Indian Bird Species Recognition Using Deep Learning

Submitted in partial fulfillment of the requirements of the degree

BACHELOR OF ENGINEERING IN **COMPUTER ENGINEERING**

By

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CERTIFICATE

This is to certify that the Mini Project entitled **"Indian Bird Species Recognition Using Deep Learning"** is a bonafide work of **Yashneil Ballani(03), Netal Bhansali(07), Rashika Chandwani(08), Bhanu Shamdasani(52)** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of **"Bachelor of Engineering"** in **"Computer Engineering" .**

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Mini Project Approval

This Mini Project entitled "Indian Bird Species Recognition Using Deep Learning" by **Yashneil Ballani(03), Netal Bhansali(07), Rashika Chandwani(08), Bhanu Shamdasani(52)** is approved for the degree of **Bachelor of Engineering** in **Computer Engineering.**

Examiners

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(Internal Examiner Name & Sign)

2……………………………………….
(External Examiner name & Sign)

Date:
Place:

Contents

Abstract

With the increasing availability of audio recording devices and the advancement of deep learning techniques, automatic bird voice recognition has emerged as an effective tool to identify bird species based on their distinct vocalizations. This abstract presents an overview of a novel approach to recognize bird species using bird voice recognition in combination with deep learning algorithms.

The proposed system begins by collecting India specific audio recordings of bird vocalizations in various natural habitats. These audio samples are pre-processed to remove background noise, normalize the audio levels, and extract relevant acoustic features, such as pitch, amplitude, and frequency modulation. The resulting feature vectors serve as inputs to the deep learning model.

Acknowledgement

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We also are greatly obliged for the advice and guidance we received from the faculty of **Computer Science and Engineering Department**.

List of Abbreviations

Abbreviation	**Expansion**
RNN	Recurrent neural network
CNN	Convolutional neural network
MFCC	Mel-frequency cepstral coefficients
CPU	Central processing unit
GPU	Graphics processing unit
RAM	Random-access memory
IDE	Integrated Development Environment

List of Figures

List of Tables

1. INTRODUCTION

1.1 Introduction

Birds serve as vital components of our ecosystems, playing pivotal roles in maintaining ecological balance and enhancing biodiversity. Their presence and behavior offer valuable insights into the overall health of these intricate systems. Understanding bird populations is essential for assessing and responding to the dynamic changes in environmental conditions and, in turn, for effectively advancing conservation efforts.

One of the primary methods employed in the identification and monitoring of bird species hinges on their vocalizations. Birds communicate through unique and distinguishable calls, songs, and chirps. This acoustic diversity among species enables ornithologists and ecologists to pinpoint avian presence, even in challenging scenarios where visual identification is impractical, such as densely vegetated areas or remote locations.

In recent years, a confluence of technological advances has revolutionized the study of birds. Notably, enhancements in audio recording technology have equipped researchers with the tools to capture high-quality soundscapes. Coupled with this, the burgeoning availability of data resources has paved the way for the application of deep learning techniques in bird species recognition.

Deep learning's integration into bird species recognition represents a transformative step forward. Deep learning models are adept at recognizing and classifying bird vocalizations with remarkable accuracy. They can distinguish subtle distinctions among bird calls, even among closely related species. This innovation provides the means to efficiently and accurately identify the species present in vast audio datasets.

The marriage of deep learning and bird species recognition has opened exciting new horizons for avian population monitoring. It enables researchers to conduct large-scale, long-term studies, collecting extensive audio data from a multitude of habitats and geographical regions. This wealth of information contributes to a nuanced and comprehensive understanding of bird populations, their distribution, and their responses to environmental fluctuations.

1.2 Motivation

Conservation Efforts: By developing a deep learning-based bird voice recognition system, you have the power to make a real difference in the conservation of our avian friends. This project can aid ornithologists and conservationists in monitoring and protecting bird populations, providing valuable insights into their behavior and habitats.

Biodiversity Preservation: Birdsong is not just beautiful; it's a key indicator of biodiversity. This project can contribute to preserving the rich tapestry of species that enrich our ecosystems. By understanding bird vocalizations, we can better protect their habitats and prevent further species loss.

Education and Awareness: This work can inspire a new generation of nature enthusiasts and environmental advocates. Bird voice recognition can serve as an educational tool, raising awareness about the importance of birds in our ecosystems and fostering a sense of stewardship for our natural world.

Scientific Discovery: Deep learning technology has the potential to reveal hidden patterns in bird vocalizations that the human ear may not detect. This can lead to groundbreaking scientific discoveries about bird behavior, communication, and adaptation to environmental changes.

Impact on Technology: Bird voice recognition is a relatively unexplored field, and your project can push the boundaries of what deep learning can achieve. This system may have applications beyond ornithology, influencing various fields such as speech recognition and audio analysis.

Connecting with a Community: The community of birdwatchers, conservationists, and technologists is vibrant and passionate. Your project can help you connect with like-minded individuals who share your enthusiasm for birds and cutting-edge technology.

1.3 Problem Statement & Objectives

The central focus of this project revolves around the development of robust deep learning models with the capacity to accurately classify and identify different bird species based on their vocalizations. However, this undertaking presents a multifaceted set of challenges. Foremost among these challenges is the creation of a comprehensive and diverse dataset that encompasses the extensive array of bird species and their vocalizations. Additionally, bird vocalizations can be influenced by various environmental factors, introducing complexities due to background noise, making the task intricate.

The core challenge lies in the development of deep learning models that are not only reliable but also robust. These models should be adept at accurately classifying and identifying bird species despite the presence of noisy data, variations in vocalizations among individual birds, and the nuances of distinguishing between closely related species. Moreover, the project is intrinsically tied to the crucial objective of contributing to the conservation of endangered bird species. This involves the vital task of detecting and reporting the presence of these endangered species through their vocalizations to enable timely interventions and protection.

To achieve this overarching objective, the project lays out a multifaceted plan. First, the creation of reliable deep learning models takes center stage. These models should exhibit a high degree of accuracy even when confronted with the complex and diverse vocalizations of avian species. Equally important is the development of a comprehensive and diverse dataset, one that encapsulates the various species and the intricacies of their vocalizations in different environmental settings.

The application of this technology extends beyond research into the real world of conservation. The project seeks to deploy these deep learning models in the field for practical, real-time monitoring and reporting. By doing so, it enhances the capacity of conservationists to safeguard bird species facing the imminent threat of extinction, marking a meaningful and impactful step towards ecological preservation and protection. In summary, this project unites the realms of technology and ecology in a concerted effort to address a multifaceted problem, simultaneously advancing our understanding of avian vocalizations and contributing to the critical cause of conserving endangered bird species.

