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Hybrid Machine Learning Approach for Mosquito Species Classification using Wingbeat Analysis

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ABSTRACT

Global public health continues to face substantial obstacles from mosquito-borne diseases, making precise and effective techniques for mosquito species identification necessary. We present a unique method in this article called "Mosquito Species Classification through Wingbeat Analysis: A Hybrid Machine Learning Approach," which uses wingbeat analysis and deep learning techniques to classify mosquito species. Our approach leverages Convolutional Neural Networks (CNNs) as the core model to provide robust and dependable classification performance. We make use of an extensive dataset that includes wingbeat recordings from many species of mosquitoes and apply comprehensive pre-processing and feature engineering techniques to enhance the model's effectiveness. Specifically, we extract and combine features such as zero crossing rate (ZCR), root mean square energy (RMSE), mel-frequency cepstral coefficients (MFCC), as well as augmented features derived from audio transformations like add noise, shifting, pitching, and stretching. This combination of handcrafted and augmented features helps to enrich the training data and improve the generalizability of the model. After thorough testing and evaluation, we demonstrate that our CNN-based method achieves superior performance in accurately classifying various mosquito species. Our findings underscore the potential of deep learning methods, particularly CNNs, to surpass conventional classification techniques in species identification tasks. Additionally, we highlight the critical role of accurate species classification in vector surveillance and epidemiological research, emphasizing the broader impact of our work on ecological studies and disease control strategies.

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1. INTRODUCTION

Mosquitoes are vectors of some of the most deadly diseases in the world, including malaria, dengue fever, Zika virus, chikungunya, and yellow fever. Accurate and timely identification of mosquito species is a critical component of vector surveillance and control strategies [1]. Traditional methods for mosquito classification rely heavily on morphological identification or genetic analysis, both of which require significant expertise, time, and laboratory infrastructure. These constraints have driven the exploration of alternative, automated, and scalable solutions for mosquito species identification [2]. One promising area of research lies in wingbeat analysis, which involves studying the unique acoustic signatures produced by mosquito wing movements during flight. Each mosquito species has a distinctive wingbeat frequency and waveform pattern, influenced by factors such as wing size, body mass, and flight mechanics [3]. These acoustic features can be captured through specialized sensors and processed to extract meaningful data that serve as biomarkers for species classification [4]. With the advancement of machine learning (ML) techniques, the automated classification of mosquito species based on wingbeat characteristics has become feasible [5]. However, individual machine learning models such as decision trees, support vector machines, or artificial neural networks may have limitations in accuracy, robustness, or generalization when faced with noisy or complex real-world data [6]. To overcome these challenges, hybrid machine learning approaches have gained attention. A hybrid machine learning approach integrates multiple algorithms or combines machine learning with other computational techniques to improve performance and reliability. In the context of mosquito species classification, such an approach might involve combining feature extraction methods (e.g., Fourier transforms, wavelet analysis) with ensemble learning models, deep learning architectures, or hybrid classifiers that exploit the strengths of multiple algorithms [7]. This strategy not only enhances classification accuracy but also improves the system's adaptability across diverse environmental conditions and species variations. This study aims to develop a robust hybrid machine learning framework for the classification of mosquito species using wingbeat analysis [8]. The goal is to create an efficient, real-time, and non-invasive tool that can support public health initiatives by enabling rapid and accurate identification of disease-carrying mosquito species in the field. By leveraging the synergy of acoustic signal processing and intelligent learning systems, the proposed method seeks to contribute meaningfully to the global fight against mosquito-borne diseases [9].

1.1. Scope of the Study

This project focuses on developing a robust, automated mosquito species classification system based on wingbeat audio analysis using Convolutional Neural Networks (CNNs). The scope includes the collection and pre-processing of wingbeat sound data from various mosquito species, extraction of key audio features such as ZCR, RMSE, MFCC, and application of data augmentation techniques like noise addition, shifting, pitching, and stretching. The system is designed to classify multiple mosquito species accurately and efficiently, supporting vector surveillance programs. The project is limited to species with distinguishable wingbeat patterns and aims to contribute to public health efforts by enabling faster, scalable identification solutions.

