# Bioacoustic Neural Inference for Avian Taxonomy

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***Abstract*—In this paper, we investigate the classification of bird species from their sounds with convolutional neural networks. Bird species monitoring is crucial in assessing ecological restoration projects and comprehending biodiversity change. Conventional monitoring, however, takes a lot of time, is costly, and has a limited physical and temporal capital. Sounds of birds can be examined to monitor biodiversity more effectively in the long term and across large areas. This can improve the effectiveness of biodiversity assessment and give a more comprehensive understanding of the relationship between bird species restoration and change.**

**One of the most important techniques for assessing the effectiveness of ecological restoration and interpreting the shift in biodiversity is bird species monitoring. The technique captures the sound of birds, which is useful for more precise and efficient long-term, large-scale monitoring of biodiversity. The results demonstrate how such a strategy can transform biodiversity measurement by increasing the knowledge of the relationship between bird species dynamics and restoration. The effective and reliable technologies also advise the health practitioners, which results in more informed, current, and strategic ideas beyond stability. Our results show that the proposed CNN-based bird sound classification approach is efficient and effective in energy saving, and with more such implementations, it will lead to deeper understanding and adaptive strategies in ecological monitoring.**

***Index Terms*—Bird Species Identification, Deep Learning, Convolutional Neural Networks (CNN), Audio Classification, Acoustic Signal Processing, Background Noise Handling, Spectrogram Analysis.**

## I. Introduction

Birds are integral components of ecosystems, performing essential roles such as seed dispersal, pollination, and insect control, which significantly influence ecosystem dynamics and functionality. In addition, bird populations act as vital indicators of environmental health, with fluctuations often signaling larger ecological changes. Studying bird species distributions, behaviors, and interactions is crucial for designing effective conservation strategies and protecting biodiversity. However, traditional methods for classifying birds rely on manual observation, which is laborious, time consuming, and prone to human error. Our approach will capitalize on advances made in computer vision and audio processing to allow machines to learn hierarchical representations directly from raw data using deep learning. In particular, CNN has proven to work exceptionally well in image classification tasks, whereas MLP have shown their effectiveness in audio-related tasks such as speech and sound classification.

### A. Motivation

The motivation for this project arises from the growing need for effective and efficient methods to monitor avian populations and their habitats, which are vital to understanding biodiversity and ensuring conservation efforts. Bird identification is critical for monitoring population changes, habitat changes, and general patterns. Traditional monitoring methods such as surveys and inspections usually involve human resources, are time consuming, and yield inconsistent results because of variations in the level of inspectors and the environment. This has created a need for solutions that can perform well on big data. Matching mode on video and audio recordings. The main goal is to create a strong and robust ability to identify bird species; this will reduce the dependency on manual methods and help speed up and accurately document more writing. In this way, the project aims to improve our ability to monitor birds and ecosystems in real time, which would lead to increased awareness of conservation practices, biodiversity assessment, and ecosystem management strategies.

### B. Problem Statement

As the number of bird species increases worldwide, it is becoming increasingly important to develop effective and accurate methods for monitoring and protecting bird species. Traditional bird monitoring methods, including manual surveys and field observations, are labor intensive, time-consuming, and often subject to observer bias or environmental errors. These methods may also be inappropriate for large areas or diverse ecosystems. It is difficult to identify bird species quickly and accurately from large images and sound recordings.

The task of identifying bird species using deep learning, especially images and sounds, can help overcome the limitations of traditional methods. However, this requires the development of a powerful force that can control the bird's different positions, facial changes, and vocal signals. The lack of an effective and efficient way to classify bird species limits the ability to monitor birds, thereby delaying conservation efforts.

### C. Objective

- **Implement a CNN Model for Audio Classification:** Develop and train a Convolutional Neural Network(CNN) model to process and classify bird species based on their unique sound patterns. This model should be able to differentiate between various bird species by analyzing features from bird calls, songs, and other vocalizations.
- **Feature Extraction from Audio Files:** Extract relevant features (such as Mel-frequency cepstral coefficients (MFCC), spectrograms, or chroma features) from audio recordings of bird sounds, enabling the CNN model to learn important characteristics that differentiate species.
- **Preprocessing Audio Data for Model Training:** Implement preprocessing techniques, such as noise reduction, audio normalization, and segmentation, to ensure that the audio data is clean, uniform, and ready for model input. This will improve the accuracy of the audio-based classification.

