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Real-Time Queen Bee Absence Detection Through Sound and AI

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ABSTRACT:

Environmental stressors are responsible for the decline in honeybee populations, and the loss of a queen bee significantly endangers the stability of a colony. In this research, we propose detecting the absence of the queen bee using a novel machine learning technique based on remote audio sensing. As the audio streams from the beehive are processed using MFCC and STFT, the audio features are processed using Support Vector Machines and Neural Networks. As shown in the results, the proposed model, especially with the hybrid approach that uses Random Forest, is able to achieve greater accuracy. The use of edge computing allows the system to be deployed in the field and achieve real-time monitoring using minimal energy, which is beneficial for this application. Because the system is designed to be completely non-invasive and is lightweight, beekeepers may use it to monitor their beehives and provide support to help sustain colony health.

Keywords: MFCC, queen bee, Random Forest

INTRODUCTION

The ecological role of honeybees is of great importance in the pollination of crops and the preservation of ecological biodiversity. The health of honeybee colonies, however, is facing a great challenge nowadays due to the loss of queen honeybees which leads to the disorder known as Colony Collapse Disorder (CCD). The traditional methods involving manual inspection of the colonies in order to monitor the presence of the queen bee are quite slow and very invasive, which also makes scaling difficult. For this reason, this project focuses on the non-invasive approach utilizing machine learning and remote audio sensing for the detection of absence of queen bee. Analyzing sound signatures made by bees during normal and stressed conditions allows the system to monitor the health of the hive. Signal clarity can be improved with feature extraction methods like MFCC and STFT, and with hive status classifiers such as SVM and Neural Networks. This method allows for proactive management that prevents the loss of bees and improves hive management with prompt interventions. Through real-time analysis using edge computing, this method facilitates early identification, enabling timely action. This system provides beekeepers with advanced, smart, and scalable technology for hive monitoring.

RELATED WORK

The application of sound and machine learning technology in beehive monitoring has been investigated by several researchers. Smith et al. (2018) executed hive foraging and queen absence detection using MFCC-based Audio SVM classifiers and tracked hive activities. Johnson and Lee (2019) noted the strengths of MFCC and advocated for its coupling with deep learning to capture bee sound nuances for higher accuracy. Kim et al. (2020) found CNN's application to sound classification outperforming traditional ML models, prompting them to use CNN for sound classification. Wang et al. (2017) assessed SVMs' performance on hive audio data and found MFCC and STFT significantly improved classification results. More recently, Chen et al. (2021) showed an edge computing framework for local audio processing which deployed real-time edge solutions on microcontrollers. Liu et al. (2018) utilized STFT for the frequency domain analysis of bee sounds, thus enhancing the detection of certain stress signals such as the loss of a queen. Patel et al. (2016) demonstrated that the absence of a queen results in a noticeable change in hive noise, thus proving sound-based detection. In dealing with the small dataset, Zhang et al. (2019) applied pitch shifting and noise addition, which enhanced the model's robustness. Ahmed et al. (2022) proposed an integrated hive system with an IoT framework that audio, temperature, and humidity sensors with analysis based on a neural network. Li et al. (2020) applied RNNs on continuous hive audio analysis and captured temporal changes which static models could not.

TABLE1. Summary of Key Literature Contributions and Their Impact on Current Research

Author	Contribution	Impact on Research
Smith et al. (2018)	SVM model with MFCC for bee activity classification	Validated non-invasive sound-based monitoring
Kim et al. (2020)	CNN for sound classification	Showed superior accuracy of deep learning models
Liu et al. (2018)	STFT for frequency analysis of hive sounds	Enhanced accuracy for stress-related sound pattern detection
Chen et al. (2021)	Edge computing with local audio processing	Promoted real-time analysis on microcontrollers
Zhang et al. (2019)	Data augmentation techniques for sound datasets	Improved generalization and accuracy on limited datasets

