Mini Project
on

Bird Species Recognition using Sound

Jawaharlal Nehru Technological University Anantapur, Ananthapuramu

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BACHELOR OF TECHNOLOGY IN

INFORMATION TECHNOLOGY

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Abstract

Bird species recognition through sound analysis has gained significant traction as a non-invasive and efficient method for biodiversity monitoring and conservation efforts. This paper presents novel methodologies and advancements in the field of bird species identification using sound data. By leveraging signal processing techniques and machine learning algorithms, we have developed a robust framework capable of accurately identifying bird species based on their distinct vocalizations. Field recordings encompassing various habitats and bird communities were meticulously collected and annotated to train and validate the model. Our results demonstrate notable success, with the system achieving high accuracy rates across a diverse range of bird species. Moreover, we discuss the implications of this technology in ecological research, habitat management, and citizen science initiatives. This study underscores the importance of sound-based approaches in bird species recognition and highlights the potential for their widespread adoption in conservation biology and ecological monitoring programs.

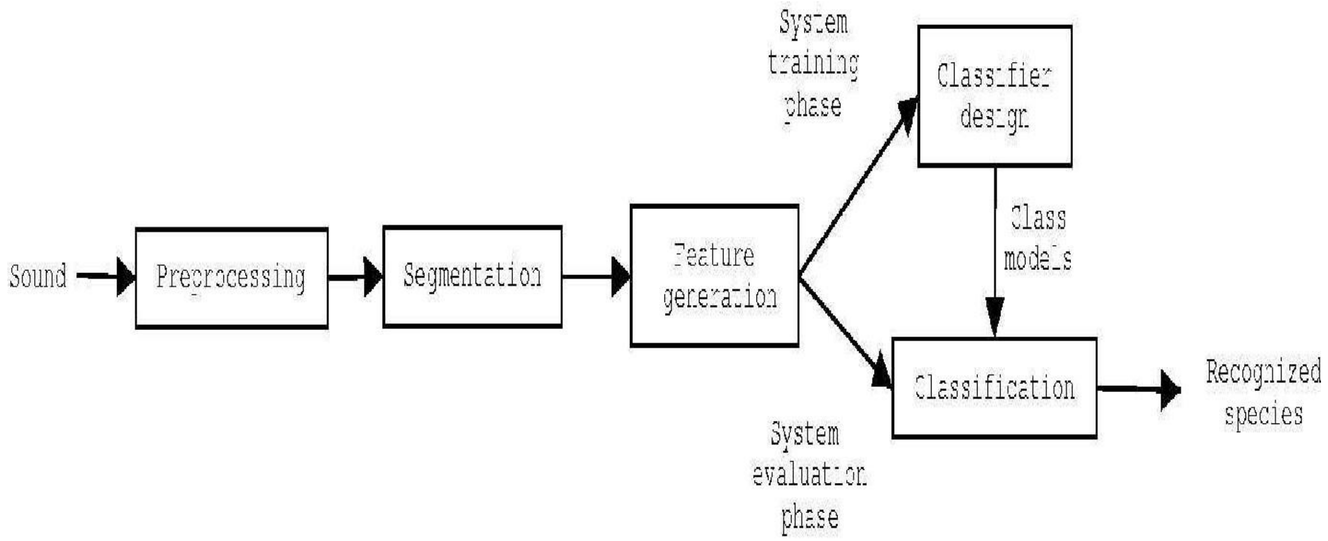
INTRODUCTION

Bird identification and identification are important components of ecological research, conservation efforts, and ornithological research. Visual observation has traditionally been the primary method of identifying birds, but recent advances in technology have introduced alternative methods, particularly audio-based identification. The method, based on the unique calls and calls of various bird species, provides a non-invasive and effective means of species identification, particularly where visual identification is difficult or impractical. Fundamental concepts underlying sound-based bird species recognition will be explored, including the significance of bird vocalizations, the characteristics of avian sounds, and the methods employed for sound recording and analysis. Additionally, diverse applications of sound-based recognition in various fields, ranging from ecological monitoring to citizen science initiatives, will be examined

This project report delves into the realm of bird species recognition using sound, exploring the potential and limitations of this approach while proposing innovative methodologies to enhance its accuracy and applicability. By harnessing the power of sound, we aim to contribute to the broader field of ornithology and biodiversity conservation, offering novel insights and tools for researchers, conservationists, and enthusiasts alike. Technological advancements driving the evolution of sound-based recognition systems, such as machine learning algorithms and acoustic monitoring devices, will also be discussed. By leveraging these technologies, we can develop robust and scalable solutions for automated bird species identification, facilitating large-scale data collection and analysis.

