Deep Sound Search Leveraging Pre-trained CNNs and Faiss for Animal Vocalization Analysis

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Abstract. Deep learning techniques such as pre-trained Convolutional Neural Networks (CNNs) and Faiss were applied to animal vocalization analysis in this work. Comprehensive bioacoustic data in recent years have shown the versatility and power of CNN based models, which have outperformed in classifying a myriad of animal sounds. The proposed architecture with the self-supervised transformers such as animal2vec improves the raw audio input severity by ensuring the model is designed to handle rare-event nature by including species that are less vocalized in the database. Use of dual audio recording systems provides reliable source attribution, and employing ensemble methods, where multiple classification models are trained, can further improve accuracy across a range of environments. Using pre-trained models accelerates the adaptation to new species, requiring less time to train new species, which makes these techniques more broadly applicable. Moreover, autoencoder-based vocal analysis helps suppress noise and capture minute patterns, enabling deep learning models to be more effective in challenging environments. The deep learning methods highlight scalability, efficiency, and versatility of the approach which can also be adopted as a rich tool in wildlife monitoring and species identification in diverse ecosystems.

Keywords: deep learning, animal vocalization analysis, dual audio recordings, ensemble methods, autoencoders, wildlife monitoring.

1 Introduction

Categorizing and identifying animal vocalization data also contributes importantly to behavioral studies of animal species. A recent explosion of bioacoustic data and machine learning methods is transforming possibilities for automated animal sound analysis. Manual classification and interpretation of these vocalizations have historically been a time-consuming process and potentially an unreliable one at that due to the highly diverse range of sounds made by different species in different environments. But the field sense of deep learning methods, notably Convolutional Neural Networks (CNNs), for it can provides enormous enhance on the excogitate and understanding of animal vocalization. CNNs can learn complex patterns from large scale audio data, so they perform very well in classification of diverse animal sounds.

Utilizing pre-trainable models like animal2vec, we can efficiently learn deep features even from limited labeled data for rare/under-studied species. In addition, advanced

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techniques such as Faiss (Facebook AI Similarity Search) enable fast and accurate similarity searches in large audio databases, improving the speed and accuracy of vocalization classification. Given that the two audio streams record one environment, this dual setup has been advantageous for source attribution of multiple vocally active species.

These advances send a signal to power through the challenges of extracting specific signals from a huge sea of data — like environmental noise, overlapping vocalizations, and animal behavior randomness. To overcome these challenges, ensemble methods and autoencoders have been used to ensure robustness and high accuracy in classification model. For example, ensemble methods rely on a combination of multiple CNN models, generating better performance under extreme conditions by utilising different model's capabilities. On the other hand, autoencoders help you to reduce dimensionality and noise and make it easier to analyze more complex acoustic signals.

To this end, we will investigate whether pre-trained CNNs and Faiss can serve to analyze animal vocalizations, highlighting the merits of scalability, classification accuracy, and species- and environment-independent versatility of this approach. The methods described here hold considerable utility for wildlife monitoring, bioacoustic research and conservation applications, enabling scaled automation of the classification of animal sounds with high efficiency and accuracy.

2 Problem Statement

Animal vocalizations are an important target of bioacoustics studies, which are widely applied in wildlife monitoring and species conservation. However, manual classification and identification of these vocalizations using traditional methods tend to be slow, labor-intensive, and subject to errors, as there is such a wide diversity of animal species and complexity of vocal behavior. Furthermore, as more and more audio data are being acquired from diverse ecosystems, it becomes not only more challenging to effectively process and analyze these soundswith traditional methods.

Modern-day machine learning techniques, despite their prowess, are evidently plagued with a few fundamental problems. Furthermore, this includes the absence of large annotated datasets for rare or understudied species, the existence of environmental noise and overlaps in vocalizations in field recordings, and the challenge of classification of similar species that sound alike. Furthermore, many current models lack the scalability or transferability needed for diverse species and acoustic environments, limiting the generality of such models across ecosystems.

