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Conceptual

Machine-Learning Identification of Mosquito Species From Images of Adult Mosquitoes and Larvae

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ABSTRACT

This research aims to develop a web-based application for the identification of mosquito species using image data of adult mosquitoes and larvae. Mosquitoes are known carriers of various diseases and their accurate identification is crucial for effective control and prevention strategies. The system utilizes a dataset of adult mosquitoes and larvae, consisting of various species and their corresponding features such as morphological characteristics extracted from image datasets. The results demonstrate the effectiveness of machine learning algorithms in accurately identifying mosquito species based on adult mosquitoes and larvae data. The mosquito identification module will be based on machine learning and image processing techniques. The system shows promising potential in providing rapid and reliable mosquito species identification, which can aid in the surveillance and control of mosquito-borne diseases. The proposed system offers a valuable tool for entomologists, public health officials, and researchers working on mosquito control and disease prevention, ultimately contributing to improved strategies for combating mosquito-borne diseases. The adult mosquito identification model achieved a test accuracy of 83.55% and the larvae genera identification model achieved a test accuracy of 87.30%. But the prototype validation, according to the user-supplied images, produced accuracies of 69.57% and 60.47.%, highlighting the challenges in real-world deployment. The findings show the potential of machine learning based image analysis to support mosquito surveillance and public-health monitoring tasks.

Keywords: Mosquito Identification, Machine Learning, Image Processing, Mosquito Species, Web Based Applications

INTRODUCTION

Mosquitoes are a major threat to human health, transmitting gravely dangerous diseases such as Dengue, Malaria, Chikungunya, Yellow Fever, Zika virus, West Nile virus, etc. Any disease that is spread from mosquito to human or animal is known as a “mosquito-borne disease”. According to the statistics, approximately 390 million people are infected each year with dengue and hundreds of thousands more are affected by Zika, Chikungunya, and Yellow Fever (WMD, 2026b). There are more than 3000 species of mosquitoes in the world and the most common, and most dangerous, are the various species in the Culex, Anopheles, and Aedes genera (WMD, 2026a). Mosquitos are vector of various diseases and their identification in crucial in controlling and preventing the spread of such diseases including Malaria, Dengue, and Zika virus. They are small, flying insects that that belong to the family Culicidae and have a complex life cycle, consisting of four stages such as egg, larva, pupa, and adult. The larvae of mosquitoes are aquatic and are found in a variety of water sources, including stagnant pools, ponds, and even containers such as discarded tires or flower pots. Adult mosquitoes feed on nectar from flowers, while the female mosquitoes require a blood meal to produce eggs. Vector-borne diseases account for more than 17% of all infectious diseases, causing more than 700,000 deaths annually. They can be caused by either parasites, bacteria or viruses. Dengue is the most prevalent viral infection transmitted by Aedes mosquitoes. More than 3.9 billion people in over 129 countries are at risk of contracting dengue, with an estimated 96 million symptomatic cases and an estimated 40,000 deaths every year. Malaria is a parasitic infection transmitted by Anopheline mosquitoes. It causes an estimated 219 million cases globally, and results in more than 400,000 deaths every year. Most of the deaths occur in children under the age of 5 years (WMD, 2026d). In Sri Lanka, dengue is an increasing health concern, along with other mosquito-borne diseases such as Zika and Chikungunya. The World Health Organization reported that in 2017, Dengue cases were more than triple the average for the same period between 2010 and 2016, with 34,274 dengue cases in Colombo and 186,101 across Sri Lanka (WMD, 2026c).

One way to control the spread of these diseases is by identifying mosquito species in different areas and destroying their breeding places. Hence, this research project will investigate to development of a software system that can accurately identify mosquito species using images of adult mosquitoes and larvae. The research will use a primary data set which will be collected from Provincial Department Of Health Service North Central Province well as a validated secondary dataset which is obtained from the online resource (Ong, 2022; R. K. P. Pise et al., 2022) . It will process this data to identify Culex quinquefasciatus, Anopheles stephensi, Aedes aegypti, and Aedes albopictus species by using machine learning and image processing techniques and using a sufficient number of sample images of those species. To do this research, it is essential to know about the life cycle of a mosquito and its lifetimes. All types of mosquitoes have similar life cycles (Nazeer, 2026). A mosquito egg hatches into a larva. A larva becomes a pupa (Nazeer, 2026). An adult mosquito emerges from the pupa (CDC, 2026). Knowing the different stages of the mosquito's life will help prevent mosquitoes and also help to choose the right pesticides needed if one decides to use them (EPA, 2026). As adult female mosquitoes spread diseases, it is advantageous to identify them within the larva stage and make solutions to kill them.

Identifying mosquito species is crucial for effective mosquito control measures, as different species may have different breeding and feeding habits. Several methods can be used for mosquito identification, including using adult mosquitoes and larvae. Adult mosquitoes can be identified based on their morphology, which includes the size and shape of their wings, legs, antennae, and other body parts. Larvae of mosquitoes can be identified based on their morphology, which includes the shape and number of their body segments, as well as the presence or absence of various structures, such as siphons, hairs, and spines. This research proposes studying body shape, colour patterns, colour patches, wings, body parts, hairy or non-hairy, and other physical attributes to identify the distinguishing features of mentioned species and achieve the project aim. For example, the easiest larvae to identify by its genus is Anopheles since it has no siphon tube in its tail. The Culex Larvae and Aedes Larvae are a bit similar in their siphon, but if we observe closely, we can identify that the Aedes Larva has got a 'barrel-sized' short siphon, whereas Culex Larva has got much longer thin siphon and lighter color compared to with Aedes (De Silva & Jayalal, 2020).