## II. Literature Review

Bird species identification has emerged as an integral part of biodiversity monitoring research because birds are important indicators of ecosystem health and environmental change. Traditional brand identification methods are highly dependent on observation and expert brand identification, which is often time-consuming, expensive, and prone to human error. These challenges are exacerbated in diverse or remote ecosystems where comprehensive studies are difficult to conduct in this area. This has led to a process where species identification has become highly efficient and accurate, with the ability to analyze recorded data and imagery in large quantities without much human interference. This change improves biodiversity monitoring and opens up new avenues for conservation strategies and real-time ecological assessments.

### A. BirdCLEF 2016: Audio-Based Bird Species Identification

Sprengel et al. (2016) introduced a groundbreaking deep learning-based approach for bird species identification using audio recordings, which earned first place in the BirdCLEF 2016 Recognition Challenge. Their approach addresses the very fundamental limitations of methods such as neighbor joining or decision trees, which usually suffer from noise, overlap, and incompetence. They present an efficient and powerful automatic bird classification framework by leveraging convolutional neural networks (CNN) and advanced preprocessing and data augmentation techniques.

Key contributions of their work included:

- **Signal/Noise Separation:** This method, in a way, identifies bird sounds amidst wind or rain noise, thereby sending cleaner input into the CNN model.
- **Spectrogram-Based Analysis:** Transformation of this noise into spectrograms where the visual display of noises over time will help fragment it into chunks of uniform size so that the CNN model might be able to catch some sort of pattern-very convenient for bird calls.
- **Data Augmentation:** It encompasses the use of techniques like time shifting, pitch shifting, and noise injection to increase its robustness and coverage by resolving discrepancies such as the lack of data gaps in it and closed file.

Their system achieved a median probability (MAP) of for identifying the most important bird species in the data, setting a new benchmark in the field. This work not only demonstrates the ability of deep learning to accomplish complex bioacoustic tasks but also paves the way for further developments in sound type identification. The BirdCLEF 2016 approach has paved the way for bird taxonomy and ecological research through solving important issues like noise and insufficient data.

### B. Challenges in Bird Species Identification

Several bird identification problems result from biological, technical, and environmental problems.

- **Background Noise**: Increasingly difficult to identify bird vocalizations with recordings that commonly involve superimposed noise such as wind, water, insects, or man-made presence.
- **Variability of Vocalization**: Model generalization is prevented by variation in bird calls among species, geographic locations, and personal characteristics such as age or gender.
- **Data Imbalance**: Unbalanced models because of the lack of rare species recordings impact conservation.
- **Temporal Variations**: Adaptation and data gathering should be continuous for seasonal and time-dependent calls.
- **Acoustic Similarities**: Misidentification becomes more likely in species with similar calls, particularly those within the same genus.
- **Real-Time Applications**: It remains challenging for edge devices to process with low latency and high precision.

### C. Research Gaps

Even with improvements in the classification of bird sounds, there are still a number of study gaps:

- Current models rely heavily on spectrograms for audio representation, which may not capture all relevant features. Exploring hybrid approaches with temporal features like MFCC could improve performance.
- Handling environmental noise is another challenge, as existing methods often fail in complex soundscapes with overlapping calls.

- Variability in bird vocalizations due to age, season, or context limits model generalization, highlighting the need for domain adaptation techniques.
- Data imbalance further skews model accuracy, favoring over-represented species.

### *D. Advancements in Deep Learning for Acoustic Analysis*

Acoustic analysis has made significant progress due to recent advances. It now includes the detection and classification of sound events and makes extensive use of neural networks and recurrent neural networks due to its ability to capture sound and physical data.Fusion of Convolutional and Recurrent Architectures:

Takahashi et al. (2016) demonstrated the strength in combining CNN with data augmentation for event detection; it uses the spatial feature extraction of the CNN with robust time modeling capabilities.

These distinct frequency patterns of calls may be captured by CNN and the sequential nature of song bird may be modeled to the RNN that shows better detection and classification in bird calls.