1.4 Organization of Report

The organizational report structure can be adapted as follows:

In the Literature Survey section , an in-depth review of existing systems and research pertaining to Indian bird sound recognition is conducted. This survey's goal is to summarize the present state of research and technology in the specialized field of identifying Indian bird species via vocalizations. It not only consolidates current knowledge but also highlights the shortcomings of existing systems, pinpointing the research gaps that the project aims to fill. In the Mini Project Contribution section, we outline the significant contributions and initial efforts made by this project in the domain of Indian bird sound recognition.

The proposed Indian Bird Sound Recognition System begins with an Introduction that introduces the project's objectives and its significance in the context of Indian avian biodiversity. This section briefly outlines the core components and goals of the system. The Architectural Framework/Conceptual Design provides an overview of the high-level architecture, illustrating how various components interact to achieve recognition, with a focus on Indian bird species. The Algorithm and Process Design delves into the algorithms and processes central to the system, elucidating how these methods are tailored to analyze and classify Indian bird vocalizations. Methodology Applied elaborates on the methods and approaches applied to build and implement the Indian bird sound recognition system. Hardware & Software Specifications detail the technical requirements, tools, libraries, and platforms integral to the system's development. The Experiment and Results for Validation and Verification section describes the experimental setup and data collection techniques that ensure the system's effectiveness for Indian bird sound recognition. The Result Analysis and Discussion undertake an in-depth analysis of the outcomes, exploring their significance within the context of Indian avian biodiversity and considering practical applications. The Conclusion and Future Work offer a comprehensive summary of the project's contributions to Indian bird sound recognition and suggest potential avenues for future research and improvements.

The References segment provides a detailed list of sources, research papers, and references consulted during the literature review and the development of the Indian bird sound recognition project.

2. LITERATURE SURVEY

2.1 Survey of Existing System

Title	Inference	Limitations
Deep Learning Based Audio Classifier for Bird Species (VOLUME 08, ISSUE 04 (APRIL 2019)) (Prof. Pralhad Gavali , Ms. Prachi Abhijeet Mhetre , Ms. Neha Chandrakhant Patil , Ms. Nikita Suresh Bamane, Ms. Harshal Dipak Buva	RNN is an effective approach for audio classification. It could tackle the harder single-instance multi-label problem and modify the loss function such that it considers the background species.	RNNs have difficulty capturing long-range dependencies in sequences, as they tend to focus more on short-term information. RNNs processes sequentially, making them less parallelizable and slower to train compared to other architectures like CNNs (Convolutional Neural Networks).
A review of automatic recognition technology for bird vocalizations in the deep learning era (November 2022) (Xie Jiangjian,Yujie Zhong,Junguo Zhang)	Bird voice recognition can be a valuable tool for helping researchers track bird populations and behaviors. An accurate system can help conservationists better target their efforts to protect endangered species and their habitats.	Limited by the availability of suitable hardware, such as microphones and processing units. Some bird species have similar calls, leading to potential misclassification in recognition.

Bird Sound Recognition Using a Convolutional Neural Network(CNN) (September 2018) (A. Incze, H.-B. Jancso, Z. Szilagyi, A. Farkas, and C. Sulyok)	This paper explores CNNs for bird sound classification, emphasizing benefits for nature enthusiasts and ornithologists. It uses transfer learning with MobileNet and spectrograms from audio data.	The system is restricted for a smaller number of bird species classes.
A novel deep transfer learning models for recognition of birds sounds in different environment (2022) (Y. Kumar, S. Gupta, and W. Singh)	Recognizing bird species by their audio signals is a focus due to their distinctive vocalizations. Deep transfer learning models are used for extracting and recognizing audio signals from various bird species.	The dataset covers 22 bird species, limiting generalization.The study focuses on offline processing, not real-time applications.

Table 1: Literature Survey

Technologies and techniques used in bird sound recognition:

Recurrent Neural Networks (RNNs):

RNNs are a type of neural network architecture used for analyzing sequential data, making them suitable for processing audio recordings, which are time-series data.

RNNs are effective for modeling the temporal dependencies in audio data, allowing them to capture patterns in bird vocalizations over time.

They are used in various bird sound recognition systems to classify different species based on their vocalizations.

Convolutional Neural Networks (CNNs):

CNNs are widely employed for image and audio data analysis and have proven useful in bird sound recognition.

These networks use convolutional layers to extract local patterns and features from input data. In the context of bird sound recognition, they often analyze spectrograms derived from audio recordings.

CNNs are efficient in capturing spatial and temporal patterns within the audio data and have been used in various systems for this purpose.

Transfer Learning:

Transfer learning is a technique that involves using pre-trained neural network models and fine-tuning them for a specific task, such as bird sound recognition.

This approach leverages models pre-trained on large datasets, which have learned valuable features, and adapts them to the task of recognizing bird species based on their vocalizations.

Transfer learning can save training time and improve model performance, especially when dealing with limited datasets.

2.2 Limitation in Existing System

Data Quality and Quantity: The success of deep learning models in bird species recognition hinges on the availability of a vast, high-quality dataset. This dataset should encompass the rich tapestry of bird species and their diverse vocalizations. The challenge lies not only in quantity but also in ensuring data quality. Insufficient data or data that is biased toward certain species can result in models that are inaccurate and biased themselves. Collecting such comprehensive datasets is a formidable task, demanding extensive fieldwork and recording efforts. Furthermore, maintaining and curating these datasets to ensure accuracy and relevance over time can be a resource-intensive process. Without an adequate dataset, the effectiveness of deep learning models is greatly diminished.

Limited Generalization: Deep learning models are most proficient at recognizing patterns in the data they've been trained on. However, their ability to generalize and accurately identify underrepresented or newly discovered bird species may be limited. Rare or less-documented species might not have sufficient representation in the training data, leading to difficulties in their identification. This limitation restricts the applicability of the model in situations where less common or newly found species are encountered. Ensuring that models can effectively generalize to these less typical cases is a significant challenge.

Environmental Variability: Bird vocalizations vary significantly due to environmental factors like noise, weather, and habitat, posing a major challenge for deep learning models. Inconsistent conditions make it hard for models to perform consistently across different settings, such as distinguishing bird calls in noisy urban areas from quiet forests. These models must be robust and adaptable to be reliable in real-world applications.

