DeepSquitoes: A Mobile System Framework for the Surveillance of Disease-Carrying Mosquitoes

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Abstract. Insects that spread diseases like malaria, chikungunya and Lyme disease are found all over the world because of climate change, economic fluctuations, human migration, and international trade. In this study, we propose *DeepSquitoes*, a mobile system framework for insect identification and fast data dissemination, with the goal of improving the management of public health hazards. *DeepSquitoes* specialises in the quick identification of mosquitoes, which are common in tropical areas, and can be used to monitor insect population movements in real-time. To maximise user interaction and data accuracy, the application includes geolocation-based identification, sophisticated preprocessing, and specialised annotation. Image preprocessing techniques like Gaussian Blur and contour extraction are applied on mosquito wing images to ensure data quality. Deep learning algorithms are trained on the preprocessed images for mosquito species classification. The image recognition model performs well, with a 93% training accuracy and a 74% validation accuracy using MobileNetV2 from TensorFlow. Our local dataset, which included 154 images of eight different insect species, had a commendable recognition accuracy rate of 76%.

Keywords: Entomological Surveillance System · Deep Learning · Image Classification

1 Introduction

Bloodsucking insects are involved in the transmission of causative agents of diseases of parasitic (malaria, leishmaniasis, trypanosomiasis, filariasis), viral (chikungunya, dengue, phlebovirus, bluetongue, fever, Rift Valley, West Nile fever) or bacterial origin (bartonellosis, heartwater, Lyme disease) [1]. They are also responsible for the dissemination of pathogens by phoresy (passive transport) that cause foodborne diseases.

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Climatic disturbances, global economic development, migration and the intensification of intercontinental trade have led to striking changes in their worldwide distribution. For instance, there has been the introduction and colonisation of new climatic areas by the tiger mosquito (Aedes Albopictus), an established vector of chikungunya and dengue viruses in several countries, including Mauritius and France [2].

Mosquitoes are vectors of various pathogens that can cause diseases such as dengue fever, malaria, chikungunya, West Nile fever, yellow fever, heartworm disease and filariasis [3]. Mosquitoes belong to the order Diptera (two-winged flies) and suborder Nematocera, which also includes many flies of economic importance like sand flies, midges, mothflies, and black flies [4]. Mosquito-borne diseases are those spread by the bite of an infected mosquito and often cause outbreaks resulting in immense suffering for humans. They have become increasingly widespread and pose a major worldwide public health problem [5]. The species mostly involved in the transmission of infections are contained in the genera Aedes, Culex, Anopheles, Ochlerotatus and Mansonia, belonging to the subfamilies Anophelinae and Culicinae [6].

In Mauritius, the most abundant species are Aedes Albopictus, Culex Quinquefasciatus and Anopheles Arabiensis[1]. Aedes Albopictus is known to transmit chikungunya and dengue, Culex Quinquefasciatus is known to transmit West Nile fever and Anopheles Arabiensis transmits Malaria and Filariasis. There are also some less common species like Anopheles Coustani and Aedes Fowleri that can transmit Rift Valley Fever Virus, and some rare ones like Anopheles Merus that can transmit malaria [6]. These diseases may cause major economic losses and affect many sectors, including the tourism industry, which is one of the major pillars of the Mauritian economy.

Mosquito-borne disease outbreaks can be foreseen by tracking the dynamics of pathogen-bearing mosquitoes in the field [7]. Through surveillance, entomologists can identify species composition, population dynamics, and the threat of dangerous mosquito-borne diseases. Decision-makers can use this information to choose the most effective management approach to control mosquitoes and protect community members in their area. One example of a mosquito surveillance system is the ArboNET[2], an arboviral surveillance system managed by the CDC (Centers for Disease Control and Prevention) and state health departments of the USA. ArboNET can create an online disease map to guide decision makers.

