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Hybrid Machine Learning Approach for Mosquito Species Classification Using Wingbeat Analysis

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ARTICLEINFO ABSTRACT Effective and precise techniques for mosquito species identification are required Article History: as mosquito-borne illnesses continue to pose serious threats to public health Accepted: 28 April 2024 across the world. We provide a new hybrid machine-learning technique in this Published: 05 May 2024 research work for the classification of mosquito species through the Wingbeat analysis. It analyzes the wingbeat of the mosquito species based on which it can identify the mosquito species. This method makes use of deep learning Publication Issue techniques. The hybrid technique attempts to provide robust and dependable Volume 10, Issue 3 classification performance by utilizing a wide range of machine learning May-June-2024 methods, such as k-Nearest Neighbors (KNN), Random Forest, Multi-layer Perceptron (MLP), Support Vector Machines (SVM), and Gradient Boosting. To Page Number improve feature extraction and normalization, we apply a rigorous set of 126-135 preprocessing techniques to a large dataset that includes wingbeat recordings from many mosquito species. By means of comprehensive testing and analysis, we prove that our method is effective in correctly detecting mosquito species, exhibiting better results than using separate machine learning algorithms. Our findings demonstrate how deep learning methods may support more conventional machine learning strategies in problems involving the categorization of mosquito species. We also address the implications of our results for ecological research and disease management initiatives, highlighting the significance of precise species identification in vector monitoring and epidemiological investigations. Keywords : Mosquito-borne illnesses, Hybrid machine-learning technique, Wingbeat analysis, machine learning methods, KNN, Random Forest, MLP, SVM, and Gradient Boosting.

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I. INTRODUCTION

Mosquitoes carrying parasites, viruses, and bacteria can infect cattle and individuals. Malaria, dengue, Zika virus, lymphatic filariasis, West Nile virus, yellow fever, chikungunya, and numerous kinds of encephalitis are among the serious illnesses and infections that mosquitos can carry [1]. It was claimed that about seven hundred million individuals receive a mosquito-carrier sickness annually, causing over a million fatalities [2].

The most effective approach to avoid illnesses caused by vectors is by controlling the vector, which is currently based on the usage of pesticides in Africa as well. Many strategies to control vectors include monitoring and surveillance of mosquito vector groups, which is necessary for successful treatments [1].

Several mosquito avoidance strategies are used by health officials for conducting extensive tracking and management operations. Because of the global mosquito-carrier expansion of illnesses and invading mosquitoes, several tracking mechanisms are put into implementation, including a surveillance phase employing avoidance equipment [3-6]. The absence of an automatic describing facility for the count and composition of species of caught insects is a significant shortcoming of existing vector monitoring and surveillance systems related to mosquitoes [7]. Manually examined distributed avoidance facilities might raise the expense of the monitoring operation or force concessions in the way they are constructed.

According to [8], approaches based on machine learning concepts have enabled the effective classification of the acoustic characteristics of animals like birds and bees [9, 10] owing to the advances in the arena of artificial intelligence. Thus, classifying mosquitoes got improved by employing machine learning methods centered around the frequency of the wingbeat, resulting in much more reliable practical findings [1, 11].

II. LITERATURE SURVEY

Proficient mosquito identification through acoustic information is critical for sustaining vector monitoring effectiveness and extensive prevention control efforts. The development and revolutionize can significantly public health initiatives by permitting improved prompt diagnosis and tracing of illnesses transmitted by vectors [12]. These abilities aim to lower the rate of spread, enhance the speed of reaction, and ultimately safeguard human life, signaling an important worldwide advancement in initiatives to maintain wellness and ensure the prevention of numerous diseases [8].

[13] presented an integrated system that combined transformers and a convolutional neural network for classifying distinct varieties of mosquitoes using a data set obtained via cell phones. In short, they prepared the data set by sampling the reduction of beat sounds of the wings of mosquitoes while eliminating noise-full specimens and discarding some erroneous data items. Instead of using spectograms across time, they employed unprocessed amplitudes of the wing beats as attributes.

[14] created an automated categorization method for Aedes varieties using the markers that were particular to varieties presented by Wing Interferential Patterns. A repository of data consisting of twenty-four Aedes spp. included four hundred and ninety-four photomicrographs, from those with over 10 images underwent a deep learning approach for training a convolutional neural network and verifying its efficacy in classifying specimens at 3 different hierarchical stages.

