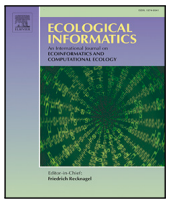
Ecological Informatics 90 (2025) 103254

Contents lists available at ScienceDirect

Ecological Informatics

journal homepage: www.elsevier.com/locate/ecolinf



A bird song detector for improving bird identification through deep learning: A case study from Doñana

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ARTICLE INFO

Dataset link: https://huggingface.co/datasets/GrunCrow/BIRDeep_AudioAnnotations, DOI: 10.57967/hf/4821, https://github.com/GrunCrow/BIRDeep_BirdSongDetector_NeuralNetworks, DOI: 10.5281/zenodo.14940479, https://github.com/GrunCrow/Bird-Song-Detector, DOI:10.5281/zenodo.15019122

Keywords:
AudioMoth
Computer vision
Convolutional neural networks
Ecoacoustics
Ecosystem health
Passive acoustic monitoring

ABSTRACT

Passive Acoustic Monitoring (PAM), which uses devices like automatic audio recorders, has become a fundamental tool in conserving and managing natural ecosystems. However, the large volume of unsupervised audio data that PAM generates poses a major challenge for extracting meaningful information. Deep Learning techniques, particularly automated species identification models based on computer vision, offer a promising solution. BirdNET, a widely used model for bird identification, has shown success in many study systems but is limited at local scale due to biases in its training data, which focus on specific locations and target sounds rather than entire soundscapes. A key challenge in bird species detection is that many recordings either lack target species or contain overlapping vocalizations, complicating automatic identification. To overcome these problems, we developed a three-stage pipeline for automatic bird vocalization identification in Doñana National Park (SW Spain), a wetland facing significant conservation threats. We deployed AudioMoth recorders in three main habitats across nine different locations within Doñana, and the manual annotation of 461 min of audio data, resulting in 3749 annotations covering 34 classes. Our working pipeline included, first, the development of a Bird Song Detector to isolate bird vocalizations, using spectrograms as graphical representations of bird audio data and applying image processing methods. Second, we classified bird species training custom classifiers at the local scale with BirdNET's embeddings. The best-performing detection model incorporated synthetic background audios through data augmentation and an environmental sound library (ESC-50). Applying the Bird Song Detector before classification improved species identification, as all classification models performed better when analyzing only the segments where birds were detected. Specifically, the combination of the Bird Song Detector and fine-tuned BirdNET increased weighted precision (from 0.18 to 0.37), recall (from 0.21 to 0.30), and F1 score (from 0.17 to 0.28), compared to the baseline without the Bird Song Detector. Our approach demonstrated the effectiveness of integrating a Bird Song Detector with fine-tuned classification models for bird identification at local soundscapes. These findings highlight the need to adapt general-purpose tools for specific ecological challenges, as demonstrated in Doñana. Automatically detecting bird species serves for tracking the health status of this threatened ecosystem, given the sensitivity of birds to environmental changes, and helps in the design of conservation measures for reducing biodiversity loss.

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https://doi.org/10.1016/j.ecoinf.2025.103254
Received 14 August 2024; Received in revised form 30 May 2025; Accepted 30 May 2025
Available online 2 July 2025

1. Introduction

Natural environments face significant challenges in terms of conservation due to different drivers of global change, such as habitat loss, climate change, species invasion or anthropogenic pressure. In response to this crisis, biodiversity monitoring and species interaction assessments have become essential to understanding environmental impacts and developing conservation strategies. Effective biodiversity monitoring is fundamental for conservation efforts, as it provides the data necessary to make informed decisions. Still, it is challenging to get the necessary data at large spatio-temporal scales.

In this regard, identifying and tracking the presence of birds is crucial, as birds serve as indicators of ecosystem health (Gregory and van Strien, 2010). Although various automatic monitoring technologies, such as cameras and audio recorders, are already in use, efficiently managing and analyzing the large volumes of data generated by these devices remains a challenge. An effective technology is Passive Acoustic Monitoring (PAM), which uses audio recorders to continuously capture sounds of an environment. PAM is particularly valuable for monitoring biodiversity, as it can operate in remote and inaccessible areas, providing continuous data without disturbing habitat (Sugai et al., 2019). Using PAM, the spatiotemporal scale of monitoring can be significantly expanded, allowing more comprehensive and detailed ecological studies (Gibb et al., 2019).

In recent years, the cost of automatic recording devices has been reduced, leading to an increase in the collection of this type of data for ecological studies (Farley et al., 2018; Darras et al., 2019; Metcalf et al., 2023). Despite their advantages, they generate large amounts of unlabeled data, making analysis difficult and limiting their utility for decision making (Tuia et al., 2022). The primary objective of any PAM project is to address the challenge of efficiently extracting biodiversity information from large volumes of audio data. Thanks to this process, the identification of bird species is automated, which greatly improves data analysis efficiency in the context of environmental monitoring.

Historically, early bird vocalization recognition methods relied on basic sound feature analysis, using techniques such as Random Forests for classification. These methods focused on extracting specific audio features – such as frequency, pitch, or duration – to create a feature set that could be used for classification (Keen et al., 2021). Despite of being effective to a certain extent, these approaches were limited by their reliance on manually crafted features and often struggled with complex and overlapping sounds. Such challenges in traditional feature engineering approaches are well-documented in foundational works on Machine Learning (Hastie et al., 2009; Murphy, 2012), where the need for automated, high-level feature extraction was emphasized as a challenge for accurate classification in complex domains. The recent shift towards Deep Learning (Goodfellow et al., 2016), has enabled more advanced architectures that autonomously learn rich representations from data, addressing many limitations of earlier methods.