In low and middle-income countries (LMIC), surveying disease vectors can be quite expensive and excessively laborious for continuous and widespread monitoring. Large-scale monitoring in traditional surveillance of mosquitoes is difficult and expensive since it requires dedicated personnel to perform regular manual inspection and reporting. Novel surveillance approaches relies on smartphones and the Internet to permit people to upload pictures of mosquitoes whenever they come across them. The Mosquito Alert citizen science system[3], equipped with a specialized mobile application for the collection of geotagged photographs, serves as an illustrative example of a citizen science system [8].

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[1] Source: Vector Biology and Control Division (VBCD) of the Ministry of Health and Wellness.

[2] https://wwwn.cdc.gov/arbonet/maps/adb_diseases_map/index.html.

[3] http://www.mosquitoalert.com/en/.

The aim of this study is to implement an entomological surveillance system usable in most parts of the world and particularly in tropical and subtropical areas. The system is composed of interconnected tools that enables the rapid, cost-effective and non-destructive identification of different species of mosquitoes. It consists of a mobile phone (device and app) and a macro low-cost camera for a fast and accurate classification of mosquitoes on the field in order to have a real-time view of their evolution in terms of population and migration. This work demonstrates the application of deep learning methods integrated in a mobile system framework, for the accurate classification of mosquito species, based on wing images. The rest of the paper is structured as follows: Sect. 2 describes the related works, while Sect. 3 details the proposed solution. The results are discussed in Sect. 4 and finally, Sect. 5 concludes the paper.

2 Related Works

This section discusses related works on automatic recognition and classification of insects along with mobile insect recognition applications.

2.1 Automatic Recognition and Classification of Insects

Mosquito-borne diseases pose a considerable threat to global health. Entomological surveys, which include the collection and identification of mosquitoes, are needed to gain a better understanding of the transmission dynamics of vectors of such diseases. These surveys are therefore of paramount importance to plan for effective control measures and to monitor their impact. Species identification is the first step in entomological studies, and misidentification negatively impacts public health. In order to make species identification more efficient for entomologists, many studies have investigated the use of mobile applications coupled with image processing and machine learning algorithms for fast and accurate species classification.

In a recent survey by Martineau et al. [9], an in-depth analysis was conducted on insect classification, with emphasis on image acquisition methods, feature extraction techniques and automated classification algorithms. The authors categorized image acquisition protocols into two main types: laboratory-based and field-based images. There is a fixed protocol to acquire laboratory-based images from the insect trapping to its placement. The insect is positioned manually based on a particular set-up and the image is captured and retained for future processing. On the other hand, field-based images are taken from cultivated fields.

Furthermore, Sereno et al. [10] patented a dataset of Wing Interference Patterns (WIPs) for experiments carried out in the fields and proposed an automatic recognition system that classifies hematophagous diptera genus. Feature extraction techniques were employed for the purpose of image classification. The authors performed feature extraction with hand-crafted features using SIFT for building global representations with VLAT [11] and used linear support vector machines (SVM) to classify these genus. An improved version of this algorithm was proposed in [12] taking benefits of a Convolutional Neural Networks (CNN) architecture (MobileNetV2).

The Automatic Insect Identification System (DAIIS) is an example of a tool, which is based on wing outlines [14]. Wing outlines, being stable and diverse in nature, are used for insect identification [15]. Users are only required to upload a minimal set of images to utilize the tool, which then performs wing outline digitisation and Elliptic Fourier transformation. It carries out classifier model training by pattern recognition of SVM and model validation. The tool makes use of 120 owlfly specimens, representing seven distinct species for training an owlfly classifier. The mean accuracy for species identification varied between 90% and 98%.

In their study, Rustom et al. [16] have proposed a system based on Machine Learning (ML) and Deep Learning (DL) for classifying two distinct mosquito genera, namely Aedes and Culex. The system employs ML as well as CNN models. Feature selection was facilitated through ROI-based image filtering and wrappers-based FFS technique. The system used images from a dataset from the IEEE data port. Among the ML algorithms tested on the dataset, Extra-Tree Classification has outperformed with an accuracy of 99.2% and VGG16 has outperformed other CNN models with an accuracy of 98.6%.