[14] examined a VGG-16 network (a type of deeplearning structure)specifically designedmosquitoes.Acrosstheirdatasetcontaining mosquitoinfo,therewereatotal



of 6 varieties of mosquitoes. The previously taught structure of the network using the transfer learning approach was investigated by them and revealed the detection of various varieties of mosquitoes with a minimal percentage of loss and an appreciable percentage of accuracy. The findings of the convolutional neural network and VGG 16 were evaluated to prove the efficacy of their VGG 16 structure.

In [15], mosquito motions were recognized, monitored, and classified with the deployment of artificial intelligence, specifically by incorporating deep learning and computer vision. 2 trials were conducted: the initial one evaluated the capacity of the system to precisely identify and categorize the trajectory of motions of mosquitoes by employing multiple classification methods, including the merger of Long Short-Term Memory framework and Convolutional Neural Network framework alongside Gated Recurrent Unit framework.

[8] incorporated practical-sense-mosquito a classification technique based on the convolutional neural network by using the frequency wingbeats to recognize different species of mosquitoes, specifically, Aedes sp with a prime focus on it. They designed and evaluated 2 different approaches: a multiple-class and a binary classification structure. distinguished Their binary approach Culex quinquefasciatus and Aedes aegypti with an outstanding accuracy rate of over ninety per cent.

Identifying if the varieties of mosquitoes that spread disease exist in a specific surrounding area appears to be the initial phase towards an effective disease avoidance strategy [14]. When the transmitting mosquitoes are identified in a surrounding area, it is fair to suppose that there are more since mosquitoes breed fast.

III.PROPOSED HYBRID MACHINE LEARNING TECHNIQUE

The flow diagram of the proposed hybrid machine learning algorithm is shown in the below Figure 1. Moreover, the architecture is also represented in the following Figure 2. By using a hybrid machine learning method and cutting-edge algorithms along with extensive feature extraction techniques, our proposed system offers a substantial leap in the categorization of mosquito species. The goal of our system is to identify mosquito species based on wingbeat analysis with improved accuracy and resilience by utilizing the powers of KNN, Random Forest, SVM, MLP, and Gradient Boosting. Our methodology relies heavily on the extraction of a wide range of data, such as frequency components, amplitude fluctuations, and temporal and spectral properties, from the mosquito wingbeat recordings. Our system is engineered to provide superior performance on a wide range of datasets and situations from everyday life through comprehensive model training, optimization, and assessment using standard performance measures. To further emphasize flexibility, we include methods for ongoing learning and adaption to environmental circumstances changing and mosquito populations.

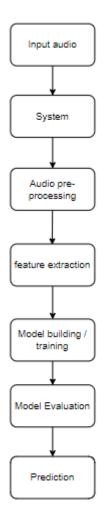


Figure 1 Flow Diagram of the proposed system

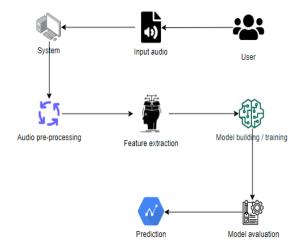


Figure 2 Architecture of the proposed system

Algorithms

The machine learning algorithms considered for developing a hybrid machine learning technique are briefed in this section.

Support Vector Machine (SVM)

With the ability to discover the best hyperplane that divides data points into distinct classes with the greatest margin, Support Vector Machines (SVMs) are strong supervised learning models that can solve classification problems. With the use of extracted features from wingbeat recordings, SVMs may efficiently learn decision boundaries in the context of classifying the mosquito species through the wingbeat analysis, making accurate distinctions between different mosquito species.

Multi-layer Perceptron (MLP)

An artificial neural network model known as a multilayer perceptron (MLP) is made up of many layers of linked neurons, including an input layer and output layer, with one or more hidden layers. Categorization applications like mosquito species categorization can benefit from the use of MLPs since they are good at capturing complicated nonlinear interactions within data. Through the process of training machine learning models (MLPs) on characteristics derived from wingbeat data, it becomes possible to distinguish between various mosquito species by utilizing their distinct wingbeat sequences.