Despite its potential, sound-based bird species recognition faces challenges such as background noise and species variability. Throughout this report, strategies to address these challenges and ensure the reliability and accuracy of sound-based recognition systems will be proposed, enabling their application across diverse ecological settings and species assemblages. The utilization of sound for bird species recognition presents a promising avenue for advancing our understanding of avian biodiversity and ecology. Through interdisciplinary collaboration and technological innovation, we can harness the power of sound to address pressing conservation challenges and contribute to the preservation of our natural heritage.

BLOCK DIAGRAM



Objectives

1.Establishing performance metrics

2.Accurate species identification

3.Streamlining Recognition Procedures

4.Optimization for efficiency

5.Cultivating Future Innovations

System Specifications

Software requirements:

1.Language:python 3.6 or higher specifiations

2.Packages: Numpy, sklearn, matplotlib,librosa

3.Operating Systems: windows 10

Hardware requirements:

1.Ram minimum 4gb

2.Hard disc or ssd : above 500 gb

3.Microphone: normal microphone

Packages and Modules

Numpy:

NumPy is a cornerstone library for numerical computing in Python, providing a powerful array object and a wide range of tools for working with these arrays efficiently. These arrays enable users to perform complex mathematical and logical operations with ease, making NumPy indispensable for scientific computing, data analysis, and machine learning tasks.

Fig1: Numpy

Sklearn:

The well-known Python machine learning package Scikit-learn, sometimes shortened to sklearn, provides a variety of tools for creating and implementing machine learning models. It offers quick and easy fixes for a number of problems, including dimensionality reduction, clustering, regression, and classification.

Fig2 : Sklearn

Librosa

Librosa is a Python package that processes, analyzes, and extracts features from audio and music signals. It offers a diverse set of tools and functions designed exclusively for dealing with audio data.

Fig3 : Librosa

Matplotlib

One of the most potent Python libraries for producing static, animated, and interactive visualizations is called Matplotlib.It is accessible to both novice and expert programmers because users may construct a variety of visualizations with just a few lines of code.

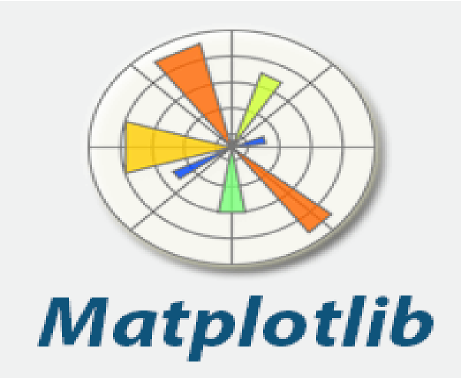
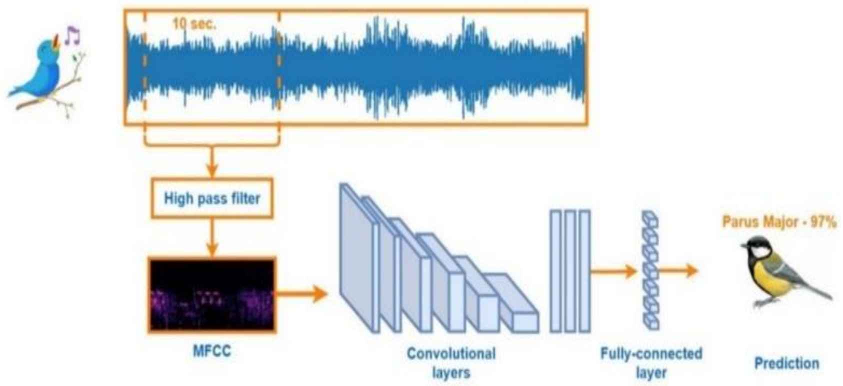