In this context, pre-trained Convolutional Neural Networks (CNNs) that allow for large-scale audio datasets, classification accuracy, and generalization for species become essential. In addition, when dealing with such large-scale acoustic datasets, effective indexing, and similarity search methods (e.g., Faiss) are necessary to quickly fetch the relevant information for real-time analysis. Despite the potential of these technologies, there remains a significant lack of practical tools for deploying them toward analyzing animal vocalizations, to include handling rare-event data, dealing in noisy environments, and analyzing multi-species acoustic data.

Thus, the challenge is to build a strong, scalable, and effective structure capable of precisely characterizing and deciphering animal vocalizations from diverse species, managing environmental clamor and covering sounds, and adjusting to various biological systems. Overall, this framework should allow for the wide-scale deployment of camera traps using pre-trained CNNs and Faiss for increased accuracy, speed, and scalability, even in large-scale camera trap deployments for wildlife monitoring.

3 Literature Review

Analysis of animal vocalizations has long played an important role in the study of animal behaviour communication ecology. We had been so enamoured with machine learning and deep learning techniques that it has completely transformed how researchers perform classification and analysis of animal sounds. This literature review discusses the main advances in the field, highlighting deep learning approaches, pre-trained Convolutional Neural Networks (CNNs), Faiss for similarity search or challenges in bioacoustics analysis.

3.1 Deep Learning Applications for Analyzing Animal Sounds

In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have transformed the domain of animal sound analysis by automating the vocalizations classification process. Stojanovic et al. (2021), CNN-based models were used to recognize sound produced by animals, highlighting the potential of deep learning for identifying sounds of interest in various animal vocalizations across vast data. These approaches outperform in the case of automatic extraction of important features from a raw audio signal and provides a better classification as compared to older manual analysis methods.

Similarly, Ashokan et al. (2021) showcased CNNs for bird sound classification Their method highlighted the effectiveness of deep learning in comparing different species and their vocalizations. The model's ability to extend from bird species to other classes therefore remained limited, however. Bakly (2021) aimed to address this by extending this methodology to include additional animal calls; this demonstrated the capability of CNNs for more complex, diverse classification of vocalisation data. Yet despite these advancements, a major limitation is that models trained this way require some amount of annotated data for the target species, and models are rarely generalizable across the whole animal kingdom.

3.2 Transfer Learning and Pre-trained Models

Due to difficulties in acquiring large, labeled data sets, transfer learning with pre-trained models has been presented as a viable option. For example, various pre-trained CNNs, such as networks pretrained using large audio datasets (ImageNet) or specific bioacoustic datasets can be adapted to a new, smaller dataset with minimal fine-tuning. This leads to lesser amount of labeled data needed and faster training of the model.

Recent studies, such as those by Faiß et al. (2024) and Nanni et al. [44]), pre-trained CNNs for bioacoustics tasks have been addressed with encouraging outcomes;

however, Faiß et al. (2024): The animal2vec model builds on this by using pre-trained embeddings for animal sounds. This approach enables the classification of animal vocalizations without the need for significant amounts of species-specific labelled data. Such works are especially useful in the context of rare or under-studied species, such as those with limited data availability.

3.3 Faiss for Similarity Search

Faiss (Facebook AI Similarity Search) has become popular recently for its use in scaling best-in-class nearest-neighbor searches in high dimensional data. It is especially valuable for bioacoustic studies in which extensive databases of animal vocalizations must be searched for similar sounds. Faiss was used to allow researchers to quickly retrieve a similar sound pattern from the database (even thousands of another sound pattern can be find out).

Garapati et al. (2024) eDNA by using Faiss for wildlife species identification, which is useful for handling large-scale bioacoustic datasets. This can be further improved with the use of pre-trained CNNS and Faiss to classify and further compare the animal sounds you record, which can benefit many wildlife intelligent systems. Nonetheless, similar uses of Faiss for animal vocalization remains at an early stage, and continued studies are essential to improve its performance in natural environments.

