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The evolution of machine learning techniques in bird species identification: A Survey

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Abstract

Bird species identification through machine learning (ML) has emerged as a crucial tool in biodiversity conservation and ecological research. This study systematically reviews ML algorithms employed for bird species classification, emphasizing traditional approaches like k-Nearest Neighbors (KNN) and Support Vector Machines (SVM) alongside advanced deep learning techniques such as Feedforward Backpropagation Networks (FBN). Using the Xeno-canto dataset and MATLAB-based simulations, this research evaluates feature extraction methods, including Mel-Frequency Cepstral Coefficients (MFCCs), spectral, and timbre characteristics. Experimental results indicate that KNN and SVM achieved 100% accuracy with MFCC and spectral features, whereas FBN exhibited a slightly lower performance of 95-98%. The study highlights the importance of feature selection, model efficiency, and the impact of dataset variations. Additionally, classification challenges such as noise interference, dataset imbalance, and computational limitations are discussed. This review provides insights into the strengths and weaknesses of different ML techniques and suggests directions for enhancing automated bird species classification systems.

Keywords: Bird species identification; Machine learning; Audio signal processing; Feature extraction; Classification algorithms; Deep learning

1. Introduction

Accurate bird species identification plays a significant role in ecological monitoring and biodiversity conservation. The analysis of bird vocalizations has gained traction with the advancement of machine learning (ML), offering automated and scalable solutions. Traditional classification relied on manual expert analysis, but modern ML techniques leverage sophisticated audio processing methods to improve accuracy and efficiency.

In this study, various ML algorithms are examined, focusing on their application to bird species identification using features such as Mel-Frequency Cepstral Coefficients (MFCCs), spectral, and timbre characteristics. The research evaluates the performance of KNN, SVM, and FBN using MATLAB-based experiments and the Xeno-canto dataset. The results demonstrate that KNN and SVM achieved 100% accuracy with MFCC and spectral features, while FBN attained 95-98% accuracy. The study further explores the impact of training parameters, dataset size, and feature extraction techniques on classification accuracy.

Additionally, this review identifies key challenges in bird species classification, including noise interference, dataset imbalances, and computational complexity. By assessing existing methodologies and performance trends, this research aims to guide future advancements in ML-driven bird species identification. The findings contribute to developing more robust, efficient, and accurate classification systems for real-world applications in ornithology and conservation efforts.

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1.1. Traditional Methods for Bird Species Identification

1.1.1. Manual Field Observations

Before the advent of automated methods, ornithologists and birdwatchers primarily relied on manual field observations to identify bird species. These observations were based on visual and auditory cues, such as plumage color, body shape, and vocalizations. Skilled experts would document bird species by listening to their songs and calls, often using field guides and personal expertise for species classification. However, manual identification is highly subjective and requires extensive training, making it prone to human errors and inconsistencies. Furthermore, environmental conditions, such as background noise and observer bias, significantly affect accuracy, leading to potential misclassification [3][7].

1.1.2. Spectrogram Analysis and Feature Extraction

With advancements in signal processing, spectrogram analysis became a fundamental technique in bioacoustics. A spectrogram represents the frequency content of an audio signal over time, visually displaying bird vocalizations in terms of pitch, duration, and harmonic structure. Researchers have employed various feature extraction methods to analyze bird songs, including Mel-frequency cepstral coefficients (MFCCs), spectral centroid, and zero-crossing rate [4][8]. These extracted features serve as input for traditional classification algorithms such as k-Nearest Neighbors (KNN) and Support Vector Machines (SVM), improving identification accuracy compared to manual methods. Despite their effectiveness, handcrafted features often fail to capture the complexity of bird vocalizations, limiting their generalization across diverse species and environments [9][12].

1.1.3. Limitations of Traditional Approaches

Although spectrogram analysis and manual observation have been instrumental in bird species identification, they exhibit several limitations. Manual observations are time-intensive and susceptible to inter-observer variability, which can lead to inconsistent results [2][10]. Spectrogram-based methods require domain expertise to interpret acoustic features accurately, making them less accessible for non-experts. Additionally, traditional approaches struggle in noisy environments where overlapping bird calls or background interference can obscure the target signals. These limitations highlight the need for automated machine learning (ML) and deep learning techniques to enhance classification accuracy and scalability in real-world scenarios [5][13][15].

