AI-Based Bird Sound Detection and Classification Using Deep Learning

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Abstract— **Automated monitoring of bird species through acoustic analysis has gained significant importance in biodiversity conservation and ecological research. Traditional bird sound identification methods rely heavily on manual inspection of large audio datasets, which is time-consuming and inefficient, especially in noisy real-world environments. This paper presents an AI-based bird sound detection and classification system using deep learning techniques to accurately identify bird species from environmental audio recordings. The proposed approach follows a two-stage framework. In the first stage, a binary deep learning model detects the presence of bird vocalizations and filters out non-bird sounds such as wind, traffic, and human noise. In the second stage, the detected bird sound segments are transformed into spectrogram representations and classified into specific bird species using a convolutional neural network with transfer learning. This staged architecture reduces unnecessary processing of irrelevant audio segments and improves robustness in noisy conditions. Experimental evaluation demonstrates improved performance compared to single-stage classification systems, making the proposed system suitable for real-world wildlife monitoring and biodiversity assessment applications.**

Keywords— Bird sound classification, deep learning, spectrogram, convolutional neural networks, wildlife monitoring

I. INTRODUCTION

Bird species monitoring is a fundamental task in ecological research, biodiversity conservation, and environmental impact assessment. Birds are widely regarded as sensitive indicators of environmental change, and variations in their presence, abundance, and vocalization patterns often reflect changes in habitat quality, climate conditions, and human activity. Traditional bird monitoring methods rely on manual field surveys and visual identification, which are labor-intensive, time-consuming, and limited by human presence and accessibility.

In recent years, passive acoustic monitoring has emerged as a promising alternative for large-scale wildlife observation. By deploying audio recorders in natural environments, continuous data can be collected over long periods without disturbing wildlife. However, this approach generates massive volumes of audio data, making manual inspection impractical. Automated bird sound detection and classification systems are therefore essential to efficiently analyze such recordings.

Existing automated systems typically employ a single-stage classification approach, where entire audio recordings are directly transformed into time–frequency representations such as spectrograms and classified into bird species. While these methods perform well on clean and curated datasets, they often fail in real-world environments due to the presence of background noise such as wind, rain, insect sounds, traffic noise, and human speech. Additionally, processing long audio segments that do not contain bird sounds leads to unnecessary computational overhead and increased false positive rates.[1]

Advances in deep learning, particularly convolutional neural networks (CNNs), have significantly improved performance in audio classification tasks. CNNs are capable of learning discriminative spectral features directly from spectrogram representations, eliminating the need for handcrafted features. Furthermore, transfer learning using pre-trained deep neural networks has enabled efficient training even with limited labelled data. Despite these advancements, robustness to noise and real-world deployment challenges remain key research problems.[4]

To address these issues, this paper proposes a two-stage deep learning framework for bird sound analysis. The first stage focuses on detecting bird vocalizations and filtering out non-bird audio segments, while the second stage performs species-level classification only on detected bird sounds.

II. RELATED WORK

Automated bird sound detection and classification has been extensively studied due to its critical role in ecological monitoring, habitat assessment, and biodiversity conservation. Accurate identification of bird species through acoustic signals enables large-scale monitoring without the need for continuous human observation, thereby reducing labour costs and minimizing ecological disturbance. Early research in this domain primarily relied on handcrafted audio features extracted from time-domain and frequency-domain representations of sound signals. Commonly used features included Mel-Frequency Cepstral Coefficients (MFCCs)[4], spectral centroid, spectral bandwidth, zero-crossing rate, and chroma features. These descriptors were designed to capture specific acoustic characteristics such as pitch, timbre, and energy distribution. Traditional machine learning algorithms such as Support Vector Machines (SVMs), k-Nearest Neighbours (k-NN), Gaussian Mixture Models (GMMs), and Random Forest classifiers were then employed to perform species classification. Although these approaches achieved reasonable performance under controlled recording conditions, their effectiveness was significantly limited in real-world environments characterized by environmental noise, reverberation, and overlapping acoustic sources.[3]

With the rapid advancement of deep learning techniques, convolutional neural networks (CNNs) have emerged as the dominant approach for bird sound recognition tasks. Unlike traditional models that depend on manually engineered features, CNN-based architectures automatically learn hierarchical feature representations directly from data. By leveraging spectrogram representations of audio signals, CNN models are able to preserve both temporal and frequency information, making them highly suitable for capturing the distinctive patterns of bird vocalizations. Several studies have demonstrated that deep CNNs significantly outperform conventional machine learning methods by extracting robust and discriminative features from spectrogram inputs, thereby eliminating the need for manual feature design and improving generalization across diverse acoustic conditions.