In addition to the identification of mentioned species, the proposed system will provide some other information about relevant species, diseases that will spread from them, symptoms of those diseases, and health guidelines to prevent mosquito-borne diseases to fulfill our hope to save billions of lives that would otherwise be lost because of mosquito-borne diseases.

LITERATURE REVIEW

Mosquito Identification

The research by Minakshi et al presented explores using a smartphone application and machine learning to automate mosquito species identification. They utilized 60 images of seven species, optimizing with dimensionality reduction and noise removal. The system achieved over 83% accuracy for five species. Challenges include species similarity and execution complexity. Future plans involve expanding the database, employing deep learning, and creating a user-friendly smartphone app for both experts and citizens (Minakshi et al., 2017). Fuchida et al. (2017) propose an automated mosquito classification system using computer vision and SVM-based machine learning. The system employs a camera module and image processing algorithm for feature extraction, focusing on color, shape, and texture. With 400 images, SVM II achieves a 98% recall, while SVM III reaches 92%. Future plans include hardware development, online field trials, and exploring alternative learning approaches (Fuchida et al., 2017). Siddiqua et al. (2021) propose a novel method for detecting Aedes Aegypti mosquitoes carrying Dengue using Faster R-CNN and InceptionV2. This deep learning-based approach achieves high accuracy (97.68%) in mosquito detection. Challenges include limited online images and real-world applicability. Future work aims to apply the method in dynamic environments, detect other mosquito species, and use larger datasets.

The research by Mulchandani et al. (2019) focuses on mosquito species identification using wingbeat recordings. They employ Machine Learning and Computer Vision technologies, utilizing Multi-Layer CNN, ResNet, DenseNet, and XGBoost models. The dataset includes 279,566 wingbeat recordings from 6 mosquito species. Multi-Layer CNN achieves the highest accuracy (86%), demonstrating potential for cost-effective mosquito species detection systems (Mulchandani et al., 2019). The research by R. Pise et al. (2022) focuses on classifying Aedes and Culex mosquito genera using a Deep Convolutional Neural Network (DCNN) with transfer learning. They employ pretrained models, including VGGNet, ResNet, and GoogLeNet, on a constructed dataset. GoogLeNet demonstrates the highest accuracy (94.3%), addressing challenges of a small dataset through data augmentation and suggesting potential for transfer learning improvements in future work. Minakshi et al. (2018) propose a smartphone-based system for automated mosquito species classification using image processing, unsupervised clustering, and SVM-based machine learning. The system achieved a 77.5% overall accuracy in identifying nine mosquito species. Their approach involves steps like image resizing, noise removal, and background segmentation, demonstrating potential for citizen-driven mosquito monitoring, aiding public health efforts. This study highlighted the importance of accurate mosquito classification for vector disease prevention. Researchers proposed and AI-based mosquito species and gender identification system that combined image processing mechanisms with deep learning models to identify mosquito species and their gender. The results show that AI-based image analysis can effectively help mosquito identification attempts. Furthermore, this study strictly focus only on mosquitoes and not address prototyping validation (Wu et al., 2026). A comprehensive systematic review analyzed studies between 2000 and 2024 regarding image-based mosquito identification using machine learning mechanisms. Convolutional Neural Networks, and transfer learning models, and ways to overcome traditional approaches were found in the review. They also reported that most existing works focused on controlled datasets and laboratory environment with limited attention given to practical deployment in real-world conditions (Adebayo, 2025; Nazari et al., 2026).

Larvae Identification

Asmai et al. (2020) propose an Intelligent Mosquito Larvae Detection Mobile Application (iMOLAP) utilizing a Convolutional Neural Network (CNN), specifically the Inception V3 model. The app aims to detect and classify Aedes mosquito larvae, combating Dengue. Developed with TensorFlow, Firebase Database, and Android Studio, iMOLAP facilitates community reporting, tracks larvae locations on a map, and aids authorities in prompt dengue prevention actions (Asmai et al., 2020). The paper addresses the global health threat posed by Aedes-borne diseases and proposes a CNN method for efficient Aedes larvae identification. Utilizing the Alexnet architecture, the system achieves a promising average accuracy of 96.88% for Aedes classification, suggesting its potential for real-time implementation through mobile devices, improving vector control and reducing infection rates (Sanchez-Ortiz et al., 2017). The research proposes a ResNet50 CNN model to automatically identify Aedes mosquito larvae, addressing the spread of Dengue. Using digital amplification without microscope lenses, the model achieves 86.65% accuracy. Pre-processing techniques enhance accuracy to 98.76%. The application potential includes a mobile app for crowdsourcing and extends to identifying multiple larvae in a single image, aiding disease control efforts (De Silva & Jayalal, 2020) . The study addresses the challenge of manually annotating mosquito images for disease control. Vision Transformers (ViTs) and CNN models (ResNet-18, ConvNeXT) are compared for Aedes and Culex larvae classification. ConvNeXT outperforms others, likely due to combining transformer and CNN techniques. ViTs, less applied in mosquito-related tasks, show lower performance, potentially due to limited data. Future work includes developing a hybrid model for efficient mosquito larvae classification (Surya et al., 2022). Developed a machine-learning and augmented reality-based educational framework for mosquito and larval identification. This work focused on specifically on larval classification and incorporated with augmented reality to enhance learning experiences in health science education. This study shows that the machine-learning mechanisms can improve larval identification accuracy while providing an interactive environment for the users. The system basically aimed at educational applications and did not integrate adult mosquito identification or real-world implementation.(Kajornkasirat et al., 2026)