## III. Data Preprocessing and Feature Engineering

Data preprocessing and feature engineering are significant steps in developing a good bird sound classification model. Preprocessing includes cleaning audio files by removing background noise and normalizing noise to ensure that the noise across the recording is consistent. Often, denoising, attenuation, and filtering technologies are applied to improve the quality of the data. Segmentation of long sounds into short sounds will also assist in separating different sounds of individual birds, thereby it is easy to check data for training.

However, additional features like MFCCs, chromaticity features, and zero-shift values help capture some significant moments along with Spectral features. Combining several features facilitates enhanced model performance by offering more distributed information concerning strange patterns. The approach also helps to overcome real-world data imbalances and thus enhances model quality. Generally, a pre-existing and well-designed data extraction process is crucial in addressing the problems of environmental noise, vocal diversity, and data insufficiency in birdsong.

### *A. Dataset Overview*

The datasets for bird sound classification are sourced from two primary platforms:

1) **Xeno-Canto**:
   Xeno-Canto is a popular community-driven repository of bird sound recordings from around the world. It provides extensive and diverse audio samples of bird vocalizations across various habitats and species. The recordings are contributed by ornithologists, researchers, and bird enthusiasts, making it a rich source for research. Every recording is augmented with comprehensive metadata, such as species name, location, date, and time of recording, which may be utilized for more advanced processing such as habitat-specific modeling or domain adaptation.
2) **Kaggle – BirdCLEF 2024 Competition**:
   BirdCLEF dataset is a big test bird sound classification dataset released on Kaggle for the 2024 competition. There are thousands of tagged bird cry sounds covering a broad spectrum of species across varied geographic areas. The dataset is specifically selected to mimic real-world conditions such as species overlap, background noise, and class imbalance. It is well suited for model scalability and generalizability testing. Baseline models and evaluation metrics are also made available with the BirdCLEF dataset to ensure a fair comparison of methods.

Both datasets have unique strengths: BirdCLEF competition dataset provides standardized labels and challenging baseline for model testing, whereas Xeno-Canto provides high-density data and community-maintained diversity. Together, these datasets allow for complete model development and testing across acoustic regimes and bird species.

### *B. Audio Preprocessing Techniques*

As real recordings usually have interfering sounds, plenty of background noise, and changing recording environments, audio preprocessing is a very essential process in bird species classification. Through the improvement of input data quality, effective preprocessing enables deep learning models to extract meaningful features and improve the accuracy of classification. Noise reduction, segmentation, feature extraction, and normalization are some of the essential steps in the preprocessing process that are pivotal to peak performance.

*1) Noise Reduction and Filtering:* We employ sophisticated filtering and noise elimination methods to remove background wind noise, rain, human traffic noise, and other ambient noises in an effort to enhance bird calls recordings. The process enhances precision in the bird calls classification, preserves vital acoustic features, and enhances signal clarity.

- **Short-Time Fourier transform:** Through the application of the Fourier Transform, this operation breaks down sound signals into overlapping, brief durations of time. This is how frequency content changes over time through the provision of a time-frequency representation. With the exposure of spectral characteristics, STFT provides noise isolation and filtering by frequency to improve bird call intelligibility. The derived spectrograms are informative inputs for CNN-based bird call classification.
- **Hanning Window Function:** Audio signals are subjected to this mathematical windowing process through Short-Time Fourier Transform (STFT). It reduces spectral leakage, the phenomenon of signal power spilling over into the adjacent frequencies, by rounding off the boundaries of every signal segment with a smooth, cosine curve. The Hanning window retains valuable frequency information by reducing such distortions, rendering the spectrograms accurate and interpretable for the classification of bird calls.

We can improve performance by applying such noise reduction techniques to provide a cleaner and more consistent input signal to classification models.

*2) Audio Segmentation:* It is necessary to segment big bird recordings into smaller, manageable pieces because these recordings usually contain several different types of vocalizations, as well as silence. Although the aim is to get temporal features of the bird calls, segmentation makes sure the model gets the same inputs. The following are the methods of segmentation utilized:

- **Minimum Segment Length:** In order to make sure that only significant portions of sound are being processed in the process, we have set a Minimum Segment Length of 5 seconds. Shorter segments are discarded so that auditory feature integrity can be maintained and more precise bird species classification by full vocalizations can be achieved, avoiding truncated calls and spurious noise.
- **Silence Detection:** A threshold-based approach is used to detect and remove long silent sections from the recordings, thereby reducing computational overhead and improving model efficiency.
  By implementing these segmentation techniques, we improve feature extraction accuracy and reduce computational overhead, leading to better classification outcomes.