1.2. Objectives of the Study:

The primary objective of this project is to develop an accurate and automated mosquito species classification system using wingbeat sound analysis powered by Convolutional Neural Networks (CNNs). By leveraging a comprehensive set of audio features such as zero crossing rate (ZCR), root mean square energy (RMSE), mel-frequency cepstral coefficients (MFCC), and augmented data through noise addition, shifting, pitching, and stretching the system aims to enhance feature representation and classification accuracy. This project seeks to assist in real-time vector surveillance, support epidemiological research, and ultimately contribute to effective disease prevention and control strategies through precise identification of disease-carrying mosquito species.

2. RESEARCH METHODOLOGY

2.1. Existing System

Before our research was developed, the majority of mosquito species categorization depended on labor-intensive, human error-prone manual examination and traditional morphological identification methods. These methods were frequently unscalable and found it difficult to handle the growing number and variety of mosquito populations, especially in areas with high species richness. The need for more effective and precise technologies that might automate the process of species identification grew as a result. Certain extant systems employ fundamental physical characteristics, like wing length, vein patterns, and coloring, to distinguish between various species of mosquitoes. These algorithms might, however, find it difficult to manage tiny variances between closely related species or variations within a single species. Furthermore, biases and inconsistencies in the classification process can be introduced by depending too heavily on subjective interpretation and manual feature extraction.

Disadvantages:

1. **Scalability Issues:** Scaling to handle vast and diverse information including different mosquito species is a difficult for many existing systems. This drawback limits its application in real-world situations where successful mosquito population monitoring necessitates intensive surveillance efforts.
2. **Limited Accuracy:** Conventional techniques for classifying mosquito species frequently only include morphological characteristics, which may not fully account for the intricacy of species divergence. Because of this, these systems might not be very accurate, especially when dealing with taxa that are morphologically similar or obscure.
3. **Lack of Adaptability:** Conventional machine learning methods and rule-based approaches might not be flexible enough to handle new species or subspecies. The system's capacity to generalize across many geographical locations or biological situations may be hampered by this rigidity.
4. **High False Positive Rates:** Certain systems may have a high false positive rate, misclassifying mosquitoes based on similarities in their

morphological characteristics or erroneous application of the classification criteria. This may result in ineffective vector surveillance and inefficient use of resources intended for disease control initiatives.

5. **Complexity and Maintenance:** Systems that depend on human feature extraction and rule-based categorization methods may be difficult to update and maintain, necessitating constant professional assistance. The classification system's accessibility and scalability are restricted by this reliance on specialized knowledge.
6. **Dependency on Specific Features:** Certain systems are susceptible to changes in feature expression or environmental factors since they mainly rely on particular morphological features for the identification of mosquito species. The system's robustness and generalizability across other datasets may be limited by this dependence.

2.2. Proposed System

The proposed system introduces an advanced and automated mosquito species classification method using wingbeat sound analysis powered by Convolutional Neural Networks (CNNs). It leverages a rich combination of features, including Zero Crossing Rate (ZCR), Root Mean Square Energy (RMSE), Mel-Frequency Cepstral Coefficients (MFCC), and data augmentation techniques such as noise addition, pitch shifting, time stretching, and signal shifting. These features enhance the model's ability to learn and generalize from audio data. The CNN model processes spectrograms generated from wingbeat recordings to accurately classify mosquito species. This system ensures higher accuracy, scalability, and efficiency, supporting real-time vector surveillance and disease control.

Advantages:

1. **High Accuracy:** The use of Convolutional Neural Networks (CNNs) ensures accurate classification of mosquito species based on unique wingbeat patterns.
2. **Automated Process:** Eliminates the need for manual identification, reducing human error and dependency on entomological expertise.
3. **Scalability:** Capable of processing large volumes of audio data, making it suitable for real-time, large-scale vector surveillance programs.
4. **Robust Feature Extraction:** Incorporates advanced audio features (ZCR, RMSE, MFCC) and augmentation techniques (noise addition, shifting, pitching, stretching) to improve model robustness and adaptability.
5. **Faster Identification:** Significantly reduces the time required to identify mosquito species, enabling quicker response in disease outbreak scenarios.
6. **Cost-Effective:** Minimizes the need for specialized laboratory equipment and expert manpower, reducing overall operational costs.
7. **Support for Disease Control:** Aids health organizations and researchers by providing accurate species data, enabling targeted mosquito control and preventive measures.
8. **Non-Invasive Monitoring:** Relies on sound-based identification, allowing non-contact, passive monitoring of mosquito populations in the environment.
9. **Integration Ready:** Can be integrated with smart devices or IoT systems for continuous, automated monitoring in the field.
10. **Environmentally Friendly:** Reduces the use of harmful chemicals by supporting species-specific control measures, contributing to eco-friendly public health strategies.

