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Hernan S. Alar
Ateneo de Manila University

Proceso L. Fernandez Jr
Ateneo de Manila University, pfernandez@ateneo.edu

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Classifying mosquito presence and genera using median and interquartile values from 26-filter wingbeat acoustic properties

Hernan S. Alar[a]*, Proceso L. Fernandez[b]

[ab]*Ateneo de Manila University, Quezon City, Philippines*

Abstract

Mosquitoes are known to be one of the deadliest creatures in the world. There have been several studies that aim to identify mosquito presence and species using various techniques. The most common ones involve automatic identification of mosquito species from the sounds produced by flapping its wings. The development of these important concepts and technologies can help reduce the spread of mosquito-borne diseases. This paper presents a simple model based on mean and interquartile values that aim to solve the mosquito classification. Despite its simplicity, the proposed model significantly outperforms a Convolutional Neural Network (CNN) model in identifying the mosquito genus from the classes of Aedes, Anopheles and Culex, with an additional fourth class of No-Mosquito. A dataset of sound recordings from the Humbug Zooniverse, collected by researchers from Oxford University, and augmented with locally collected audio recordings of mosquitoes in the Philippines were used in this study. The proposed technique uses the numerical data from a series of 26 different pass-band filter values generated from spectrograms of audio recordings, specifically computing the statistical measures of median and interquartile values for each filter from instances of the same class. To predict the class of an instance, the sum of squares of differences was computed between the actual values of the instance against the expected values of each class on each of these three statistical measures. The average classification accuracy of our proposed model was 92.8%, and this was higher than the 86.6% classification accuracy yielded by the CNN model. Moreover, the proposed model required much less time for both training and classification than the CNN model. As the proposed model outperformed the CNN model in accuracy and efficiency, the results offer a promising technique that may also simplify the process of solving other sound-based classification problems.

Keywords: Mosquito; Audio Classification; Genus; Spectrograms, Descriptive Statistics;

* Corresponding author. Tel.: +632 88408416;
E-mail address: hernan.alar@obf.ateneo.edu

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1. Introduction

Mosquitoes are considered one of the most dangerous species on the planet because they have the ability to spread many deadly diseases. Almost 700 million people contract a mosquito-borne illness every year resulting in greater than one million deaths. The United State Centers for Disease Control and Prevention (CDC) reported that mosquitoes kill more than one million people a year just from the transmission of malaria [22]. In recent years, the rate of infection spread has increased dramatically, and a growing number of scientists are concerned because global warming could lead to the explosive growth of the mosquito-borne diseases worldwide. These are some of the most common diseases spread around the world by mosquito bites: Zika virus, West Nile virus, and chikungunya virus infections, dengue fever, and malaria. There is no vaccine to prevent or medicine to treat most of these diseases [1]. This alarming scenario has brought researchers to study mosquito behavior and identify mosquito presence. In the field of machine learning and artificial intelligence, different initiatives have been undertaken to develop a model to classify mosquitoes.

Among the different technologies and approaches in solving classification problems that is proven to be effective is the use of different deep learning models [4],[15]. Regardless of the input data being used (images, videos and audio), these computational models have been able to identify unique features from different datasets that make them reliable models for classification. Studies exist that apply a deep learning model in classifying small creatures such as mosquitoes, bees, hornets and bugs [2],[6],[10],[18],[19],[20],[21]. Specifically for mosquitoes, we identified the present approaches used to solve these classification problems. We further looked for certain aspects of these models where research gaps exist and other aspects that can be further improved. Using some insights from previous studies, we then explore the possibility of developing a simpler model based on audio type inputs and yet more accurate and efficient technique for this classification problem. The classification problem centers around identifying three most common mosquito genera -- Aedes, Anopheles and Culex. A fourth class -- the No-mosquito class -- is added so that the classification model can also determine the presence or absence of a mosquito from an audio recording.

This paper is divided into the following sections: section 2 presents the existing studies and approaches in solving the audio classification problem to identify the research gap; section 3 summarizes the data collection, data pre-processing and model development stages of the study; section 4 presents the results and interprets each findings; lastly, section 5 concludes the study and itemizes possible future work to improve the presented algorithm.

2. Related Studies

This section presents different studies [3],[7],[8],[11],[13] that address the mosquito classification problems. Shown in Table 1 are the summarized details about these existing approaches.