In the case of bird vocalization recognition, Deep Learning techniques have represented a revolution for monitoring bird populations (Xie et al., 2023; Stowell, 2022). One of the most popular models of bird vocalization recognition is BirdNET (Kahl et al., 2021), which has proved to be successful in many cases (Pérez-Granados, 2023; Wood and Kahl, 2024; Schuster et al., 2024). These models were tested in environments where the base model was especially well trained, mainly in Northern America and central-Northern Europe. This means that the model was initially trained on a dataset that closely resembles the conditions of the test environment, thereby increasing its predictive accuracy. While BirdNET performs well in regions it was trained on, its accuracy declines in unfamiliar soundscapes due to local variations in bird vocalizations, background noise, and overlapping bird vocalizations (Beery et al., 2019; Lauha et al., 2022; Pérez-Granados, 2023). In these cases, False Positives (FPs) often arise from other vocalizing animals not being birds, anthropogenic sounds, or weather conditions (Stowell et al., 2019; Kahl et al., 2021; Clark et al., 2023).

Foundational models like BirdNET also struggle to recognize species they were not trained on. In theory, it is possible to retrain an existing model to add missing species, known as fine-tuning (Lalor et al., 2017). Alternatives such as Google's Perch model (Hamer et al., 2023) and custom models based on BirdNET with fine-tuning for local conditions have been developed (Brunk et al., 2023; Sossover et al., 2024; Ghani et al., 2024; Pérez-Granados et al., 2025). These fine-tuned models aim to improve accuracy by accounting for the unique characteristics of local bird populations (Lauha et al., 2022). However, this task is quite challenging as it requires Machine Learning expertise similar to having to train models from scratch. While recent studies have demonstrated progress in applying Machine Learning to accelerate the annotation process in ecoacoustics (Martin et al., 2022; Sethi et al., 2024), these approaches are still under development and not yet widely implemented.

To address these limitations, we have been inspired by methodologies used in camera trap projects (Beery et al., 2019; Rigoudy et al., 2023), in which a detector is applied prior to species classification on captured images. Similarly, we propose a two-stage pipeline approach that uses first a generalizable bird vocalization detector combined later with a classifier, improving accuracy and reducing false positives. In particular, we have developed a Bird Song Detector based on the YOLOv8 model (You Only Look Once v8; Jocher et al., 2023) trained with data from our case study in Doñana National Park. Once the audio segments containing bird songs have been detected, we applied several classifier models, and in all of them, we have proven an improvement of the classification when the detector was present (Fig. 1).

The added value of this pipeline lies in its ability to isolate relevant segments of audio that contain bird vocalizations before applying a more computationally intensive species classifier. This process not only reduces the number of non-bird segments incorrectly identified as bird vocalizations but also simplifies the fine-tuning of the species classifier, as the model is optimized to work with segments that are already confirmed to contain bird sounds. By separating the detection and classification stages, we minimize background noise interference and focus the classifier's resources on the most relevant audio data, leading to improved overall system performance. The generalization ability of the Bird Song Detector also ensures that it can identify bird vocalizations for locally abundant species for which it was not originally trained, making this approach robust for real-world applications with diverse species compositions.

As a study case, we applied this pipeline to the PAM program developed by the BIRDeep project at Doñana National Park (SW Spain) (Birdeep.org, 2025). This area presents a high conservation concern due to the alarming decline of its bird populations over time due to different human impacts. Monitoring bird diversity through PAM serves then as a proxy for assessing the health status of Doñana's endangered ecosystems.

2. Material and methods

2.1. Preprocess

2.1.1. Field study site and PAM design

Soundscapes were recorded at Doñana National Park (SW Spain). This area corresponds to the marshes of the Guadalquivir delta and is one of the most important wetlands in Southern Europe, where millions of migrating birds stopover and winter every year (Rendón et al., 2008; Green et al., 2016). The area has serious conservation threats due to water over-exploitation for agriculture and tourism, climate and land-use change, and pollution due to a mine spillover in 1998, among others (Green et al., 2024), which poses serious concerns both at the local and European administration levels. These threats are particularly affecting bird populations, which are in decline over the last years (Camacho et al., 2022; Campo-Celada et al., 2022). Doñana includes four major habitats, which are differentiated by their