2.2 Mobile Insect Recognition Applications

Various architectures have been proposed for deployment on mobile devices for real-time applications [17]. Minakshi et al. [13] proposed a mobile phone application, which allows any user with a smartphone to take images of a still mosquito, after spraying or trapping. The species identification approach comprised several steps, including image resizing, noise removal, background segmentation, feature extraction, dimensionality reduction and finally unsupervised clustering and classification using the Support Vector Machine algorithm. The authors reported an overall accuracy of 77.5%, which could be highly improved by the use of deep learning and transfer learning algorithms.

Conversely to most applications, the model developed by Munoz et al. [18] performs image recognition of mosquito species by classifying images of mosquito larvae, pupa and eggs. For accurate classification of the genus of larvae, close-up photos of the head and tail are imperative. To achieve this, images are captured using a smartphone camera, with a 60X Clip Light-Emitting Diode (LED) microscope affixed to the device. The centrally located recognition module uses a CNN classifier to predict the possible class of the insect. The resulting data can be streamlined to a visualisation tool using Google Maps. The authors believe that the performance of their system could be improved by executing the classification algorithm on the user application.

Zhu et al. [19] investigated the use of an application embedded in smartphones and image processing approaches for the rapid and precise identification and enumeration of insects in stored grain. The objective of the work was to preprocess the acquired insect image characterized by non-uniform brightness and dark background. One sliding window-based binarization was adopted to normalize the non-uniform brightness in insect photographs captured via mobile phones. Subsequently, domain-based histogram statistics were implemented to identify and enumerate the insects in the stored grain. By adapting the sliding window size, the system was able to distinguish tiny insects. The model achieved a counting accuracy of 95%, which surpasses that of conventional methods.

He et al. [20] used an approach based on deep learning to detect oilseed rape pests. They built a dataset consisting of 3,022 images and divided them into 12 categories. The dataset consisted of images captured using both a mobile phone and a digital camera. The Single Shot Detector (SSD) was selected as the meta-architecture for the optimal detection model, owing to its multiscale capabilities and rapid high-accuracy feature. Additionally, a mobile application was also developed to enable farmers to capture the images of the pests and detect the oilseed rape pests in real time. It also provided suggestions on pest controlling.

Motta et al. [21] used a model based on a CNN, capable of recognizing adult mosquitoes from the species Aedes Aegypti, Aedes Albopictus and Culex Quinquefasciatus. The authors trained their neural networks using a dataset comprising over 4000 mosquito images. DC light traps and suction tubes were utilised for capturing the adult insects. The collected insects were next euthanised with ethyl acetate and stored in entomological collection tubes. Their images were then taken using a digital camera or a mobile phone. Automatic taxonomic classification of the insects was performed through the image feature acquisition techniques that enabled differentiation between species. Three neural networks, including LeNet, AlexNet and GoogleNet were used for this purpose.

Chudzik et al. [22] came up with a mobile real-time grasshopper detection framework, MAESTRO, which employs deep learning techniques on RGB images for insect identification. The framework includes a mobile application that performs real-time detection of grasshoppers locally based on a deep learning model. The mobile application also performed data aggregation and collected ancillary information such as temperature, soil moisture, wind speed, and solar radiation. Upon availability of internet connection, the data is relayed to a cloud system for the purpose of forecasting grasshoppers movements and outbreaks.

