



Bird Sound Identification Using Machine learning

Kartik Patil¹, Mallamma V Reddy²

¹MCA Student, Department of Computer Science, Rani Channamma University, Belagavi, Karnataka, India

²Assistant Professor, Department of Computer Science, Rani Channamma University, Belagavi, Karnataka, India

ABSTRACT :

Rising temperatures, changed precipitation patterns, and a rise in the frequency of extreme weather events are all signs of climate change in India, and they all have a significant effect on vegetation, agriculture, and human health. Changes in growing seasons and erratic rainfall pose a danger to food security and agricultural livelihoods, especially for smallholder farmers. Simultaneously, alterations in climate patterns intensify health hazards, such as heat stress, vector-borne infections, and disorders linked to air pollution. In addition, problems that affect plants and ecosystems include habitat loss, a drop in biodiversity, and changed ecosystem services that are essential to maintaining ecological balance and human well-being

Keywords: Climate Data Analysis, Data Preprocessing, Logistic regression, Machine learning, Neural networks, Rainfall Prediction, Random Forest, Temperature Trends.

Introduction :

The identification of bird sounds is a rapidly developing topic that is essential to species behavior study, biodiversity protection, and ecological monitoring. Manual observation is required for traditional methods of classifying bird species based on their vocalizations, which can be laborious and prone to human mistake. The development of automatic bird sound recognition systems has drawn a lot of attention due to advances in machine learning and audio signal processing. By evaluating bird calls and songs in an effective and scalable manner, these systems offer important information into ecosystem health, bird populations, and their habitats. By real-time tracking and detection of endangered species, these techniques benefit conservation efforts in addition to being helpful for researchers and environmentalists. Utilizing cutting-edge computational methods, bird sound recognition systems have the ability to revolutionize wildlife monitoring and species preservation.

Literature Survey :

[1] Stowell D. & Plumbley, M. (2014). "Automatic classification of bird sounds." *IEEE Transactions on Audio, Speech, and Language Processing*. This paper focuses on early attempts at automatic bird sound classification, introducing methods like feature extraction and machine learning algorithms to recognize bird species. [2] Xie L. et al. (2020). "Acoustic scene analysis for bird sound classification." *IEEE Access*. This study explores the use of acoustic scene analysis for bird sound identification, applying machine learning techniques to large datasets of bird vocalizations. [3] Fink D. et al. (2017). "An open-source platform for automated bioacoustic monitoring." *Methods in Ecology and Evolution*. This paper presents an open-source platform that enables the automatic monitoring of wildlife, including birds, using sound analysis and machine learning. [4] Kahl, A. et al. (2018). "Bird song recognition using deep learning." *Journal of Ornithology*. A study that employs deep learning techniques, specifically convolutional neural networks (CNNs), to improve bird song recognition accuracy. [5] Mitrovic, S. et al. (2020). "Machine learning for real-time bird identification." *Ecological Modelling*. This paper discusses a real-time bird identification system that uses machine learning algorithms to process bird sound recordings in the field. [6] Stowell, D. et al. (2016). "Improved bird sound classification with deep learning." *Bioacoustics*. The authors demonstrate how deep learning, particularly recurrent neural networks (RNNs), can improve bird sound classification over traditional methods. [7] O'Neill B. et al. (2020). "Deep learning for bird song classification." *Journal of Field Ornithology*. This paper introduces the use of transfer learning for bird song classification, allowing for more accurate predictions in small datasets. [8] Huang, C. et al. (2020). "Automated classification of bird species from audio recordings." *Animal Conservation*. The study focuses on classifying bird species using a combination of traditional machine learning techniques and deep learning models on large-scale audio datasets. [9] Mitchem, L. et al. (2019). "Applications of sound analysis in bird conservation." *Journal of Wildlife Management*. This paper examines the practical applications of bird sound analysis in conservation, focusing on how automated systems can help identify endangered species. [10] Kremers, R., et al. (2020). "Advancements in the identification of avian vocalizations." *Journal of Applied Ecology*. The study discusses advancements in bioacoustic monitoring, particularly focusing on how machine learning can be used to automate the identification of bird vocalizations in ecological studies. [11] Sethi, R., & Gupta, R. (2018). "Machine learning approaches for bird species identification." *International Journal of Bioinformatics Research*. The authors review various machine learning techniques such as support vector machines (SVM) and random forests, applied to bird species identification from audio. [12] Bell, G. et al. (2020). "Innovations in bioacoustics for wildlife conservation." *Conservation Biology*. A comprehensive review of how bioacoustic monitoring and