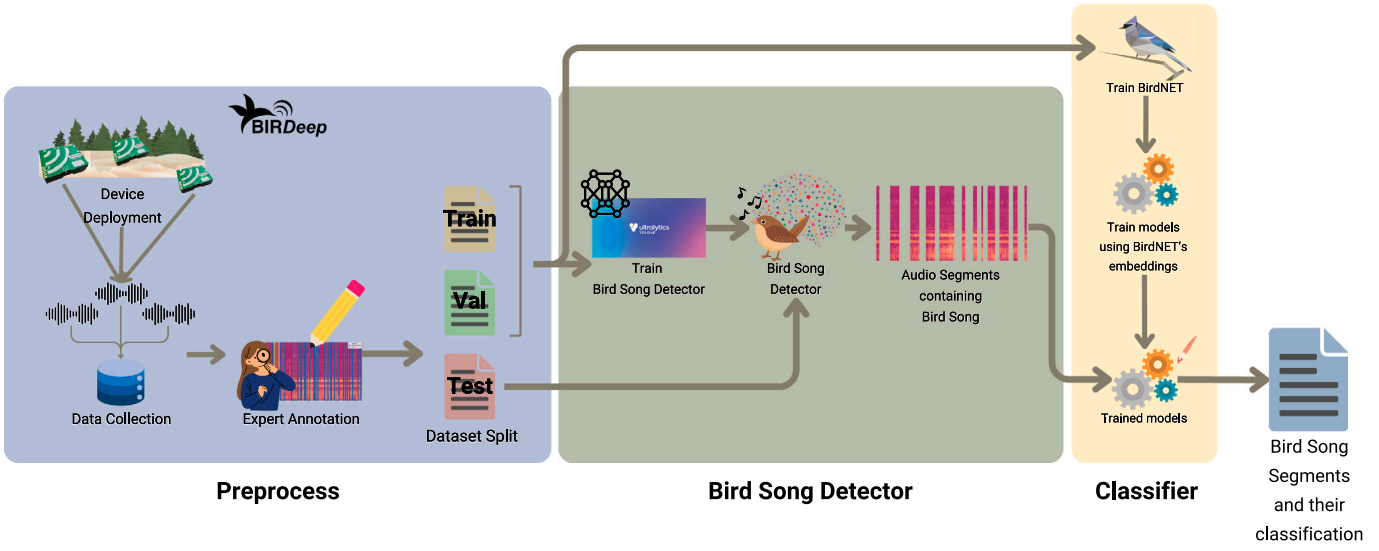


Fig. 1. Pipeline used for the development of our Bird Song Detector. The process was divided into three main stages: (1) *Preprocess*: This stage involved deploying automatic recording devices (AudioMoths) in natural habitats of Doñana to collect audio data, as a part of the BIRDeep project. Audio recordings were then annotated by experts to identify bird vocalizations, followed by splitting the dataset into training, validation, and test sets. (2) *Bird Song Detector*: We trained the Bird Song Detector using the annotated dataset. Our Detector was derived from YOLOv8, which is a state-of-the-art model suitable for detecting objects in images. The Bird Song Detector was developed to identify segments of the audio recordings that contained the sonogram of a bird vocalization (only the presence/absence of any bird species). After training, the Detector model was applied to the test dataset, producing segments that contained potential bird vocalizations. (3) *Classifier*: The final stage consisted first of a fine-tuning of BirdNET model, using the audio from Doñana annotated by experts. Second, this fine-tuned BirdNET model was then used to extract feature embeddings and train other Machine Learning algorithms. Finally those algorithms were validated and tested with the segments that were previously identified by the Bird Song Detector as containing bird songs. After applying this pipeline, we were able to greatly improve the classification of bird species from Doñana present in each segment. Classifications using the detector first vs. those only using BirdNET, the state-of-the-art approach, improved: True Positives were increased, and False Negatives were reduced.

flooding regime and vegetation: coastal dunes, scrublands, marshlands, and the ecotone or transition among them. The deployment design of the BIRDeep project included nine AudioMoth recorders (Hill et al., 2019) that were distributed among three of these habitats: two in the marshland, three in the ecotone and four in the scrubland, differentiating high and low scrubland (see Fig. 2). AudioMoths are low-cost automatic audio recording devices with open-source hardware (Hill et al., 2018). They continuously recorded 1 min of audio every 10 min. Configuration parameters of deployed AudioMoth included a sampling rate of 32 kHz, a medium gain, and a filter band focused on bird frequencies (0.6–16.0 kHz).

2.1.2. Acoustic data annotation by experts

Although devices have been continuously recording since their deployment, for this study, we selected a manually annotated subset spanning from March to October 2023 for logistic reasons. From the total of audios, we selected 461 min. We tried to balance representation across sites and habitats while keeping the annotation effort manageable. We also prioritized periods of high bird activity, primarily the morning chorus, to maximize the number of detectable vocalizations in the annotations (Robbins, 1981).

Annotation was carried out manually by two co-authors with ornithological expertise (ESG and GB). The process is labor-intensive and time-consuming, requiring simultaneous listening to the audio and visualization of the spectrogram, which displays how the sound's frequency content evolves over time. Annotating these 461 min required approximately 13,445 min (about 224 h) of labor effort, with a median annotation time of 18 min and an average of 29.4 min per 1 min file. The experts used Audacity software (Audacity-Team, 2023), which facilitates species identification using auditory signals and visual patterns based on spectrograms. These annotations were then exported from the Audacity format and converted to CSV files. Each annotation consisted of bounding boxes with the minimum and maximum frequency, as well as the start and end time of each bird vocalization in the spectrogram.

When ornithological experts faced uncertainties for labeling species in the audios, they referred to field censuses done in the same sampling stations to ensure the accuracy of their annotations. These field censuses were conducted periodically (43 censuses from March 2023 until February 2024) and provided diversity data that was used to cross-validate the audio labels. By cross-validating the audio data with field observations, the annotators could confirm species presence and improve the reliability of their annotations at the same time that it helped to narrow down the number of potential species, making it easier to identify the species present in the recordings.

The number of annotations was highly unbalanced across recorders, whereas the number of annotated files was more similar, except for *Juncabalejo* site (Fig. 3). This was the most isolated site in the marshland and we found logistic problems to access the recorders to change batteries and SIM cards during the flooding time. Some recorders had a high number of annotations because their recordings were rich in bird vocalizations, likely reflecting variations in bird occurrence and activity, environmental conditions, and recording quality across sampling sites.