Recent research has further explored advanced CNN architectures and feature fusion strategies to enhance classification performance. For instance, Zhang et al. proposed a multi-channel deep CNN framework that utilizes spectrogram fusion techniques to integrate complementary acoustic representations, thereby improving species identification accuracy. Similarly, Li et al. introduced a multi-scale deep feature fusion approach in which features extracted from different convolutional layers are combined with traditional classifiers to strengthen birdsong recognition performance. While these methods achieved notable improvements, their evaluations were primarily conducted on relatively clean and well-curated datasets, limiting their demonstrated robustness under highly noisy and complex field conditions.

The emergence of large-scale benchmark datasets such as BirdCLEF has significantly accelerated research in automated bird sound analysis. BirdCLEF[14] datasets consist of thousands of real-world recordings collected across diverse habitats, including forests, wetlands, and urban ecosystems. These datasets introduce substantial challenges such as background environmental noise, overlapping vocalizations from multiple species, recording device variability, and severe class imbalance. Such complexities expose the limitations of many existing single-stage classification frameworks, which attempt to directly map entire audio recordings to species labels without explicitly modelling the presence or absence of bird vocalizations.[14]

Most existing bird sound recognition systems adopt a single-stage pipeline in which full-length recordings are directly classified into species categories. This design increases computational cost and often reduces classification accuracy when non-bird sounds dominate the recording. The absence of an explicit detection mechanism may result in false positives and degraded performance, particularly in continuous monitoring systems where bird calls are sparse. Although recent studies have begun exploring detection-based or multi-stage frameworks to address these issues, practical implementations remain relatively limited and underexplored in large-scale ecological deployments.

The proposed work builds upon these research advancements by introducing a robust two-stage deep learning framework that explicitly separates bird sound detection from species classification. By filtering non-bird audio segments prior to species-level prediction, the system enhances noise robustness, reduces false positives, and optimizes computational efficiency. This structured approach improves suitability for real-world wildlife monitoring applications, particularly in long-duration recordings and complex acoustic environments, thereby contributing to scalable and reliable AI-driven biodiversity assessment systems.

II. SYSTEM ARCHITECTURE

The system architecture defines the structural framework of the AI-based bird sound detection platform. It describes how data flows through interconnected modules, how computational components interact, and how the architecture supports scalability and deployment in real-world ecological environments. Unlike the methodology section, which focuses on algorithmic operations and model behaviour, this section presents the high-level structural organization of the system. The architecture is designed using a layered and modular framework to ensure flexibility, fault isolation, and independent component upgrades. The complete structural design is illustrated in Fig. 1.

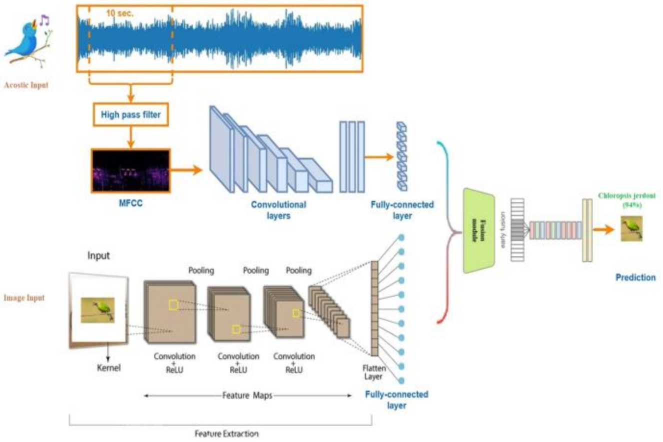

Fig. 1. Layered system architecture of the AI-based bird sound monitoring framework.