Buschbacher et al. [23] have proposed DeepABIS, a system based on the foundational principles of the Automated Bee Identification System (ABIS). It is a mobile Android application capable of identifying live bees both in indoor and outdoor environments. Automated feature generation using deep convolutional neural networks (CNN) was used for species identification. Additionally, it facilitates participatory sensing and the collaborative gathering of data and insights. DeepABIS adopts the MobileNetV2 architecture and utilizes two distinct datasets for its operations: the *Apoidea* dataset, comprising bee images collected from Germany, Brazil, the United States and China and *Lepidoptera* dataset featuring butterflies collected from Germany, Italy, Spain and Kazakhstan. ABIS reports identification results with an average top-1 accuracy of 93.95% and a top-5 accuracy of 99.61% applied to data material.

Table 1 provides a comparative analysis of the related works. It can be observed that none of the studies has considered the classification of mosquito species based on wing images. The approach used in the present study for image capture and classification is based on a mobile system, which can be easily deployed in-the-field. The design and development of *DeepSquitoes* is described in detail in the following section. As articulated in the preceding section, the primary objective is to devise a low-cost approach for implementing an entomological surveillance system while maintaining a commendable recognition accuracy.

3 Materials and Methods

3.1 Data Acquisition

Experiments were carried out at the Vector Biology and Control Division (VBCD) laboratory of the Ministry of Health and Wellness to first build the dataset of wing images. Samples of different labelled species of mosquitoes were gathered for the project, mainly for the construction of the dataset of mosquito species. This dataset was further augmented with data images captured from the microscope and mobile device. Figure 1 shows how the microscope was set up to capture images of mosquito wings.

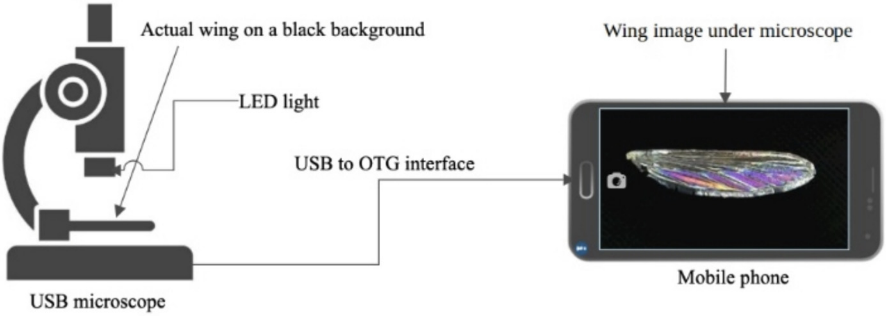

Fig. 1. Microscope and mobile device set-up

The mosquito wings were carefully dissected from their body using a precision tweezer, placed on a black background surface, and viewed under the microscope connected to the mobile device. A black background projects a better image quality in terms of colours and shape of the wing. The mobile app, MScope was used to view the digital image. To maintain consistency, the orientation of the wing was aligned as depicted in Fig. 1. The LED's light brightness was minimised to avoid any undesirable luminescence. Lastly, for each species, the picture of the wing obtained from MScope was saved to its respective folder.

3.2 Model Training

Upon completion of image capture, the dataset was ready for the preprocessing and model training phases. The wing images were preprocessed using the OpenCV package[4]. Their width, height and RGB colour channel was saved in a temporary matrix, after which, Gaussian Blur was applied to ensure a smooth background. After generating the wing outline, the image was cropped, and the canvas converted to dataURL jpeg file format.

In this work, the Tensorflow Hub MobileNetV2 model architecture was utilized, given its optimization for mobile device compatibility [24]. However, hyperparameter tuning was needed to ensure optimum performance. The input image size was changed to 116 x 256 pixels and the batch size was changed from 32 (default) to 16 since the

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[4] https://docs.opencv.org/4.x/.