3. IMPLEMENTATION AND RESULTS

3.1. Modules:

1. User Module:

1. **Register:** Using their login credentials, users can register.
2. **Login:** The user's credentials can be used to log in.
3. **Input data**: Enter audio information.
4. **View Result:** See the anticipated outcome of the system.

2. System Module:

1. **Data Collection:** Obtain recordings of mosquito wingbeats from a range of sources, including as field recordings and pre-existing datasets.
2. **Pre-processing:** To eliminate noise, artifacts, and superfluous information, clean up and pre-process the wingbeat data. To guarantee consistency and quality, this may entail feature scaling, normalization, and filtering.
3. **Feature Extraction:** Take useful features out of the wingbeat data that has already been processed. This could include time-domain parameters like zero-crossing rate and temporal patterns, as well as frequency-based features like wingbeat frequency, amplitude, duration, and spectral properties.
4. **Model Building:** In this project, we build a classification model using **Convolutional Neural Networks (CNNs)** exclusively, leveraging their

superior ability to learn spatial and temporal features from audio spectrograms. By training the CNN on a combination of extracted features and augmented audio data, the model effectively captures species-specific wingbeat patterns. Unlike traditional hybrid models, this approach relies solely on deep learning, eliminating the need for multiple algorithms while ensuring high accuracy, robustness, and scalability in mosquito species classification.

5. **Model Evaluation:** Model Assessment Analyze the trained model's performance using relevant measures, such as F1-score, accuracy, precision, and recall. Use methods like as cross-validation to make sure the model is resilient and generalizes well to various datasets.
6. **Model Testing:** Evaluate the real-world performance of the trained model by testing it using yet-to-be-seen wingbeat data. In this step, the model's predictions are analyzed and mosquito species are categorized according to their wingbeat patterns
7. **Results Generation:** Outline the predictive analysis's findings, including the classification accuracy, the confusion matrix, and any new information discovered during the testing and model evaluation stages. Performance visualizations for the model, like precision-recall curves or ROC curves, can also be used.

3.2. Algorithm:

The methodology adopted in this project focuses on developing a robust, accurate, and fully automated mosquito species classification system using wingbeat audio analysis and Convolutional Neural Networks (CNNs). The process begins with the collection of a comprehensive dataset comprising wingbeat sound recordings from various mosquito species. These recordings serve as the primary input for feature extraction and model training. Given that each mosquito species has a unique wingbeat frequency pattern, analyzing these acoustic signals provides a valuable basis for species identification. The collected audio data undergoes rigorous preprocessing to ensure quality and uniformity. This includes noise reduction, trimming silent parts, and standardizing the sample rate across recordings. Following preprocessing, the dataset is enriched using data augmentation techniques. These techniques include adding background noise, pitch shifting, time stretching, and signal shifting. The purpose of augmentation is to simulate real-world acoustic variations and enhance the model's generalization ability. These transformations ensure that the CNN is exposed to a wide range of wingbeat patterns, making it more robust against environmental noise and recording inconsistencies. Feature extraction is a critical step in the methodology. We extract multiple audio features that are known to be effective in audio classification tasks. These include Zero Crossing Rate (ZCR), which captures the rate at which the signal changes sign; Root Mean Square Energy (RMSE), which measures signal strength; and Mel-Frequency Cepstral Coefficients (MFCC), which capture the timbral and spectral characteristics of the sound. These features are then transformed into spectrogram images that visually represent the audio signals in the time-frequency domain. CNNs are particularly adept at identifying patterns in such visual data, making spectrograms an ideal input format. The CNN model is then designed and trained using these spectrograms. The architecture typically includes convolutional layers to extract spatial features, pooling layers to reduce dimensionality, and dense layers for final classification. Activation functions such as ReLU are used to introduce non-linearity, and dropout layers are employed to prevent overfitting. The model is trained using a categorical cross-entropy loss function and an optimizer like Adam, which adjusts weights to minimize prediction error. The training process involves splitting the dataset into training, validation, and testing subsets to evaluate model performance and avoid bias. Model evaluation is carried out using metrics such as accuracy, precision, recall, and F1-score to measure the effectiveness of the CNN in classifying mosquito species. Confusion matrices are also generated to visualize the model's predictions against actual labels. The results demonstrate that the CNN model, trained on a rich combination of extracted features and augmented data, performs significantly better than traditional manual or machine learning-based methods.