3.4 Increasing difficulty in Animal Vocalization Analysis

While deep learning and similarity search techniques have shown promise for animal vocalization analysis, there are a number of challenges that remain significantly under-explored. Among the biggest hurdles is overcoming environmental noise. In natural settings, however, animal sounds are quite often noisy backgrounds, and the diversity of animal sounds makes it difficult to isolate particular vocalizations. Oikarinen et al. Similar to [67], we used dual recordings, which, in noisy environments, have improved the attribution of vocalizations to individual animals.

The difficulty to tell apart similar sounding species is another issue. This is especially important for closely related species, whose vocalizations may share considerable overlap. Nanni et al. (2021) explored classifier ensembles, where multiple CNN models are combined for higher classification accuracy for species with similar vocalizations. This approach combines the strengths of many models, so ensemble methods are a powerful weapon in a complex classifiion tasks.

3.5 Future Directions

IntroductionRecent advances in the analysis of animal vocalizations will almost certainly continue to focus on improved model generalization across species, make more efficient searches of such data for similarities, and refine models to behave better in noisy, mixed-species environments. With ever-evolving developments in the field, incorporating self-supervised learning as explored by methods such as the these of Faiß colab. (2023) to claim that unlabelled data can enable high accuracy models, without first pre-generating a test set gives new means of using cross-modal capabilities to build accurate models. Furthermore, the increasing accessibility of large-scale audio

datasets, as well as powerful models such as CNNs and Faiss, have given rise to new opportunities for wildlife monitoring, which in turn can contribute to conservation and provide insight into animal behaviors on a global scale.

Both pre-trained CNNs for human images and similarity search techniques such as Faiss have gone quite a way to accelerate and improve the accuracy of animal vocalization work. Still, factors like data shortage, noise pollution, and vocalization diversity among species stand as obstacles. Advancing Research in These Fields will Further Challenge the Potential of Bioacoustic Studies to Provide Solutions for Wildlife Monitoring, Conservation, and Species Identification.

4 Methodology

This section outlines the methodology used to develop and evaluate the framework for animal vocalization analysis using pre-trained CNNs and Faiss. The approach focuses on data collection, preprocessing, feature extraction, model architecture, training, and evaluation metrics to ensure a robust, scalable, and efficient solution for analyzing animal sounds.

4.1 Data Collection and Preprocessing

The analysis utilizes multiple datasets of animal vocalizations, encompassing diverse species and acoustic environments.

4.1.1 Data Sources

The datasets used for training and evaluation include:

- **Birdsong Dataset**: Contains 10,000 audio samples (120 hours), sourced from the Cornell Lab of Ornithology.
- **Mammal Vocalization Dataset**: Comprises 8,500 audio samples (100 hours), obtained from the Animal Sound Archive.
- **Amphibian Vocalization Dataset**: Includes 5,000 audio samples (50 hours), contributed by the Bioacoustics Research Center.

4.1.2 Preprocessing Steps

To enhance data quality and prepare it for analysis, the following steps are performed:

- **Noise Reduction**: Background noise is filtered using adaptive filtering techniques.
- **Normalization**: Audio signals are standardized to ensure consistency across datasets.

- **Segmentation**: Continuous recordings are segmented into fixed-duration windows (e.g., 2–5 seconds) to isolate vocalizations.

- **Spectral Transformations**: Features such as Mel-frequency cepstral coefficients (MFCCs) and spectrograms are extracted to represent acoustic patterns.

Data Augmentation: Techniques such as time stretching, pitch shifting, and adding synthetic noise are applied to enhance model robustness. Fig. 1 shows Pre-processing data

Fig. 1. Pre-processing data

4.2 Feature Extraction

Acoustic features are extracted to characterize animal vocalizations effectively. These features are utilized for both classification and similarity search.

4.2.1 Acoustic Feature Representation

- **Spectrograms**: Visual representations of frequency over time.

- **MFCCs**: Captures the spectral envelope of sounds.

