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Dengue Vector Surveillance using Acoustic Signals through Sequential Model of Convolutional Neural Networks

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Abstract:

Dengue fever is among the most dangerous infectious viral diseases transmitted through the bite of infected *Aedes Aegypti* mosquitoes. One way to decline the spread of dengue is by raising awareness in the community about mosquito habitats through continuous surveillance. The traditional surveillance techniques of *Aedes Aegypti* are difficult, time taking, and can lead to severe health risks. This paper presents a possible way of dengue vector surveillance through acoustic signals generated by the wingbeat of *Aedes Aegypti* using a sequential model of convolutional neural network. Mel-frequency cepstrum coefficients generated from the audio signal are given as an input feature to the sequential model that significantly improves classification performance up to 93% accuracy. The model has been trained on low-dimensional Mel-frequency cepstrum coefficients by executing discrete cosine transform to improve the efficiency of the system. The system generates notifications through a specially designed android application to alert detected *Aedes Aegypti* mosquitoes in the region. It is helpful in continuous monitoring of dengue vectors to take early precautionary measures for effective control and prevention.

Keywords: *Aedes Aegypti, CNN, Mel-frequency, android application, discrete cosine transform*

1 Introduction

Mosquitoes are responsible for over one billion cases of diseases and over one million deaths worldwide in a year. The danger of contracting dengue fever has increased significantly since the 1940s due to the increase in urbanisation, long-distance travel, and population growth [1]. Today, around 40% of people live in regions of the world where there is a danger of contracting dengue. In Pakistan, Health authorities are responding to an ongoing outbreak of dengue fever. On 8 July 2019 first outbreak was reported from the Khyber Teaching Hospital in Peshawar, Khyber Pakhtunkhwa (KP) territory. Afterward, there have been cases of dengue fever reported from Punjab, Sindh, Balochistan, Islamabad Capital Territory, and Azad Jammu and Kashmir [2].

To prevent dengue outbreaks and to ensure an effective control mechanism it is necessary to perform continuous surveillance of dengue mosquito habitats. Traditional mosquito survey methods, such as human landing catches (where the person conducting the survey uses themselves as bait to attract the mosquitoes), are time-consuming, risky, expensive, and spatially limited. There is a need to develop an automated mosquito surveillance system that can provide real-time

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Aedes Aegypti detection and identification without risk to human health.

This paper is organized as follows: Section 2 presents a brief review of the existing mosquito surveillance systems and the need to develop the proposed system. Section 3 presents the dataset used for experimental evaluation and the description of the proposed approach. This is followed by the results of the experiments and a brief discussion in Section 4. Conclusions are given based on the working and applications of the proposed system for automated surveillance of the *Aedes Aegypti* mosquito that causes very serious dengue fever.

2 Literature Review

In the literature, a few traps have been proposed to monitor different mosquitoes, for instance, CDC Miniature Light Trap that releases carbon dioxide (CO2) as an attractant and a fan that force mosquitoes downwards into the collection net. This trap has been designed to trap *Aedes Ablbopictus* and *Aedes Aegypti* but there are a few issues such as the trap needs a continuous power supply that causes the battery to run out quickly and monitoring of mosquitoes has to be done by physically visiting each trap daily [3].

In another study, New Jersey Light Trap has been installed 5-6ft above the ground and used dry ice as an attractant. It could trap a large number of mosquito species as well as other larger insects that interrupt the mosquito surveillance process [4]. In [5], Gravid Traps were introduced that used stagnant water as an attractant to mosquitoes. A battery-powered fan was used to blow mosquitos into the container. This trap was inefficient for dengue mosquito surveillance as dengue larvae grow in clean water. The water must be treated to avoid adult mosquito growth from the trapping medium that needs human intervention for frequent water changes.

It is important to note that mosquitoes produce sounds to find their mates and communicate with each other. Mosquitoes produce sounds by different mechanisms such as wing-beating, flying, or chewing. In [6], the author proposed a methodology to identify and classify mosquito species (*Aedes Aegypti*, *Anopheles Arabiensis*, and *Culex Pipiens*) by using acoustic signals produced by the wing-beat frequency of mosquitoes. The findings revealed a significant difference in male and female mosquito sounds. In another study, female mosquito sound was used to attract male *Aedes Aegypti* by using a low-cost battery-powered acoustic trap that performed better than other lures [7].