Table 1. Comparative table of the related works

Mobile Application	Region	Type of Insect/Dataset	Image capture details (how are images taken)	Type of equipment used	Image processing details	Algorithms used	Visualisation	Challenges/Limitations
[14]	China	Owlflies	Owlfly images were captured using a digital camera	Canon 60D, 60 mm lens	Outline Digitization and Elliptic Fourier Transformation Pattern recognition of SVM machines	SVM and EF coefficients	In tool	The tool has not been tested on data other than owlflies wings
[13]	Tampa, Florida, USA	9 different vector-carrying mosquito species	Take images of still mosquito, either alive or dead, after spraying or trapping	Smartphone camera, Mosquito traps with CO_2 used as a bait to attract female mosquitoes	Reduce image size to 256 × 256 pixels for faster processing and run-time execution Noise removal using median filters Background segmentation Feature extraction	Unsupervised clustering and SVM for species classification	N/A	Since the dataset consisted of only 303 images, Deep Learning techniques could not be applied
[18]	New York, USA	4 possible labels for mosquito species, Images of egg, larva and pupa	Images taken are saved in cloud storage, together with its geolocation, Use of overlays to assist the user in taking a picture	60X Clip LED microscope that can be attached to any Android smartphone, Smartphone camera	Automatically by the CNN	Deep Learning	Google Maps	Image recognition is quite slow, since the recognition module is centrally located
[19]	China	tiny storage grain insects	Image captured using smartphone camera	Android OPPO R7 rear 13 million HD camera	Image preprocessing based on Sliding Window	Sliding window with changeable optimal threshold used for binary processing	On the mobile application	The separation of the connected domain is a key issues to improve identification accuracy
[20]	China	Oilseed rape pests (3,022 images divided into 12 categories)	Image captured using smartphone camera	HUAWEI Honor V10 mobile phone	Cuts the input image into a fixed size	SSD (single-shot multibox detector)	On the mobile application	Inappropriate detection when two pests overlap
[21]	Salvador, Bahia, Brazil	Aedes aegypti, Aedes albopictus and Culex quinquefasciatus	CDC light traps and suction tubes were used to collect adult insects Image species were then taken using a digital camera or a mobile phone	Digital camera or mobile phone. Exact model not mentioned	Automatically by the CNN	LeNet, AlexNet and GoogleNet	N/A	Dataset is limited in size and its balance between the different classes

(continued)

Table 1. (*continued*)

Mobile Application	Region	Type of Insect/Dataset	Image capture details (how are images taken)	Type of equipment used	Image processing details	Algorithms used	Visualisation	Challenges/Limitations
[22]	Inner Mongolia, China	Grasshoppers, GHCID dataset	RGB images of adult grasshoppers collected from the wild using a smartphone	Huawei P20 Pro and Nubia Z11 mini smartphones	Images are re-scaled proportionally so that their dimensions lie between 800 and 1333 pixels	Deep Learning, CNN, Multibox SSD MobileNetV2, stochastic gradient descent (SGD) training algorithm	On the mobile application	The detection performance of the stationary method and the mobile App are 78 and 49 percent respectively. The detection performance of the mobile model is low
[23]	Germany, Brazil, US, China	Live bees, butterflies	Picture of a bee's wing is captured from camera or chosen from storage		Automatically by the CNN	Deep Learning, CNN	On both the mobile and the web application	Incorporating additional information about species like their geographic distributions may result in wrong predictions
[16]	USA, Pakistan	Mosquitoes (Aedes and Culex), Dataset - IEEE data port			Uses ML and CNN for mosquito identification	Machine Learning, Deep Learning, CNN		Dataset consisted of only 1404 images

number of images was limited. Batch size is proportionate to the learning rate of training. Table 2 shows the dataset built for this project as well as the number of images in each species.

Table 2. Dataset

Species name	Family	Genus	Number of images
Albopictus	Culicidae	Aedes	23
Arabiensis	Culicidae	Anopheles	18
Fowleri	Culicidae	Aedes	23
Mascarensis	Culicidae	Anopheles	14
Arboricollis	Culicidae	Orthopodomyia	21
Quinquefasciatus	Culicidae	Culex	30
Tigripes	Culicidae	Lutzia	14
Tritaeniorhynchus	Culicidae	Culex	11

The training and validation dataset was built using the images acquired. Our dataset comprises 154 images, spanning eight distinct species. It is imperative to designate the directory where the image folders for each species are stored, with each subfolder named according to the species it represents. In our configuration, 20% of the data were allocated for validation purposes, while the remaining 80% were utilized for training. None of the images used for training were used for validation and only one image of each sample was taken. For the testing dataset, new images of pre-labelled mosquitoes were captured at the VBCD using the *DeepSquitoes* app.