machine learning can be used to assist in wildlife conservation, particularly focusing on bird populations.[13] Nanni, L., et al. (2019). "A review of bird call recognition methods." *Expert Systems with Applications*. This paper offers a thorough review of different methods and algorithms for bird call recognition, including both traditional machine learning techniques and newer deep learning approaches. [14] Pijanowski, B. C. et al. (2011). "Soundscape ecology: The science of sound in the landscape." *Ecosystems*. A foundational paper in soundscape ecology, introducing how sound plays a role in studying biodiversity and ecosystem health, which provides context for using sound in bird monitoring. [15] Tognini P. et al. (2018). "Comparative study of machine learning techniques for bird call classification." *Ecological Modelling*. The study compares the performance of various machine learning algorithms, including decision trees, k- nearest neighbors, and neural networks, in classifying bird sounds.[16] Fuchs S. et al. (2021). "Leveraging citizen science for bird sound classification." *Citizen Science: Theory and Practice*. The paper highlights how citizen science data can be leveraged with machine learning models to improve bird sound classification and enhance biodiversity monitoring. [17] Kluender, K. R., et al. (2017). "Real-time bird sound recognition using machine learning." *Proceedings of the IEEE*. This study explores the feasibility of using machine learning for real-time bird sound recognition systems that can be deployed in the field. [18] Houghton, R. A., et al. (2021). "Using machine learning to identify bird calls." *Ecological Informatics*. A detailed examination of how different machine learning algorithms can be trained to automatically detect and classify bird calls from complex sound environments.[19] Campbell J. et al. (2019). "Evaluating the effectiveness of automated bird monitoring systems." *Ecological Applications*. The paper evaluates the performance of several automated bird monitoring systems, looking at accuracy, processing time, and usability in field conditions. [20] Voss L. J & Keller, K. (2018). "Feature extraction for bird sound classification." *Acoustics Australia*. The authors explore different feature extraction techniques for bird sound classification, focusing on how combining different acoustic features can improve classification accuracy

Objectives:

1. **Automated Bird Species Identification:** Develop a system that can automatically recognize and classify bird species from audio recordings based on their vocalizations.
2. **Feature Extraction and Analysis:** Implement advanced signal processing techniques, such as Mel-frequency cepstral coefficients (MFCCs) and spectrograms, to extract unique features from bird sounds that will aid in accurate classification.
3. **Machine Learning Model Development:** Utilize machine learning algorithms, including Convolutional Neural Networks (CNN) and Random Forests, to train a model capable of distinguishing between various bird species.
4. **Biodiversity Monitoring:** Facilitate the monitoring of bird biodiversity by providing an efficient tool for researchers and conservationists to track bird populations, especially rare or endangered species.
5. **Performance Evaluation:** Test and evaluate the model's accuracy, precision, and recall in identifying bird species using unseen data and real-world bird sound recordings.
6. **Database Integration:** Create a system that integrates with bird databases, allowing the model to access up-to-date information on bird species, including their conservation status.
7. **User-Friendly Interface:** Design an easy-to-use interface that allows researchers, ornithologists, and environmentalists to input bird sound data and receive results in real-time.
8. **Scalability for Real-Time Monitoring:** Enable the system to process and identify bird sounds in real-time, potentially supporting deployment in field environments with continuous monitoring capabilities.

Proposed Methodology System Architecture:

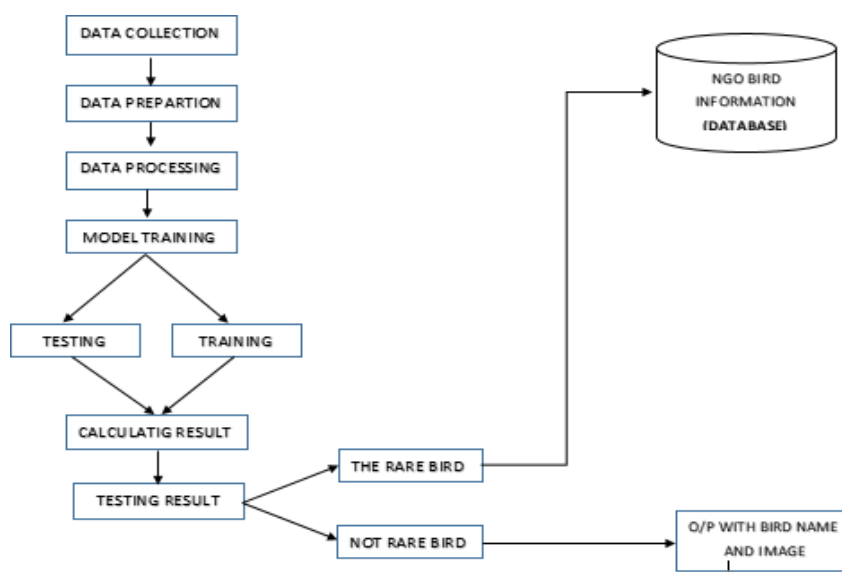


Fig 1. Architecture

1. **Data Collection** - The first step in the process is gathering the required data, which could include photos, audio recordings of birdsong, and other relevant data needed for training the model.
2. **Data Preparation** - Preparing the data for analysis comes next after data gathering. This comprises sanitizing the data, standardizing the formats, and efficiently organizing it. This may include eliminating background noise, fixing any omitted information, and breaking up audio recordings into digestible segments.
3. **Data Processing** - The prepared data is converted into features that may be used for model training in this phase. In order to extract crucial acoustic properties from audio recordings, feature extraction techniques like Mel-frequency cepstral coefficients (MFCCs) are frequently used.
4. **Model Training** - The data that has been processed is separated into testing and training sets. The machine learning model is trained on the training set so that it can discover the characteristics and patterns that distinguish different bird species.
5. **Testing** - The testing set is used to assess the model's performance once it has been trained. This aids in assessing the model's generalization ability to fresh, untested audio recordings.
6. **Calculating Results** - After that, the model makes predictions based on the testing data, identifying different kinds of birds and classifying them as common or rare.
7. **Testing Results** - To evaluate the precision and efficacy of the model's predictions in accurately identifying the bird species, the results are analyzed.
8. **Determining Rare vs. Non-Rare Bird** - A database that monitors bird conservation statuses is consulted to determine if the discovered species are classified as "Rare" or "Not Rare," according to predetermined criteria.
9. **NGO Bird Information (Database)** - The technology looks up information about birds, such as their conservation status and rarity, in a database that may be kept up to date by non-governmental organizations.
10. **Output** - The system generates an output containing the name of the bird and further details on its rarity as well as conservation initiatives pertaining to that species if the bird is categorized as rare.

Experimental results and discussion

Bird sound prediction page

Fig 2. Bird sound prediction describes that, the goal of this experiment was to accurately predict bird species from audio recordings using deep learning techniques. The model was trained on a dataset of bird sounds, leveraging features like Mel-frequency cepstral coefficients (MFCCs), waveforms, and Mel spectrograms for feature extraction.