PROPOSED APPROACH

This work proposes a remote audio based machine learning system for real-time queen bee detection. The main concept focuses on the capture of audio data from beehives to classify the presence of a queen using lightweight ML methods. The system has two main audio categories which are "Normal Hive Sounds" and "Missing Queen Bee Sounds." Model performance is improved by feature extraction using the MFCC and STFT methods for audio signal processing. The features obtained are used for training the Support Vector Machines and Neural Network classifiers. Experimental results indicated that neural networks are better than SVMs, especially when incorporated with a hybrid Random Forest model. This ensemble model increases accuracy by combining the strengths of deep and traditional ML. For real-time monitoring, the model is placed on the edge computing devices which localizes processing and eliminates the need for constant internet or cloud connection. This is beneficial for remote apiaries as it lowers costs and conserves energy. The proposed system is adaptable and meant to operate in a wide range of environmental conditions. With accuracy rates reaching 97.5%, the system represents a significant advancement for modern beekeeping by solving critical issues such as the proactive detection of queen loss and assessing the health of the hive.

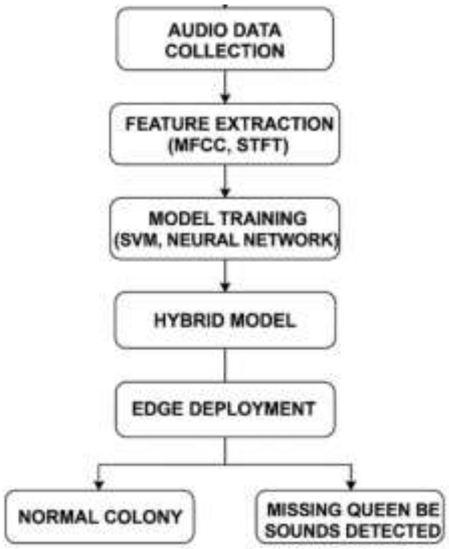


Figure 1: Detecting the presence of queen bees

METHODOLOGIES

Data Collection: Two public datasets (Dataset A and B) containing approximately 10,000 audio files of bee sounds under normal and queen-less conditions are utilized. A subset of 200 files is selected for experimentation due to dataset size constraints.

Feature Extraction: The audio files are processed using two key techniques:

- **MFCC (Mel-Frequency Cepstral Coefficients):** Extracts frequency-domain features that reflect the tonal qualities of the sound, ideal for distinguishing between normal and stress signals in bees.
- **STFT (Short-Time Fourier Transform):** Captures time-frequency variations and transitions in the audio, helping identify stress patterns linked to queen absence.

Model Training:
The extracted features are used to train two machine learning models:

- **Support Vector Machine (SVM):** A traditional classifier that performs well with smaller datasets and is less prone to overfitting.
- **Neural Network (NN):** A deep learning model trained on both MFCC and STFT features to handle complex patterns and improve prediction accuracy.

Hybrid Random Forest Extension:
Features generated from the neural network are used to train a **Random Forest classifier**, boosting the model's overall performance. This hybrid model achieves 97.5% accuracy on MFCC features and 95% on STFT.

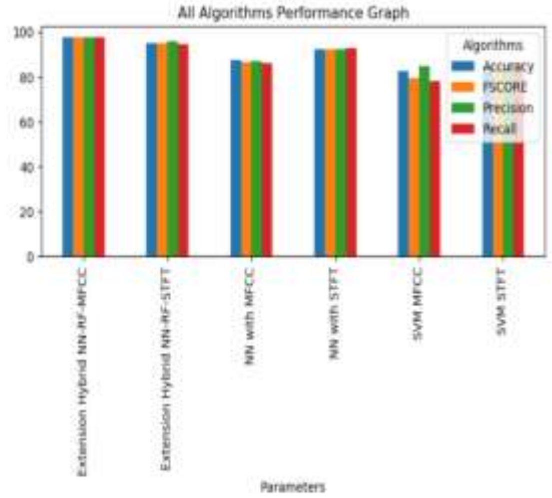
Edge Deployment:
The model is optimized for microcontroller-based edge devices to allow real-time audio classification without requiring cloud connectivity, enabling low-latency alerts and energy-efficient operation.