After standardizing the annotations, a total of 3749 annotations were created, spanning 34 different classes, as shown in Fig. 4. In addition to the species-specific classes, we have distinguished other general classes: *Sturnus* sp., *Passer* sp., and *Lanius* sp., which were used when the species was unknown but the genus could be identified; *Alaudidae*, *Fringillidae*, and *Sylviidae*, used when only the bird family could be determined; a general *Bird* class for cases where the sound was identified as avian but further classification was not possible. Finally, there was a *No Bird* class for recordings that contain soundscapes without bird songs or any non-avian biotic sound. For the Bird Song Detector, which only distinguishes between two classes *Bird* and *No bird*, all bird-related classifications were re-labeled as *Bird*. For the species classifiers, to avoid confusion, general classes that overlapped with specific species (e.g., *Alaudidae*, *Bird* and *Fringillidae*) were removed. *Upupa epops* was also removed, due to split considerations, explained in next Section 2.1.3. These classes, represented in orange in Fig. 4, were

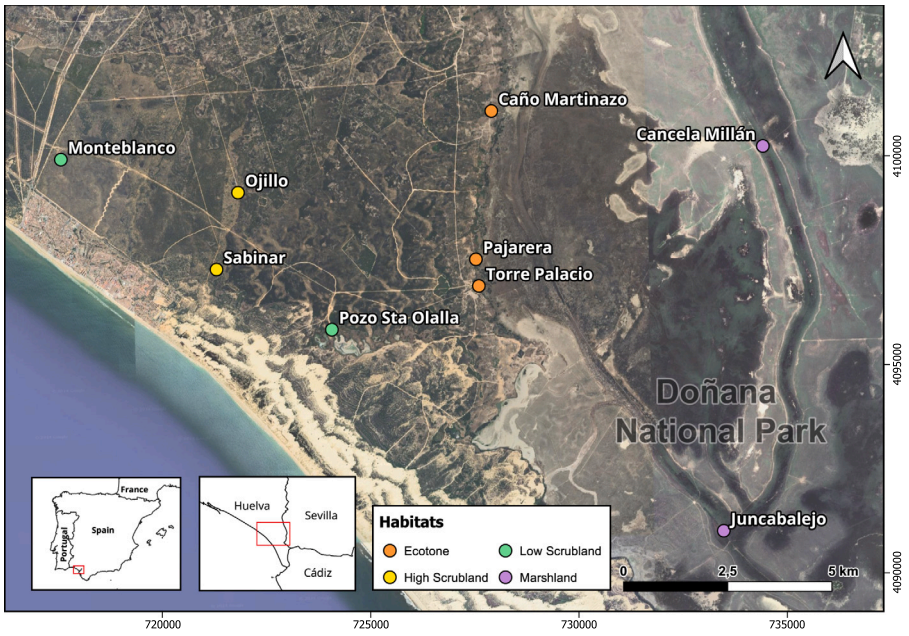
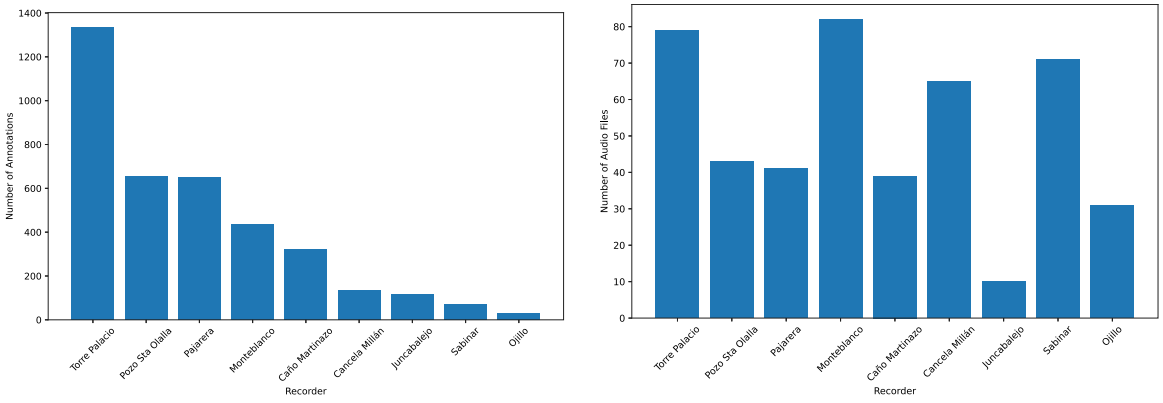


Fig. 2. Spatial distribution of the nine sampling sites where PAM devices (AudioMoths) were deployed in Doñana National Park. The sampling design included the three main habitats of Doñana: marshland, scrubland (high or low), and ecotone. Each habitat type is distinguished by a different color in the map. Names of study sites belong to the local denomination by the ICTS-Doñana (ICTS Doñana, 2025) permanent infrastructure where the devices were installed.



(a) Total number of vocalization annotations per recorder.

(b) Number of unique audio files per recorder.

Fig. 3. Number of annotations and audio files across sampling sites (see Fig. 2 for reference of site names), illustrating the varying levels of annotation effort across recorders.

excluded to ensure a clear distinction between general and specific labels.

It is important to note that the dataset (Márquez-Rodríguez et al., 2025) exhibits class imbalance, with varying frequencies of annotations across different classes. Additionally, the dataset contains inherent challenges related to environmental noise (see Section 3.1).

2.1.3. Dataset split

The dataset (Márquez-Rodríguez et al., 2025) was divided into training, validation, and test sets, with the aim of achieving an 80–10–10 proportion per species (Hardy, 2010). However, maintaining independence and avoiding correlation among subsets to avoid overestimation during model evaluation was challenging (Kattenborn et al., 2022), as some audios were multilabeled and contained vocalizations from more than one species (see Fig. 3). This made it difficult to strictly adhere to the desired 80–10–10 ratio. To mitigate these issues, we prioritized ensuring that no audio file appeared in more than one subset, even if it contained multiple species, to maintain independence. In the particular case of *Upupa epops*, all vocalizations of this species were contained within a single audio file assigned to the validation set, which also included annotations of other species. Consequently, *Upupa epops* was placed exclusively in the validation set and excluded from both training and testing tests to prevent bias during detector evaluation. This species was not included in the classifier due to the lack of additional audio recordings (Fig. 4). The final distribution of sets reflects these adjustments that balance classes as much as possible but also consider independence constraints (Fig. 5).