In [8], the authors conducted a study to classify mosquito species based on wingbeat with infrared emitters and receivers. The expectation-maximization algorithm (EM-GMM) was used with the Gaussian mixture to classify the wingbeat of different mosquito species. In another study, six mosquito species (*Aedes Aegypti, Aedes Albopictus, Anopheles Arabiensis, Anopheles Gambiae, Culex Pipiens, Culex Quinquefasciatus*) were classified using deep learning techniques based on the audio recording of their wingbeats [9]. Recently, there has been another study to identify *Aedes Aegypti* by using machine learning. They used audio analysis recorded from commercially available smartphones and given spectrogram as input to multiclass, binary, and an ensemble of binary classifiers. The result shows that the ensemble model provides better classification accuracy as compared to the multiclass and binary class models [10].

Despite several studies and promising results, there is still a challenge to collect enough datasets to improve automated classification accuracy based on acoustic signals. In this paper, we proposed an automated system linked with a user-friendly mobile application to ensure continuous data collection of dengue mosquito acoustic recordings from different parts of the world, and the results of classification are displayed on a web-based dashboard. The proposed system can classify *Aedes Aegypti* mosquitoes accurately using a sequential model of Convolutional Neural Network (CNN) under quiet to moderately noisy environments. This system can be used as a community-level tool to raise timely awareness in the regions where there is evidence of *Aedes Aegypti* mosquitoes.

3 Materials and Methods

The process of mosquito identification consists of three sub-processes, first: feature extraction using Mel-frequency spectrum; second: web services development for results visualization; third: android application development to enable acoustic data collection anywhere anytime. Fig. 1 presents a graphical illustration of the proposed methodology containing several steps including data collection, prepossessing, data segmentation, model training, and validation, and then connecting the server to the mobile application.

3.1 Dataset

We have used a dataset containing wing-beat sounds of 20 clinically important mosquito species for training and testing. This dataset is publicly available at Dryad Digital Repository [11]. The dataset contains wing-beat sounds of *Aedes Aegypti* mosquito species collected from the field and recorded in labs under a controlled environment.

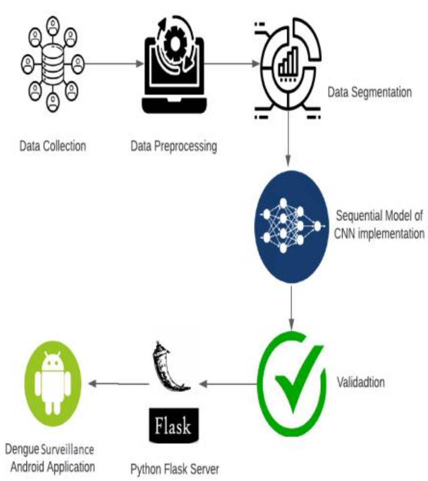

Fig. 1. Graphical illustration of the proposed methodology to develop automated mosquito surveillance system.

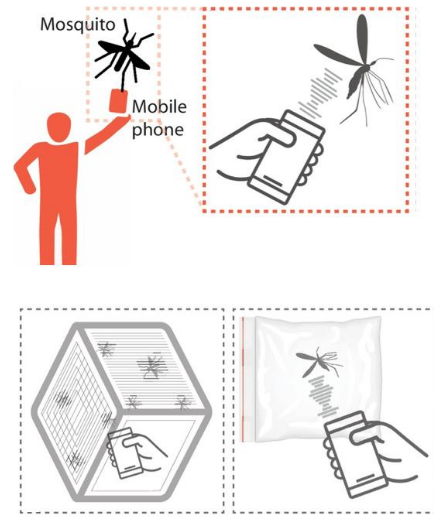

Fig. 2. Graphical illustration of mosquito sound collection in labs and open areas using mobile phones. Noise level ≤ 50 dB, distance between mobile microphone and mosquito ≤ 50 mm. A similar setup was used for dataset collection in [11].

The mosquitos were collected alive and their sounds were recorded, using sensitive microphones attached to mobile phones during free flights or in a zip lock bag, to collect the required dataset. There were 20 audio samples of the *Aedes Aegypti* mosquito to be used for experiments.

We isolated wingbeat frequency data of *Aedes Aegypti* mosquito for around 50 ms sample window. This window was achieved by finding the peak frequency range on the spectrogram from each recorded audio sample.

For more details on the dataset, please refer to [11]. For validation, we have used our own recorded sounds of mosquitoes in a quiet to moderately noisy environment (noise level ≤ 50dB).

This data was collected in labs and closed spaces by keeping a distance of ≤50mm between the mobile phone (Samsung Galaxy A51) microphone and mosquito sound. Fig. 2 presents an illustration of mosquito sound collection using mobile phones.

