https://doi.org/10.1038/s41598-020-57875-1
25. Pise, R., Patil, K., Laad, M., & Pise, N. (2022a). Dataset of vector mosquito images. Data in Brief, 45, 108573. https://doi.org/10.1016/j.dib.2022.108573
26. Pise, R., Patil, K., & Pise, N. (2022b). Automatic Classification of Mosquito Genera Using Transfer Learning. Journal of Theoretical and Applied Information Technology, 100(7), 1929–1940.
27. Rustam, F., Reshi, A.A., Aljedaani, W., Alhossan, A., Ishaq, A., Shafi, S., Lee, E., Alrabiah, Z., Alsuwailem, H., Ahmad, A., & Rupapara, V. (2022). Vector mosquito image classification using novel RIFS feature selection and machine learning models for disease epidemiology. Saudi Journal of Biological Sciences, 29(1), 583–594. https://doi.org/10.1016/j.sjbs.2021.09.021
28. Sasmita, H.I., Neoh, K.B., Yusmalinar, S., Anggraeni, T., Chang, N.T., Bong, L.J., Putra, R.E., Sebayang, A., Silalahi, C.N., Ahmad, I., & Tu, W.C. (2021). Ovitrap surveillance of dengue vector mosquitoes in bandung city, west java province, Indonesia. PLoS Neglected Tropical Diseases, 15(10), 1–18. https://doi.org/10.1371/journal.pntd.0009896
29. Siddiqui, A.A.I., & Kayte, D.C. (2022). Mosquito tracking, classification, and identification: A glance at the technologies available. International Journal of Mosquito Research, 9(2), 104–110. https://doi.org/10.22271/23487941.2022.v9.i2b.606
30. Silva, D.F., De Souza, V.M.A., Batista, G.E.A.P.A., Keogh, E., & Ellis, D.P.W. (2013). 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, 1, 99–104. https://doi.org/10.1109/ICMLA.2013.24
31. Spitzen, J., & Takken, W. (2018). Keeping track of mosquitoes: a review of tools to track, record and analyse mosquito flight. Parasites & Vectors 2018 11:1, 11(1), 1–11. https://doi.org/10.1186/S13071-018-2735-6
32. Valan, M., Makonyi, K., Maki, A., Vondráček, D., & Ronquist, F. (2019). Automated Taxonomic Identification of Insects with Expert-Level Accuracy Using Effective Feature Transfer from Convolutional Networks. Systematic Biology, 68(6), 876–895. https://doi.org/10.1093/sysbio/syz014
33. WHO (2000). Vector-borne diseases. Retrieved June 3, 2023, from https://www.who.int/news-room/fact-sheets/detail/vector-borne-diseases
34. Virginio, F., Domingues, V., da Silva, L. C.G., Andrade, L., Braghetto, K.R., & Suesdek, L. (2021). WingBank: A Wing Image Database of Mosquitoes. Frontiers in Ecology and Evolution, 9(April), 1–15. https://doi.org/10.3389/fevo.2021.660941
35. Weiss, K., Khoshgoftaar, T.M., & Wang, D.D. (2016). A survey of transfer learning. In Journal of Big Data (Vol. 3, Issue 1). Springer International Publishing. https://doi.org/10.1186/s40537-016-0043-6
36. Wilke, A.B.B., De Oliveira Christe, R., Multini, L.C., Vidal, P.O., Wilk-Da-silva, R., De Carvalho, G.C., & Marrelli, M.T. (2016). Morphometric wing characters as a tool for mosquito identification. PLoS ONE, 11(8), 1–12. https://doi.org/10.1371/journal.pone.0161643
37. Wilson, A.L., Courtenay, O., Kelly-Hope, L.A., Scott, T.W., Takken, W., Torr, S.J., & Lindsay, S.W. (2020). The importance of vector control for the control and elimination of vector-borne diseases. In PLoS Neglected Tropical Diseases (Vol. 14, Issue 1). https://doi.org/10.1371/journal.pntd.0007831
38. Xia, D., Chen, P., Wang, B., Zhang, J., & Xie, C. (2018). Insect detection and classification based on an improved convolutional neural network. Sensors (Switzerland), 18(12), 1–12. https://doi.org/10.3390/s18124169