2.1.4. Data preparation

The audio data were transformed into spectrograms, which are graphical representations that display how the signal's energy is distributed across different frequencies over time. This transformation makes the application of Deep Learning models based on image processing techniques, i.e. Convolutional Neural Networks, suitable for audios (Carvalho and Gomes, 2023). A log-scaled spectrogram is a variant of a spectrogram where the frequency axis is represented logarithmically, emphasizing lower frequencies while preserving the visibility of higher frequencies. This scaling is particularly suitable for analyzing bird vocalizations, as it provides greater resolution in the lower frequency range where many bird songs and calls are concentrated, while

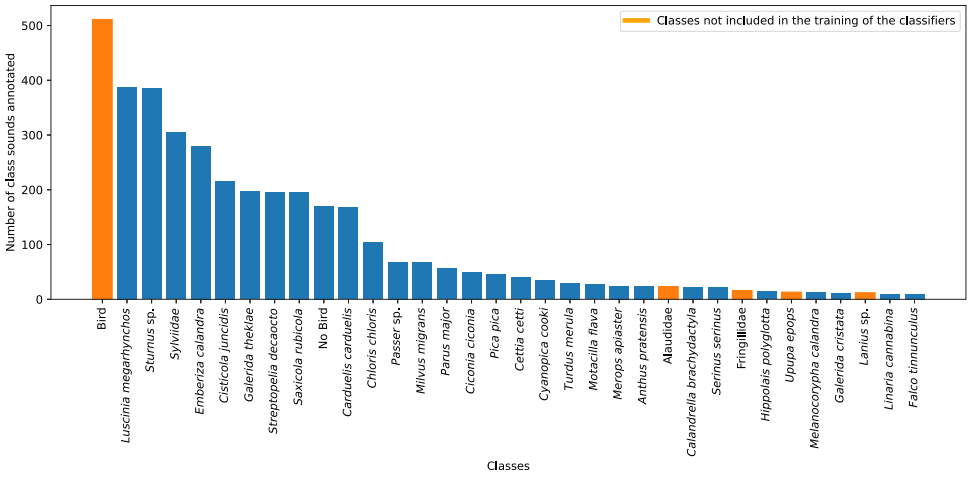


Fig. 4. Number of annotations of the 34 annotated classes in the dataset. All annotated classes, including genus- and family-level labels (e.g., *Sturnus* sp., *Fringillidae*) and the general *Bird* label, were used to train the Bird Song Detector by relabeling them under a unified *Bird* class. For species classification, only the 29 classes shown in blue were retained. The orange bars represent general or ambiguous classes (e.g., family-level or uncertain identifications) that were excluded from classifier training to ensure specificity.

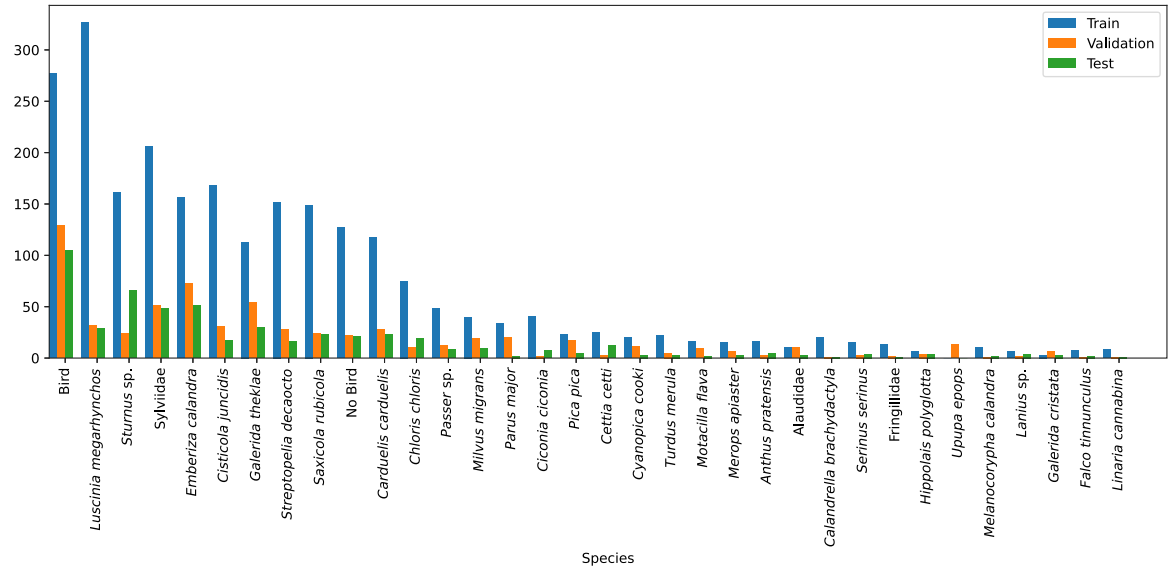


Fig. 5. Distribution of the number of annotations per class across training (blue), validation (orange), and test (green) sets.

still capturing harmonics and other features that extend into higher frequencies (Wyse, 2017).