*3) Feature Extraction:* Transforming raw waveforms into structured representations is essential for efficient classification. Feature extraction techniques help highlight key spectral and temporal patterns in bird calls:

- **Spectrograms:** Spectrograms provide a visual representation of the frequency components of a sound over time, allowing convolutional neural networks (CNNs) to recognize distinct patterns in bird vocalizations.
- **Mel-Frequency Cepstral Coefficients (MFCCs):** MFCCs help capture timbral properties of bird calls by analyzing spectral envelope characteristics, making them highly useful for classification tasks.

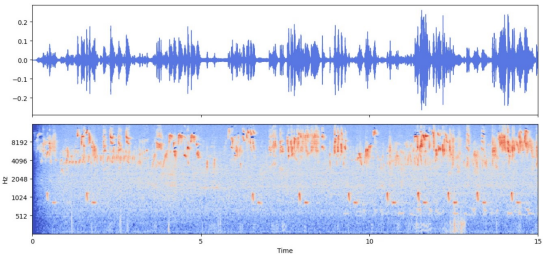


Fig. 1. Refined feature extraction and classification pipeline.

*4) Data Augmentation:* Data augmentation artificially expands the dataset by applying transformations to existing data, enhancing model robustness, reducing overfitting, and improving generalization through variability in training samples.

- **With Background Noise:** To simulate outdoor recording conditions such as wind, rain, or humans, controlled noise is introduced in audio samples to simulate realistic sound environments. Controlled noise addition improves the noise-robustness of the model by training the model under diverse acoustic conditions with the requirement of separating a bird cry from noise. Training with diversity in acoustic conditions improves the generalization capability of the model to deal with unseen noise-corrupted inputs.
- **Without Background Noise:** Clean, noise-free audio samples are used to preserve pure bird calls. With this approach, the model's ability to identify unique frequency patterns and tone attributes is improved, enabling it to focus on underlying acoustic features. Pure data that is free from external interference helps the model achieve a good grounding for accurate identification of bird species. These techniques prevent overfitting, improve adaptability to unseen data, and reduce computational power requirements.

*5) Normalization:* Through reducing input signal variability, normalization ensures that audio data is of the same amplitude and feature scale, making it easy to train models stably and reliably.

- **Amplitude Normalization:** Removes the variable recording effect by ensuring that all the samples are of equal loudness levels.
- **Min-Max Normalization:** Standardizes extracted features to fall within a fixed range, ensuring consistency in model inputs.
- **Range Selection:**The frequency range is standardized between fmin = 40 Hz and fmax = 15000 Hz, focusing on the most relevant acoustic features of bird calls. This approach retains important frequency components while effectively filtering out low and high frequencies that may introduce noise or irrelevant data into the model. By normalizing the dataset, we ensure that all input data adheres to a uniform standard, improving the model's ability to learn effectively from diverse samples.

*6) Final Preprocessing Pipeline:* The Final Preprocessing Pipeline includes noise reduction, segmentation, feature extraction, and normalization, delivering high-quality inputs to the classification model. We used two types of audio samples: with noise (simulating real-world conditions like wind, rain, and human activity) to enhance model resilience, and without noise to focus on fundamental acoustic features for accurate bird species identification. This approach ensures model adaptability and classification accuracy, as shown in Figure 2.

### *C. Feature Extraction Methods*

Feature extraction plays a crucial role in bird species classification by transforming raw audio signals into meaningful representations that can be effectively processed by deep learning models. Extracting the right features ensures that the model captures relevant frequency patterns, temporal dynamics, and tonal characteristics specific to bird vocalizations. The following methods were used for feature extraction:

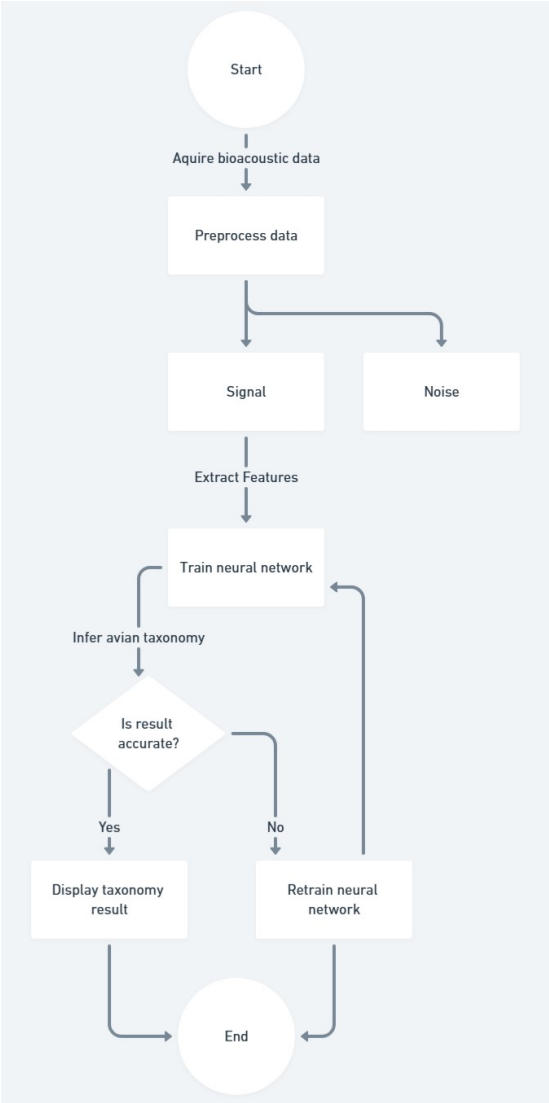


Fig. 2. Overview of the audio preprocessing pipeline.

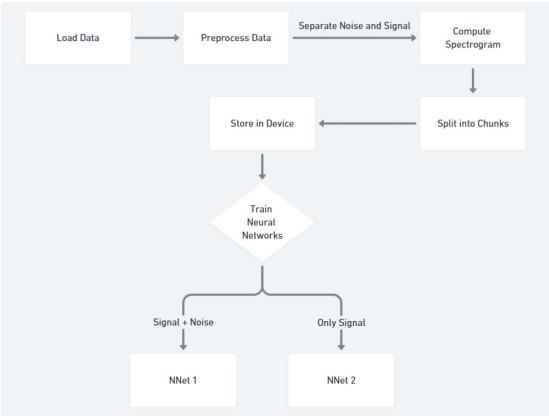


Fig. 3. Refined feature extraction and classification pipeline.

- **Mel-Frequency Cepstral Coefficients (MFCCs):** MFCCs are widely used in speech and bioacoustic analysis as they effectively capture the timbral properties of sounds. They are computed by applying a logarithmic transformation to the power spectrum, followed by a Short Time Fourier transform (STFT). This method helps in distinguishing bird species by capturing their unique vocal characteristics.
- **Spectrograms:** A spectrogram is a time-frequency representation of an audio signal, where the x-axis represents time, the y-axis represents frequency, and the color intensity indicates amplitude. By converting raw audio into spectrogram images, convolutional neural networks (CNNs) can learn discriminative patterns to classify bird species more accurately.
- **Mel Spectrograms:** Mel spectrograms provide a frequency representation based on the mel scale, which better aligns with human auditory perception. This method enhances classification accuracy by emphasizing frequency components most relevant to distinguishing bird calls.
- **Short-Time Fourier Transform (STFT):** STFT breaks down audio signals into short overlapping frames, enabling time-localized frequency analysis. This method allows the model to track how frequency components evolve over time, aiding in bird species differentiation.

Model performance largely depends on feature extraction techniques since they yield the information employed to differentiate different bird species based on their sounds. For accurate and reliable bird sound classification, feature extraction is very important input to deep learning models.

## IV. Model Architecture and Training

### A. Model Selection and Training Parameters

We have utilized the EfficientNet-B0 model, a deep learning model optimized for low-processing-resource environments, in this study. Network breadth, depth, and resolution are all proportionally scaled by the optimized deep model EfficientNet. In low-resource environments, the B0 variant is particularly optimal for real-time inference.

Research articles are referenced to give an in-depth description of EfficientNet-B0 and its architectural components. To facilitate understanding, a sample diagram of the structure of the model is also provided.