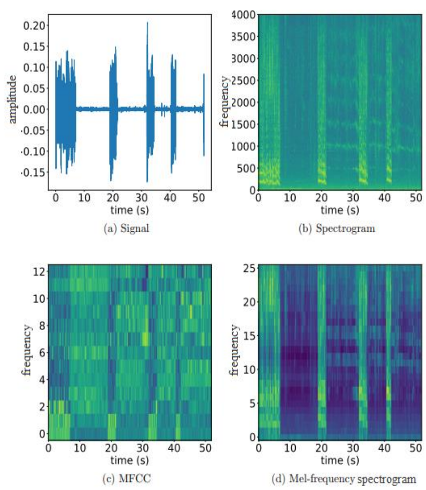

Fig. 3. Conversion of raw audio signal into mel-frequency spectrogram for

3.2 The proposed approach

Sequential models are machine learning models that input and output sequences of data in multiple layers. In this paper, we have used the Sequential model of CNN in *Keras* [13]. Instead of giving raw audio waveforms as input in the first layer, we have generated Mel-frequency Cepstral Coefficients (MFCCs) and given them as input to the first layer of the sequential model.

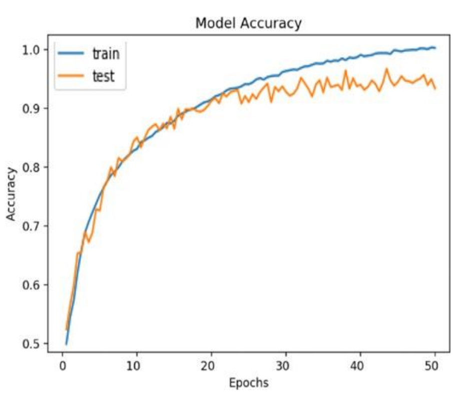

Fig. 4. Classification accuracy of the proposed model.

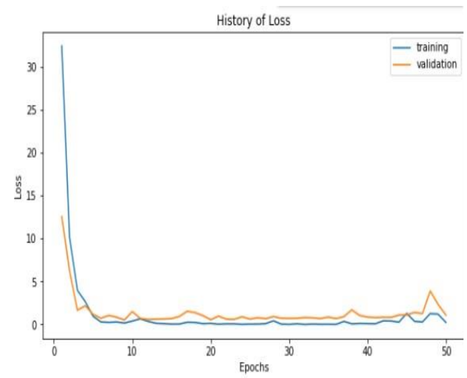

Fig. 5. Value loss graph of Sequential Model Neural Network.

MFCCs are one of the most extensively utilised audio features in speech recognition and acoustic classification, with a variety of audio representations. The Mel-scale resembles the scale of pitches that human perceives such that the frequency filters are spaced linearly at low frequencies and logarithmically at higher frequencies. This is done with the help of a filter bank [14].

Discrete Cosine Transform (DCT) is used to convert Mel-spectrum into time-domain generating cepstrum coefficients as shown in Fig. 3. This conversion typically reduces a high-dimensional spectrum to a considerably smaller dimension, in our case: 13-dimensional coefficients. As a result, it is ideal for use in low-power gadgets.

TABLE I. Performance comparison of related techniques used in the literature with the proposed model.

Study	Methodology	Accuracy
[10]	CNN	90%
[15]	SVM	92%
[16]	CNN	82%
[17]	ANN	85.7%
[18]	FCN	84%
The proposed methodology	The Sequential neural network	93%

In the second layer of the sequential model, the output of the first layer has been grouped (reshaped) to make it suitable for training. In the third hidden layer, the data given for training purposes has been separated and features were extracted. In the hidden layer, the *Relu* activation function has been used which is a piecewise linear function. The fourth layer used an activation function *Softmax* which is a mathematical function that converts a vector of numbers into a vector of probabilities, where the probabilities of each value are proportional to the relative scale of each value in the vector.

4 Results and Discussion

For testing and evaluation, we divided the original dataset into training and testing sets with a ratio of 70:30. The proposed sequential model was evaluated using Google Colab linked with Google drive where the dataset was stored. The average accuracy of the proposed model was 93% (Fig. 4) and the average value loss is 0.311% (Fig. 5). Loss value implies how well a specific model performs after each iteration of optimization.

A confusion matrix (Fig. 6) of sequential model has been generated that represents the 92% true positive and 94% true negative records of the acoustic dataset. We validated our model by the unknown audio recordings of mosquitoes for which the model was not trained. The validation data has been recorded using the techniques presented in Section 3.1. Upon successful classification, the files were stored in the library to enhance the dataset for training in the future.

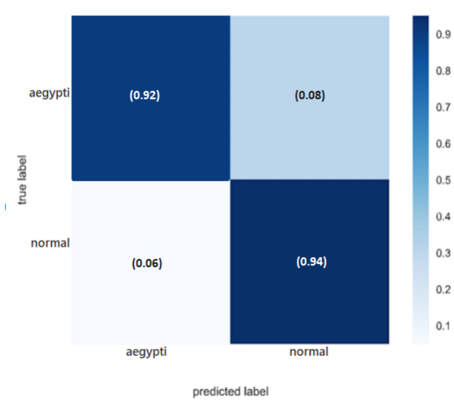

Fig. 6. Confusion matrix of sequential model presenting the 92% true positive and 94% true negative records of the acoustic dataset.