Table 1. Existing Research on Mosquito Classification Domain

Paper	Author	Type	Model	Accuracy
Real-Time Mosquito Species Identification using Deep Learning Techniques	Mulchandani P., et al 2019	Audio-based	CNN	86%
Mosquito Detection with Neural Networks: The Buzz of Deep Learning	Kiskin et. al, 2017	Audio-based	CNN	85%
A Deep Learning-Based Automatic Mosquito Sensing and Control System for Urban Mosquito Habitat	Kim et. al, 2019	Video-based	FCN	84%
Application of convolutional neural networks for classification of adult mosquitoes in the field	Motta et al., 2019	Image-based	CNN	82%
CNN Architecture Performance Evaluation for Image Classification of Mosquito in Indonesia	Amiruddin et. al, 2020	Image-based	CNN	80%

It is evident from the presented data in Table 1 that most approaches utilize CNN models to solve the mosquito classification problem. Image-based approach was used in a previous research [11] where a convolutional neural network (CNN) was used to classify close-up mosquito images. The classification was limited to species such as *Aedes aegypti*, *Aedes albopictus*, and *Culex quinquefasciatus*. The model yielded a classification accuracy of 82% for *Aedes* female mosquitoes. Though it was able to classify Aedes female mosquitoes, which are main carriers of dengue virus, the said technique is not very practical for real-world deployment since mosquitoes are very small and capturing images for the classification model will be very difficult.

To address the issue on static image-based classification, a research [7] presented a new approach that uses video as an input rather than static images. In this study, a model that paired a Fully Convolutional Network (FCN) and a neural network-based regression model was utilized, yielding an overall accuracy of 84%. Though the use of videos instead of images addresses the issue of impracticality of mosquito images as an input, the use of video also has its own set of disadvantages. Capturing videos of tiny insects requires good lighting, high quality cameras and other devices that are capable of segregating the video background and focus on little subjects of videos for each frame.

With mosquitoes being difficult to see, especially in darkness, image and video processing are generally complex and impractical. A common alternative which has been used by the majority of the published papers of this domain is to process audio file samples [14],[18]. Studies suggest that the flapping of the mosquito's wings commonly beat up to 1,000 times per second. This flapping of wings is responsible for producing the buzzing sound of the mosquitoes. Since each genera of mosquitoes varies in terms of size and wing structure, then these sounds produced by their wings may have unique features that can be distinctive between different classes.

The sounds produced by mosquitoes, in the form of an audio recording can be presented using various representations such as waveforms, frequency domain representation and spectrogram. Studies [8], [12] and [13] used the spectrogram-based technique in their respective research that focused on the development of a model that classifies mosquitoes using deep learning techniques like CNN. Their models yielded 86% and 85% classification accuracies respectively. Though spectrogram-based CNN gives promising results in solving audio classification, deep learning models commonly use an architecture that requires high compute power and long training time. This is because of the high number of parameters (network link weights) that have to be learned in this model.

In this paper, we present our development of a simple yet accurate and efficient technique to solve the mosquito classification problem without the need for a compute-heavy deep learning model. Our proposed algorithm also makes use of the spectrogram of mosquito wingbeats to classify mosquito genus accurately. We apply statistical analysis to identify the mosquito class from a given audio recording. The basic statistical measures used are the median and the interquartile values. Finally, we compare the performance of our proposed model against a CNN model trained on the same dataset, and we show that the proposed model is significantly superior in terms of accuracy and speed.

3. Materials and Methods

Audio Resources

Majority of the mosquito audio recordings used in this research came from an open-source dataset from Zooniverse.org. It consists of recorded mosquito sounds from the laboratory of Oxford University in the United Kingdom and from the wild forests in Thailand [9]. This dataset is publicly accessible online and is intended to be used in understanding and analyzing the flight tones of mosquitoes. The research group from the Oxford University used this dataset in their research [8] which starts with the conversion of the audio signals into frequency features and the training of a model that learns the signature pattern created by mosquitoes in flight. The said group aimed to strengthen its model by providing more dataset instances during the learning process - making their recordings public on the Zooniverse website and letting other people analyze and contribute to the data preprocessing tasks [9].