### B. Training Parameters and Model Optimization

To optimize the model, we use several training hyperparameters, including:

- **Number of training instances:** 182 bird audio input of training to ensure model convergence.
- **Epochs:** The model is trained for 7 to 12 epochs, depending on early stopping criteria.
- **Loss Function:** Categorical Cross-Entropy Loss, which is widely used for multi-class classification problems.
- **Optimizer:** AdamW, an improved version of the Adam optimizer that includes weight decay regularization.

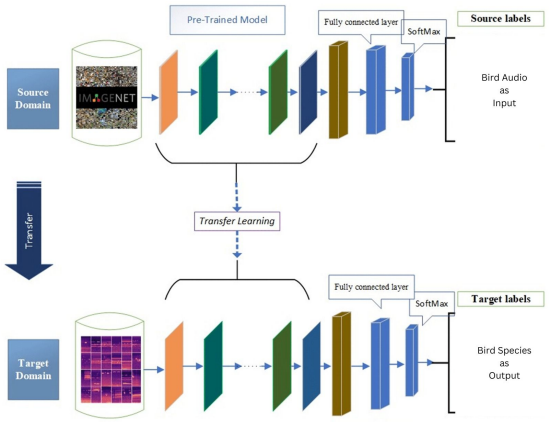


Fig. 4. Transfer Learning Process Using EfficientNet-B0 for Bird Species Classification.

- **Batch Size:** 96, which balances computation efficiency and generalization.
- **Activation Function:** Softmax, applied in the final classification layer to normalize logits into probability values.

### C. Justification for Using AdamW Optimizer

AdamW is preferred over traditional Adam due to its better generalization ability. It prevents overfitting by decoupling weight decay from gradient updates, making it more suitable for deep CNN architectures.

### D. Dataset and Preprocessing Steps Dataset Overview

The dataset used in this research consists of audio recordings from 182 different bird species, sourced from publicly available bird sound repositories and field recordings. Each recording captures various vocalizations, including calls, songs, and background noises, ensuring a diverse and representative dataset. The recordings vary in duration and quality, containing both clean and noisy samples.

To enhance model performance, preprocessing techniques such as noise reduction, spectrogram conversion, and data augmentation were applied to refine the dataset and improve classification accuracy.

### E. Implementation of the STFT process

To transform raw waveform data into a spectrogram representation, we use the Short-Time Fourier Transform (STFT). This helps convert time-domain signals into time-frequency representations. The following Librosa function generates Mel spectrograms from the audio signal:

Explanation of Parameters:

- **y=arr:** The input audio signal as a NumPy array.
- **sr=sr:** Sampling rate of the audio.
- **fmin=40, fmax=15000:** Frequency range to be analyzed (40 Hz to 15 kHz).
- **power=2.0:** Square magnitude of the spectrogram (power representation).

This function converts raw waveforms into Mel spectrogram representations, which are then fed into the EfficientNet-B0 model for classification.

### F. Model Architecture and Training Procedure

*1) CNN-Based Audio Classification Model :* The deep learning architecture is based on EfficientNet-B0, with modifications for audio-based classification. The input to the model is a Mel spectrogram representing the time-frequency features of bird sounds.

*2) Architecture Overview :*

- **Input Layer:** Accepts Mel spectrogram images.
- **Convolutional Layers:** Extracts spatial frequency patterns from the spectrogram.
- **Batch Normalization:** Stabilizes activations and improves training speed.
- **Pooling Layers:** Reduces dimensionality while preserving key features.
- **Fully Connected Layers:** Learns complex relationships between extracted features.
- **Softmax Classifier:** Outputs a probability distribution across 182 bird species.

*3) Training Strategy:*

- The cross-entropy loss function* is optimized using the AdamW optimizer.
- Early stopping is applied to prevent overfitting.
- Data augmentation techniques* such as time stretching, pitch shifting, and background noise addition are used to improve model robustness.

## V. Results and Evaluation

### A. Model Performance

The performance of the proposed CNN model is evaluated using the **Macro-Averaged ROC-AUC Score with Class Filtering** technique. This statistical approach provides a robust measure of classification effectiveness by:

i) Computing the ROC-AUC score for each class separately.

ii) Ignoring classes where no true positives exist to ensure meaningful evaluation.

iii) Averaging the scores across all valid classes (Macro-Averaging).