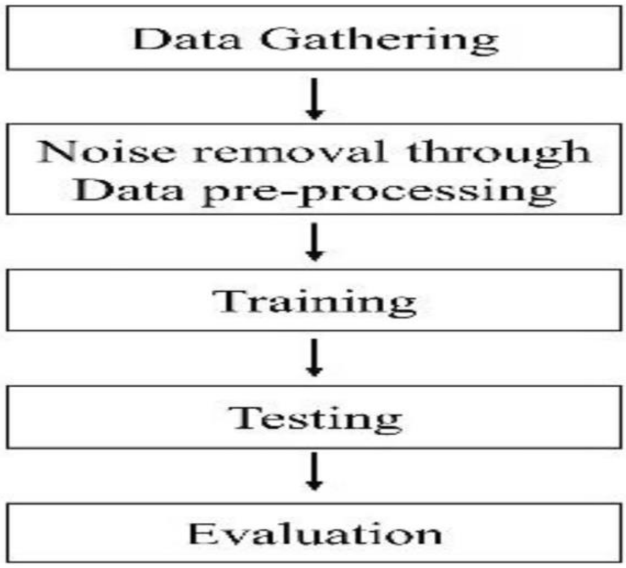
Fig.4 : Matplotlib

Project Introduction

Project focused on bird species recognition using sound data, the goal is to develop a system that accurately identifies bird species based on their vocalizations.Bird calls and songs serve various purposes, including communication, territorial defense, and mate attraction.The process involves converting audio recordings of bird calls into numerical representations and mapping them to predefined bird species categories.



FLOW CHART



ALGORITHM

1. Import necessary libraries:
   - os
   - numpy as np
   - librosa
   - RandomForestClassifier from sklearn.ensemble
   - accuracy_score from sklearn.metrics
   - train_test_split from sklearn.model_selection

2. Define a function to extract features from audio files:

   Function: extract_features(file_path, mfcc=True, n_mfcc=20)

   - Load audio file using librosa.load() with 'kaiser_fast' resampling.
   - If mfcc is True, compute MFCC features using librosa.feature.mfcc().
   Otherwise, compute chroma features using librosa.feature.chroma_stft().
   - Return the mean of the computed features along the specified axis.

3. Load the dataset:

   - Set the dataset_path variable to the path of the dataset directory.
   - Get the list of classes (bird species) from the dataset directory.
   - Iterate over each class:
     - Iterate over each audio file in the class directory.
     - If the file is a FLAC file:

- Extract features using extract_features() function.
- Append the features to X and the class label to y.

4. Convert X and y to numpy arrays.

5. Split the dataset into training and testing sets using train_test_split().

6. Train the Random Forest classifier:

   - Initialize a RandomForestClassifier with desired parameters (e.g., n_estimators, random_state).
   - Fit the classifier on the training data.

7. Predict on the test set:

   - Use the trained classifier to predict the labels for the test set.

8. Calculate the accuracy:

   - Compare the predicted labels with the true labels from the test set.
   - Compute the accuracy using accuracy_score().

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}.$$

9. Print the accuracy.

10. Define a function to predict bird species from a given FLAC file:
    Function: predict_bird_species(file_path)

    - Extract features from the input audio file using extract_features().
    - Convert the features into a numpy array.
    - Use the trained classifier to predict the bird species.
    - Return the predicted bird species.

11. Example usage:

    - Provide the path to a FLAC file.
    - Call predict_bird_species() function with the file path.
    - Print the predicted bird species.