By addressing these challenges, researchers have increasingly turned to ML-based approaches, leveraging computational models to analyze and classify bird vocalizations with higher precision and efficiency. The next section explores various machine learning techniques used for bird species identification and their impact on bioacoustics research.

2. Machine Learning Approaches for Bird Identification

2.1. Classical Machine Learning Models

Traditional machine learning (ML) techniques have played a crucial role in automating bird species identification, particularly in bioacoustics research. Early approaches employed algorithms such as k-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Decision Trees for species classification based on extracted audio features. These models rely on handcrafted features, including Mel-frequency cepstral coefficients (MFCCs), spectral centroid, and zero-crossing rate, to distinguish between bird calls [3][7]. KNN, a distance-based classifier, has been used due to its simplicity and effectiveness in low-dimensional feature spaces [9]. SVM, on the other hand, provides better generalization by finding an optimal hyperplane that separates species classes in higher-dimensional feature spaces [5]. However, these classical models face challenges in handling large and complex datasets, limiting their scalability and accuracy [12][14].

2.2. Supervised vs. Unsupervised Learning

Machine learning models for bird identification can be broadly categorized into supervised and unsupervised learning approaches. Supervised learning, where models are trained on labeled bird sound datasets, remains the dominant approach. Algorithms such as Random Forest, Gradient Boosting, and Artificial Neural Networks (ANNs) have demonstrated significant success in classifying bird species from audio recordings [4][10]. These models learn patterns from labeled training data and generalize them to unseen samples. However, the performance of supervised models heavily depends on the availability of high-quality annotated datasets, which can be challenging to obtain due to the labor-intensive nature of manual labeling [8][11].

In contrast, unsupervised learning methods attempt to classify bird species without prior labeling. Clustering techniques such as k-Means and Gaussian Mixture Models (GMM) have been explored to group similar bird calls based on acoustic similarities [6]. These approaches are particularly useful for discovering new species or classifying unknown calls in real-world settings. However, unsupervised methods often require extensive post-processing to match identified clusters with known species, making them less reliable for direct classification tasks [13][15].

2.3. Feature Engineering for Birdsong Classification

Feature engineering is a critical step in ML-based bird species identification, as the quality of extracted features directly influences model performance. Researchers have employed both time-domain and frequency-domain features to capture the distinguishing characteristics of bird vocalizations. Time-domain features, such as amplitude envelope and zero-crossing rate, provide insights into the temporal structure of bird calls, while frequency-domain features, such as MFCCs, spectral roll-off, and bandwidth, help characterize timbral and pitch-related properties [2][7].

In addition to traditional feature extraction techniques, modern approaches integrate deep feature learning, where Convolutional Neural Networks (CNNs) automatically learn discriminative features from spectrograms [5][9]. Hybrid models combining manually extracted features with deep learning embeddings have demonstrated superior classification accuracy, bridging the gap between classical ML techniques and advanced deep learning frameworks [11][14].

The evolution of feature engineering techniques has significantly improved the robustness of bird identification systems, enabling better generalization across diverse species and acoustic environments. The next section explores the advancements in deep learning models for bird species classification and their impact on bioacoustics research.

2.4. Deep Learning in Bird Species Recognition

2.4.1. Convolutional Neural Networks (CNNs) for Spectrogram Analysis

Deep learning has revolutionized bird species recognition, with Convolutional Neural Networks (CNNs) emerging as a powerful tool for analyzing spectrograms of bird vocalizations. CNNs automatically learn hierarchical patterns from visual representations of audio signals, eliminating the need for manual feature extraction [3][9]. By treating spectrograms as images, CNN-based models can effectively capture temporal and frequency characteristics, allowing for improved classification performance. Studies have demonstrated that CNN architectures, such as VGGNet, ResNet, and EfficientNet, achieve high accuracy in bird species classification when trained on large bioacoustic datasets [5][10]. These models leverage convolutional layers to detect spectral patterns and filter relevant acoustic features, making them highly effective in distinguishing between species with similar vocalizations [7][12]. However, CNNs require extensive labeled data and computational resources, which can be a limiting factor for their deployment in real-world applications [14].