3.3 *DeepSquitoes* Mobile Application

The *DeepSquitoes* mobile app, which is the main component of the *DeepSquitoes* mobile system framework, is a full REST API-based application with the front-end directly connected to the Firebase services without using a middleware. Figure 2 shows how the mobile app is connected to different Firebase services using Javascript API. Firebase authentication is used to manage the registration and login from the back-end. Firebase Storage is used to store mosquito images uploaded by registered users along with their annotations, which are saved in Firebase Firestore NoSQL database. Firebase hosting is used as the web server to publish the *DeepSquitoes* website and Firebase API is used to get all the verified data of the uploaded mosquito instances.

The *DeepSquitoes* mobile app was developed using Android Studio IDE. To get the address location of a specific mosquito, a user can either manually enter an address or use the smartphone GPS to get the exact location. Each captured image of the wing undergoes preprocessing to remove excess background before being uploaded to an online Firebase database. After the object detection and image classification, the user is redirected to a page dedicated to the identification of mosquito species. Upon successful classification,

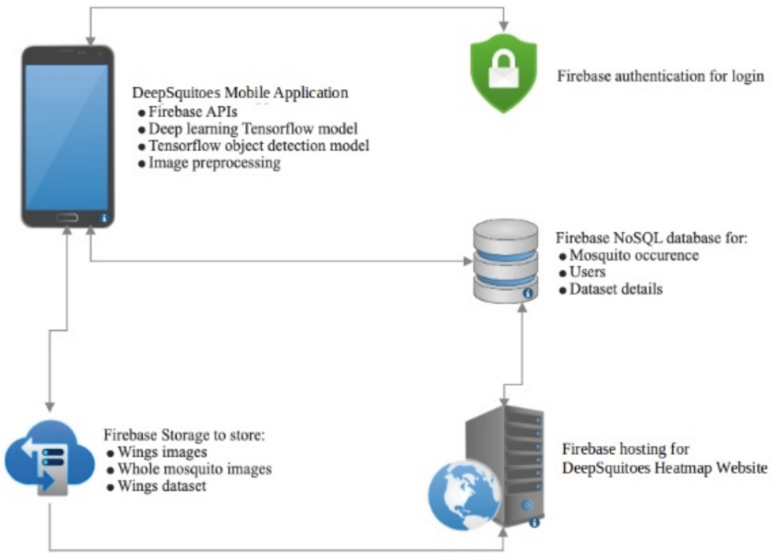


Fig. 2. Architecture Diagram

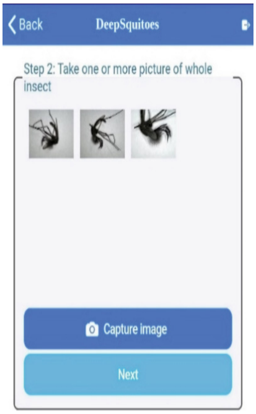
the name of the mosquito species is displayed within the mobile app. Expert users have the additional facility to annotate a mosquito species and append comments for further clarification. In addition, following the classification process, an expert user is presented with the option to review three potential matching outcomes, each accompanied with the species name and corresponding percentage match.

4 Results and Discussion

The *DeepSquitoes* mobile app enables users to upload images of insects for subsequent classification into eight different species. The images and their classification are uploaded on a cloud platform and the *DeepSquitoes* website retrieves all the insects' information and displays them on a map along with their images. The microscope was controlled directly from the mobile app due to API limitations. Native application provided by the microscope was used for taking pictures that were uploaded into the mobile application as shown in Fig. 3 and Fig. 4. For the testing phase, *DeepSquitoes* allows the user to capture multiple images of the same insect for a more accurate classification.