Data preparation and cleanup

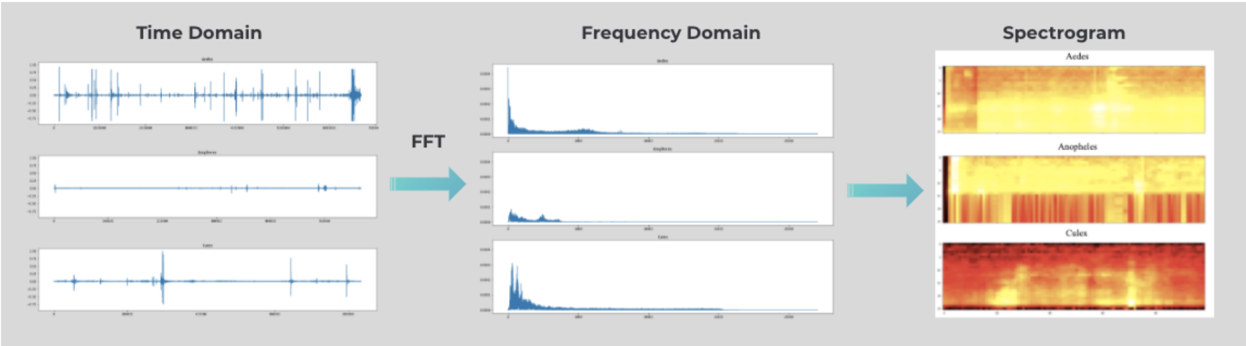
With the diversity of the sources of the data sets, it is important to preprocess the audio recordings to ensure the quality of the inputs for the training of the classification models. The data preparation and cleanup processes in this study involved removing dominant noise, trimming, and excluding some audio files which seems questionable in terms of the presence of the mosquito flight tones. As a result of the data preprocessing step, the original audio recording dataset that consists of four hundred five (405) instances was trimmed down to three hundred sixty five (365) instances. Each instance was also labeled properly resulting in 100, 77, 88 and 100 instances for Aedes, Anopheles, Culex and No-mosquito recordings respectively. Refer to Table 2 for a summary of the distribution of the classes vis-a-vis the two sources of data.

Table 2. Dataset

Source	*Aedes*	*Anopheles*	*Culex*	No- mosquito	Total
Downloaded from Humbug	50	77	88	68	283
Actual Recorded	50	0	0	32	82
Total	100	77	88	100	365

Feature Extraction

After the data preparation and preprocessing, it is crucial to identify an appropriate audio representation that can be used to build a classification model. Since the audio files presented in waveforms (see Fig. 1(a)) cannot be used in its present form due to variations in terms of amplitude across all files of the same class, we then transformed these time-domain representations into frequency-domain format using Fast Fourier Transform (FFT) (see Fig. 1 (b)). FFT is commonly used to identify the presence of each frequency in the signal presented in a form of a magnitude [5],[16].



(a) (b) (c)

Figure 1. Feature Extraction Process

As shown in Figure 1(b), the frequency domain format of the audio recordings clearly shows the distinctive features of the audio recordings based on the magnitude. However, examining individual audio recordings in its frequency-domain form, we came across some sample instances of different classes that had similar representations. As shown in Fig. 2, the representation in the frequency domain form of two sample test instances, one from Anopheles genus and the other on the Culex genus, looked very similar.

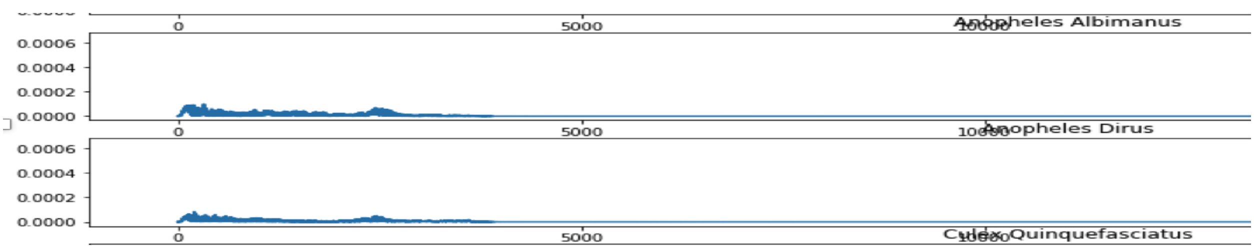


Figure 2. FFT of sample individual mosquito recordings for *Anopheles Dirus* and *Culex Quinquefasciatus*

As a result, we further explored other forms of representations. Aiming to identify the characteristics of these mosquito flight tones for better classification results, we transformed the frequency-domain format of audio files into an audio spectra and mapped it to a 26-value filter bank. The 26 filter value is an array of band-pass filters that separates the input signal into multiple components [17]. In this approach, the higher the frequency, the wider the filter - making a set of features from each filter that creates distinctive properties for each class. Under this transformation, each audio recording is represented by a 26-element vector that was used as input to our proposed classification model.