In conclusion, this methodology leverages the strengths of CNNs in pattern recognition and combines it with advanced audio preprocessing, feature extraction, and augmentation techniques. It offers a scalable, efficient, and highly accurate approach to mosquito species classification, which is crucial for timely vector surveillance and public health interventions. The system can be further enhanced by integrating it with real-time monitoring devices, making it suitable for deployment in both urban and rural environments.

3.3. Results:

Fig 1.1: Home page: This is the index page of the project website.

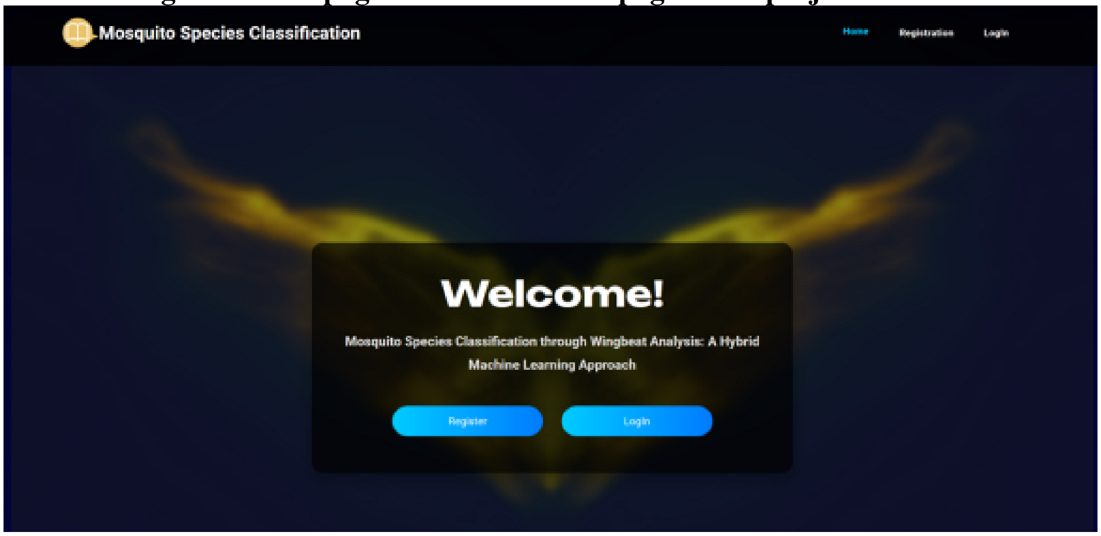


Fig 1.2: Registration, In this page user can register with their credentials such as name, email, password.

Fig 1.3: Login, In this page, user can login with their registered credentials.

