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Hybrid Machine Learning Approach for Mosquito Species Classification using Wingbeat Analysis: A Review

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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. LITERATURE REVIEW

[1] J. H. Rony, et.al 2023, This paper investigates the possibility of using wingbeat sound characteristics to identify various flying mosquito species. Before mosquito-borne diseases develop, it is possible to recognize and classify various flying mosquito species by utilizing machine learning to analyze ambient sound. This research provides a hybrid model that uses support vector machines (SVM) and convolutional neural networks (CNN) to analyze audio and classify various species in order to achieve identification and classification. The suggested model mitigates the shortcomings of individual models and demonstrates a notable degree of accuracy in identifying and categorizing various kinds of flying mosquitoes. Widespread adoption of the hybrid model may contribute to a decrease in the number of deaths and diseases spread by mosquitoes.

[2] Karuppaiah, et.al, Aedes, Anopheles, and Culex species cause a variety of mosquito-borne illnesses, including West Nile fever, Chikungunya, Dengue, Lymphatic filariasis, and Zika. Determining these species is therefore essential to developing preventative measures against such illnesses. Additionally, classifiers that are able to identify mosquitoes based on background noise might be very helpful in a variety of urban applications. In this study, we provide a hybrid network that uses transformers and a convolutional neural network to classify several mosquito species from a dataset gathered from cell phones. In conclusion, we pre-processed the dataset by eliminating a few erroneous data points and down sampling the mosquitoes' wing beat recordings without eliminating the noisy samples. Instead of using spectograms over time, we employ raw wing beat amplitudes as features. Next, we use supervised learning to train our proposed hybrid network on the preprocessed features. Our multi-classifier therefore attains 81.27% (0.93) accuracy. Moreover, we demonstrate that it outperforms earlier research models in areas like the classification of overlapping frequency distribution species.

[3] Annet, A., et.al 2023, Aedes genus hematophagous insects have been shown to be proven vectors of medically significant viral and filarial infections. Aedes albopictus's rapid global spread has made it a vector of rising importance. To improve efforts in the entomological survey of arthropods of medical relevance, identification methods with field application are needed in light of the changing global climate and the rise of zoonotic infectious illnesses. The large number of recognized species further complicates the necessity for knowledgeable experts and/or expensive technical equipment for extensive and proactive entomological surveys of Aedes mosquitoes. In this work, we utilized the species-specific identifier provided by Wing Interferential Patterns to construct an automatic classification method for Aedes species.A convolutional neural network was trained using a deep learning methodology on a database including 494 photomicrographs of 24 species of Aedes spp.; the accuracy of the network's classification of samples at the genus, subgenus, and species taxonomic levels was tested. Out of the three subgenera that were evaluated, we obtained an accuracy of 95% at the genus level and >85% for two (Ochlerotatus and Stegomyia). Last but not least, out of the ten Aedes sp. that underwent training, eight had an accuracy rate of >70% overall. Taken together, these findings show the methodology's potential for identifying Aedes species and will serve as a tool for next large-scale entomological studies.

[4] K. Mostafa, et.al, 2024, Mosquitoes transmit bacteria, viruses, and parasites that afflict millions of people worldwide. They are therefore considered disease vectors. It is essential to comprehend their flying patterns and behaviors for the purposes of disease modeling, ecological study, and creating efficient control strategies. Automated techniques offer a potential substitute for labor-intensive and time-consuming traditional manual methods for analyzing mosquito flight records. In this study, artificial intelligence (AI), specifically computer vision and deep learning, was used to recognize, track, and classify insect movements. Two tests were conducted. In the first, the accuracy with which the system could identify and categorize mosquito movements' directions was evaluated using a variety of classifiers, including the Gated Recurrent Unit (GRU) and the Convolutional Neural Network model with Long Short-Term Memory model (CNN-LSTM). The results reveal a high 96.67% accuracy rate. In the second trial, a CNN model based on movement heatmaps demonstrated the system's capacity to distinguish between Aedes aegypti mosquitoes that were male or female. The accuracy ranges found in the results are 89.84% to 99.73%.

[5] Abadi, et.al (2016), this study introduces TensorFlow, a comprehensive open-source system for large-scale machine learning applications. Designed with scalability and flexibility in mind, TensorFlow supports deep learning model construction, training, and deployment across heterogeneous platforms. The architecture enables distributed computing, automatic differentiation, and high-level APIs that streamline the implementation of complex models. In the context of mosquito species classification via wingbeat analysis, TensorFlow serves as a robust platform for building and deploying hybrid machine learning models that integrate both convolutional and traditional classifiers.

[6] Kingma, et.al (2014), this paper proposes Adam (Adaptive Moment Estimation), a novel stochastic optimization technique that combines the benefits of AdaGrad and RMSProp. Adam is particularly effective for handling sparse gradients and noisy datasets, making it ideal for training deep neural networks on complex data such as wingbeat audio signals. Its efficiency and adaptive learning rate properties facilitate faster convergence and better generalization in classification models, especially those involving acoustic data with variability across mosquito species.