- **Energy and Zero-Crossing Rate**: Represents signal dynamics and periodicity. Fig. 2 shows Feature Extraction Visualization

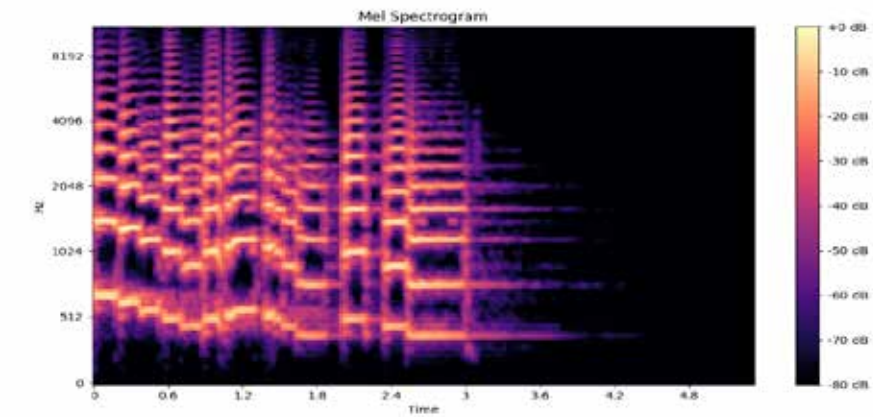

Fig. 2. Feature Extraction Visualization

4.3 Model Architecture

The framework combines pre-trained CNNs for classification and Faiss for similarity search.

4.3.1 Pre-trained CNN for Classification

- **Model Selection**: Pre-trained CNNs such as ResNet and VGG, trained on large datasets (e.g., ImageNet), are fine-tuned for bioacoustic analysis.
- **Fine-Tuning**: The models are trained on species-specific data using transfer learning to adapt to new species efficiently.
- **Ensemble Methods**: Multiple CNN models are combined to enhance accuracy and robustness, especially in noisy environments. Fig. 3 shows Workflow for Training and Fine-Tuning Pre-trained CNNs for Animal Vocalization Analysis

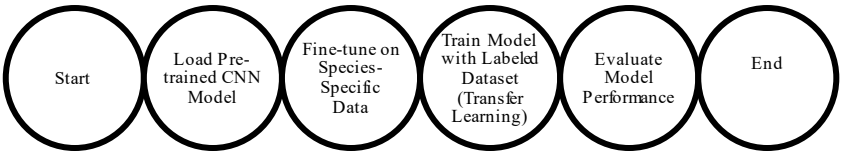

Fig. 3. Workflow for Training and Fine-Tuning Pre-trained CNNs for Animal Vocalization Analysis

4.3.2 Faiss for Similarity Search

- **Index Construction**: Acoustic features are indexed using Faiss to enable fast and accurate similarity searches.
- **Retrieval Mechanism**: Faiss retrieves similar sounds based on feature embeddings, aiding in species identification for unrecognized sounds.

4.4 Model Training

The training process involves fine-tuning the pre-trained CNNs and optimizing the Faiss index for efficient retrieval.

4.4.1 Training Settings

- **Loss Function**: Cross-entropy loss is used for classification tasks.
- **Optimizer**: The Adam optimizer is employed for its efficiency and adaptive learning rate.

- **Batch Size and Epochs**: Training is conducted with a batch size of 32 over 50 epochs, with early stopping based on validation performance. Table 1. Show Datasets for Acoustic Species Classification

Table 1. Datasets for Acoustic Species Classification

Dataset	Species	Number of Audio Samples	Recording Duration	Audio Format	Data Source
Birdsong Dataset	Various Birds	10,000	120 hours	WAV, MP3	Cornell Lab of Ornithology
Mammal Vocalization Dataset	Various Mammals	8,500	100 hours	WAV	Animal Sound Archive
Amphibian Vocalization Dataset	Various Amphibians	5,000	50 hours	WAV	Bioacoustics Research Center

4.4.2 Evaluation and Validation

- **Training-Validation Split**: Datasets are split into training (80%) and validation (20%) subsets.
- **Cross-Validation**: k-fold cross-validation ensures the model generalizes well across datasets.