Spectrograms were generated using the `librosa` Python library (McFee et al., 2015), a popular toolkit for audio analysis. The Short-Time Fourier Transform (STFT) was applied to the audio signal to compute the spectrogram, and the amplitude of the resulting frequency bins was converted to a decibel (dB) scale. The frequency axis was displayed on a logarithmic scale. The frequency range of the spectrograms was set to a minimum of 1 Hz and a maximum of 16,000 Hz, which encompasses the typical range of bird vocalizations while excluding inaudible frequencies or irrelevant noise. The dimensions of the output spectrogram images were 930 × 462 pixels. Although our annotations originally included frequency windows for each vocalization, to simplify detection given the limited data, bounding boxes spanned the entire frequency y-axis. This choice prioritizes the temporal localization of bird vocalizations, which are the primary signal for subsequent classification (see Fig. 6 as an example).

To enhance the dataset and improve the robustness of downstream models, additional preprocessing steps were applied. Specifically, synthetic audio samples were generated by adding random noise (using `NumPy` Python library Harris et al., 2020), to simulate background interference and slightly adjust the intensity of the signals. These modifications aimed to increase the number of training examples that contained only background noise, ensuring a more diverse dataset for both detection and classification tasks.

The annotations were further processed to adopt the format required by the YOLOv8-based object detection model (Jocher et al., 2023). A detailed explanation of the mathematical conversion from YOLOv8's normalized coordinates to temporal annotations in seconds is presented in Appendix A.

2.2. Bird Song Detector model development

We chose a pre-trained YOLOv8 model to develop our Bird Song Detector because it is the state-of-the-art for real-time object detection models. YOLOv8's architecture consists of multiple convolutional layers followed by fully connected layers that predict bounding boxes, objectness scores, and class probabilities for detected objects. YOLOv8 divides each input image into a grid and predicts bounding boxes for the presence of these image events, along with a confidence score for each

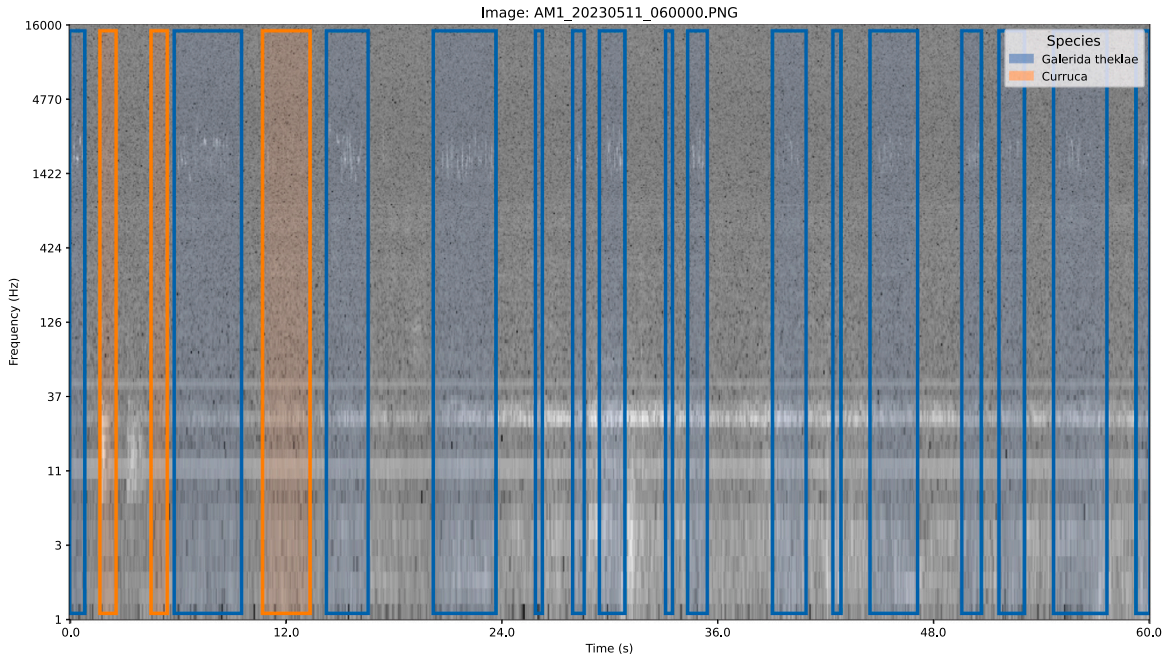


Fig. 6. An example of a log-scaled spectrogram, in gray scale for clearer visualization, from the Doñana dataset with annotations (i.e., blue and orange rectangles) for temporal windows and the complete frequency spectrum for the annotated vocalizations of two bird species.

prediction. In our case study, the input images were spectrograms, and the relevant events were bird vocalizations represented as sonograms in the images. Given the nature of our local audio data, which contains a mix of bird sounds and background noise, we chose YOLOv8s (small version of YOLOv8) for distinguishing relevant events. This reduced version was more effective in maintaining high detection accuracy while minimizing computational load at initial experiments (Pasupa and Sunhem, 2016).

The training of the Bird Song Detector model was done using the previously described spectrograms that were annotated with the bird vocalizations from Doñana. We performed data augmentation techniques to improve the robustness of the model: YOLO's internal augmentation methods, which involve modifications such as changes in HSV (hue, saturation, and value), temporal translations (shifting the audio in time), and *mixup* (Zhang et al., 2017; Tokozume et al., 2017), a technique widely used in audio data augmentation. The dataset was also supplemented with additional samples from an external dataset (Piczak, 2015-10-13) to further enrich model training (see Section 3.1 below).

2.2.1. Evaluation metrics for detections

Currently, there are no widely available, general-purpose bird vocalization detectors trained for global-scale datasets. As a result, a direct comparison of our Bird Song Detector with another state-of-the-art bird vocalization detector is not possible. Existing tools like BirdNET, while primarily designed for species classification, also includes background training data. Therefore, BirdNET can serve as a baseline detector for identifying audio segments containing bird vocalizations and we compared it with the Bird Song Detector developed in our study. More information about BirdNET is provided in Section 2.3.1.