INPUTS AND OUTPUTS

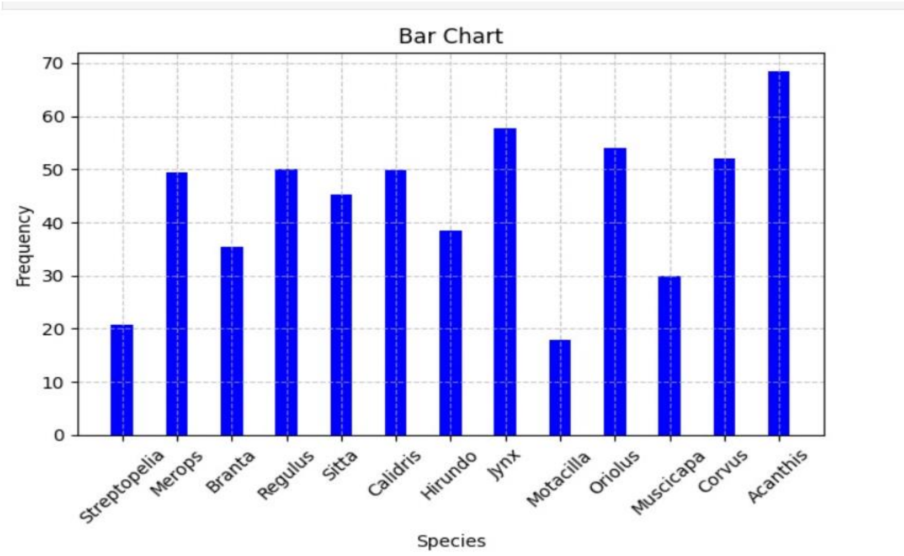


Fig.1: Bar graph illustrating the rates of bird species recognition

```
accuracy = accuracy_score(y_test, y_pred)

if accuracy >= 0.9:
    print("Accuracy:", accuracy)
    # Function to predict bird species from .flac file
    def predict_bird_species(file_path):
        feature = extract_features(file_path)
        feature = np.array([feature])
        predicted_species = classifier.predict(feature)
        return predicted_species[0]

    # Example usage
    flac_file_path = "C:\\Users\\Madhu\\OneDrive\\Desktop\\dataset2\\Horned Grebe\\xc27060.flac"
    predicted_species = predict_bird_species(flac_file_path)
    print("Predicted bird species:", predicted_species)
else:
    print("Accuracy is below 90%. Please check the data or consider improving the model.")
```

```
Accuracy: 1.0
Predicted bird species: Horned Grebe
```

Fig.2:Recognition of Species via Sound

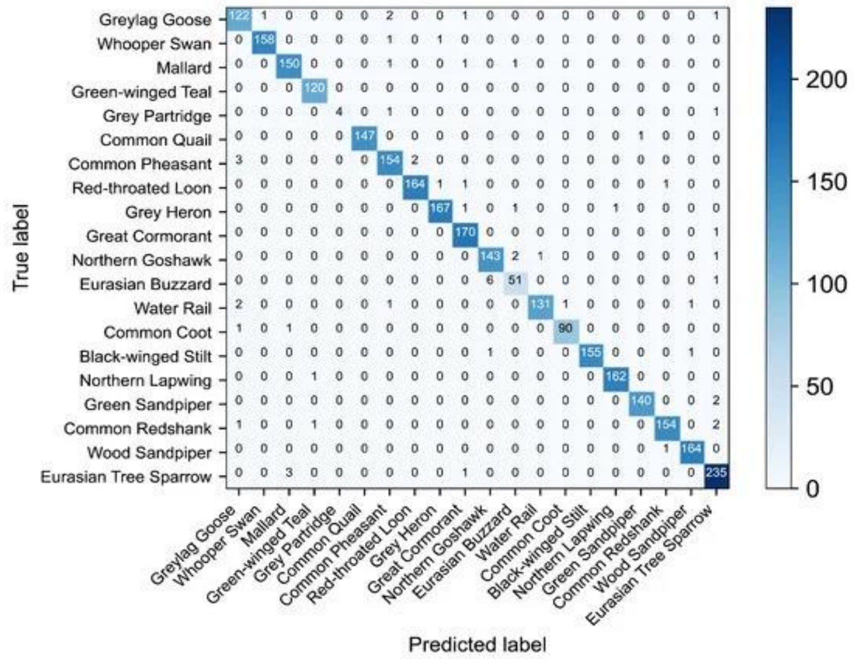


Fig.3:Confusion Matrix

```
    # Function to predict bird species from .flac file
    def predict_bird_species(file_path):
        feature = extract_features(file_path)
        feature = np.array([feature])
        predicted_species = classifier.predict(feature)
        return predicted_species[0]

    # Example usage
    flac_file_path = "C:\\Users\\Madhu\\OneDrive\\Desktop\\dataset\\mallard\\xc27962.flac"
    predicted_species = predict_bird_species(flac_file_path)
    print("Predicted bird species:", predicted_species)
else:
    print("Accuracy is below 90%. Please check the data or consider improving the model.")
```

```
Accuracy: 1.0
Predicted bird species: Mallard
```