Literature Gap

The previous studies have reported high classification accuracies using Machine Learning and Deep Learning architectures for mosquito and larvae species identification and most studies focused on either adult mosquitoes or larvae and commonly implemented classification models. Limited works have been integrated both adult mosquito species identification and larvae genera identification within single framework. Few studies have evaluated their implemented model performance using controlled laboratory datasets while investigated systems performed under realistic user-generated images. Existing works basically highlighted classification accuracy and algorithm deployment with limited completion of web-based system accessible to non-experts. Therefore this research addresses these gaps by developing an integrated web-based platform capable of identifying both mosquito species and larval genera using machine learning models by evaluating prototype, performance and usability metrics.

PROPOSED APPROACH

Project Methodology

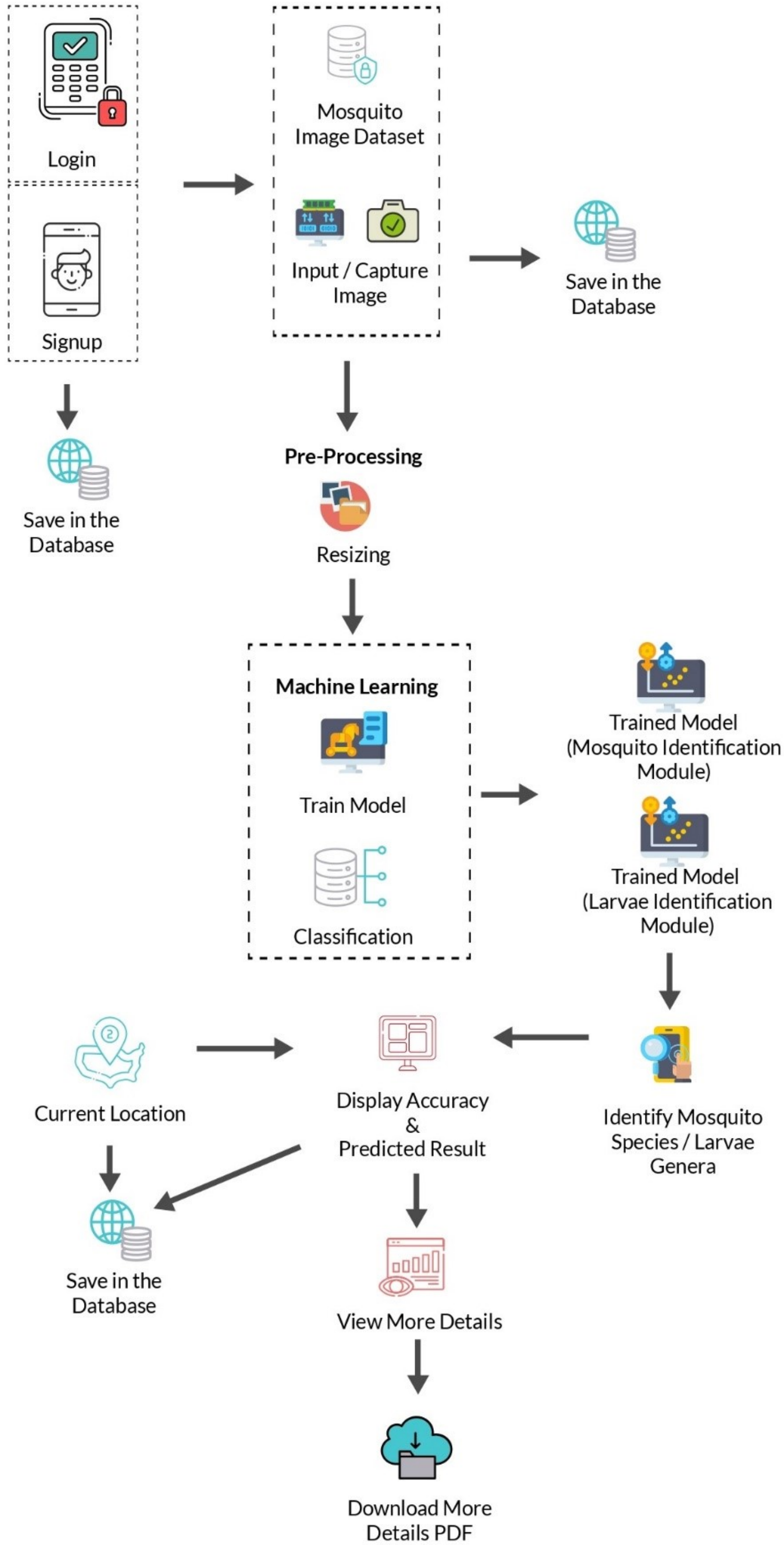
In the proposed research design, we discussed the process of mosquito species identification. On the home page of the web application, the user will be able login, signup, and access the user catalog and search history. In the middle of the home page it displays the images of the mosquito spreading preventions and details of the developers with quick access to the pages via the footer section. In the user catalog it displays the user manual for whole system for the easy use of the system. First of all, a user must signup to the system. Then the user can login to the system. If user already has an account, they will be able to login to the system directly. If user successfully signs up, it displays the login page. In the login and signup page it displays email, password, and user role. After successfully loggin in, the user will be able to display the successfully message and if it fails it also display a message to the user. For the login and signup processes there are database functionalities.