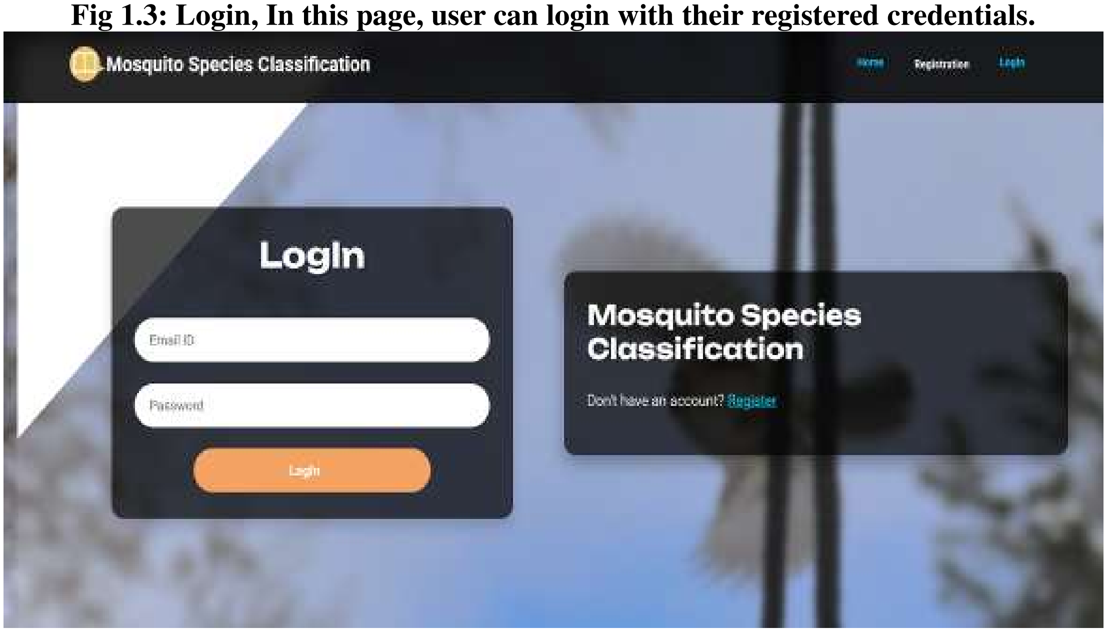


Fig 1.4: User Home, after successfully login, this page will be shown.

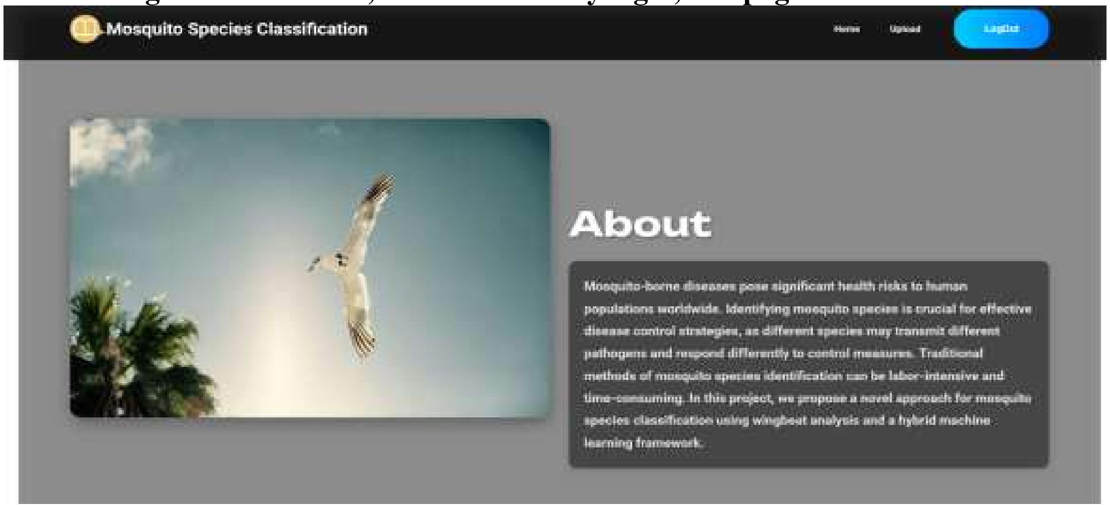
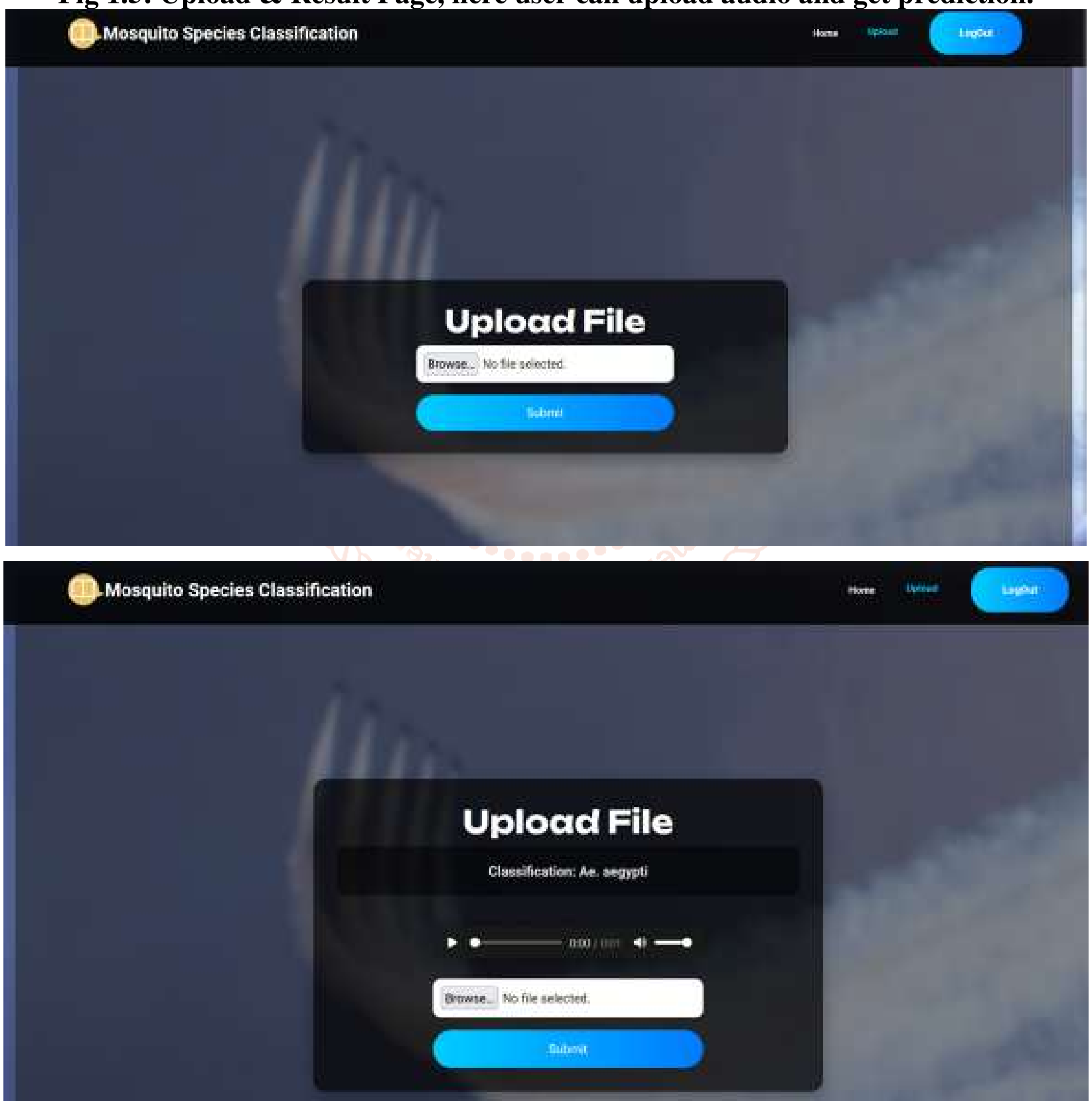