Random Forest

The purpose of random forests is to minimize variation by averaging many decision trees that were trained on various portions of the same training set. By combining the predictions from several decision trees, it can handle high-dimensional feature spaces obtained from the recordings of Wingbeat and produce reliable classification results in the backdrop of categorizing the mosquito species.



Gradient Boosting

Another ensemble learning method called gradient boosting minimizes the loss function by gradually adding weak learners, usually decision trees, to create a strong prediction model. Gradient Boosting can help mosquito species classification tasks attain excellent accuracy in classification by continually increasing the performance of the model and successfully capturing complicated correlations within the wingbeat data.

k-Nearest Neighbors (kNN)

To classify data, the k-Nearest Neighbors (kNN) approach, which is straightforward but efficient, first determines the majority class among the knearest neighbors for each data point. When it comes to classifying mosquito species using wingbeat analysis, kNN is very helpful for non-parametric classification problems since it can categorize wingbeat recordings by comparing them to labeled occurrences in the feature space.

Hybrid Approach

We employ the complementary capabilities of KNN, Random Forest, MLP, SVM, and Gradient Boosting algorithms in our hybrid machine learning strategy to effectively classify mosquito species. Our goal is to improve the performance, generality, and resilience of the classification over a range of mosquito populations and environmental variables by using ensemble approaches or other integration procedures.

1) Advantages

The advantages of the proposed hybrid machinelearning technique for the classification of mosquito species through the Wingbeat analysis are mentioned below:

1. Enhanced Accuracy: Compared to conventional morphological approaches, our suggested system is anticipated to attain greater

accuracy in the classification of mosquito species by utilizing a hybrid machine learning technique and extensive feature extraction techniques.

- 2. **Resilience:** By extracting a variety of feature representations from wingbeat data, the use of numerous machine learning methods improves the system's resilience and increases its capacity to reliably distinguish between mosquito species.
- **3. Comprehensive Feature Representation:** Through the extraction of various features from wingbeat recordings, our system can capture subtle aspects of mosquito flight patterns, which results in a more comprehensive representation of wingbeat signatures peculiar to a species and enhanced classification performance.
- 4. Adaptability: Our system's ability to adjust to new species and changes within current species is made possible by the processes for ongoing learning and adaptation. This ensures that our system will remain relevant and effective throughout time.
- **5. Scalability:** Real-world vector monitoring programs and disease control initiatives can use the suggested system because of its capacity to scale efficiently to handle huge and diverse datasets.

IV.RESULT AND DISCUSSION

In this section, we present the implementation screenshots of our Wingbeat investigation-based mosquito species classification attempt by relating to every module built into our framework.

Implementation Screenshots

In the below, we are presenting the screenshots of all the five modules that have been built into our framework.



Home page

The below figure 3 shows the home page, revealing just the major theme of our work concerning wingbeat investigation-based hybrid mosquito species classification framework using machine learning techniques.



Figure 3 Screenshot showing home page

Registration Page

The below figure 4 shows the registration page, wherein the registration of the users has been enabled in our work concerning wingbeat investigation-based hybrid mosquito species classification framework using machine learning techniques.

Registration	
raut@gmail.com	
Email ID	Mosquito Species Classification
	Already have an account? Login
Conform password	
Register	

Figure 4 Screenshot showing registration page

Login Page

The below figure 5 shows the login page, wherein the users are provided with the login option by using their credentials, in this work concerning wingbeat investigation-based hybrid mosquito species classification framework using machine learning techniques.

uito Species Classification	Nomi Registration Lagin	
Login		
ut@gmail.com		
	Mosquito Species Classification	
Login		
	Login ut@gmail.com	LogIn ut®gmai.com Mosquito Species Classification

Figure 5 Screenshot showing login page

User home Page

The below figure 6 shows the home page of the users, that is visible to them after logging in using their credentials, in this work concerning wingbeat investigation-based hybrid mosquito species classification framework using machine learning techniques.