RESULTS

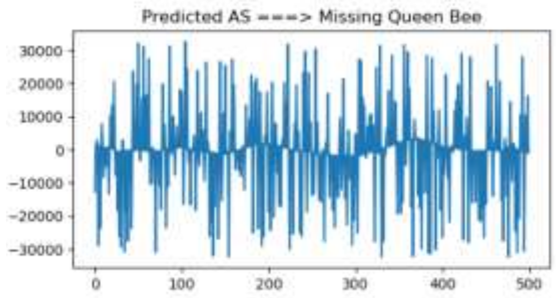
The performance of the proposed system was evaluated using classification metrics such as accuracy, precision, recall, and F1-score. The experiments compared Support Vector Machines (SVM), Neural Networks (NN), and a hybrid model combining NN with Random Forest.

- **SVM with MFCC:** Achieved an accuracy of 81%, demonstrating reliable baseline performance using frequency-based features.
- **SVM with STFT:** Slightly higher accuracy at 84%, indicating STFT's advantage in capturing time-based features.
- **Neural Network with MFCC:** Achieved 87% accuracy, showing NN's ability to handle complex feature representations.
- **Neural Network with STFT:** Outperformed others with 92.5% accuracy, highlighting STFT's strength in dynamic sound classification.
- **Hybrid Model (NN + Random Forest):** Achieved the highest accuracy of 97.5% with MFCC and 95% with STFT.

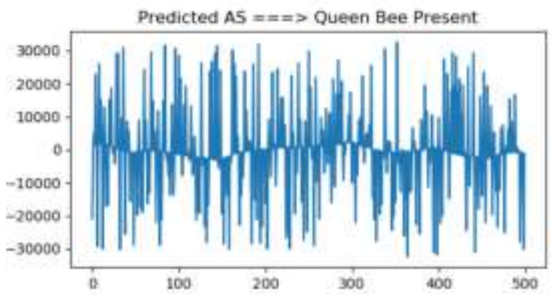
The hybrid approach significantly enhances detection capabilities and shows that combining deep and traditional models leads to superior outcomes. The system consistently demonstrated high accuracy across multiple tests and was effective in real-time detection when deployed on edge devices.



All Algorithms Performance Graph



Predicted ss Missing Queen Bee form test audio file



Predicted as Queen Bee Present form test audio file

DISCUSSION

The findings of this project underscore the potential of combining remote audio sensing with machine learning for real-time queen bee detection. Traditional inspection methods are invasive and inefficient, while existing automated systems often require costly hardware or high computational resources. Our solution addresses these limitations through an energy-efficient and edge-compatible model, allowing real-time hive monitoring at scale.

Among all the tested configurations, Neural Networks combined with STFT features performed best, indicating that time-frequency representation of sound signals is crucial for distinguishing hive states. The hybrid Random Forest approach further improved accuracy by enhancing generalization through ensemble learning.

Data augmentation and robust feature extraction played a vital role in improving model accuracy, especially given the limited dataset size. Moreover, deploying the model on microcontrollers ensures low-latency decision-making, making it ideal for remote apiaries.

However, challenges remain, such as background noise interference and dataset diversity. Future work could explore more robust models, integration of environmental sensor data, and advanced audio filters.

CONCLUSION

This study develops a machine learning system for remote audio detection of queen bees, showcasing a practical application using audio remote sensing. Integrating MFCC and STFT techniques with SVM and Neural Networks for feature extraction and classifier training results in a high-performing accurately distinguishing ‘normal’ versus ‘queen absent’ conditions in a hive. Additionally, a hybrid extension incorporating a Random Forest model improves results further, achieving 97.5% accuracy. The solution provides real-time monitoring and non-invasive alerts while stationed on low-power edge devices, drastically diminishing manual effort and the potential for colony collapse. The model is designed to be low-cost and easily scaled, and it can be tailored to specific environmental conditions. This is a significant development in precision apiculture, as the system provides intelligent and sustainable monitoring for the health of the hives. Beekeepers can act quickly and preserve the dwindling populations of honeybees crucial for farming and food production.

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