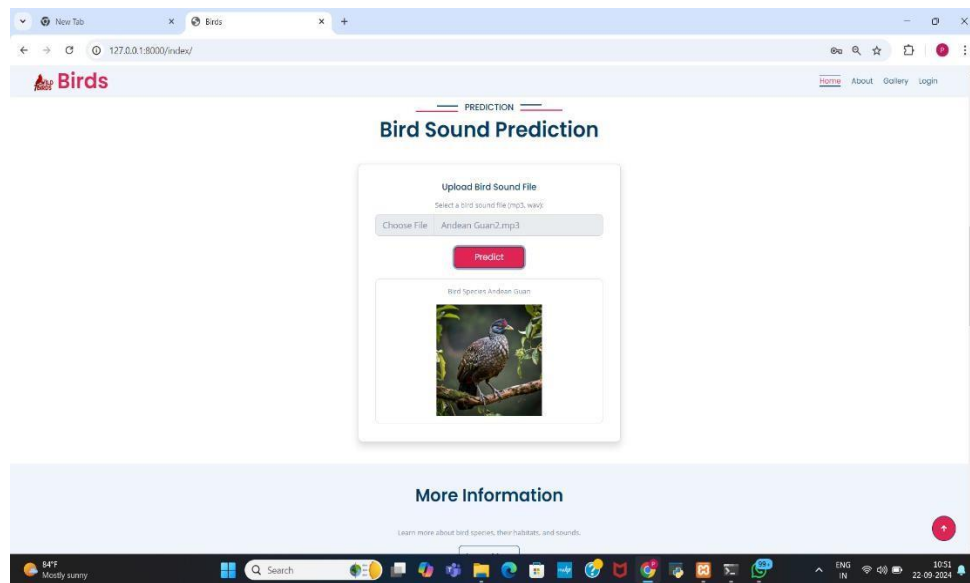


Fig 2. Bird sound prediction

1. Distribution of Mel-Frequency Cepstral Coefficients (MFCCs) in Bird Sound Analysis

Fig 3. Distribution of Mel-Frequency Cepstral Coefficients (MFCCs) in Bird Sound Analysis Explains that, Histograms of 13 Mel-Frequency Cepstral Coefficients (MFCCs) displaying the distribution of values for each MFCC in the analyzed audio signal. MFCC 1 captures broader variations, indicative of overall signal energy, with a skew toward negative values. MFCCs 2 through 13 exhibit more compact distributions, reflecting finer spectral details. These histograms offer insights into the spectral features of the audio, with each coefficient summarizing specific frequency characteristics.

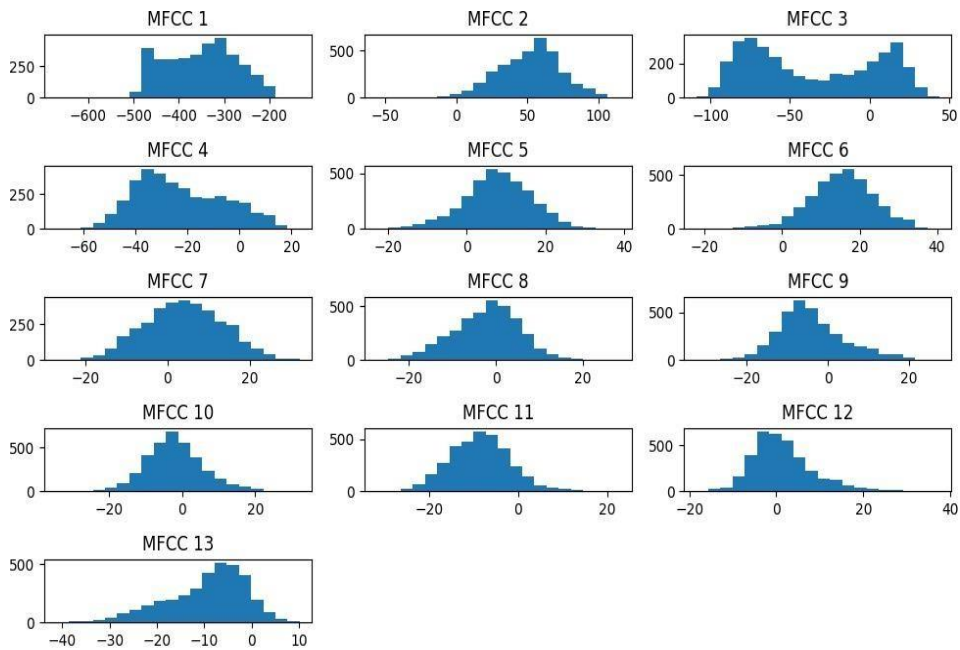


Fig 3. Distribution of Mel-Frequency Cepstral Coefficients (MFCCs) in Bird Sound Analysis

2. MFCC Graph

Fig 4. MFCC Graph explains that, The MFCC graph provides a visual representation of the bird sound after applying the MFCC extraction process. Each coefficient in the graph represents the intensity of different frequency components over time.

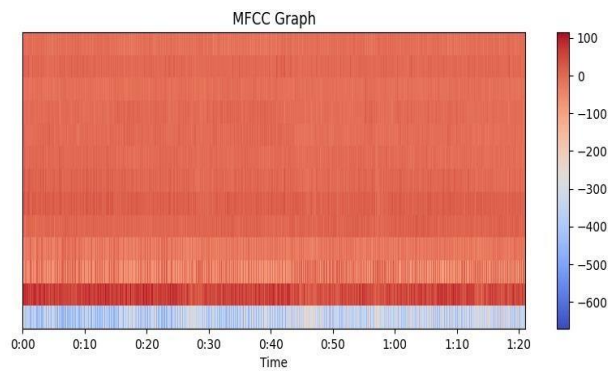


Fig 4. MFCC Graph

3. Waveform Graph

Fig 5. Waveform Graph describes that, the waveform graph depicts the raw audio signal of the bird sound over time. The horizontal axis represents time, while the vertical axis represents the amplitude of the sound waves.