Model Development

Convolutional Neural Network (CNN)

Since the majority of the current approaches in solving mosquito classification use deep learning models and commonly CNN, we decided to make use of this as a benchmark model from which we compare the performance of our proposed approach. The CNN architecture used in this study followed the model used in the study [13] which involved different network layers as detailed in Table 3. It was built using multiple 2D convolutional layers, a max-pooling layer, and dense layers. The spectrogram of the audio recordings were used as an input for the training and validation phases of the CNN model.

Table 3. CNN Model Structure

Layer (type)	Output Shape	Param #
Conv2d_1 (Conv2D)	(None, 13, 9, 16)	160
Conv2d_2 (Conv2D)	(None, 13, 9, 32)	4640
Conv2d_3 (Conv2D)	(None, 13, 9, 64)	18496
Conv2d_4 (Conv2D)	(None, 13, 9, 128)	73856
max_pooling2d_1 (MaxPooling2D)	(None, 6, 4, 128)	0
dropout_1 (Dropout)	(None, 6, 4, 128)	0
Flatten_1 (Flatten)	(None, 3072)	0
dense_1 (Dense)	(None, 128)	393344
dense_2 (Dense)	(None, 64)	8256
dense_3 (Dense)	(None, 4)	195
Total params: 498,947 Trainable params: 498,947 Non-trainable params: 0		

The model was trained using the cleaned and preprocessed data set that consist of 365 labeled instances. Training the benchmark model with ten (10) epochs yielded a validation accuracy of 86.6%. It was observed that the CNN model started to overfit after the 10th epoch.

Median and IQR-based Model

With complexities of deep learning models that require high compute-power, we proposed a model that utilizes simple statistical measures in solving the same mosquito classification problem. In particular, we used the median and interquartile values for each of the 26 filter values in the spectrogram of a specific instance from the dataset. We then compared these values to the generated baseline values.

The baseline values were computed using the same measures of mean and interquartile values applied on each of the 26 specific filter indices of the spectrogram for each class. The generation of these values is the training phase of the model. As a result, a set of 26 lookup tables were generated for each class and for each statistic recorded, with each column corresponding to a specific filter index.

For the prediction process, the same process of extracting the median and interquartile values for each of the 26 spectrogram indices was applied to every validation data instance. For each index, the square of difference was computed between the generated value of the test instance against the expected value generated from the training phase. The algorithm of the scoring process is presented in Fig. 3.

Algorithm 1 Proposed Model - Quartiles and Median

Input: the array M representing the trained model, and an array x representing a specific spectrogram of one validation data instance

Output: integer (1, 2, 3 or 4) representing the predicted class

for $c \leftarrow 1$ to 26 **do** ▷ filter indeces
    for $i \leftarrow 1$ to 4 **do** ▷ representing the 3 genera and 1 no mosquito class
        $Qrtls[c] \leftarrow (\mathrm{x[i][c]} - \mathrm{Q1[i][c]})^2 + (\mathrm{x[i][c]} - \mathrm{Q3[i][c]})^2$ ▷ quartile score
        $\tilde{x}[c] \leftarrow (\mathrm{x[i][c]} - \mathrm{M[i][c]})^2$ ▷ median score
    end for
end for
for $i \leftarrow 1$ to 4 **do** ▷ representing the 3 genera and 1 no mosquito class
    $Q[c] \leftarrow \mathrm{Qrtls_{score}}$ ▷ consolidated quartile score
    $\tilde{x}[c] \leftarrow \mathrm{\tilde{x}_{score}}$ ▷ consolidated median score
    $S[c] \leftarrow \mathrm{Q[c]} + \mathrm{\tilde{x}[c]}$ ▷ total score
end for
$P \leftarrow \min(\mathrm{S_{Aedes}}, \mathrm{S_{Anopheles}}, \mathrm{S_{Culex}}, \mathrm{S_{No-Mosquito}})$ ▷ Predicted class

Output: P

Figure 3. Median and IQR-based Model Algorithm

The comparison process involves getting the sum of the square of difference between the lookup values and the test instance across all 26 filters. The class with the smallest value of the sum of squares of the difference is deemed the most similar to the given test instance and is thus the class predicted by the model.

4. Results and Discussion

We performed a 5-fold stratified cross-validation to evaluate the performance of the benchmark model (CNN) and the proposed model (Median and IQR-based model). All the preprocessed audio recordings from the final data set that consist of 365 instances was distributed proportionally in the 5 folds or strata (see Table 4 for the distribution).