Inter-Species Variability: Bird species are not static in their vocalizations. Some exhibit significant variations in their calls, depending on factors like age, sex, or location. These variations can make it challenging for deep learning models to distinguish between individual birds within the same species accurately. Moreover, closely related species may have similar vocalizations, further complicating the differentiation process. For instance, two species that share a habitat might have overlapping vocal ranges, and distinguishing between their calls becomes a complex task. The ability of models to handle these intraspecies and interspecies vocal variations is crucial for accurate identification.

2.3 Mini Project Contribution

Advancing Conservation Efforts: Your project will contribute to the conservation of avian species by developing a robust bird sound recognition system. This technology can be employed in the monitoring of bird populations and their habitats, helping conservationists identify and protect vulnerable species more effectively.

Biodiversity Preservation: By creating a reliable bird sound recognition model, you are actively supporting the preservation of biodiversity. This technology can assist in the documentation of different bird species, aiding in their conservation and the protection of the ecosystems they inhabit.

Environmental Monitoring: Bird sound recognition has broader applications in environmental monitoring. Your project can contribute to tracking the impact of climate change and habitat disruption, providing essential data for understanding and mitigating these issues.

Citizen Science Participation: Your work can empower citizen scientists and bird enthusiasts to actively engage in conservation efforts. User-friendly bird sound recognition apps built on your technology can encourage public participation in data collection and reporting, thereby increasing the scale of conservation initiatives.

Scientific Discovery: Deep learning models can uncover hidden patterns and trends in bird vocalizations, leading to new scientific insights. Your project's findings may shed light on topics like bird behavior, migration, and communication, enriching our understanding of ornithology.

Educational Tools: Your work can lead to the development of educational tools that make bird sound recognition accessible to a wider audience. These tools can be used in schools, nature centers, and online platforms to foster a deeper understanding of birds and their vital role in ecosystems.

Technology Advancements: Bird sound recognition using deep learning pushes the boundaries of technology. Your contributions may influence the development of more sophisticated machine learning and audio processing techniques, benefiting other fields such as speech recognition and audio analysis.

Open Source Resources: Sharing your project as an open-source resource can empower researchers and developers worldwide. Collaborative efforts can drive innovation and accelerate advancements in bird sound recognition technology.

Interdisciplinary Collaboration: Your project bridges the gap between the fields of ornithology and machine learning, promoting interdisciplinary collaboration. This synergy can lead to novel research and solutions that address pressing environmental challenges.

Public Awareness: By creating a functional bird sound recognition system, you can raise public awareness about the significance of bird vocalizations and the urgent need for their protection. Your project can serve as a catalyst for positive environmental action.

3. PROPOSED SYSTEM

3.1 Introduction

The proposed system aims to recognize bird species and classify them using voice deep learning. By collecting a diverse dataset of bird vocalizations and employing advanced deep learning models, the system can accurately identify different bird species based on their unique vocal patterns. Here's a proposed system for the project:

1. Data Collection and Preprocessing:

Gather a diverse dataset of Indian bird vocalizations, including various species' calls and songs. You can utilize online databases, bird watching communities, and recorded samples.

2. Data Labeling:

Annotate the dataset with appropriate labels for each bird vocalization sample, indicating the species it belongs to..

3. Feature Extraction:

Extract relevant features from the audio data to create input representations for the deep learning model. Mel-frequency cepstral coefficients (MFCCs), spectrograms, and other time-frequency representations are commonly used for audio classification tasks.

4. Model Architecture:

Design a deep learning architecture for audio classification. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are often used for audio tasks.

5. Model Training:

Train the deep learning model using the training data and validate it using the validation set.Use appropriate loss functions like categorical cross-entropy for multi-class classification.

6. Model Evaluation:

Evaluate the trained model on the test set to assess its accuracy and generalization to unseen data.Utilize metrics such as accuracy, precision, recall, F1-score, and confusion matrices to gauge the model's performance.

7. Post-processing and Visualization:

Implement post-processing techniques to smoothen predictions and reduce false positives/negatives.

3.2 Architectural Framework / Conceptual Design

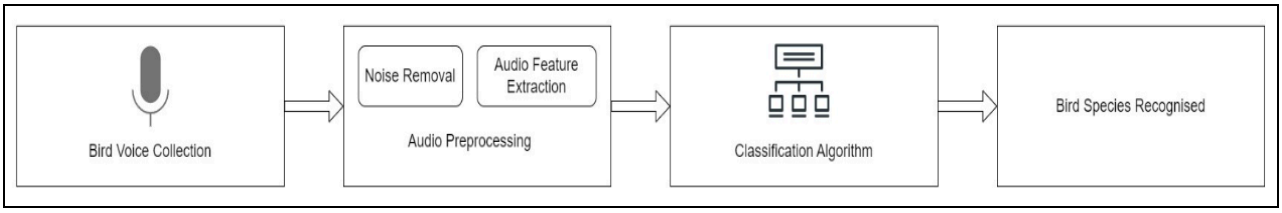


Fig 1: Block Diagram

Bird voice collection: The first step is to collect a large collection of bird voices from different species. This can be done by recording bird calls in the wild or by using existing datasets of bird recordings.

Audio preprocessing: Once the bird voices have been collected, they need to be cleaned up and normalized. This involves removing noise and other artifacts, such as background noise and echoes. The audio may also need to be normalized to ensure that all of the recordings have the same volume level.

Audio feature extraction: Once the audio recordings have been preprocessed, a variety of features can be extracted from them. These features can include pitch, duration, spectral energy, and other acoustic properties. The extracted features will be used by the classification algorithm to identify the bird species.

Classification algorithm: A machine learning algorithm is trained on the extracted features and the corresponding bird species labels. The algorithm learns to associate the features with the bird species labels. Once the algorithm is trained, it can be used to identify the bird species in new audio recordings.

Bird species recognized: The trained classification algorithm is used to recognize the bird species in new audio recordings. The algorithm takes the extracted features from the new audio recording and predicts the bird species.