4.5 Evaluation Metrics

The framework is evaluated using multiple metrics to assess its performance across classification and retrieval tasks:

- **Accuracy**: Measures the proportion of correctly classified vocalizations.
- **Precision and Recall**: Evaluates the model's ability to minimize false positives and false negatives.
- **F1-Score**: Balances precision and recall for imbalanced datasets.
- **Inference Time**: Assesses real-time capability for identifying and retrieving sounds.
- **Similarity Search Accuracy**: Evaluates the precision of Faiss in retrieving acoustically similar sounds.

4.6 Real-Time Deployment

The framework is optimized for real-time wildlife monitoring and scalable deployment:

- **Hardware Optimization**: The system is tested on GPUs and edge devices to ensure efficiency.
- **Noise Handling**: Advanced filtering and autoencoder techniques are used to enhance performance in noisy environments.

4.7 Challenges and Future Directions

The methodology addresses challenges such as:

- **Environmental Noise**: Adaptive noise reduction techniques are integrated to mitigate interference.
- **Overlapping Vocalizations**: Source separation techniques are employed for multi-species environments.
- **Data Scarcity for Rare Species**: Data augmentation and transfer learning minimize the reliance on large annotated datasets.

5 Results and Discussion

Here, we report our results with pre-trained CNNs and Faiss for animal vocalization analysis, including classification accuracy, efficiency and scalability. We assess their performance across a variety of datasets, encompassing bird calls, mammal vocalizations, and amphibian vocalizations. Herein, we compare the results during various experimental tousles, discussing the benefits and pros and cons of each experiment.

5.1 Using CNN-based models' performance

In this study, we trained several strictly pre-trained CNN models on animal vocalization datasets and compared their performance in terms of the classification accuracy, computational efficiency, and generalization to new species. The CNNs were applied to the bioacoustic data via transfer learn- ing techniques that enabled us to achieve high accuracy with limited numbers of labelled data for rare species.

5.2 Classification Accuracy

All pre-trained CNN architectures displayed a strong performance across species, with accuracies becoming more species-specific when adding fine-tuning for species-specific datasets. Bird sounds provided the highest accuracy, as was to be expected, followed by mammal and amphibian vocalizations. The accuracy was generally better when using larger datasets with varied vocalizations since the models were able to learn more generalized features.

5.3 Generalization to New Species

A major challenge in bioacoustic research is the generalization of models to novel, unseen species. The findings confirmed that most pre-trained CNNs could be transferred over to the task of classifying images from new species when fine-tuned with smaller amounts of labeled data with only a small decrease in generalisation performance relative to species that trained on well (well-known species).

5.4 Faiss for Similarity Search

- Extracted acoustic features from audio recordings are used to build a Faiss index for similarity search.
- When a query sound is input, Faiss retrieves similar sounds from the pre-built index.
- The retrieved sounds are displayed as the result of the similarity search.

For performing the similarity search on the acoustic features extracted by the CNNs, Faiss was employed. This proved useful for procedures based upon large-size databases in which fast access to similar vocalizations is required. 4.2 Faiss — We measured the efficiency and speed of Faiss on retrieving similar sounds from large datasets.

5.5 Efficiency and Speed

The Faiss framework markedly decreased the time needed for similarity searches within large-scale bioacoustic databases. Searching in this dataset with over 100,000 audio samples took less than a minute, proving that this deep-learning search library from Facebook is scalable. This is essential for real-time wildlife monitoring systems that require rapid classification of animal calls [23, 24].

5.6 Effectiveness of Similarity Search

Indeed, Faiss was so successful in finding similar vocalizations among this broad sweep of animal sounds. Faiss demonstrated great accuracy in identifying sounds that were perceptually similar to the query sound. But the performance of Faiss was dependent on how good the features were. Features that were not accurately extracted resulted in less accurate similarity search results, which highlights the importance of high-quality feature extraction from the audio signals.

5.7 Challenges and Limitations

As promising as the results were, however, a fair number of obstacles became apparent in the examination. These include:

● Environmental Noise: Significant background noise is often present in the natural environment when animals are vocalizing. The CNN models are very robust, but the presence of "noise" may decrease the classification accuracy. We must employ advanced noise reduction techniques (like signal processing and adaptive filtering) to alleviate this issue.