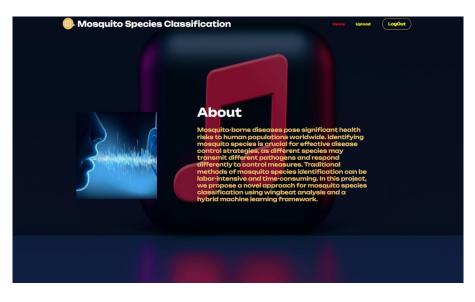


Figure 6 Screenshot showing home page of the users



Upload & Result Page

The below figure 7 shows the page where the uploading of the data (needed audio) and result viewing is being facilitated in our work concerning wingbeat investigation-based hybrid mosquito species classification framework using machine learning techniques.

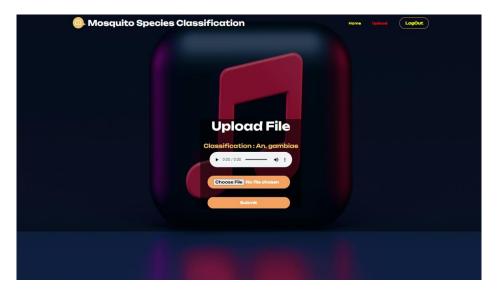
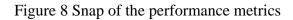


Figure 7 Screenshot showing upload and result page

Summary of Results

In this work concerning wingbeat investigationbased hybrid mosquito species classification framework using machine learning techniques, the following were obtained and are now presented below. The below figure 8 presents the snap of the performance metrics being assessed concerning the methods used and the following figure 9 presents the corresponding confusion matrix of the same.

Accuracy: 0.9	5618915159944	36		
Accuracy: 0.70	5944444444444	45		
lassification	n Report:			
	precision	recall	f1-score	support
0	0.59	0.66	0.62	53
1	0.82	0.70	0.76	73
2	0.75	0.81	0.78	52
	0.68	0.89	0.77	53
4	0.84	0.67	0.75	64
	0.94	0.91	0.92	65
accuracy			0.77	360
macro avg	0.77	0.77	0.77	360
eighted avg	0.78	0.77	0.77	360



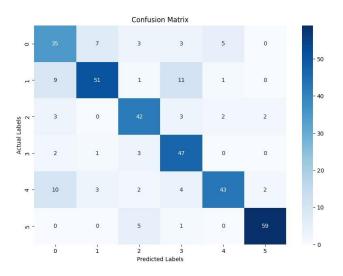


Figure 9 Snap of the Confusion Matrix

V. CONCLUSION

An important development in the fields of disease prevention and vector surveillance was made possible by this research endeavor. Through the application of a hybrid machine learning technique, we have created a reliable system that can effectively classify the species of mosquito depending on wingbeat analysis. This system integrates algorithms such as KNN, Random Forest, MLP, SVM, and Gradient Boosting.

By using several heterogeneous algorithms, each with distinct advantages and skills, our method is superior at identifying the subtleties and complex patterns seen in wingbeat recordings, allowing accurate distinction between different mosquito species. For efficient vector surveillance and disease control initiatives, robustness, dependability, and flexibility are ensured by this hybridization.

The scalability, precision, and practical application of our system have been demonstrated through validation of its performance on a variety of datasets and situations from everyday life. We have overcome the drawbacks of conventional techniques by utilizing machine learning, providing a more effective and automated approach for the categorization of mosquito species.

Our project creates opportunities for further study and improvement in the future. The system's performance and capacity for generalization may be improved by further refining the hybrid strategy, investigating new machine-learning approaches, and incorporating cutting-edge feature extraction techniques. The system's performance will also need to be continuously monitored and adjusted to changing mosquito populations and environmental circumstances across time.

By offering a cutting-edge method for classifying mosquito species, our effort advances vector monitoring, disease management, and public health activities. We provide stakeholders with accurate, dependable, and scalable solutions to efficiently control mosquito-borne illnesses by utilizing hybrid machine learning methodologies.