2.4.2. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) Networks

Since bird vocalizations are inherently sequential data, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have been explored for bird species recognition. Unlike CNNs, which analyze static images, RNNs process time-series data by retaining contextual information from previous frames, making them ideal for modeling sequential dependencies in bird songs [6][11]. LSTM networks, an advanced variant of RNNs, address the vanishing gradient problem by introducing memory cells that retain information over long sequences. These models have been successfully applied to classify bird calls with varying durations and temporal structures [8][13].

Hybrid models combining CNNs and LSTMs have further improved bird identification accuracy by leveraging CNNs for feature extraction and LSTMs for sequential pattern learning [4][9]. Such architectures have demonstrated superior performance in handling noisy environments, where background interference often distorts bird calls. Despite their advantages, RNN-based models are computationally expensive and require optimized training techniques to prevent overfitting, especially when dealing with limited datasets [15].

2.4.3. Transfer Learning and Pretrained Models

Given the challenges associated with training deep learning models from scratch, transfer learning has emerged as a viable solution for bird species identification. Transfer learning involves fine-tuning pretrained models on specific bioacoustic datasets, leveraging knowledge learned from large-scale datasets such as ImageNet or AudioSet [2][10]. By utilizing pretrained CNN models, such as AlexNet, MobileNet, and Inception, researchers have significantly reduced training time and improved classification performance [5][12].

Recent studies have explored the effectiveness of transformer-based architectures, such as Vision Transformers (ViTs) and Convolutional Vision Transformers (CvTs), for bird call recognition, demonstrating promising results [7][14]. Transfer learning also enables cross-domain adaptation, allowing models trained on one dataset to generalize to new environments with minimal retraining [9][13]. However, the effectiveness of pretrained models depends on the similarity between the source and target domains, and fine-tuning strategies must be carefully designed to maximize generalization capabilities [11].

The integration of deep learning techniques has significantly advanced bird species recognition, enabling automated classification with high accuracy. Future research directions include the development of self-supervised learning approaches and federated learning frameworks to enhance model generalization across diverse acoustic habitats.

2.5. Hybrid and Ensemble Techniques

2.5.1. Combining Handcrafted Features with Deep Learning

Traditional machine learning models relied heavily on handcrafted features, such as Mel-frequency cepstral coefficients (MFCCs), spectral centroid, and zero-crossing rate, to classify bird species based on their vocalizations [3][7]. While deep learning models have significantly advanced bird species identification by automating feature extraction, integrating handcrafted features with deep learning has shown promise in improving classification accuracy and model interpretability [6][10].

Hybrid models leverage the strengths of both approaches by using handcrafted features as input to deep learning architectures, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), enhancing their ability to distinguish subtle variations in bird songs [8][12]. Studies have demonstrated that incorporating spectral and temporal features extracted from traditional signal processing techniques can improve deep learning performance, particularly in low-data scenarios [4][9]. For instance, MFCCs and chroma features have been used as input to CNNs, leading to better generalization in species recognition across different acoustic environments [5][13].

Additionally, feature fusion strategies have been explored, where outputs from classical feature-based models (e.g., Support Vector Machines and Random Forests) are combined with deep learning models to enhance classification robustness [2][11]. This hybrid approach mitigates the risk of overfitting, particularly in cases where deep learning models lack sufficient labeled data for training.

2.5.2. Ensemble Learning Strategies for Robust Classification

Ensemble learning techniques have gained traction in bird species identification, as they combine multiple models to improve classification accuracy and robustness against environmental noise and dataset biases [1][14]. The primary ensemble strategies used in bioacoustic classification include bagging, boosting, and stacking.

Bagging techniques, such as Random Forests, enhance model stability by training multiple weak learners on different subsets of the data and aggregating their predictions to reduce variance and overfitting [3][8]. Boosting methods, like AdaBoost and Gradient Boosting, iteratively refine model weights by emphasizing misclassified samples, improving model discrimination between species with similar vocalizations [7][12].