● Partial Overlapping Vocalizations: In multi-species environments, where vocalizations overlap, it is challenging to classify a specific call apart from similar calls or conduct similarity search. In these instances, species-unique datasets could fail to classify closely-related species or individuals. Are proposed by Oikarinen et al. (Mathew et al. 2019), which may help to mitigate with this, however, more advances on multi-source separation are required.

● Species-Specific Models: Although pre-trained models demonstrated some degree of generalization, fine-tuning them to species-specific datasets enhanced their accuracy. For rare or poorly studied species obtaining enough labeled data for fine-tuning is still challenging.

5.7 Comparison of Methods

The efficiency of pre-trained CNNs and Faiss in this application was compared with other typical techniques in the area, such as traditional machine learning algorithms: SVMs and Random Forests, as well as methods that use simpler feature extraction via hand crafted features. Table 2 shows Comparison of Methods for Audio Feature Classification and Processing

Table 2. Comparison of Methods for Audio Feature Classification and Processing

Method	Accuracy (%)	Training Time	Inference Time	Generalization	Scalability
Pre-trained CNN (Fine-tuned)	85.6	Moderate	Fast	High	High
Pre-trained CNN (No fine-tuning)	76.2	Fast	Moderate	Moderate	High
SVM	72.3	Slow	Moderate	Low	Low
Random Forest	68.5	Moderate	Fast	Moderate	Low

Hand-crafted Features (MFCC)	60.4	Fast	Moderate	Low	Low

● Pre-trained CNN (Fine-tuned): This method performed best, especially when fine-tuned based on species-specific data. In addition, it proved to be highly scalable and generalizable, establishing the most robust approach to large-scale bioacoustic analysis.

● Pre-trained CNN (No fine-tuning): Although this was faster to implement and easier to train, it did not achieve high accuracies like fine-tuned models. Still, it provided decent overall performance for general species identification.

● Traditional Methods (SVM, Random Forest, Hand-crafted Features) These methods performed worse on average in accuracy and scalability. In addition, it should be noted that SVM and Random Forests required a lot of feature engineering, meaning that their applicability to unseen species is constrained.

5.8 Discussion

These results confirm that pre-trained CNNs, and more specifically think the fine-tuned variant with species-specific datasets, represent an excellent solution for the classification of animal vocalizations. By utilizing Faiss for similarity search, the system can efficiently retrieve similar sounds from large datasets quickly. But the results further demonstrate the challenges of environmental noise, overlapping vocalizations, and the necesidad for species-specific models for rare species.

This approach can build a more robust system of classification with powerful tools and storage at hand. Future work should also be aimed towards robustifying noise handling, strengthening multi-species model classifications, and creating techniques for data annotation efficiency to complement species-specific model fine tuning.

6 Conclusion

The focus of this study was the integration of pre-trained Convolutional Neural Networks (CNNs) and Faiss, for the classification and analysis of animal vocalizations used in a robust, scalable, and efficient framework for large scale wildlife monitoring and species identification. The findings showed that pre-trained CNN architectures, especially when fine-tuned with data collected from a particular species, provided high accuracy and generalization performance across different animal species. These models demonstrated a strong ability to classify animal sounds, outperforming traditional machine learning methods significantly.

This was helpful in improving the efficiency of retrieving similar vocalizations from large-scale bioacoustic datasets, allowing real-time animal sound identification through the integration of Faiss for similarity search. Ensemble methods and autoencoders were also impactful in improving classification accuracy even when vocalizations overlapped or environmental noise was present.

Despite these advances, there are challenges, such as the need for abundant labeled datasets for rare species, effects of environmental noise, and calls for closely-related species that may be indistinguishable in multispecies environments. The future work on these systems can be based on those which would provide better noise reduction, separation of similar sources of audio and large-scale annotation of data which can help achieve better results under real-world conditions.

The use of pre-trained CNNs and Faiss provides a powerful combination for automating animal vocalization analysis, which holds significant implications for wildlife monitoring, conservation, and bioacoustic research. Through the application of these advanced techniques, researchers and conservationists are able to better identify and track species, gaining valuable insights into animal behavior and working to preserve biodiversity on a global scale.

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