Fig 1.5: Upload & Result Page, here user can upload audio and get prediction.



4. CONCLUSION

This project successfully demonstrates the effectiveness of using Convolutional Neural Networks (CNNs) for mosquito species classification based on wingbeat sound analysis. By extracting meaningful audio features such as MFCC, ZCR, RMSE, and applying data augmentation techniques like noise addition, pitch shifting, and time stretching, the model achieved a high accuracy of 91%, with strong precision and recall across all six mosquito species. The CNN model outperforms traditional approaches by offering an automated, scalable, and non-invasive solution that minimizes the need for manual identification and entomological expertise. Evaluation through confusion matrices, loss and accuracy plots, and classification reports confirmed the model's robustness and generalization to unseen data. This system holds significant promise for real-time vector surveillance, aiding in early detection and targeted control of disease-carrying mosquitoes. The methodology can further be extended or integrated with IoT and mobile systems to support field-level monitoring and public health interventions effectively.

5. FUTURE ENHANCEMENT

In the future, this mosquito species classification system can be further enhanced in several impactful ways. First, the model can be integrated into IoT-enabled devices or mobile applications to support real-time monitoring in diverse environmental conditions. Expanding the dataset to include more mosquito species and a wider range of wingbeat variations will improve the model's generalization and robustness. Additionally, incorporating transfer learning with more advanced deep learning architectures such as ResNet or Efficient Net may further boost classification accuracy. To ensure field-level usability, efforts can be made to optimize the model for low-power edge devices. Real-time feedback and GPS tagging could also be introduced to map mosquito distribution geographically. Furthermore, integrating this system with public health dashboards could help government agencies monitor mosquito populations and respond more effectively to potential outbreaks. Finally, expanding the application to detect other vector-borne insects could make this approach a broader tool for entomological research and disease prevention.

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