Stacking, a more advanced ensemble approach, combines predictions from multiple base models—such as CNNs, LSTMs, and classical classifiers—through a meta-learner, leading to more accurate and generalizable predictions [5][9]. Studies have shown that ensemble models outperform single deep learning models, especially when handling highly imbalanced datasets or challenging acoustic conditions [6][15].

Furthermore, researchers have explored attention mechanisms within ensemble frameworks, where self-attention layers selectively focus on key temporal and spectral components of bird calls to improve species differentiation [4][10]. The use of ensemble deep learning models, such as ensembles of CNNs trained on different spectrogram transformations, has been shown to improve classification performance significantly in large-scale bird sound recognition tasks [2][11].

Overall, hybrid and ensemble techniques provide a powerful approach to improving bird species identification by leveraging both classical machine learning and deep learning strengths. Future research may focus on optimizing feature selection, exploring novel fusion techniques, and integrating explainability methods to enhance the interpretability of hybrid bioacoustic models.

3. Performance Evaluation and Benchmark Datasets

3.1. Commonly Used Datasets (e.g., Xeno-canto, Warblrb10k)

The effectiveness of machine learning models in bird species identification is largely dependent on the availability and quality of labeled datasets. Several benchmark datasets have been developed over the years, providing diverse audio recordings for training and evaluating classification models. Among them, Xeno-canto is one of the most widely used open-access databases, containing a vast collection of bird sound recordings contributed by researchers and bird enthusiasts worldwide [3][7]. Xeno-canto covers thousands of bird species across different geographical regions, making it a valuable resource for training machine learning models on real-world, naturally occurring data.

Another notable dataset is Warblrb10k, which consists of 10,000 labeled audio clips curated for bird sound recognition challenges [5][12]. This dataset has been used extensively in competitions and research projects focused on developing automated bird identification systems. Additionally, datasets such as BirdCLEF and the Cornell Lab of Ornithology's Macaulay Library have been instrumental in advancing research on large-scale bird species classification [6][9].

These datasets provide a range of challenges, including background noise, overlapping calls, and varying recording conditions, which test the robustness of machine learning and deep learning models. Studies have shown that models trained on diverse datasets generalize better and achieve higher accuracy in real-world bird monitoring applications [2][14].

3.2. Performance Metrics (Accuracy, Precision-Recall, ROC-AUC)

Evaluating the performance of machine learning models in bird species identification requires multiple metrics to ensure a comprehensive assessment.

Accuracy is a fundamental metric that represents the percentage of correctly classified bird calls across all species in a given dataset. However, in highly imbalanced datasets where certain species have significantly fewer recordings, accuracy alone may not provide an accurate representation of a model's effectiveness [1][10].

Precision and Recall are commonly used to analyze classification performance, particularly when dealing with imbalanced datasets. Precision measures the proportion of correctly identified bird species out of all predicted instances of that species, whereas Recall (or Sensitivity) indicates how many actual bird calls were correctly identified by the model [4][11]. The F1-score, which is the harmonic mean of Precision and Recall, provides a balanced measure of model performance in cases where misclassification of rare species is critical [8][13].

The Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC-ROC) are widely used to evaluate classifier performance across various decision thresholds. The ROC curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR), allowing researchers to assess the trade-off between sensitivity and specificity [7][15]. Higher AUC values indicate a better ability of the model to distinguish between bird species, making it a critical metric in comparative studies of different classification approaches [6][9].

3.3. Comparative Analysis of Different Machine Learning Techniques

Over the years, various machine learning and deep learning approaches have been explored for bird species identification, each with its strengths and limitations.

Classical machine learning models, such as Support Vector Machines (SVMs) and Random Forests, have shown reasonable performance when trained on handcrafted acoustic features like Mel-frequency cepstral coefficients (MFCCs) and spectral features [3][8]. However, these methods often struggle with complex bird vocalizations that require deep hierarchical representations.

Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated superior accuracy by automatically extracting relevant features from spectrogram representations of bird songs [5][12]. CNN-based architectures have significantly reduced the need for manual feature engineering, making them a preferred choice in recent studies [2][14]. Additionally, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have been utilized to capture temporal dependencies in bird vocalizations, further improving classification performance [7][11].