After successfully login, the user can display the main page of the system. In this page it displays search history of the relevant user and current date and time. Then the user can enter an image into the system by using insert image from the device's gallery or capture image. In this process, the system checks for a correct file format of the selected image. Once the user has uploaded the image successfully, the system displays the message and saves the uploaded image in both the database and the device folder. After the user uploads the image, the image is then processed according to the pre-processing methodology with resizing. Also, the uploaded image is saved into the database and device folder in the parallel time. According to the trained model, once it gets the image from the database and image folder, it will classify the prediction classes with machine learning techniques and display the prediction results on the web page which open after they click the mosquito identifier or larvae identifier buttons.

There are text fields on the results display page for display prediction species and prediction accuracy. There is an option under the display results to save the predicted results into the database. In the middle of the web page there is a map for the current location where the mosquito found for the relevant user. So here it will display the current location, latitude and longitude of the location as well as an option to save the location details in the database. After identified the mosquito species for inserted image which of mosquito or larvae, the system will enable the view more option. When user click the option, will be able to see the relevant details of the identified mosquito species or larvae genera. As well as the location, date and time will be display on this web page and if user want to download these details, there is an option to download the relevant details. After user click on the download option, a pdf file can be download to the user's device.

For the machine learning process used secondary dataset of mosquito species such as Culex quinquefasciatus, Anopheles stephensi, Aedes aegypti, and Aedes albopictus and larvae genera such as Culex, Anopheles, and Aedes. These datasets include the images of mosquito species and larvae genera containing the folders such as training, validation and testing. During the machine learning the development team followed the VGG 19 model for the model training. In the model training phase, the development team used Adam as an optimizer and a batch size, learning rate, and number of epochs as the changed hyperparameters. Figure 1 illustrates this methodology.

Figure 1: Project Methodology

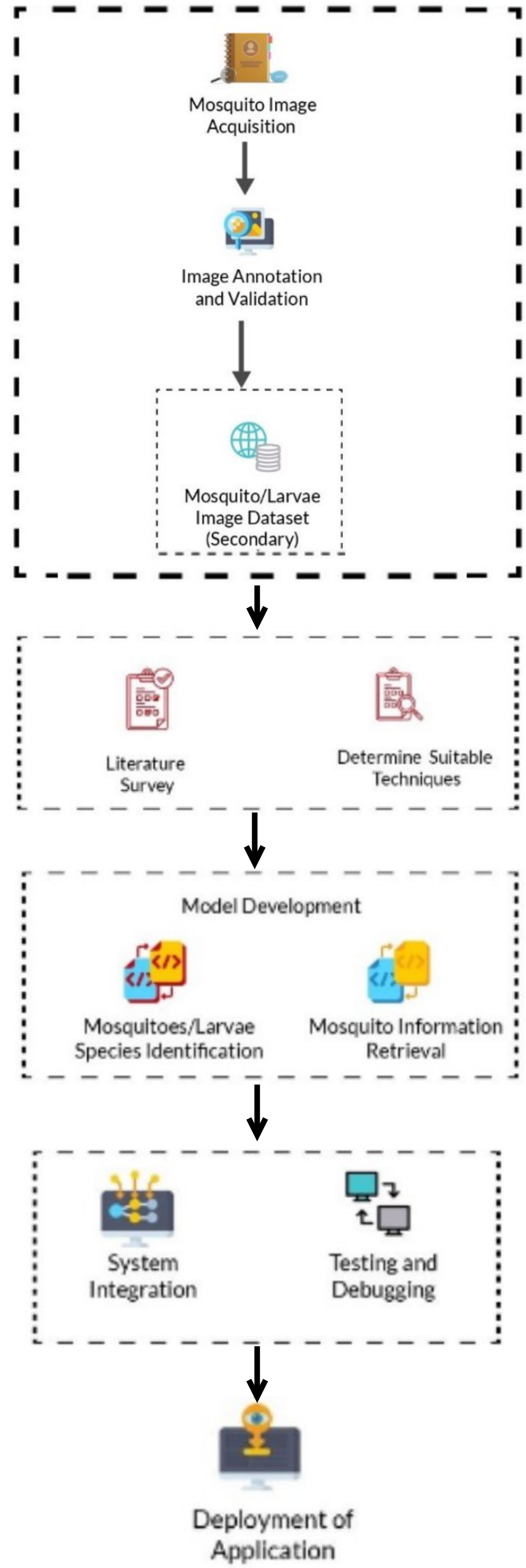


Research Design

The project mainly follows an experimental approach. The secondary dataset used for both training model and testing processes. The secondary dataset was obtained from online source.