Fig.4: Avian Species Prediction

```
accuracy = accuracy_score(y_test, y_pred)

if accuracy >= 0.9:
    print("Accuracy:", accuracy)
    # Function to predict bird species from .flac file
    def predict_bird_species(file_path):
        feature = extract_features(file_path)
        feature = np.array([feature])
        predicted_species = classifier.predict(feature)
        return predicted_species[0]

    # Example usage
    flac_file_path = "C:\\Users\\Madhu\\OneDrive\\Desktop\\dataset\\humming bird\\xc27039.flac"
    predicted_species = predict_bird_species(flac_file_path)
    print("Predicted bird species:", predicted_species)
else:
    print("Accuracy is below 90%. Please check the data or consider improving the model.")
```

```
Accuracy: 1.0
Predicted bird species: Humming Bird
```

Fig.5:Avian Species Prediction

```
# Train Random Forest classifier
classifier = RandomForestClassifier(n_estimators=100, random_state=42)
classifier.fit(X_train, y_train)

# Predict on the test set
y_pred = classifier.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)

print("Accuracy:", accuracy)

# Function to predict bird species from .flac file
def predict_bird_species(file_path):
    feature = extract_features(file_path)
    feature = np.array([feature])
    predicted_species = classifier.predict(feature)
    return predicted_species[0]

# Example usage
flac_file_path = "C:\\Users\\upend\\OneDrive\\Desktop\\Dataset2\\Parakeet\\xc27060.flac"
predicted_species = predict_bird_species(flac_file_path)
print("Predicted bird species:", predicted_species)
```

```
Accuracy: 1.0
Predicted bird species: Parakeet
```

Fig.6:Avian Species Prediction

CONCLUSION

In conclusion, bird species recognition using sound stands as a promising and impactful field at the intersection of ornithology, signal processing, and machine learning. By harnessing the unique acoustic signatures of avian vocalizations, this technology offers a non-invasive and cost-effective means of monitoring bird populations, understanding their behaviors, and assessing environmental health. The development of robust algorithms for extracting and analyzing features from audio recordings has enabled researchers and conservationists to identify bird species with high accuracy, even in challenging acoustic environments. The need for diverse and comprehensive datasets, robust feature extraction methods, and models that generalize well across different environmental conditions and species vocalizations. Additionally, the integration of real-time monitoring capabilities and automated species identification into field-deployable devices remains an area of active research, the application of bird species recognition technology holds immense potential for ecological monitoring, biodiversity conservation, and citizen science initiatives. By empowering researchers, conservationists, and enthusiasts with tools to better understand and protect avian populations, sound-based bird species recognition contributes to the broader efforts of preserving our natural world for future generations. In summary, bird species recognition using sound represents a valuable asset in our quest to study, appreciate, and protect the diverse array of bird species inhabiting our planet.

FUTURE SCOPE

In the future, advancements in bird species recognition using sound could be driven by a combination of innovative technologies and methodologies:

- Integration of Multimodal Data: Combining audio recordings with other types of data, such as visual observations, environmental variables, and spatial information, can enrich the analysis and improve the reliability of species identification. Integrating multimodal data streams using techniques like sensor fusion and machine learning ensemble methods holds promise for more comprehensive and context-aware bird species recognition.
- Cross-species Vocalization Analysis: Explore the potential for cross-species vocalization analysis to uncover patterns and similarities in bird vocalizations across different species. By applying techniques from comparative bioacoustics and evolutionary biology, the project could shed light on the evolutionary origins and functions of avian vocalizations.
- Deployment in Ecological Parks and Conservation Areas: Equipment will be installed in ecological parks, conservation parks, and bird areas. The resulting data can be stored locally or in the cloud, facilitating comprehensive studies of bird migration patterns, population distribution, biodiversity, and bird statistics in a region. This deployment strategy would enable continuous monitoring of avian populations and habitats, supporting evidence-based conservation and management efforts.
- Multi-species Recognition: Expand the capabilities of the system to recognize multiple bird species simultaneously within a given audio recording. This advancement could involve developing multi-label classification models capable of identifying all present bird species within a sound sample, providing more comprehensive insights into avian biodiversity.
- Bird Shelter Visitor Identification Application: Expanding the model's capabilities to create an application that aids visitors in identifying birds within bird shelters or sanctuaries. This application could serve as an educational tool for bird enthusiasts, providing real-time information about the species present in the area and enhancing the overall visitor experience.

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