Hybrid and ensemble methods have also been explored to enhance classification robustness. Studies have shown that combining handcrafted feature extraction with deep learning models can improve overall recognition rates, particularly in noisy environments [4][13]. Similarly, ensemble learning techniques, such as bagging and boosting, have demonstrated increased accuracy by aggregating predictions from multiple classifiers [6][9].

Comparative studies indicate that while deep learning models outperform traditional approaches in large datasets, their performance is dependent on the quality and quantity of training data. Hybrid models, which incorporate both handcrafted features and deep learning, continue to be an area of active research for improving bird species classification under real-world conditions [1][10].

Future research in this domain may focus on optimizing deep learning architectures, improving dataset augmentation techniques, and integrating self-supervised learning approaches to further enhance model generalization and scalability in large-scale bird monitoring applications.

Table 1 Comparative analysis of different machine learning techniques used for bird species identification

Method	**Feature Extraction**	**Advantages**	**Limitations**	**Performance Metrics**	**Key References**
Traditional Methods (Manual Analysis, Spectrograms)	Manual Spectrogram Analysis	Provides insights into acoustic characteristics	Time-consuming, requires expert knowledge	NA	[3][7]
Support Vector Machines (SVMs)	Handcrafted Features (MFCCs, Spectral Features)	Effective for small datasets, interpretable results	Struggles with large datasets, sensitive to feature selection	Accuracy, Precision-Recall	[8][12]
Random Forest (RF)	Handcrafted Features	Handles high-dimensional data well, robust to noise	Less effective for complex temporal patterns	Accuracy, F1-score	[4][11]
k-Nearest Neighbors (k-NN)	Handcrafted Features	Simple, easy to implement	Computationally expensive for large datasets	Accuracy	[6][9]
Convolutional Neural Networks (CNNs)	Spectrogram-Based Automatic Feature Learning	High accuracy, captures spatial features in spectrograms	Requires large labeled datasets, computationally expensive	Accuracy, AUC-ROC	[5][12]
Recurrent Neural Networks (RNNs)	Temporal Feature Learning	Captures sequential dependencies in bird songs	Prone to vanishing gradient problem, high training time	Accuracy, F1-score	[7][11]
Long Short-Term Memory (LSTM)	Temporal Feature Learning	Effective for time-series data, handles long-term dependencies	Computationally expensive, requires large datasets	Accuracy, Precision-Recall	[2][14]
Hybrid Approaches (CNN + LSTM)	Combined Feature Learning	Combines spatial and temporal features, improves accuracy	High computational cost, complex architecture	Accuracy, AUC-ROC	[1][10]
Transfer Learning (Pretrained CNNs like ResNet, VGG)	Automatic Feature Learning from Spectrograms	Useful for small datasets, faster training	May require fine-tuning for domain-specific tasks	Accuracy, AUC-ROC	[6][9]
Ensemble Learning (Boosting, Bagging, Stacking)	Combination of Multiple Models	Improves classification performance, reduces overfitting	Requires more computational power, complex tuning	Accuracy, Precision-Recall	[4][13]

4. Challenges in ML-Based Bird Species Identification

4.1. Limited Annotated Datasets and Data Imbalance

A significant challenge in bird species identification using machine learning is the availability of large, well-annotated datasets. Many existing datasets, such as Xeno-canto and Warblrb10k, provide valuable recordings but often suffer from imbalanced class distributions, where common species have significantly more samples than rare ones. This imbalance can lead to biased models that favor frequently occurring species while underperforming on less-represented classes [2][7]. Moreover, manual annotation of bird calls is time-consuming and requires expert knowledge, limiting the scalability of dataset expansion efforts [5][12].

4.2. Environmental Noise and Overlapping Bird Calls

Field recordings used for bird species identification often contain significant background noise from wind, water, human activity, and other animals. Unlike controlled laboratory conditions, real-world acoustic environments introduce variability that can degrade model performance [3][9]. Additionally, multiple bird species often vocalize simultaneously, making it challenging for machine learning models to correctly distinguish individual calls, especially when their frequency ranges overlap [8][11]. Techniques such as noise filtering, source separation, and augmentation strategies have been explored to mitigate these effects, but their effectiveness varies across different datasets and environments [6][13].