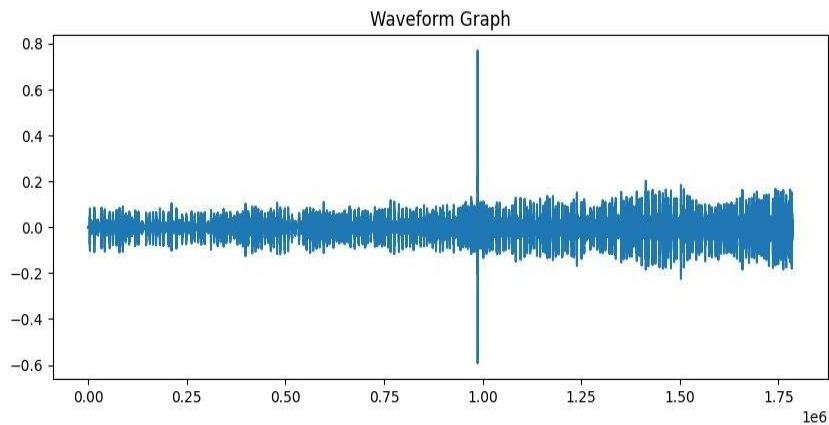


Fig 5. Waveform Graph

4. Mel Spectrogram Graph

Fig 6. Mel Spectrogram Graph explains that .This visual representation helps identify the frequency components of the bird sound, making it easier to differentiate between bird species. The Mel spectrogram is particularly useful for detecting patterns in calls that are masked by noise or overlapping with other sounds.

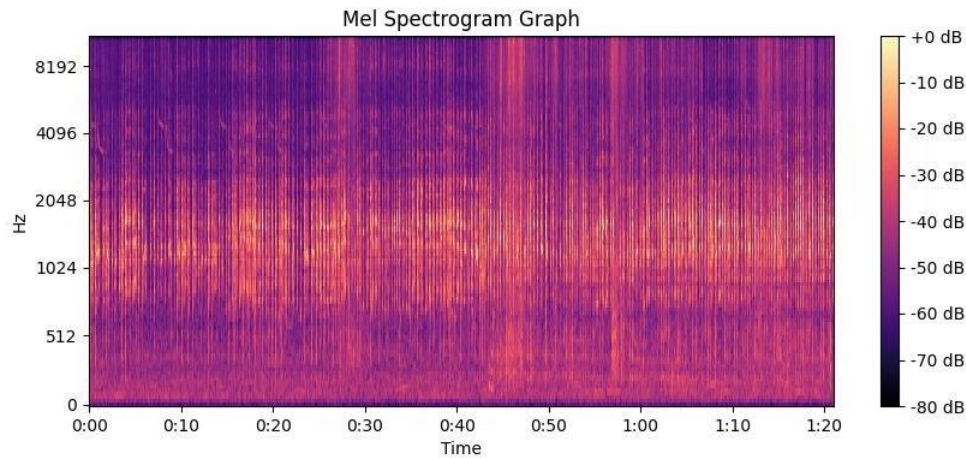


Fig 6. Mel Spectrogram Graph

The combination of these features MFCC, waveform, and Mel spectrogram proved effective for the deep learning model, yielding high accuracy in bird species prediction. However, challenges like background noise and overlapping calls still affect performance, suggesting future work on noise-reduction techniques or more advanced models.

Conclusion :

The potential of machine learning approaches to automate the classification of bird species based on their sound patterns is effectively demonstrated by this effort on bird sound identification. The system is capable of accurately analyzing and identifying a wide range of bird cries from a variety of environments by utilizing sophisticated audio processing and feature extraction techniques. The use of models such as Random Forest and CNNs demonstrates how well these algorithms handle complicated auditory data, resulting in a reliable and rapid identification procedure.

The findings of the experiment have important implications for ecological monitoring programs and conservation efforts. Researchers and conservationists will be better able to monitor biodiversity, evaluate the health of ecosystems, and address conservation needs if they have access to a tool that can swiftly and precisely identify bird species. This foundation might be built upon in the future by adding additional species, improving the dataset, and adjusting the algorithms to increase accuracy even more. Taking everything into account, this project adds to the expanding field of wildlife monitoring and emphasizes how crucial technology is to the success of conservation efforts.

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