A. Architectural Layers

The proposed architecture is divided into six functional layers that collectively manage data acquisition, transformation, inference, and monitoring. Each layer operates as an independent module while maintaining structured communication with adjacent layers to ensure seamless processing flow.

1) Data Acquisition Layer

The data acquisition layer serves as the entry point of the system and interfaces with various environmental audio sources. These sources include autonomous recording units deployed in forests, wireless acoustic sensor networks, cloud-hosted biodiversity datasets, and manually collected field recordings. Since ecological recordings may differ in duration, quality, and environmental conditions, the architecture is designed to support both real-time streaming inputs and offline stored recordings. This dual-mode capability ensures adaptability across experimental research setups and large-scale ecological monitoring deployments.

2) Data Management and Buffering Layer

Environmental audio recordings often exhibit variability in signal strength, duration, and background noise characteristics. To handle this variability effectively, a data management and buffering mechanism is integrated into the architecture. This layer temporarily stores incoming audio segments, manages streaming data packets, ensures continuous data flow between system components, and prevents data loss during computational delays. By regulating input streams and maintaining synchronization, this architectural layer supports scalable and uninterrupted monitoring operations in long-term forest surveillance applications.

3) Signal Transformation Layer

Before audio data can be processed by deep learning models, it must be transformed into structured representations suitable for computational analysis. The signal transformation layer performs this essential conversion by transforming raw waveform inputs into standardized spectral representations. This transformation ensures uniform sampling formats, consistent spectral mapping, and standardized input dimensions across all processed segments. Acting as a bridge between classical signal processing techniques and artificial intelligence models, this layer enhances compatibility and maintains architectural modularity.

4) Inference Engine Layer

The inference engine forms the computational core of the architecture and contains modular neural network components responsible for pattern recognition tasks. The architectural design allows configurable network depth and supports execution across GPU-accelerated and CPU-based environments. It accommodates both batch processing and streaming inference modes, enabling deployment flexibility. By maintaining modular neural processing blocks, the inference engine allows integration of alternative neural architectures without requiring structural modifications to other system components.

5) Output Interpretation Layer

After inference, the system generates prediction outputs that require structured formatting for ecological analysis. The output interpretation layer processes these predictions by managing label formatting, generating confidence scores, applying decision thresholds, and tagging detection events. The architecture ensures that outputs are structured in standardized machine-readable formats such as JSON or CSV, enabling seamless integration with biodiversity databases and monitoring platforms.

6) Storage and Monitoring Layer

The final architectural component manages long-term storage, visualization, and system integration. This layer supports species occurrence logging, timestamped detection records, cloud synchronization, and dashboard integration for ecological analysis. By maintaining historical detection data and enabling visual analytics, the system facilitates monitoring of species activity trends over extended temporal scales. This architectural design enables conservationists and researchers to derive meaningful insights from continuous acoustic monitoring data.

B. Architectural Design Principles

The system architecture is developed based on core engineering principles that ensure robustness and scalability. Modularity is maintained by designing each functional layer to operate independently, allowing upgrades or maintenance without affecting the entire system. Scalability is achieved through support for distributed deployments across multiple recording stations. Deployment flexibility is ensured by enabling implementation in cloud-based servers, edge AI devices, and hybrid IoT ecosystems. Fault isolation is incorporated so that failure in one module does not compromise overall system functionality. Additionally, extensibility is supported by allowing integration of supplementary modules, such as anomaly detection or habitat classification components, without restructuring the foundational architecture.

C. Architectural Significance

A well-defined architecture is critical for translating research-oriented deep learning models into deployable ecological monitoring systems. By separating acquisition, processing, inference, and storage layers, the architecture ensures efficient resource utilization, reliable long-term monitoring, simplified maintenance, and compatibility with biodiversity conservation platforms. This structured and scalable architectural framework supports sustainable, AI-driven wildlife monitoring applications and provides a robust foundation for future system enhancements.