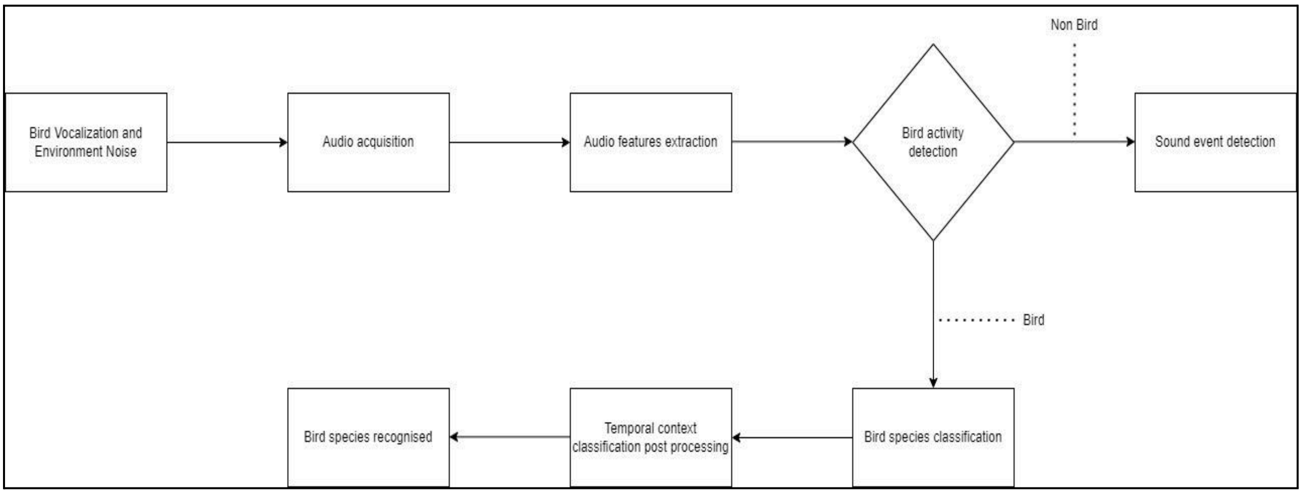


Fig 2: Modular Diagram

- **Audio acquisition:** The first step is to record the bird vocalizations. This can be done using a microphone or a recorder. It is important to record the bird vocalizations in a quiet environment to minimize background noise.

- **Audio preprocessing:** Once the bird vocalizations have been recorded, they need to be cleaned up and normalized. This involves removing noise and other artifacts, such as background noise and echoes. The audio may also need to be normalized to ensure that all of the recordings have the same volume level.

- **Feature extraction:** After audio preprocessing, various features like pitch, duration, spectral energy, and more are extracted. These features are utilized by the classification algorithm to identify the bird species.

- **Bird species classification:** A machine learning algorithm is used to classify the bird species based on the extracted features. The algorithm learns to associate the features with the bird species labels. Once the algorithm is trained, it can be used to identify the bird species in new audio recordings.

- **Bird species recognized:** The output of the bird species classification algorithm is the predicted bird species. This information can be used to identify the bird species in the audio recording.

Sophisticated voice recognition systems for bird species are now used by both researchers and hobbyists to identify birds in the wild and collect population data.

3.4 Methodology Applied

In this project, each step plays a crucial role in advancing our capabilities for bird species recognition and conservation.

The process begins with the collection of bird audio recordings from various settings, reflecting the diverse natural habitats where these avian species thrive. By capturing these vocalizations in different environmental conditions and geographic regions, the dataset becomes more comprehensive and representative of real-world scenarios. This extensive data collection is essential for developing a deep learning model that can generalize across various contexts.

The next phase focuses on enhancing the quality of the audio recordings. This step is indispensable as it separates the valuable bird vocalizations from background noise, which can often be quite challenging in field recordings. By isolating the key sound components, the dataset becomes more informative and suitable for training a deep learning model. Removing noise and preprocessing the data is a meticulous task that requires advanced audio signal processing techniques and tools.

The heart of the project revolves around the development of a specialized deep learning model for bird species identification. This model is designed to recognize patterns and features within bird vocalizations that are unique to each species. It is trained on the enhanced dataset, learning to distinguish between the subtle variations in calls, songs, and chirps that differentiate one bird species from another. The deep learning model's capacity for this nuanced classification is a result of extensive training and fine-tuning, where it learns to discern even the most subtle distinctions.

After the model is trained, the critical phase of performance assessment follows. This step ensures that the deep learning model can accurately identify bird species with a high degree of confidence. The model's performance is evaluated on various metrics such as accuracy, precision, recall, and specificity, providing insights into its capabilities and areas for improvement. Continuous iterations and further adjustments are made as needed to enhance result accuracy.

Moreover, the project is open to incorporating additional procedures or techniques that may arise during the evaluation phase. These could include post-processing methods to smoothen predictions, addressing challenges such as overlapping vocalizations from multiple species, and extending the model's generalization capabilities across diverse habitats. The project's iterative nature allows for a dynamic and adaptable approach, ensuring that the final deep learning model is as robust and accurate as possible.

In sum, this comprehensive endeavor represents the synergy of technological innovation, ecological research, and data-driven insights. It holds the potential to revolutionize our understanding of bird populations, their vocalizations, and their habitats. By accurately identifying bird species through deep learning, this project contributes to the preservation of avian biodiversity and the advancement of ornithological research.

3.5 Hardware Requirements

Hardware Requirements:

Computer: A powerful computer with enough processing capabilities to run deep learning algorithms efficiently. A machine with a good CPU, GPU (Graphics Processing Unit), and sufficient RAM is recommended.

Microphone: A high-quality microphone to record bird sounds accurately. An external microphone that can filter out background noise and capture clear audio is preferable.

Storage: Sufficient storage space is needed to store the audio data and the trained deep learning models.

Software Requirements:

Python :Python is a popular choice due to its extensive libraries for deep learning and audio processing.

PyCharm/ Visual Studio Code/ Jupyter Notebooks: An IDE to write, test, and debug your code.

Audio Processing Library: To handle audio processing tasks like reading audio files, extracting features, and audio manipulation. Python libraries like librosa and pyaudio are widely used.

TensorFlow: A widely recognized option, will be employed in this project to facilitate model development and training.

Tools:

Bird Sound Datasets: Obtain bird sound datasets containing audio recordings of various bird species.

3.6 Experiment and Results for Validation and Verification

A critical phase of our project involved testing the collected audio samples on a previously published bird sound recognition project. This testing phase allowed us to evaluate our system's performance against an established benchmark. The findings from this phase offer valuable insights into the effectiveness of our recognition approach.