The performance of both detectors used (Bird Song Detector and BirdNET) was assessed using standard metrics for object detection and classification tasks, including TPs, FPs, FNs, Precision, Recall, F1-score, and Accuracy. The detection metrics were calculated as follows:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{F1-Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

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

Additionally, we applied an Intersection over Union (IoU) criterion to ensure that detected segments overlapped with Ground Truth annotations, making the evaluation more consistent across different detection approaches. A prediction is considered correct if its overlap with a Ground Truth annotation meets the required threshold, quantified using the IoU metric. IoU measures the intersection between predicted and actual vocalization segments relative to their total duration. It is defined as:

$$\text{IoU} = \frac{\text{Intersection (Overlap Duration)}}{\text{Union (Total Duration of Prediction and Ground Truth)}}$$

2.2.1.1. Bird song detector. For this study, a minimum IoU threshold of 0.1 was used to determine matches. Predictions with IoU values below this threshold were classified as FP, and Ground Truth annotations without matching predictions were classified as FN. Temporal segments from the Bird Song Detector were further filtered based on a confidence score threshold to exclude low-confidence predictions.

2.2.1.2. BirdNET as a bird vocalization detector. BirdNET processes audio recordings by segmenting them into fixed 3-s intervals and classifying each segment (see Section 2.3.1). In this study, we assessed BirdNET's ability to function as a binary bird presence detector, independent of species classification. A detection was considered correct if any part of a GT annotation overlapped with a BirdNET segment, even if the GT annotation spanned multiple segments. This approach accounts for cases where annotated bird vocalizations extend across adjacent 3-s intervals.

To ensure a fair comparison with the Bird Song Detector, we applied an IoU-based evaluation. Because BirdNET operates on fixed 3-s windows, its segments do not always align precisely with ground truth annotations. Therefore, instead of a strict IoU match, we required a

minimum overlap between GT annotations and predicted segments, similar to the IoU threshold used for the Bird Song Detector.

BirdNET assigns a confidence score to each prediction, reflecting the likelihood that a species vocalization is present. To ensure a species-agnostic evaluation, we applied a uniform confidence threshold across all predictions rather than optimizing it for individual taxa. The selected confidence threshold determines how conservatively BirdNET predicts the presence of a bird vocalization:

- **Confidence Score = 0.1 (Default Value)**: This is the default BirdNET threshold. Prior studies have shown that using this threshold in real-world PAM scenarios leads to an increase in FPs, as BirdNET assigns low-confidence scores to background noise or ambiguous detections (Pérez-Granados, 2023). However, lowering the confidence threshold improves recall by reducing missed detections.
- **Confidence Score = 0.6 (Adjusted Threshold)**: Higher confidence thresholds have been recommended for improving the reliability of BirdNET predictions in complex acoustic environments. Funosas et al. (2024) found that BirdNET predictions become significantly more reliable when using thresholds above 0.7. We adopted a slightly lower threshold of 0.6 to balance precision and recall, reducing FPs while still capturing a sufficient number of detections.

To systematically evaluate BirdNET as a detector, we applied both 0.1 and 0.6 thresholds uniformly to all species, treating BirdNET's predictions as binary vocalization detections rather than species-specific classifications. This ensures that confidence score variations across species do not influence the detection performance comparison.

Different evaluations were carried out with different species lists. First, we used a full list of species from Doñana that included 412 classes, as provided by BirdNET, based on the study area coordinates. We then later reduced this list by selecting the most common species in the area and removing sporadic observations, using references from existing literature (García et al., 2000; Garrido et al., 2004) and our own field observations from expert censuses. This resulted in a shorter list of 337 species, which we have called the "expert list".

To comprehensively assess BirdNET's performance under different conditions, we tested the following four configurations:

- **BirdNET without fine-tuning at a confidence threshold of 0.6**, using the default species list for Doñana National Park coordinates.
- **BirdNET without fine-tuning at a confidence threshold of 0.6**, using the expert species list for Doñana National Park.
- **BirdNET fine-tuned at a confidence threshold of 0.6**, using classifier species classes.
- **BirdNET fine-tuned with a lower confidence threshold of 0.1**, to assess detection sensitivity.

2.2.1.3. Comparison of methods. The percentage improvements in TPs, FNs, FPs were calculated based on changes observed between both methods, using the following general formula:

$$PercentageChange = \left(\frac{NewValue - OldValue}{OldValue} \right) \times 100$$

where $NewValue$ refers to the value obtained from our Bird Song Detector and $OldValue$ refers to the value obtained from BirdNET with the specific confidence score threshold.

An increase in TPs indicates an improvement in detection accuracy, as more bird vocalizations are correctly identified. A decrease in FNs is also a sign of improved performance, as the system misses fewer bird vocalizations. Conversely, a decrease in FPs represents a reduction in erroneous detections of non-bird sounds. For all metrics, positive percentage changes in TPs and negative changes in FN and FP signify improvements, while negative changes in TPs or positive changes in FNs and FPs indicate a decline in performance.

When evaluating percentage changes in the results, it is important to consider them in absolute terms. A large percentage increase or decrease might appear significant at first glance, but its actual impact depends on the scale of the values involved. For instance, changes from small baseline values can result in high percentage variations, even if the absolute difference is relatively minor. Conversely, changes in metrics with larger absolute values might show smaller percentage shifts but represent a more substantial impact on overall performance. Therefore, it is crucial to interpret these percentages within the context of the absolute figures to avoid misinterpreting the true extent of the changes.