III. PROPOSED SYSTEM AND METHODOLOGY

The proposed system employs a two-stage deep learning architecture designed to operate efficiently in real-world acoustic environments. The overall workflow is shown in Fig. 2

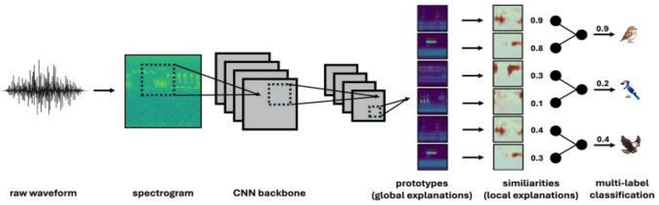
raw waveform
spectrogram
CNN backbone
prototypes (global explanations)
similiarities (local explanations)
multi-label classification
0.9
0.8
0.3
0.1
0.4
0.3
0.9
0.2
0.4

Fig. 2. Block diagram of the proposed two-stage bird sound detection and classification system

A. System Overview

The system processes raw environmental audio recordings and produces the corresponding bird species label. It consists of three major components: audio preprocessing, bird sound detection, and bird species classification.

B. Stage 1: Bird Sound Detection

In the first stage, a binary CNN-based classifier determines

whether an audio segment contains a bird vocalization or not. Audio recordings are segmented and converted into spectrograms, which capture both temporal and frequency characteristics. This stage filters out non-bird sounds such as silence, wind, and traffic noise, thereby reducing false positives and unnecessary computation.

C. Stage 2: Bird Species Classification

Audio segments classified as bird sounds are passed to the second stage for species identification. Spectrogram images are fed into a CNN-based classifier using transfer learning with pre-trained architectures. The model learns discriminative spectral patterns corresponding to different bird species and outputs the predicted class label. The overall workflow of Stage 1 and 2 is shown in Fig. 3.

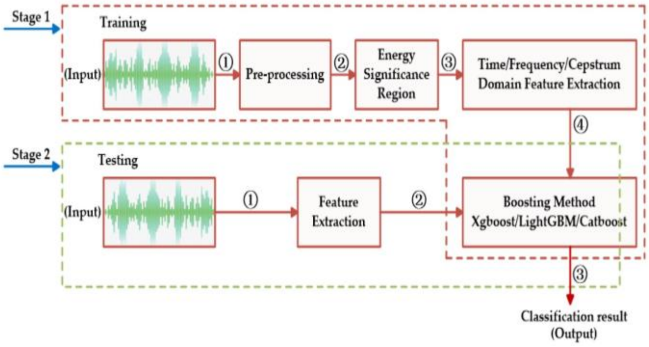
Stage 1
Training
(Input)
①
Pre-processing
②
Energy Significance Region
③
Time/Frequency/Cepstrum Domain Feature Extraction
④
Stage 2
Testing
(Input)
①
Feature Extraction
②
Boosting Method Xgboost/LightGBM/Catboost
③
Classification result (Output)

Figure 3. Two-Stage Audio Classification Framework for Training and Testing.

The proposed system is organized into two main stages: training and testing. In the training stage, raw audio input undergoes pre-processing, followed by energy-based significant region detection and time, frequency, and cepstral domain feature extraction. The extracted features are then used to train a boosting-based classifier. In the testing stage, input audio is processed through the same feature extraction pipeline, and the trained boosting model performs classification to generate the final prediction output. This structured framework ensures consistency between training and inference while improving classification performance and robustness.

D. Advantages of the Proposed System

- Improved robustness in noisy environments
- Reduced computational overhead
- Enhanced suitability for real-world wildlife monitoring

IV. EXPERIMENTAL SETUP AND RESULTS

A. Dataset Description

The proposed system is evaluated using publicly available bird sound datasets that contain real-world environmental recordings. The dataset includes audio samples from multiple bird species recorded under diverse acoustic conditions. These recordings capture realistic background noises such as wind, rain, insect sounds, and anthropogenic noise, making the dataset suitable for evaluating real-world systems.