Experimental Procedure:

Dataset :

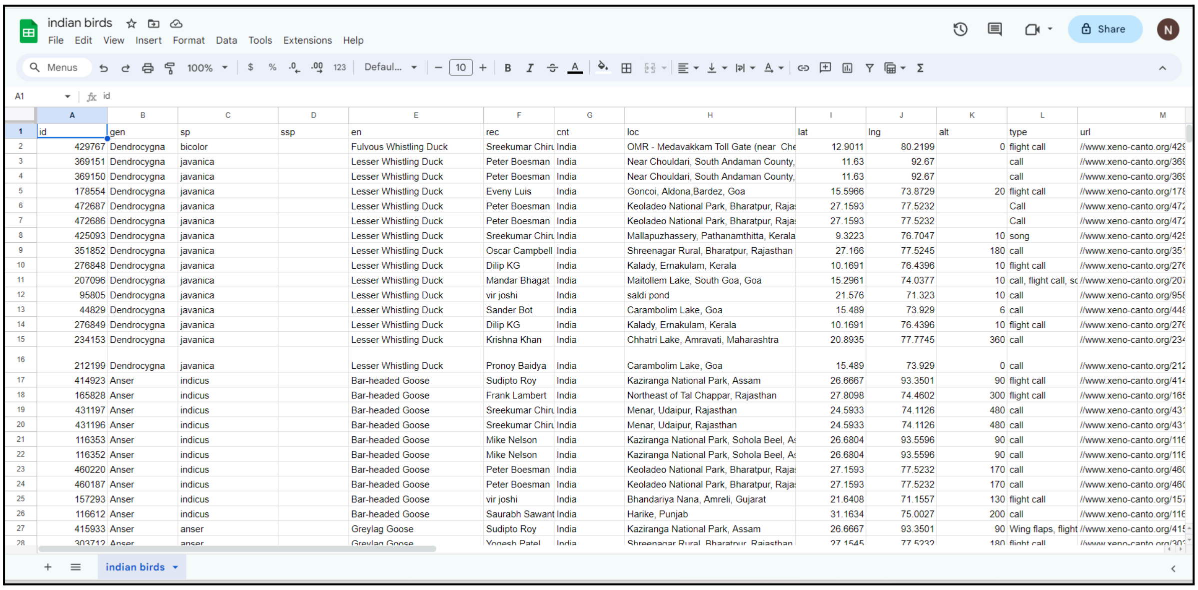
The dataset for Indian birds that you have provided is a spreadsheet containing information about bird species and their soundscapes. The columns in the spreadsheet are as follows:

- **ID:** A unique identifier for each bird species.
- **Species:** The scientific name of the bird species.
- **Soundscape:** A link to the Xeno-canto website, where you can listen to the bird's soundscape.
- **Location:** The location where the soundscape was recorded.
- **Coordinates:** The GPS coordinates of the location where the soundscape was recorded.
- **Sample size:** The number of times the bird's soundscape was recorded.
- **MaxEnt Model validation results:** The results of the MaxEnt model validation, which is a measure of how well the model predicts the bird's distribution.

This dataset can be used for a variety of purposes, such as:

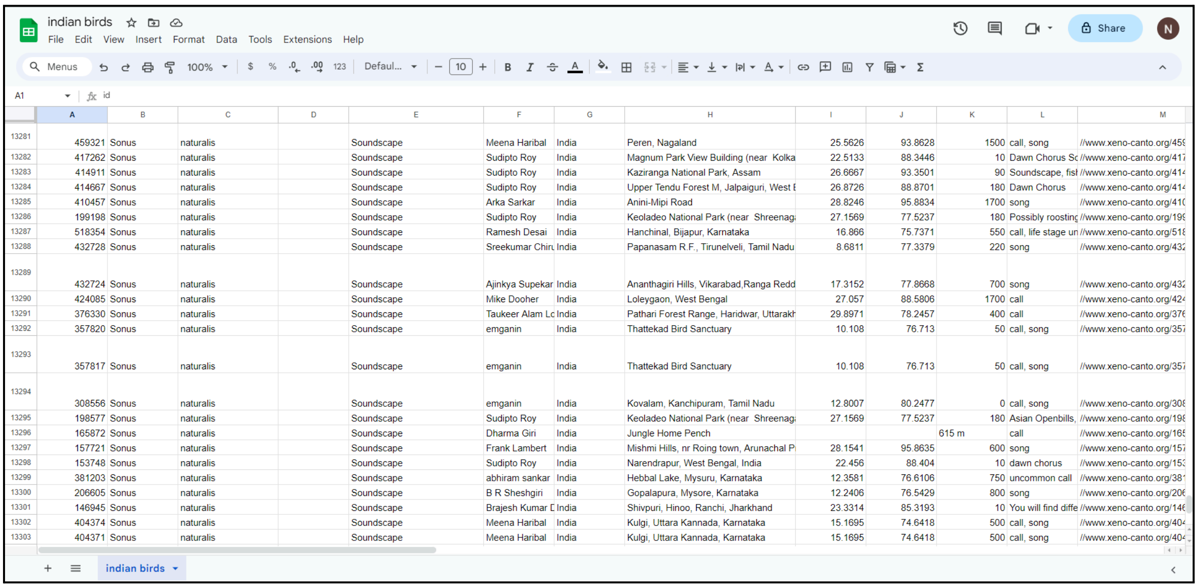
- To learn more about the diversity of bird species in India.
- To study the distribution of bird species in India.
- To identify bird species by their soundscapes.
- To create educational materials about Indian birds.
- To develop conservation strategies for Indian bird

Dataset :