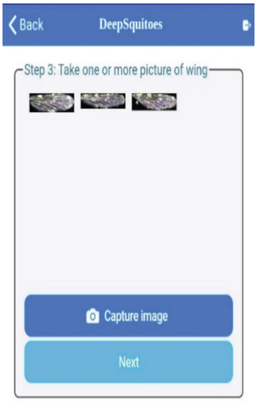
The mobile application has the capability to swiftly load deep learning and object detection models, thereby classifying images from mobile phones within a few seconds. Additionally, the application supports on-device image filtering by utilizing the OpenCV library. Furthermore, the architecture of the application is designed such that other deep learning models can be integrated seamlessly without requiring any modifications.

The deep learning model employed here is based on the MobileNetV2's feature extraction architecture from Tensorflow, selected for its superior performance; it is also consistent with the DL model created by Souchaud et al. [12]. The model achieved a validation accuracy of 74%. Despite the low quality of the microscope, the model attained a recognition accuracy of about 76% on our testing dataset, which is satisfactory given the low number of images in our dataset. Figure 5 shows the classification results of the mosquito species along with the percentage matched. In this figure, the identified species is *Arboricollis* and the matching percentage is 88%.



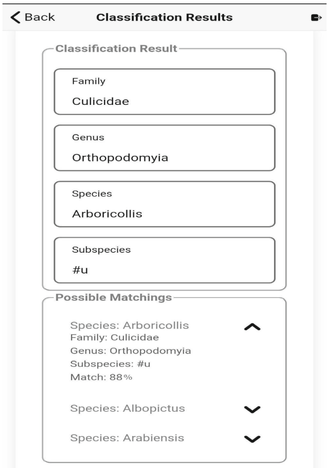
Step 2: Take one or more picture of whole insect

Fig. 3. Uploading pictures of the insect



Step 3: Take one or more picture of wing

Fig. 4. Uploading pictures of wings



Classification Result

Family: Culicidae

Genus: Orthopodomyia

Species: Arboricollis

Subspecies: #u

Possible Matchings

Species: Arboricollis
Family: Culicidae
Genus: Orthopodomyia
Subspecies: #u
Match: 88%

Species: Albopictus

Species: Arabiensis

Fig. 5. Classification example using testing data

5 Conclusion

This study presents *DeepSquitoes*, a mobile application for insect identification and fast data dissemination which has the potential to improve the management of public health hazards. The mobile application is able to identify mosquito vectors and monitor the insect population movements in real-time. *DeepSquitoes* was developed using the Ionic angular framework using Firebase as data storage. Object detection and image processing were performed using Tensorflow and OpenCV respectively. The deep learning model was developed using the Tensorflow Hub MobileNetV2 model architecture and was parameterised and adapted for the requirements of the project. The equipment set up included the mobile device, the portable microscope with LED lights and the platform to place the mosquito wings. The application is designed to be easily deployable on the iOS platform without requiring additional implementation. This system provides a viable option for monitoring the spread of various mosquito species worldwide, but limited by the quality of the citizen scientists' photos. Images submitted to the system undergo expert entomological review and labelling, serving dual purposes: informing public health agencies, and providing valuable feedback to volunteering citizens. The system is reported to be highly accurate with an area under the receiver operating characteristic curve score of 0.96. In the future, the dataset is expected to expand by increasing the number of mosquito species and the number of training images. It is also planned to host the system online to facilitate seamless updates. In addition, enhancing the microscope's capabilities for feature extraction and integrating it with an API directly into the application can significantly enhance the effectiveness of the deep learning algorithm in accurately predicting the taxonomy of a mosquito vector. Finally, techniques such as hold-out and cross-validation, although not always used in Deep Learning, can be investigated.

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