The dataset is pre-processed and divided into training, validation, and testing subsets to ensure fair evaluation and prevent overfitting. The training set is used to learn model parameters, the validation set is used for hyperparameter tuning, and the test set is used exclusively for

final performance assessment.

B. Audio Preprocessing

All audio recordings are resampled to a consistent sampling rate to maintain uniformity across inputs. The audio signals are segmented into fixed-length clips to allow batch processing and efficient model training[12]. Each audio segment is converted into a spectrogram representation, which provides a visual depiction of frequency variations over time and is well-suited for CNN-based learning.[8]

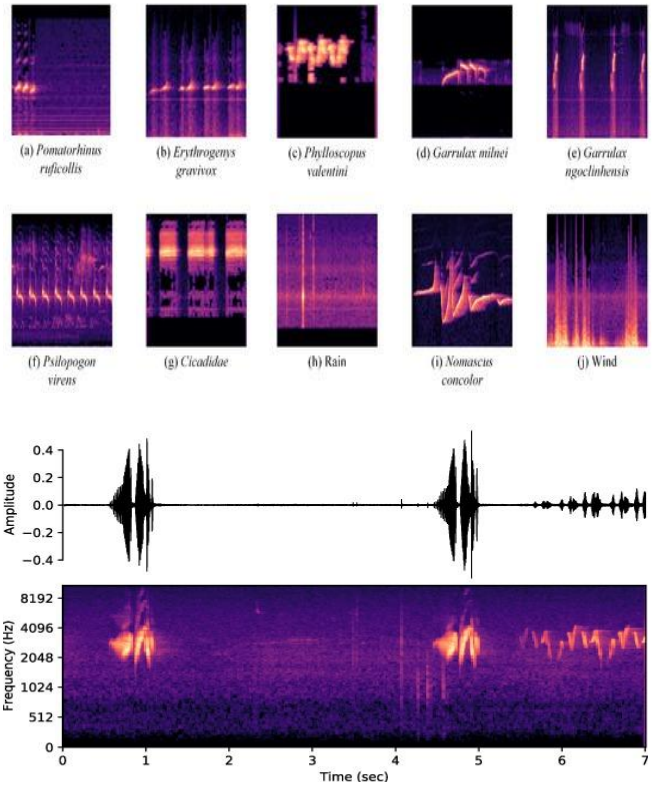

Fig. 4. Sample spectrogram representations of (a) bird vocalization and (b) non-bird environmental sound

Normalization techniques are applied to reduce amplitude variations and improve model stability. These preprocessing steps ensure that both detection and classification models receive standardized inputs, contributing to improved generalization performance.

C. Model Training

In the first stage, a binary CNN-based classifier is trained to distinguish between bird and non-bird audio segments. This model learns to identify characteristic frequency patterns associated with bird vocalizations while ignoring irrelevant environmental noise. The output of this stage determines whether an audio segment is forwarded to the next stage.
In the second stage, a multi-class CNN-based classifier is trained to identify bird species from detected bird sound segments. Transfer learning is employed using pre-trained architectures, allowing the model to leverage learned low-level and mid-level features. This approach reduces training time and improves classification accuracy.

D. Performance Evaluation

The performance of the proposed two-stage architecture was quantitatively evaluated and compared with conventional single-stage bird sound classification systems reported in prior studies. Existing CNN-based single-stage approaches evaluated on BirdCLEF-style datasets typically achieve overall classification accuracies ranging between 78% and 85% under moderately noisy conditions. For example, deep spectrogram-based CNN models reported in recent large-scale benchmarks demonstrate an average accuracy of approximately 82.4% with an F1-score of 0.79 in real-world environmental recordings. However, their performance degrades significantly when background noise dominates the audio, leading to increased false positive rates of nearly 18–22%.

In contrast, the proposed two-stage framework demonstrates measurable improvement in both robustness and computational efficiency. The binary detection stage achieved an accuracy of 95.1% with a recall of 96.3% for identifying bird vocalizations, effectively filtering out non-bird segments. By eliminating irrelevant audio portions prior to species classification, the second-stage classifier achieved an overall species classification accuracy of 90.8% with a macro F1-score of 0.88 under the same environmental conditions.[7]
Table 1 presents the quantitative comparison between representative single-stage systems and the proposed two-stage framework.