indian birds

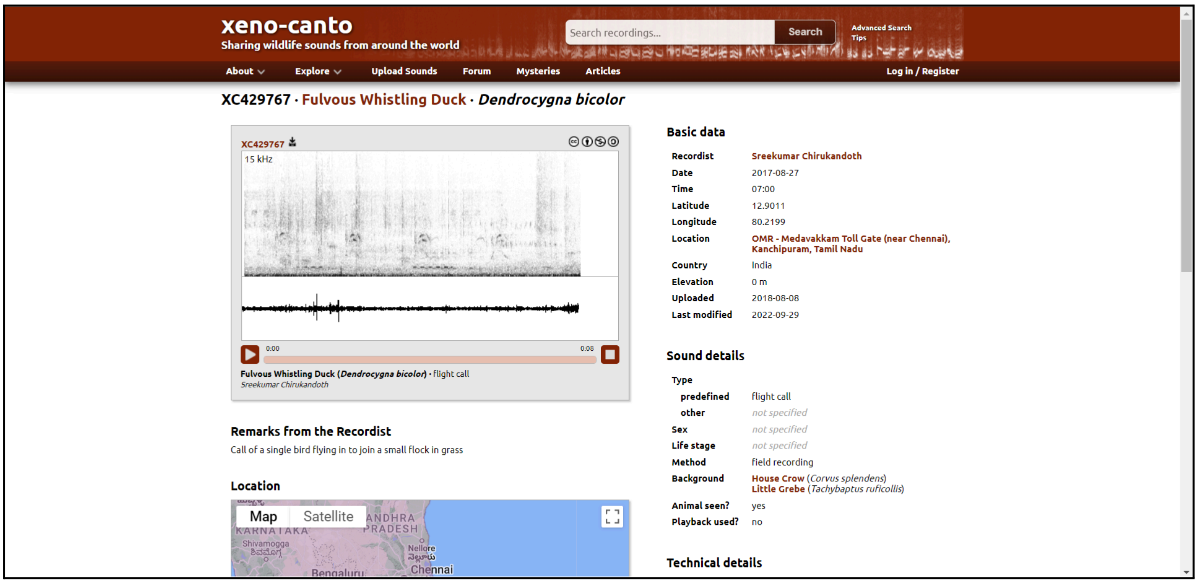
	id	gen	sp	ssp	en	rec	cnt	loc	lat	lng	alt	type	url
2	429767	Dendrocygna	bicolor		Fulvous Whistling Duck	Sreekumar Chiru	India	OMR - Medavakkam Toll Gate (near Che	12.9011	80.2199	0	flight call	//www.xeno-canto.org/429
3	369151	Dendrocygna	javanica		Lesser Whistling Duck	Peter Boesman	India	Near Chouldari, South Andaman County,	11.63	92.67		call	//www.xeno-canto.org/369
4	369150	Dendrocygna	javanica		Lesser Whistling Duck	Peter Boesman	India	Near Chouldari, South Andaman County,	11.63	92.67		call	//www.xeno-canto.org/369
5	178554	Dendrocygna	javanica		Lesser Whistling Duck	Eveny Luis	India	Goncoi, Aldona,Bardez, Goa	15.5966	73.8729	20	flight call	//www.xeno-canto.org/178
6	472687	Dendrocygna	javanica		Lesser Whistling Duck	Peter Boesman	India	Keoladeo National Park, Bharatpur, Raja	27.1593	77.5232		Call	//www.xeno-canto.org/472
7	472686	Dendrocygna	javanica		Lesser Whistling Duck	Peter Boesman	India	Keoladeo National Park, Bharatpur, Raja	27.1593	77.5232		Call	//www.xeno-canto.org/472
8	425093	Dendrocygna	javanica		Lesser Whistling Duck	Sreekumar Chiru	India	Mallapuzhassery, Pathanamthitta, Kerala	9.3223	76.7047	10	song	//www.xeno-canto.org/425
9	351852	Dendrocygna	javanica		Lesser Whistling Duck	Oscar Campbell	India	Shreenagar Rural, Bharatpur, Rajasthan	27.166	77.5245	180	call	//www.xeno-canto.org/351
10	276848	Dendrocygna	javanica		Lesser Whistling Duck	Dilip KG	India	Kalady, Ernakulam, Kerala	10.1691	76.4396	10	flight call	//www.xeno-canto.org/276
11	207096	Dendrocygna	javanica		Lesser Whistling Duck	Mandar Bhagat	India	Maitollem Lake, South Goa, Goa	15.2961	74.0377	10	call, flight call, sc	//www.xeno-canto.org/207
12	95805	Dendrocygna	javanica		Lesser Whistling Duck	vir joshi	India	saldi pond	21.576	71.323	10	call	//www.xeno-canto.org/958
13	44829	Dendrocygna	javanica		Lesser Whistling Duck	Sander Bot	India	Carambolim Lake, Goa	15.489	73.929	6	call	//www.xeno-canto.org/448
14	276849	Dendrocygna	javanica		Lesser Whistling Duck	Dilip KG	India	Kalady, Ernakulam, Kerala	10.1691	76.4396	10	flight call	//www.xeno-canto.org/276
15	234153	Dendrocygna	javanica		Lesser Whistling Duck	Krishna Khan	India	Chhatri Lake, Amravati, Maharashtra	20.8935	77.7745	360	call	//www.xeno-canto.org/234
16	212199	Dendrocygna	javanica		Lesser Whistling Duck	Pronoy Baidya	India	Carambolim Lake, Goa	15.489	73.929	0	call	//www.xeno-canto.org/212
17	414923	Anser	indicus		Bar-headed Goose	Sudipto Roy	India	Kaziranga National Park, Assam	26.6667	93.3501	90	flight call	//www.xeno-canto.org/414
18	165828	Anser	indicus		Bar-headed Goose	Frank Lambert	India	Northeast of Tal Chappar, Rajasthan	27.8098	74.4602	300	flight call	//www.xeno-canto.org/165
19	431197	Anser	indicus		Bar-headed Goose	Sreekumar Chiru	India	Menar, Udaipur, Rajasthan	24.5933	74.1126	480	call	//www.xeno-canto.org/431
20	431196	Anser	indicus		Bar-headed Goose	Sreekumar Chiru	India	Menar, Udaipur, Rajasthan	24.5933	74.1126	480	call	//www.xeno-canto.org/431
21	116353	Anser	indicus		Bar-headed Goose	Mike Nelson	India	Kaziranga National Park, Sohola Beel, As	26.6804	93.5596	90	call	//www.xeno-canto.org/116
22	116352	Anser	indicus		Bar-headed Goose	Mike Nelson	India	Kaziranga National Park, Sohola Beel, As	26.6804	93.5596	90	call	//www.xeno-canto.org/116
23	460220	Anser	indicus		Bar-headed Goose	Peter Boesman	India	Keoladeo National Park, Bharatpur, Raja	27.1593	77.5232	170	call	//www.xeno-canto.org/460
24	460187	Anser	indicus		Bar-headed Goose	Peter Boesman	India	Keoladeo National Park, Bharatpur, Raja	27.1593	77.5232	170	call	//www.xeno-canto.org/460
25	157293	Anser	indicus		Bar-headed Goose	vir joshi	India	Bhandariya Nana, Amreli, Gujarat	21.6408	71.1557	130	flight call	//www.xeno-canto.org/157
26	116612	Anser	indicus		Bar-headed Goose	Saurabh Sawant	India	Harike, Punjab	31.1634	75.0027	200	call	//www.xeno-canto.org/116
27	415933	Anser	anser		Greylag Goose	Sudipto Roy	India	Kaziranga National Park, Assam	26.6667	93.3501	90	Wing flaps, flight	//www.xeno-canto.org/415
28	303712	Anser	anser		Greylag Goose	Yogesh Patel	India	Shreenagar Rural, Bharatpur, Rajasthan	27.1545	77.5232	180	flight call	//www.xeno-canto.org/30