A literature survey has been done to determine suitable machine learning techniques and image pre-processing techniques from previous works. This helped to develop the mosquito species identification model and larvae genera identification model using images of adult mosquitoes and images of larvae. To develop information retrieval used online sources and gave the option to download the details and PDF file. At the end of these stages conduct system integration for both implemented two models. For testing on usability requirements, followed three methods. As the first method allowed end users to use final version of the application and checking some parameters of usability such as the time taken to get results, how many times did they try to get results etc. As the second method give users some images of mosquitoes and larvae to label and mark if it is true or false. Also check those images of mosquitoes and larvae by the application and mark it if it is true or false and compare both results. The third method conducts a survey to collect feedback and user satisfaction. After testing and debugging the developed system, it is deployed as the final application.

Figure 2: Research Design



MATERIAL AND METHOD

System Architecture

System architecture refers to the structure and organization of a computer system or software application. It involves designing and defining the components, modules, and their interactions to fulfill specific requirements and achieve desired functionalities. And encompasses both hardware and software aspects, considering how they work together to enable the system to perform its tasks effectively and efficiently.

Software Designing and Components

Mosquito and Larvae Dataset

In the mosquito dataset, there are 1697 training images, 1292 validation images, and 379 testing images, including the species of five classes: Aedes Aegypti, Aedes Albopictus, Culex Quinquefasciatus, Anopheles stephensi, and Unknown. For the larvae dataset, there are training images, validation images and testing images including the genera of four classes: Aedes, Anopheles, Culex and Unknown.

The unknown category was other objects apart from the mosquitoes and larvae, including other animals, objects, buildings, trees, and etc. The reason behind for such a category was to identify image which not belong to any of the target classes or when image quality was insufficient for proper identification.

The images of the dataset were collected from a validated online repository and are publicly available, as reported in the online repository. Before model training, all images were resized to 224x224 pixels and normalized. Also, data augmentation techniques such as zooming, rotation and brightness adjustment to improve model generalization and decrease overfitting. The dataset was also divided into training, validation, and testing subsets to evaluate model performance objectively.

User Input Images (Select/Capture)

When user get the application to identify the prediction results, he/she has to insert an image. For this process the user has to upload an image which he/she want get prediction by capture image from camera or select an image from the user's device.

Image File Format Checker

After user select or capture image the system will check the file format of the inserted image. In here this system accept only images with JPG, JPEG, PNG, and BMP file extensions. Otherwise the system notifies to the user as incorrect file format.

Pre-processing Model

To get a better prediction from the AI model the data has to be preprocessed. In this module the images of dataset and user inserted images will preprocess. The preprocessing plays a major role in AI model training as the data may containing missing pixel values and some incomplete data corrupted due to image noises. By the preprocessing the data will sharpening the missing pixels and will be cleaned by filtering. Therefore, preprocessing is important when it comes to training the AI model with quality enhanced images.

Mosquito/Larvae Identifier Model

The mosquito identifier model and larvae identifier model will predict the mosquito species using the preprocessed dataset. For this, the AI model will be trained using the preprocessed images of adult mosquito species and larvae genera. The AI model will do the classification according to the model data and it will predict the mosquito species for corresponding images which was uploaded by the user. The final mosquito species classification was developed using VGG19 conventional neural network architecture with transfer learning. The Adam optimizer was used for this model training. This final model was trained using a learning rate of 0.01, batch size of 32 and 100 epochs. The final larvae genera classification was developed using VGG19 conventional neural network architecture with transfer learning. The Adam optimizer was used for this model training. This final model was trained using a learning rate of 0.01, batch size of 32 and 40 epochs.

Prediction Result Generator

After complete the identification, the prediction result generator will generate the output from the mosquito identifier model and larvae identifier model. The output will contain the mosquito species and the accuracy rate of the predicted result. And it will display on the page.

Information Retrieval

If the user wants to get more details of the predicted results after completing the identification, there is an option to view the relevant details of the predicted species. After displaying the output, the user can view more details and the system will display the relevant details about the identified species. Also of user may want to download the PDF which contains the relevant information, they will be able to download the PDF successfully from the information retrieval module.

RESULTS AND DISCUSSION

The initial phase of our study involved training multiple machine-learning models using a diverse dataset comprising images of adult mosquitoes and larvae from various species. There are two models that have been trained in our system. They are the mosquito identifier model and the larvae identifier model.

We utilized Convolutional Neural Networks (CNNs) to capture both spatial and sequential patterns in the images. We used the VGG19 architecture from it. The training process involved iterative adjustments of model parameters to optimize performance. The evaluation of our models was based on a set of key performance metrics, including accuracy, precision, recall, and F1-score.

- Results of mosquito identifier model
  - Test Loss: 0.4157
  - Test Accuracy: 83.55%
  - Weighted Precision: 83.10%
  - Weighted Recall: 81.82%
  - Weighted F1-score: 81.54%
- Results of larvae identifier model
  - Test Loss: 0.3536
  - Test Accuracy: 87.30%
  - Weighted Precision: 87.09%
  - Weighted Recall: 87.30%
  - Weighted F1-score: 87.15%

The evaluation of the developed application was conducted in two stages. First, a trained VGG19 classification model for both mosquito and larvae identifier and the models were evaluated using an independent test dataset that were seperated form the training and validation dataset during the model's development. According to it, the mosquito identification model achieved a test accuracy of 83.55% and the larvae identification model achieved 87.30% of test accuracy.