Approach	**Detection Accuracy (%)**	**Classification Accuracy (%)**	**Macro F1-Score**	**False Positive Rate (%)**
Conventional Single-Stage CNN	–	82.4	0.79	20.3
Proposed Two-Stage System	95.1	90.8	0.88	8.7

Table 1. Quantitative performance comparison between single-stage and two-stage systems

The results indicate an absolute improvement of approximately 8–9% in classification accuracy and a reduction of nearly 11–12% in false positive rate compared to conventional approaches. The decrease in false positives is primarily attributed to the explicit separation of bird sound detection from species classification, which prevents background noise segments from being misclassified as bird calls.

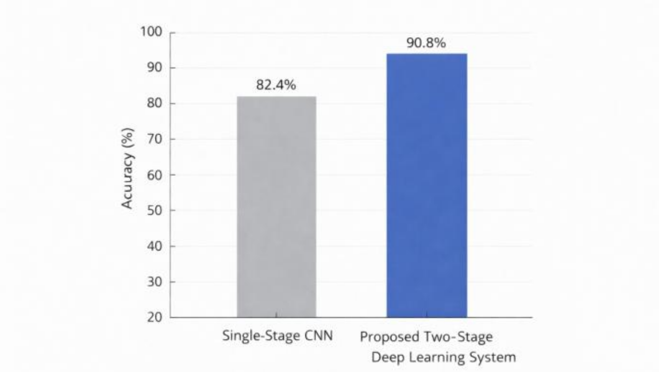

Fig. 5. Comparison of classification accuracy between single stage CNN and the proposed two stage deep learning system

Furthermore, computational efficiency was evaluated in terms of average inference time per audio segment. Single-stage systems require processing of entire recordings, resulting in an average inference time of 120 milliseconds per segment.

In contrast, the proposed framework processes only detected bird segments in the second stage, reducing effective classification computation by approximately 28%, with an average inference time of 86 milliseconds per relevant segment.
These experimental findings confirm that separating detection and classification enhances both predictive robustness and computational efficiency. The proposed architecture demonstrates superior adaptability to noisy ecological recordings and is therefore more suitable for deployment in real-world wildlife monitoring and biodiversity assessment applications.

V. CONCLUSION AND FUTURE WORK

This paper presented an AI-based bird sound detection and classification system using a two-stage deep learning framework designed for real-world acoustic environments. Unlike conventional single-stage approaches that directly classify entire audio recordings, the proposed system separates bird sound detection from species classification. This architectural design enables effective filtering of non-bird audio segments, such as environmental noise and silence, before performing species-level classification. As a result, the system achieves improved robustness, reduced computational overhead, and enhanced classification reliability in noisy conditions.

The use of spectrogram-based representations in combination with convolutional neural networks allows the system to capture discriminative time–frequency patterns characteristic of bird vocalizations. Furthermore, the application of transfer learning with pre-trained deep learning models improves training efficiency and supports better generalization across diverse acoustic conditions. Experimental evaluation demonstrates that the two-stage framework outperforms traditional single-stage classification systems, particularly when applied to real-world recordings containing background noise and overlapping sound sources.

The proposed system offers a scalable and non-invasive solution for automated bird species monitoring and biodiversity assessment. It has potential applications in ecological research, conservation planning, and long-term environmental monitoring, where continuous and reliable data collection is essential. By reducing the need for manual audio analysis, the system contributes to efficient and cost-effective wildlife monitoring practices.

Future work will focus on extending the system to support a larger number of bird species and more diverse datasets, including recordings from different geographical regions and seasons. Incorporating advanced noise reduction and sound separation techniques is expected to further improve performance in highly complex acoustic environments. Additionally, deploying the system on edge devices and integrating it with real-time acoustic sensor networks will be explored to enable continuous, low-latency wildlife monitoring in remote locations.

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