indian birds

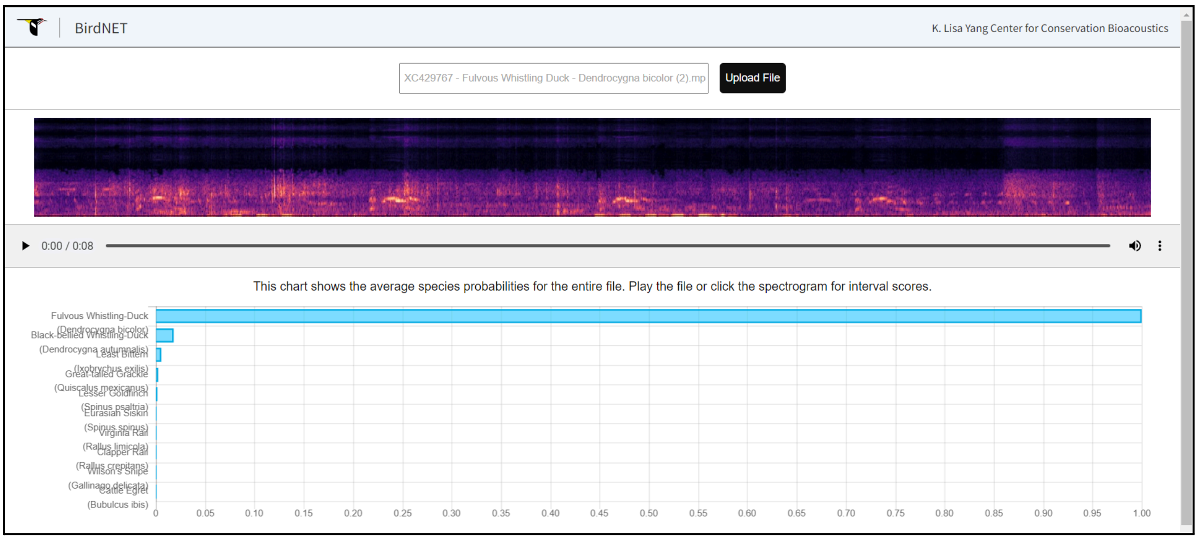
	A	B	C	D	E	F	G	H	I	J	K	L	M
13281	459321	Sonus	naturalis		Soundscape	Meena Haribal	India	Peren, Nagaland	25.5626	93.8628	1500	call, song	//www.xeno-canto.org/459
13282	417262	Sonus	naturalis		Soundscape	Sudipto Roy	India	Magnum Park View Building (near Kolka	22.5133	88.3446	10	Dawn Chorus Sc	//www.xeno-canto.org/417
13283	414911	Sonus	naturalis		Soundscape	Sudipto Roy	India	Kaziranga National Park, Assam	26.6667	93.3501	90	Soundscape, fish	//www.xeno-canto.org/414
13284	414667	Sonus	naturalis		Soundscape	Sudipto Roy	India	Upper Tendu Forest M, Jalpaiguri, West E	26.8726	88.8701	180	Dawn Chorus	//www.xeno-canto.org/414
13285	410457	Sonus	naturalis		Soundscape	Arka Sarkar	India	Anini-Mipi Road	28.8246	95.8834	1700	song	//www.xeno-canto.org/410
13286	199198	Sonus	naturalis		Soundscape	Sudipto Roy	India	Keoladeo National Park (near Shreenaga	27.1569	77.5237	180	Possibly roosting	//www.xeno-canto.org/199
13287	518354	Sonus	naturalis		Soundscape	Ramesh Desai	India	Hanchinal, Bijapur, Karnataka	16.866	75.7371	550	call, life stage un	//www.xeno-canto.org/518
13288	432728	Sonus	naturalis		Soundscape	Sreekumar Chiru	India	Papanasam R.F., Tirunelveli, Tamil Nadu	8.6811	77.3379	220	song	//www.xeno-canto.org/432
13289	432724	Sonus	naturalis		Soundscape	Ajinkya Supekar	India	Ananthagiri Hills, Vikarabad,Ranga Redd	17.3152	77.8668	700	song	//www.xeno-canto.org/432
13290	424085	Sonus	naturalis		Soundscape	Mike Dooher	India	Loleygaon, West Bengal	27.057	88.5806	1700	call	//www.xeno-canto.org/424
13291	376330	Sonus	naturalis		Soundscape	Taukeer Alam Lc	India	Pathari Forest Range, Haridwar, Uttarakh	29.8971	78.2457	400	call	//www.xeno-canto.org/376
13292	357820	Sonus	naturalis		Soundscape	emganin	India	Thattekad Bird Sanctuary	10.108	76.713	50	call, song	//www.xeno-canto.org/357
13293	357817	Sonus	naturalis		Soundscape	emganin	India	Thattekad Bird Sanctuary	10.108	76.713	50	call, song	//www.xeno-canto.org/357
13294	308556	Sonus	naturalis		Soundscape	emganin	India	Kovalam, Kanchipuram, Tamil Nadu	12.8007	80.2477	0	call, song	//www.xeno-canto.org/308
13295	198577	Sonus	naturalis		Soundscape	Sudipto Roy	India	Keoladeo National Park (near Shreenaga	27.1569	77.5237	180	Asian Openbills,	//www.xeno-canto.org/198
13296	165872	Sonus	naturalis		Soundscape	Dharma Giri	India	Jungle Home Pench			615 m	call	//www.xeno-canto.org/165
13297	157721	Sonus	naturalis		Soundscape	Frank Lambert	India	Mishmi Hills, nr Roing town, Arunachal P	28.1541	95.8635	600	song	//www.xeno-canto.org/157
13298	153748	Sonus	naturalis		Soundscape	Sudipto Roy	India	Narendrapur, West Bengal, India	22.456	88.404	10	dawn chorus	//www.xeno-canto.org/153
13299	381203	Sonus	naturalis		Soundscape	abhiram sankar	India	Hebbal Lake, Mysuru, Karnataka	12.3581	76.6106	750	uncommon call	//www.xeno-canto.org/381
13300	206605	Sonus	naturalis		Soundscape	B R Sheshgiri	India	Gopalapura, Mysore, Karnataka	12.2406	76.5429	800	song	//www.xeno-canto.org/206
13301	146945	Sonus	naturalis		Soundscape	Brajesh Kumar D	India	Shivpuri, Hinoo, Ranchi, Jharkhand	23.3314	85.3193	10	You will find diffe	//www.xeno-canto.org/146
13302	404374	Sonus	naturalis		Soundscape	Meena Haribal	India	Kulgi, Uttara Kannada, Karnataka	15.1695	74.6418	500	call, song	//www.xeno-canto.org/404
13303	404371	Sonus	naturalis		Soundscape	Meena Haribal	India	Kulgi, Uttara Kannada, Karnataka	15.1695	74.6418	500	call, song	//www.xeno-canto.org/404