While this developed application is a web-based application, the completed web-based application was evaluated using new images supplied and uploaded by developers during the user validation stage. Under the real world conditions, the mosquito identification module achieved an overall validation accuracy of 69.57% and the larvae identification model achieved an accuracy of 60.47%. These are expected reductions in performance due to the uploaded images containing variation in image quality, background noise and image resolution that were not fully fed into the model training.

Classification Model Evaluation

Model Evaluation for Mosquito Images

Table 1: Mosquito Model Evaluation

No	Mosquito Species	Test Images	Success	Fail	Validation
01	*Aedes aegypti*	100	45	55	45%
02	*Aedes albopictus*	100	99	01	99%
03	*Culex quinquefasciatus*	100	84	16	84%
04	*Anopheles stephensi*	50	47	03	94%
05	Unknown	29	26	03	89.66%
				Total Success	**83.55%**

Model Evaluation for Larvae Images

Table 2: Model Evaluation for Larvae Images

No	Larvae Genera	Test Images	Success	Fail	Validation
01	*Aedes*	16	14	02	87.50%
02	*Anopheles*	14	14	00	100%
03	*Culex*	16	12	04	75%
04	Unknown	17	15	02	88.24%
				Total Success	**87.30%**

Prototype Evaluation

Validation Accuracy of Prototype

Table 3: Mosquito Identification Validation Accuracy

No	Mosquito Species	Test Images	Success	Fail	Validation
01	*Aedes aegypti*	13	07	06	53.85%
02	*Aedes albopictus*	10	07	03	70%
03	*Culex quinquefasciatus*	06	04	02	66.67%
04	*Anopheles stephensi*	09	08	01	88.89%
05	Unknown	08	06	02	75%
				Total Success	**69.57%**

Table 4: Larvae Identification Validation Accuracy

No	Larvae Genera	Test Images	Success	Fail	Validation
01	*Aedes*	16	07	09	43.75%
02	*Anopheles*	10	08	02	80%
03	*Culex*	11	06	05	54.55%
04	Unknown	06	05	01	83.34%
				Total Success	**60.47%**

Usability evaluation of prototype

The three methods were employed to evaluate the usability of a final web application. These methods encompass measuring the average time taken to perform tasks, identifying species accuracy among different users, and gathering user feedback through surveys. The data gathered from these methods provides valuable insights into the web application's usability and serves as a basis for making improvements.

The evaluation of a web application's usability by assessing two parameters: the total time taken by four users to complete tasks within the application and the frequency of their usage. These parameters provide valuable insights into the application's user-friendliness and overall user experience. By analyzing the time taken to complete tasks, one can identify areas where the application may be slow or difficult while tracking the frequency of usage can indicate how engaging and useful users find the application. Understanding these usability metrics is crucial for making informed improvements to the application and enhancing its overall user experience.

Four participants participated for this system evaluation by physically mood. These participants from academic staff members from Rajarata University of Sri Lanka and District Health Education Officers who possessed with basic knowledge of mosquito identification and vector-borne diseases. By this testing method, data were collected for parameters such as the time taken to get the predicted result, how many attempts participants try to get results, any extra time required, and the technological knowledge level they have. These volunteers were provided access to the web-based application and instructed to perform predefined tasks including user registration, user login, image uploading, mosquito species identification, results interpretation, and retrieval of species-related additional information. The main objective for this method was to assess whether user could successfully interact with the system, obtain accurate results without requiring technical support and measure average access time for each user.

Table 5: Usability Testing Results for Application

Participant	**The time take n to get the results**	**No of system attempts**	**Level of technical knowledge**	**Need of extra help to use the system**
01	8.36 mins	1	Excellent	No
02	4.22 mins	1	Excellent	No
03	3.56 mins	1	Excellent	No
04	3 mins	1	Excellent	No

$$\text{Average Time} = \frac{\text{Total Time}}{\text{Number of Times}} labeleq : average_time \tag{1}$$

$$\begin{aligned}\text{Average Time} &= \frac{((08 \times 60 + 36) + (04 \times 60 + 22) + (03 \times 60 + 56) + (03 \times 60))}{04} \\ &= 04.97 \text{ minutes} \\ &\approx 05 \text{ minutes}\end{aligned} \tag{2}$$

All users get results at one time and all the users can use the system without any extra help. Finally, we can say nearly five minutes was required for first time users to get their first results.

The effectiveness of a web application designed to identify mosquito species was evaluated by observing the performance of five users with mosquito-related knowledge. The parameters considered included the total time taken to identify species and the frequency of application usage. Additionally, the system's ability to correctly identify mosquito species from images was assessed and compared to the users' accuracy. The results indicated that system accuracy was consistently higher than user accuracy, suggesting that system expertise remains crucial for accurate mosquito identification.

Table 6: Usability Testing Results By Person vs System

Participant	Position	Success Status
01	Academic Staff	11/16
02	Academic Staff	08/16
03	PHI	06/16
04	PHI	06/16
05	PHI	06/16
Web-based Application		14/16

In this usability testing method, 16 random images of adult mosquitoes and larvae were used. The testers provided the images to these participants and requested them to identify the species manually based on their own knowledge. After they identified the species, testers note down the detail and feed same image to the developed web-based application in parallel time to identify the species by the application. the classification generated by the participants and the web-based application were compared against the verified labels to determine identification accuracy.