[7] Srivastava, et.al (2014), The authors introduce Dropout, a regularization technique aimed at preventing overfitting in neural networks. By randomly deactivating a subset of neurons during training, Dropout reduces co-adaptation and forces the network to learn more generalizable features. In mosquito species classification tasks, Dropout is valuable for enhancing the robustness of deep models trained on limited or imbalanced wingbeat datasets, ensuring better performance on unseen acoustic recordings.

[8] Deng, L., & Yu, D. (2014), This comprehensive review presents the foundational methods, applications, and future potential of deep learning, emphasizing its impact on areas such as speech recognition, image processing, and signal analysis. The authors discuss architectures including DNNs, CNNs, and RNNs, detailing their strengths in modeling nonlinear relationships in large datasets. Their relevance to mosquito wingbeat classification lies in the similarity between speech/audio signals and mosquito flight sounds, making deep learning an effective approach for accurate species identification from bioacoustic data.

[9] Hinton, et.al (2012), this collaborative work from four leading research teams outlines the implementation and success of deep neural networks (DNNs) in modeling acoustic signals for speech recognition. It emphasizes how DNNs can capture hierarchical structures in time-series data, which directly parallels the classification of mosquito wingbeat audio. The insights provided support the use of deep learning in extracting discriminative features from wingbeat frequencies, thereby improving the accuracy of mosquito species classification.

[10] Zeiler, M. D., & Fergus, R. (2014), In this study, the authors propose methods to visualize the internal layers of convolutional neural networks (CNNs), thereby enhancing the interpretability of learned features. Through deconvolutional techniques, the study provides insights into how CNNs detect patterns at different levels of abstraction. This is particularly relevant for mosquito wingbeat classification, where understanding what features the model relies on such as harmonics or frequency modulations can lead to better model refinement and trust in automated identification systems.

3. RESEARCH METHODOLOGY

3.1. Existing System

Before our research was developed, the majority of mosquito species categorization depended on labour-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 colouring, 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.

3.2. 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.

4. 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.

5. 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.

References

[1] Chollet, F. (2017). "Deep Learning with Python." Manning Publications.

[2] Goodfellow, I., Bengio, Y., & Courville, A. (2016). "Deep Learning." MIT Press.

[3] Graves, A., & Schmidhuber, J. (2005). "Framewise Phoneme Classification with Bidirectional LSTM and Other Neural Network Architectures." Neural Networks, 18(5-6), 602-610.

[4] Oord, A. v. d., Dieleman, S., Zen, H., Simonyan, K., Vinyals, O., Graves, A., ... & Kavukcuoglu, K. (2016). "WaveNet: A Generative Model for Raw Audio." arXiv preprint arXiv:1609.03499.

[5] Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., ... &Kudlur, M. (2016). "TensorFlow: A System for Large-Scale Machine Learning." In 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 16) (pp. 265-283).

[6] Kingma, D. P., & Ba, J. (2014). "Adam: A Method for Stochastic Optimization." arXiv preprint arXiv:1412.6980.

[7] Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014).

"Dropout: A Simple Way to Prevent Neural Networks from Overfitting." Journal of Machine Learning Research, 15(1), 1929-1958.

[8] Deng, L., & Yu, D. (2014). "Deep Learning: Methods and Applications." Foundations and Trends in Signal Processing, 7(3-4), 197-387.

[9] Hinton, G., Deng, L., Yu, D., Dahl, G. E., Mohamed, A. R., Jaitly, N., ... & Kingsbury, B. (2012). "Deep Neural Networks for Acoustic Modeling in Speech Recognition: The Shared Views of Four Research Groups." IEEE Signal Processing Magazine, 29(6), 82-97.

[10] Zeiler, M. D., & Fergus, R. (2014). "Visualizing and Understanding Convolutional Networks." In European Conference on Computer Vision (pp. 818-833). Springer, Cham.

[11] Potamitis, I., Rigakis, I., & Fysarakis, K. (2015). *Insect biometrics: Optoacoustic signal processing and its applications to remote monitoring of bees. Computers and Electronics in Agriculture*, 113, 131–139. https://doi.org/10.1016/j.compag.2015.02.003

[12] Fanioudakis, E., Potamitis, I., & Tatlas, N. A. (2018). *Mosquito wingbeat analysis using deep learning and commercially available devices. IEEE International Conference on Engineering Applications of Neural Networks*, 13–23. https://doi.org/10.1007/978-3-319-99344-3_2

[13] Kiskin, I., Cobb, A. D., Wang, L., & Roberts, S. J. (2020). *Bioacoustic detection with wavelet-conditioned convolutional neural networks. Neural Computing and Applications*, 32, 915–927. https://doi.org/10.1007/s00521-018-3920-z

[14] Batista, G. E. A. P. A., Prati, R. C., & Monard, M. C. (2004). *A study of the behavior of several methods for balancing machine learning training data. SIGKDD Explorations*, 6(1), 20–29. https://doi.org/10.1145/1007730.1007735

[15] Bimbraw, K. (2015). *Autonomous cars: Past, present and future a review of the developments in the last century. 12th International Conference on Informatics in Control, Automation and Robotics*, 191–198.