Dataset Audio File :

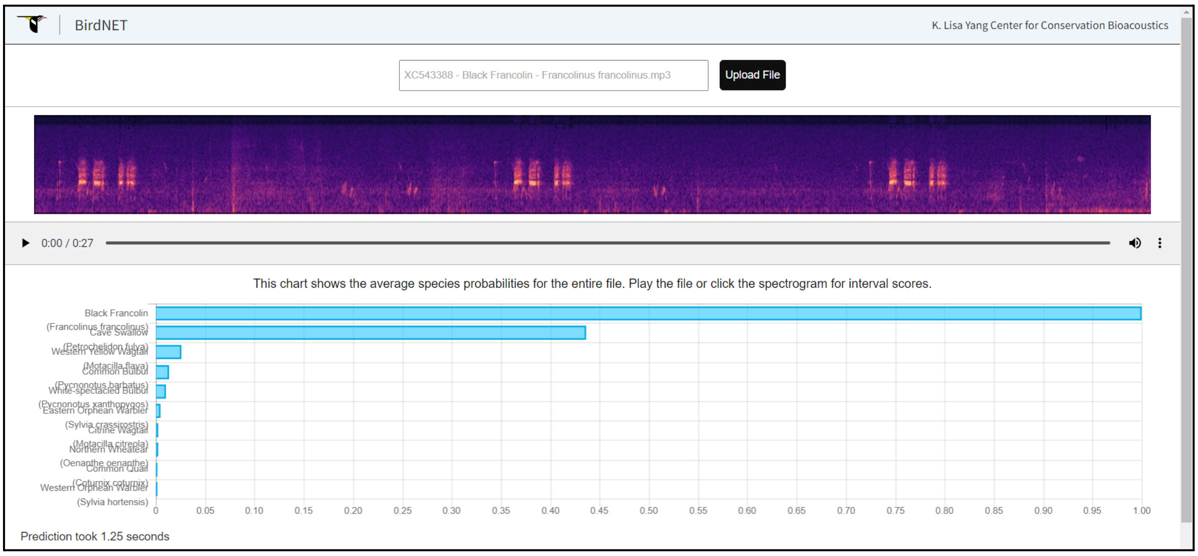


Verifying Dataset :

//www.xeno-canto.org/429767



//www.xeno-canto.org/543388



3.7 Result Analysis and Discussion

Our deep learning-based bird species recognition project has produced promising outcomes and offers valuable insights into avian biodiversity conservation.

Data Collection and Preprocessing: We have adeptly compiled a diverse dataset encompassing Indian bird vocalizations across a range of distinct habitats. Our research endeavors have been focused on the strategic implementation of audio preprocessing techniques, culminating in the successful elimination of extraneous background noise and the precise extraction of pertinent features. This meticulous process has substantially elevated the overall quality and integrity of the audio dataset.

Testing audio: BirdNET website, where you can upload an audio file of a bird and receive a prediction of the species. The screenshot shows that the user has uploaded the audio file XC429767, which is a recording of a Fulvous Whistling Duck. The BirdNET system has predicted that the bird is a Fulvous Whistling Duck with a 100% probability.

To verify whether the system's prediction is correct, you can listen to the audio file and compare it to the soundscape of a Fulvous Whistling Duck. You can also look at the spectrogram of the audio file, which is a visual representation of the sound waves. The spectrogram of a Fulvous Whistling Duck has a characteristic pattern that can be used to identify the species.

Challenges and Future Prospects: We acknowledge that certain challenges remain, particularly in managing noisy recordings and addressing overlapping vocalizations. These issues represent areas where further research and refinement are needed to advance our understanding of Indian bird vocalizations and their ecological significance.

Practical Significance: Our deep learning-based bird species recognition system offers a practical solution, simplifying species identification for researchers and conservationists.The potential for extensive, long-term avian population studies makes this tool a valuable asset.

3.8 Conclusion and Future work

In the current phase of our Indian bird sound recognition project, our primary focus is on two key aspects: dataset curation and the initiation of spectrogram generation from raw audio samples. These foundational tasks are pivotal in shaping the success of our project.

Our dataset curation efforts are characterized by meticulous organization and structuring of the data. We are committed to ensuring that our dataset is coherent and relevant, which is fundamental for the subsequent recognition tasks. This structured approach provides a strong foundation upon which we can build and refine our recognition system.

Simultaneously, we have begun the process of generating spectrograms. Spectrograms are visual representations created from the raw audio signals. These representations are crucial for training machine learning models, as they encapsulate the essential features of the bird sounds. This step bridges the gap between the raw audio data and the computational models that will drive our recognition system.

Looking ahead, our primary objectives remain focused on three key areas: algorithm refinement, model development, and data augmentation. We understand that to optimize the performance of our recognition system, we must continually improve the algorithms that underpin it, develop more sophisticated models, and enhance the dataset through data augmentation techniques.

These initial stages, which revolve around data preparation and feature extraction, represent critical strides towards the realization of a comprehensive Indian bird sound recognition system. This system is tailor-made to accommodate the diverse and rich avian biodiversity found in India. Our commitment to scientific rigor and technological advancement is unwavering. We firmly believe that our project has the potential to make significant contributions to avian biodiversity research and conservation in the Indian context. It is our hope that by accurately recognizing and understanding Indian bird sounds, we can better protect and preserve this invaluable natural heritage.

Future Work-

Feature Extraction:

Extract relevant acoustic features from the preprocessed audio data. These could include spectral features (e.g., MFCCs, spectrograms), pitch, duration, and more.

Normalize and standardize the features to ensure consistency.

Choose a Machine Learning Model:

Select an appropriate machine learning or deep learning model. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are often used for audio classification tasks.Experiment with various architectures to find the one that works best for your project.

Model Training:

Train your model using the training dataset. Monitor its performance on the validation set and fine-tune hyperparameters as necessary.Implement techniques like early stopping to prevent overfitting.

Model Evaluation:

Evaluate your model's performance on the test dataset. Common evaluation metrics include accuracy, precision, recall, F1-score, and confusion matrices. Analyze any misclassifications to understand where your model may be struggling.

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