The usability of a web application was evaluated by inviting ten users to interact with the application and providing suggestions and feedback. This approach allowed for the collection of valuable insights into the application's user experience and potential areas for improvement. By directly observing how users interacted with the application and gathering their feedback, it was possible to identify usability issues and gain a deeper understanding of user needs and expectations. This information can be used to refine the application's design and functionality, ensuring that it meets the needs of its target audience and provides a positive user experience.

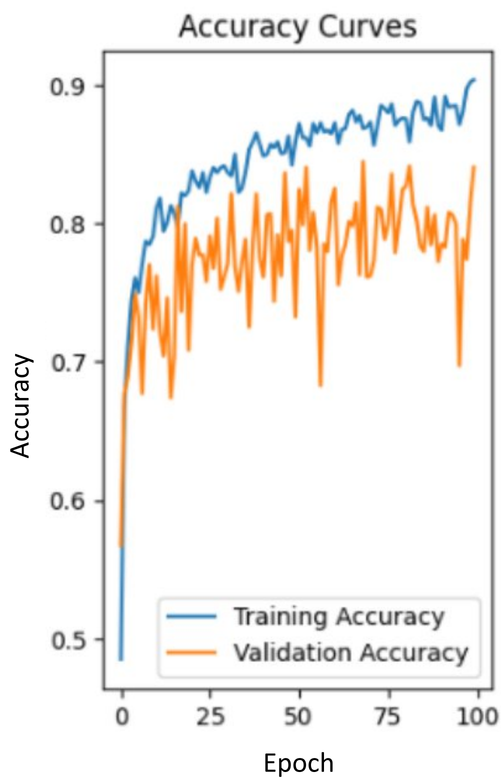
Performance evaluation of prototype

Performance testing is a type of software testing that evaluates the speed, responsiveness, and stability of a software application under a particular workload. Performance testing is important because it can help to identify and prevent performance bottlenecks that could lead to a poor user experience. TP stands for True Positives, the number of instances in which the model correctly classified as positive. TN stands for True Negatives, the number of instances in which the model correctly classified as negative. FP stands for False Positives, the number of instances in which the model incorrectly classified as positive. FN stands for False Negatives, the number of instances in which the model incorrectly classified as negative.

Test set accuracy measures the overall correctness of a classification model's predictions on a test dataset. It is calculated as the number of correct predictions divided by the total number of predictions. Precision focuses on the accuracy of positive predictions made by a classification model. It is calculated as the number of true positives divided by the total number of positive predictions. Recall, also known as sensitivity or true positive rate, assesses the model's ability to identify all positive instances in the dataset correctly. It is calculated as the number of true positives divided by the total number of positive instances in the dataset.

The loss function curve is a plot of the loss function against the number of training iterations. The loss function measures how well the model's predictions match the actual labels. A lower loss function value indicates that the model is making more accurate predictions. The accuracy curve is a plot of the accuracy against the number of training iterations. Accuracy is the proportion of correct predictions made by the model. A higher accuracy value indicates that the model is making more accurate predictions.

Figure 3: Accuracy and Lost Curves (Mosquito Model)



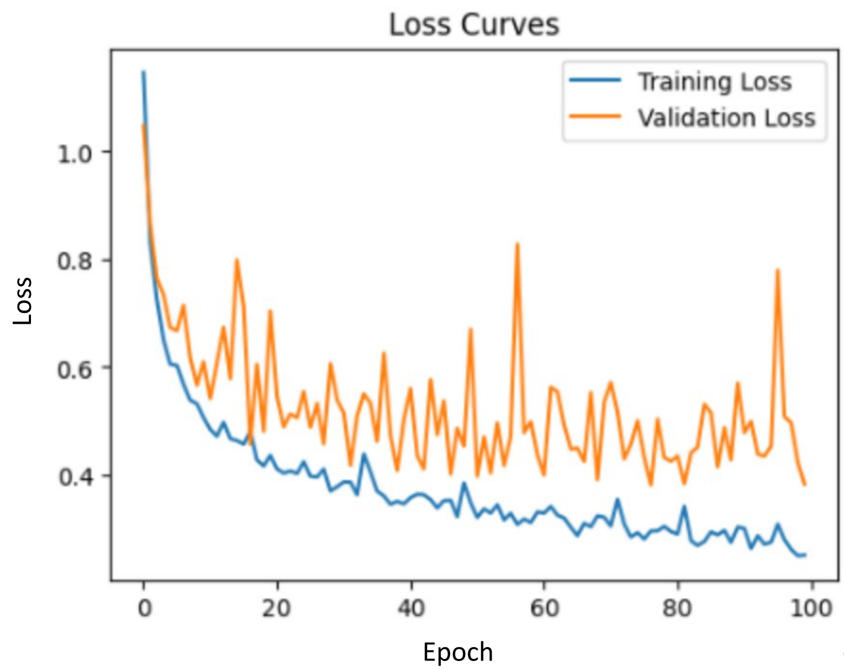
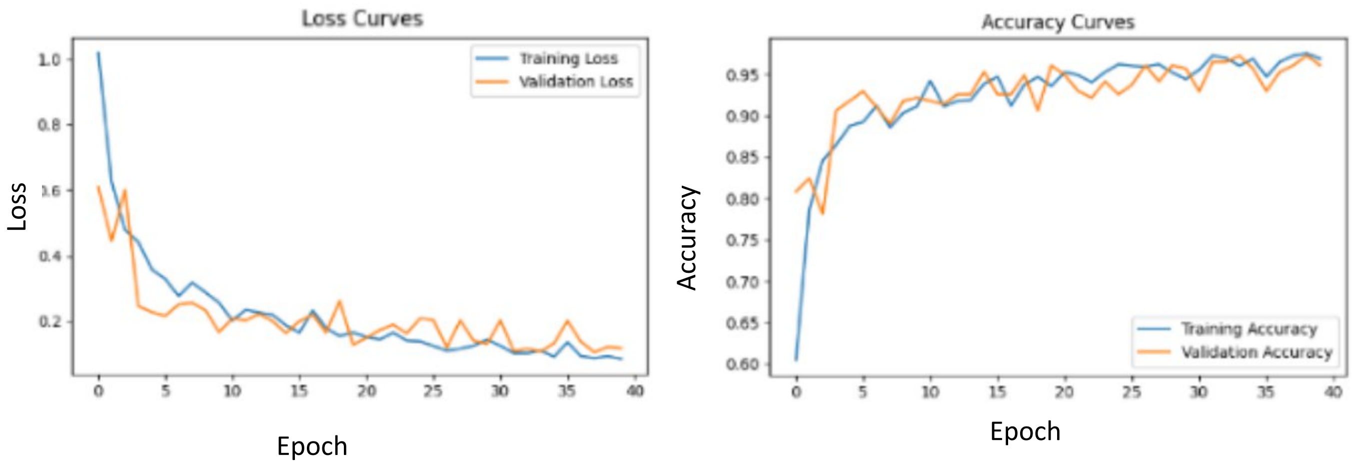