The proposed model performed well in terms of accuracy as compared to other state-of-the-art techniques. Table I shows a performance comparison of recent techniques used in the literature with the proposed model.

One of the most useful components of the study was the development of a mobile application system that can be used for community awareness and automatic acoustic data acquisition. The trained model has been integrated with the mobile application to perform automated *Aedes Aegypti*. classification to the application users in real-time. The application has a user-friendly graphical interface for sound recording and data synchronization. It has the functions to record audio, mosquito identification, and storing audio samples if recorded sound matches with *Aedes Aegypti*.

The primary challenge in using mobile phones for mosquito sound identification is recording faint mosquito sounds in noisy environments. The application is suitable to detect mosquito sounds within a distance of ≤50 mm from the microphone. Another limitation is that the application will be able to detect mosquito sounds in quiet to moderately noisy environments where noise levels are ≤50 dB. The distance between microphone and mosquito needs to be decreased drastically in louder conditions.

The application has a dashboard with additional features for providing community awareness about dengue fever symptoms and precautionary measures that should be taken to prevent outbreaks (Fig. 7). The user has to register with the application to use the data recording feature. The registration form includes information about the environment, current time, and current location. All recordings and corresponding peripheral information are synchronized to the online Python Flask Server and integrated with the Sequential model through Wi-Fi or cellular connections for real-time *Aedes Aegypti* monitoring and identification.

5 Conclusion

This paper presents an automated system for dengue mosquito identification using wing-beat frequency, and an android mobile application for data collection and real-time surveillance. The proposed system performs well in terms of accuracy (93%) and efficiency as compared to other state-of-the-art techniques. The mobile application is limited to being used in quiet to moderately noisy environments at a distance of ≤50mm between the microphone and mosquito. We are working towards removing background noise and improving the quality of signals for better surveillance in an open public place. There is a need to filter human voices from audio signals to preserve privacy.

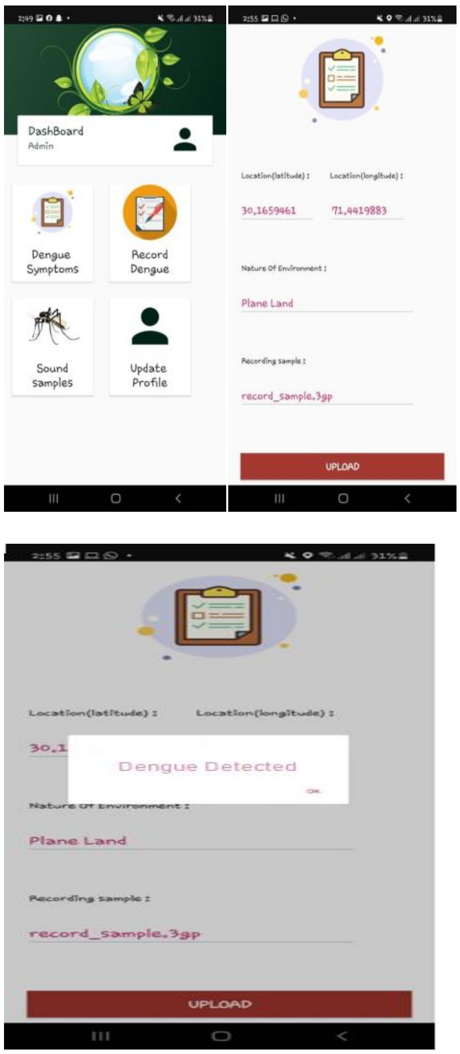

Fig. 7. Dashboard of Dengue Surveillance Application and Sound Recording of Dengue Surveillance.

The proposed system is a step forward in developing intelligent systems for mosquito surveillance that can be enhanced for surveillance of other disease vectors such as Anopheles causing malaria. In Pakistan, the system can be used in hospitals, schools, houses, offices, and parks at targeted places where there is relatively less noise. The application might be used as an effective tool to collect audio signals and metadata (location, time, environment) of various mosquito habitats that can be used to further train the machine learning model for enhanced accuracy. The application can be a very effective and safe tool for the National Institute of Health (NIH) and dengue surveillance teams to collect accurate data with little to no human interaction.

The dataset collected through the Dengue Surveillance application can be used in the future by researchers and entomologists to study the relation between the type of environment and the population density of *Aedes Aegypti* mosquitoes.

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