Our work offers several intriguing avenues for further development to increase the system's effectiveness and usefulness. First off, adding other machine learning algorithms to the mix beyond SVM, MLP, Gradient Boosting, Random Forest, and kNN can provide a deeper understanding and possibly improve classification accuracy. Improved classification performance might result from discovering new patterns in the wingbeat data through the use of techniques like ensemble approaches or deep learning frameworks. Subsequently, more useful features may be produced by continuously improving feature extraction techniques that are especially adapted to the peculiarities of mosquito species. The system's ability to discriminate between mosquito species may be improved by investigating sophisticated feature engineering methods or domain-specific feature representations. Thirdly, increased trust and comprehension of the system's judgments may result from attempts to improve model interpretability. Effective interpretation and validation of the results might be facilitated by using techniques like feature significance analysis or model visualization, which can illuminate the primary elements influencing classification outcomes. Furthermore, the system's robustness and adaptability would be increased by constantly changing operating adjusting to requirements and environmental circumstances. To respond to changing conditions, the system may be able to optimize and adjust its categorization algorithms through integration with environmental sensors or real-time data streams. Ultimately, the system's deployment in real-world scenarios depends on improvements for scalability and efficiency. Large-scale application deployment of the system might be facilitated by investigating methods for hardware acceleration, model compression, and parallelization, which could enhance performance and resource usage.

VI. REFERENCES

 [1]. E. Fanioudakis, M. Geismar, and I. Potamitis, "Mosquito wingbeat analysis and classification using deep learning," in 2018 26th European



Signal Processing Conference (EUSIPCO), 2018, pp. 2410-2414: IEEE.

- [2]. H. Caraballo and K. J. E. m. p. King, "Emergency department management of mosquito-borne illness: malaria, dengue, and West Nile virus," vol. 16, no. 5, pp. 1-23; quiz 23, 2014.
- [3]. L. K. Hapairai et al., "Evaluation of traps and lures for mosquito vectors and xenomonitoring of Wuchereria bancrofti infection in a high prevalence Samoan Village," vol. 8, pp. 1-9, 2015.
- [4]. R. Lühken et al., "Field evaluation of four widely used mosquito traps in Central Europe," vol. 7, pp. 1-11, 2014.
- [5]. G. l'Ambert, J. B. Ferré, F. Schaffner, and D. J. J. o. V. E. Fontenille, "Comparison of different trapping methods for surveillance of mosquito vectors of West Nile virus in Rhône Delta, France," vol. 37, no. 2, pp. 269-275, 2012.
- [6]. J. C. Koella, F. L. SÖrensen, and R. A. J. P. o. t. R. S. o. L. S. B. B. S. Anderson, "The malaria parasite, Plasmodium falciparum, increases the frequency of multiple feeding of its mosquito vector, Anopheles gambiae," vol. 265, no. 1398, pp. 763-768, 1998.
- [7]. H. Kampen et al., "Approaches to passive mosquito surveillance in the EU," vol. 8, pp. 1-13, 2015.
- [8]. E. Joelianto et al., "Convolutional neural network-based real-time mosquito genus identification using wingbeat frequency: A binary and multiclass classification approach," vol. 80, p. 102495, 2024.
- [9]. T. H. Truong, H. Du Nguyen, T. Q. A. Mai, H. L. Nguyen, and T. N. M. J. E. I. Dang, "A deep learning-based approach for bee sound identification," vol. 78, p. 102274, 2023.
- [10]. Q. Tang, L. Xu, B. Zheng, and C. J. E. I. He, "Transound: Hyper-head attention transformer for birds sound recognition," vol. 75, p. 102001, 2023.
- [11]. M. S. Fernandes, W. Cordeiro, M. J. C. i. B. Recamonde-Mendoza, and Medicine, "Detecting

Aedes aegypti mosquitoes through audio classification with convolutional neural networks," vol. 129, p. 104152, 2021.

- [12]. A. L. Wilson et al., "The importance of vector control for the control and elimination of vectorborne diseases," vol. 14, no. 1, p. e0007831, 2020.
- [13]. D. Karuppaiah, "A Hybrid Network Combining Cnn and Transformer Encoder to Classify Mosquitoes Based on Wing Beat Frequencies."
- [14]. A. A. Siddiqui and C. Kayte, "Transfer Learning for Mosquito Classification Using VGG16," in First International Conference on Advances in Computer Vision and Artificial Intelligence Technologies (ACVAIT 2022), 2023, pp. 471-484: Atlantis Press.
- [15]. K. Mostafa, M. Hany, M. Carnaghi, R. J. Hopkins, and A. Atia, "Aedes aegypti mosquito movements analysis and sex classification using computer vision and deep learning," in 2024 6th International Conference on Computing and Informatics (ICCI), 2024, pp. 261-267: IEEE.