A higher ROC-AUC score indicates better discrimination between classes. The model achieves a **Macro-Averaged ROC-AUC score of 0.689146 on the test dataset** and **0.738 on 1000 random audio samples**. These scores suggest that the model generalizes well across unseen data while maintaining a reliable classification ability.

### B. Comparison with Baseline Models

To evaluate the effectiveness of the proposed CNN model, we compare it with traditional machine learning approaches, such as Support Vector Machines (SVM) and Random Forest. Table I summarizes the results.

The CNN model consistently outperforms traditional methods, demonstrating its ability to learn complex patterns in bird vocalizations. Unlike SVM and Random Forest, which

| Model | Mean Average Precision (MAP) |
|---|---|
| SVM | 0.621 |
| Random Forest | 0.658 |
| CNN (Proposed) | 0.686 |

TABLE I
COMPARISON OF THE CNN MODEL WITH BASELINE MACHINE LEARNING MODELS.

rely on manually engineered features, the CNN automatically extracts relevant acoustic features from spectrograms, leading to improved classification performance.

### C. Impact of Preprocessing

The influence of preprocessing steps on model performance is analyzed through different training scenarios:

- **Raw audio data without preprocessing**
- **Preprocessed data with noise removal and spectrogram conversion**
- **Augmented dataset with additional transformations**

Table II presents the improvement in Macro-Averaged ROC-AUC score due to preprocessing.

| Preprocessing Step | Macro ROC-AUC |
|---|---|
| No Preprocessing | 0.578 |
| Noise Removal + Spectrograms | 0.645 |
| Full Preprocessing (Including Augmentation) | 0.689 |

TABLE II
IMPACT OF PREPROCESSING TECHNIQUES ON CNN MODEL PERFORMANCE.

The results indicate that preprocessing significantly improves classification performance by enhancing feature extraction and noise reduction.

### D. Discussion

The results demonstrate that the CNN model outperforms traditional machine learning models in bird species classification. The **Macro-Averaged ROC-AUC Score with Class Filtering** provides a fair and meaningful assessment of model performance, especially in imbalanced datasets.

Preprocessing is of great importance in the improvement of classification accuracy, and preprocessing methods including data augmentation, spectrogram transformation, and cancellation of noise have been extremely successful.

The results also show that a cleaned dataset always performs better than an uncleaned dataset. The ablation study also shows the importance of dropout layers and batch normalization in the optimization of the model's generalization ability. While the testing is conducted on noise-free signal data to verify the actual classification capability of the model, the training procedure utilizes both signal and noise within the data to make the learning of features robust.

The proposed CNN model is a good approach to automatic bird sound classification because it classifies various bird species with high accuracy from audio recordings and shows good generalization to new data.

## VI. SIGNIFICANCE OF THE STUDY

One of the main aspects of bioacoustics is identifying species based on the study of the song of birds, which is employed to support a number of conservation and ecological initiatives. This article presents a computer system for the accurate and efficient classification of bird species from sound recordings based on deep learning techniques.

### A. Advancement in Bioacoustics

Labor-intensive and human error-prone manual observations make up most of the conventional bird species identification processes. The research enhances bioacoustic analysis by employing a deep learning-based system that can automate species recognition at a faster and more accurate pace.

### B. Contribution to Biodiversity Monitoring

Accurate species identification is needed to monitor biodiversity in determining habitat conditions and population trends. The suggested approach offers a scalable solution for processing big audio samples with the capacity for mass and ongoing bird population tracking in different habitats.

### C. Impact on Conservation Efforts

Correct species identification and population tracking are integral parts of effective conservation. Through the provision of an automated system of bird species identification and classification from recordings, this work adds to species conservation and habitat protection initiatives.

### D. Ecological Applications

Automated bird species identification is useful in ecological research apart from conservation, such as in the study of behavior, migration patterns, and ecosystem health. The model is an appropriate tool for bird ecological scientists since it can process large sets of data at high speeds.

### E. Future Implications

The research's techniques and conclusions can be applied to additional bioacoustic uses, like sound analysis for wildlife species monitoring, marine life monitoring, and amphibian monitoring. Its usefulness in ecological study can also be increased by merging this approach with real-time monitoring frameworks.

This study lays the groundwork for future developments in automated species recognition by bridging the gap between deep learning and bioacoustics, promoting a better knowledge and preservation of avian biodiversity.

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