Table 4 Distribution of Data for Stratified Cross-Validation

Class	Fold1	Fold2	Fold3	Fold4	Fold5
Aedes	20	20	20	20	20
Anopheles	15	16	16	15	15
Culex	18	17	17	18	18
No-mosquito	20	20	20	20	20
Total	**73**	**73**	**73**	**73**	**73**

To ensure that the difference in the scores of the classification accuracy was significant, a paired T-test (see Table 5) was performed across the five (5) strata for the two models. For the Median and IQR-based Model and CNN comparison, the resulting p-value of 0.04 indicates that there is a significant difference at level α=0.05.

Table 5 Classification Accuracy

	Median and IQR-based	CNN
Fold1	0.915	0.877
Fold2	0.960	0.890
Fold3	0.941	0.822
Fold4	0.911	0.822
Fold5	0.914	0.918
Average	**0.928**	**0.866**
p-value	0.04	

The high accuracy scores are reflected with the number of true positives in the confusion matrix as presented in Table 6. This is a combination of the five strata during the testing and validation process.

Table 6. Stratified Cross-Validation Confusion Matrix (CNN)

	Aedes	*Anopheles*	*Culex*	*No-mosquito*
Aedes	90	4	5	1
Anopheles	2	68	5	2
Culex	5	2	78	3
No-mosquito	5	3	12	80

The CNN model misclassified some mosquito recordings as non-mosquito. The confusion matrix for the CNN model is presented in Table 6. Majority of the audio files were correctly classified with an 86% accuracy.

Table 7. Stratified Cross-Validation Confusion Matrix (Median and IQR-based Model)

	Aedes	*Anopheles*	*Culex*	*No-mosquito*
Aedes	95	5	3	1
Anopheles	2	70	4	3
Culex	0	1	84	7
No-mosquito	0	0	0	90

It was clearly observed that there is a high accuracy between classifying across the three mosquito genuses and non-mosquito audio recording. This is supported by the confusion matrix of the mean and IQR-based model presented on Table 7.

Training Time

As a compute-heavy algorithm, the CNN model required more training time than the Median and IQR-based model. The difference between the training times (in seconds) in each fold is presented in Table 8.

Table 8. Training Time (sec): CNN VS Median and IQR-based Model

	CNN	**Median and IQR-based Model**
Fold1	199.17	98.33
Fold2	137.58	62.88
Fold3	111.84	66.28
Fold4	114.28	51.12
Fold5	192.31	77.19
Average	**151.036**	**71.16**

A paired T-test was performed on the training time across the five (5) strata for the two models. The resulting p-value of 0.00056 indicates that there is a significant difference at level α=0.05.

Predicting Time

Compared to the training time, the difference in predicting time between the CNN and Mean and IQR-based model is smaller as presented in Table 9. Although the difference is small, the Mean and IQR-based model was able to classify and predict the data set faster than the CNN model across all folds of the stratified validation. Furthermore, the small difference was still statistically significant.

Table 9. Predicting Time (sec): CNN VS Mean and IQR-based Model

	CNN	**Mean and IQR-based Model**
Fold1	63.8	46.4
Fold2	55.2	47.9
Fold3	58.1	44.3
Fold4	49.2	44.8
Fold5	48.7	45.0
Average	**55.00**	**45.68**

We performed a paired T-test on the predicting time across the five (5) strata for the two models. Yielding a p-value of 0.03, the differences across the five folds are considered significant at level α=0.05.

5. Conclusion

In this paper, we present a new method in solving mosquito classification problems using the 26 filter values generated from the spectrogram of the audio recordings. Our proposed approach uses Median and IQR values aggregated for each filter index to identify a mosquito presence and genus from its recorded wingbeat sounds. The same dataset consisting of 365 instances of audio recordings was used in the training and testing of the proposed model and a Convolutional Neural Network (CNN) model that replicates the architecture of a previous study. Their performances were evaluated in terms of classification accuracy, training time and predicting time. The accuracy of our proposed Median and IQR-based model was 92.8%, and this was higher than the 86.6% accuracy yielded by the CNN model. As impressive as the accuracy results, the median and IQR-based model also required much less training time and also lower classification time than the CNN model.

To possibly improve the results further, it is recommended to explore different post processing steps that can further improve the classification accuracy. The same concept can also be applied to other domains or research subjects other than mosquitoes. It is further recommended to explore other approaches in classifying audio files by modifying the existing median and IQR-based models such as performing classification on a per filter basis, utilizing other descriptive statistics measures and developing other unique approaches in feature extraction. Another approach that can be considered includes the possibility of taking wavelet transform as vectors and significant spectra components without filters. This involves applying statistical filtering at an early stage such as taking only amplitudes and corresponding phases of Fourier transform with amplitude value larger than 5-25% of all amplitudes (upper quantiles).

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