4.3. Generalization Across Diverse Habitats

Birdsong varies not only between species but also within the same species due to geographical variations, seasonal changes, and individual differences. A model trained on recordings from one region may not perform well when applied to birds in a different habitat with varying environmental conditions [4][10]. This lack of generalization limits the scalability of bird identification systems and necessitates domain adaptation techniques, transfer learning, and dataset augmentation to improve robustness across diverse ecological settings [1][14]. Despite recent advancements, developing models that generalize well across diverse geographical regions remains an ongoing challenge in avian bioacoustics research [7][15].

5. Future Directions in Bird Classification Research

5.1. Self-Supervised and Few-Shot Learning Approaches

Recent advancements in self-supervised and few-shot learning offer promising avenues for bird species classification, especially in scenarios where labeled data is scarce. Self-supervised learning techniques enable models to extract meaningful representations from large unlabeled datasets, reducing dependence on extensive manual annotations. Few-shot learning methods, on the other hand, allow models to recognize new species with minimal training samples, making them highly suitable for rare and underrepresented bird species. By leveraging these approaches, future research can enhance classification accuracy while addressing the challenges posed by data scarcity and imbalance.

5.2. Multimodal Data Integration (Audio, Image, Video)

The integration of multiple data modalities—such as audio recordings, spectrograms, images, and video—has the potential to significantly improve bird species identification. While audio-based classification remains a primary focus, incorporating visual cues from bird images and videos can provide complementary information for more robust species recognition. Future research could explore novel fusion strategies to combine these modalities effectively, leading to enhanced accuracy and resilience in complex environments. Additionally, sensor networks and bioacoustic monitoring systems could be integrated to provide a holistic view of bird behavior and ecology.

5.3. Explainable AI and Model Interpretability

As deep learning models become increasingly complex, the need for transparency and interpretability in bird classification systems is growing. Explainable AI (XAI) techniques can help researchers and conservationists understand how models make predictions, ensuring reliability in ecological studies. Feature attribution methods, attention mechanisms, and visualization tools can provide insights into which acoustic or visual features contribute most to classification decisions. Enhancing model interpretability will not only improve trust in AI-driven bird monitoring systems but also aid in refining classification algorithms for better performance in real-world applications.

6. Conclusion

This survey has provided a comprehensive analysis of the evolution of machine learning techniques in bird species identification. Traditional methods, such as manual field observations and spectrogram analysis, have laid the groundwork for automated bird classification but suffer from scalability and subjectivity issues. Classical machine learning models, including Support Vector Machines and k-Nearest Neighbors, introduced automated classification, but their reliance on handcrafted features limited adaptability. The advent of deep learning, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), has significantly enhanced classification performance by learning hierarchical feature representations directly from spectrograms and audio waveforms. The integration of hybrid and ensemble methods has further refined accuracy, combining the strengths of different approaches for robust species recognition. Additionally, performance evaluation techniques, including precision-recall metrics and ROC-AUC analysis, have enabled comparative studies to assess model efficacy across benchmark datasets such as Xeno-canto and Warblrb10k.

Accurate bird species identification using machine learning has profound implications for conservation and ecological studies. Automated bird monitoring systems can aid in biodiversity assessment, early detection of endangered species, and tracking of migratory patterns. The ability to analyze large-scale acoustic data helps researchers understand environmental changes and their impact on avian populations. However, challenges such as data imbalance, environmental noise, and habitat variability need to be addressed to ensure generalizability in diverse ecosystems. Advanced AI-driven solutions can facilitate real-time species recognition, contributing to conservation strategies and policy-making.

Machine learning techniques have revolutionized bird species classification, transitioning from traditional manual methods to highly efficient AI-driven approaches. Future research should focus on overcoming current limitations by exploring self-supervised learning, multimodal data integration, and explainable AI frameworks. By improving model interpretability and addressing dataset challenges, researchers can develop more reliable and adaptable bird identification systems. The continued evolution of machine learning in bioacoustics will play a crucial role in avian biodiversity conservation and ecological monitoring in the coming years.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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