Figure 4: Accuracy and Loss Curves (Larvae Model)



The difference between model testing accuracy and prototype validation accuracy shows the challenges associated with integrating image classification frameworks in real-world environments. While the trained models worked well on accurate datasets, real images captured by users introduced additional variability that negatively affected classification performance. These findings highlight the importance of expanding future training datasets with more diverse real-world collected images of mosquitoes and larvae.

Ethical Considerations

This study complied with the ethical approval requirements of the ethical review committee, Faculty of Applied Sciences, Rajarata University of Sri Lanka and was conducted in accordance with the committee's ethical guidelines. Ethical considerations were also incorporated throughout the research work. All the participants were informed regarding the purpose of evaluation and voluntarily provided feedback. And the user evaluation tasks were conducted solely for the application's usability assessment and did not involve clinical, medical or behavioral experimentation. All the secondary image datasets used for model development were got from publicly available sources and validated that permitted educational and research use. Furthermore, uploaded images, user information and geolocation data were stored only for the application's functionality and evaluation process. Access to the stored data was restricted to authorized members involved in this work. No personal information was disclosed outside the research team.

CONCLUSIONS

The approaches used can only identify 4 species of mosquitoes (Culex quinquefasciatus, Anopheles stephensi, Aedes aegypti, and Aedes albopictus) and 3 genera of larvae (Culex, Aedes, and Anopheles). The accuracy of the mosquito species identification system may be impacted by lighting circumstances, the quality of the image, and the distance between the camera and the mosquito. Future developments for the identification of mosquito species through machine learning using images of adult mosquitoes and larvae focus on refining the user interface for enhanced attractiveness and user-friendliness. A well-designed interface can significantly improve user experience and facilitate broader adoption. Hope to enhance the accuracy of the machine learning models and use the primary dataset to train the model. Furthermore, the system's capabilities can be expanded to identify a broader range of mosquito species and larvae, contributing to a more comprehensive approach to mosquito-borne disease surveillance. Additionally, the development of a multilingual web application can extend the system's accessibility, ensuring that it can be utilized effectively in regions with diverse linguistic backgrounds. This approach aligns with a commitment to inclusivity and global health, making the technology more widely available for communities around the world. Mosquitoes pose a significant threat to human health. Effectively combating the spread of mosquitoes requires accurate identification of mosquito species and targeted eradication of their breeding grounds. The development of an automated machine learning system for mosquito species identification using images of adult mosquitoes and larvae has the potential to support mosquito surveillance and control activities and disease prevention efforts. This innovative approach has garnered notable success in achieving accurate and rapid identification, providing a rapid and potentially useful additional tool for mosquito identification. This technology offers several advantages over traditional manual identification methods, including increased accuracy, speed, and scalability. The accuracy of the mosquito identifier model is 83.55%, while the larvae identifier model stands at 87.30%. While the prototype validation produced lower accuracies of 69.57% and 60.47%, showing the impact of real-world image variability on classification performance. Moreover, it can be deployed in a variety of settings, including resource-limited areas, where access to trained entomologists may be limited. By focusing on key species such as Culex quinquefasciatus, Anopheles stephensi, Aedes aegypti, and Aedes albopictus, this approach addresses major vectors of diseases like Dengue, Malaria, Chikungunya, Yellow Fever, Zika virus, and West Nile virus. Depending solely on visual inspection for mosquito identification can be unreliable, particularly when dealing with mosquito species that share morphological similarities. The laboratory testing of larvae samples, while effective, is a time-consuming and cumbersome process that often necessitates expert intervention and the transportation of samples. Future works should focus on expanding the dataset with field-collected images, improving model accuracy and increasing the number of identifiable mosquito species and larvae genera.

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