2.3. Bird-song classifier model development

2.3.1. BirdNET

As the third step in our pipeline (Fig. 1), we fine-tuned BirdNET v2.4 to create a feature extractor specifically adapted to the ecological context of Doñana. BirdNET is a Deep Learning model designed to classify bird species using audio inputs. It segments audio recordings into 3-s clips, it transforms the audio into spectrogram images, and it performs the classification into a bird species using a deep Convolutional Neural Network (Kahl et al., 2021). BirdNET v2.4 uses an EfficientNetB0-like backbone with a final embedding size of 1024 for feature extraction and classification. It covers frequencies from 0 Hz to 15 kHz, and it is trained for 6522 classes (including 10 non-event classes), making it suitable for the identification of diverse bird species all over the world. Non-event classes refer to categories that represent sounds or signals that are not related to bird vocalizations, such as background noise, human-made sounds, or other environmental noises.

The fine-tuning was performed in the BirdNET v2.4 GUI v1.5.1 (Kahl, 2021), with the default training parameters. The training mode was set to `replace`, ensuring that the original classification layer was overwritten and only the newly trained classes remained. To address class imbalance, `repeat` upsampling was applied, with minority classes resampled at 10% of the majority class frequency. This fine-tuning step adapted BirdNET to the bird species and soundscapes of Doñana, intending to reduce bias and improve model performance for audio recordings from the region.

Once fine-tuned, the model was used to extract feature embeddings—1024-dimensional vector representations capturing essential audio characteristics. These embeddings served as input features for subsequent classifiers.

The training data for fine-tuning were derived directly from the expert annotations (Márquez-Rodríguez et al., 2025). Each annotated time window was segmented and organized into folders corresponding to their respective annotated classes, adhering to BirdNET's required training input structure.

2.3.2. Other classifiers

In addition to the fine-tuned BirdNET model, we explored other classification approaches: a Machine Learning classifier, and two Deep Learning models.

For the Machine Learning approach, we used Random Forest, a well-established method in bioacoustics for species classification due to its ability to handle structured data efficiently and provide stable predictions (Breiman, 2001). The model was trained using BirdNET embeddings (1024-dimensional feature vectors) extracted from the same dataset used for fine-tuning.

The Random Forest model was implemented using the `RandomForestClassifier` from the `scikit-learn` library (Pedregosa et al., 2011) of Python. The optimal configuration included a maximum depth of 50, with a minimum of 2 samples per leaf and 10 samples per split.

For Deep Learning models, we trained ResNet50 and MobileNetV2 using the `Keras` Python library (Chollet et al., 2015), initializing both with pre-trained *ImageNet* weights. The original classification layer was removed, and all layers were initially frozen. A new classification head was added, consisting of a Global Average Pooling layer, followed by a

256-unit dense layer with ReLU activation and a final softmax layer for classification. The model was first trained with only the newly added layers, keeping the pre-trained base frozen. After this initial phase, the entire model was unfrozen for a final fine-tuning step across all layers. MobileNetV2 was selected due to its reduced dimensionality, which helps to prevent overfitting, especially given the relatively small dataset size, while also reducing training time and computational requirements. Both deep learning models were trained using 3-s spectrograms generated from the segments used for the fine-tuned BirdNET.

During evaluation, the models were tested using both full 1 min audio files (segmented into 3-s windows) and shorter audio segments identified by the Bird Song Detector. When these detected segments were shorter than the required 3-s input length, they were padded with zeros — representing silence — to match the model's input size.

We compared these four classifiers (fine-tuned BirdNET, Random Forest, and two Deep Learning models) with and without previously using the Bird Song Detector. This allowed us to evaluate how the Bird Song Detector improved bird classification in different approaches.

2.3.3. Evaluation metrics for classifiers

All BirdNET-based classifiers were evaluated using a fixed confidence score threshold of 0.1, both with and without the Bird Song Detector. If BirdNET did not assign any species a confidence score above this threshold, the segment was classified as background. However, for other classifiers trained specifically for this study (e.g., Random Forest, ResNet50, MobileNetV2), a separate *Background* class was included in the model itself. Since these classifiers explicitly learned to distinguish bird vocalizations from background noise, no confidence threshold was applied, and the species classification with the highest confidence score was selected for each segment, whether it was a bird species or background noise. This approach ensured that BirdNET adhered to a stricter filtering process, while other models relied on their learned classification structure.

The classification performance of the models was evaluated using standard metrics from the `scikit-learn` Python library (Pedregosa et al., 2011), including the confusion matrix, accuracy, precision, recall, and F1-score, along with custom indices designed to assess the classifier's ability to estimate the total number of bird vocalizations.

Beyond standard classification metrics, we introduce the Idx Pred/Ann metric to further analyze model behavior. This metric helps evaluate not only classification accuracy but also the ability of models to filter additional false positives, providing insight into whether the classifier tends to over-predict or under-predict species occurrences:

- **Number of Predictions**: The total number of predictions made by the classifier, regardless of their correctness.
- **Idx Pred/Ann**: Index of Predictions per Annotation. This index quantifies the degree to which the classifier overestimates (Idx Pred/Ann $>$ 1) or underestimates (Idx Pred/Ann $<$ 1) the number of bird vocalizations in the test set. A value close to 1 indicates that the classifier predicts a number of vocalizations similar to the number of annotated ground truth segments, while deviations highlight either an excessive or insufficient number of predictions. It evaluates the capability of detection and filtering additional false positives.

3. Experiments

3.1. Bird Song Detector training

To select the Bird Song Detector, multiple YOLOv8 models with different configurations were trained, and their performance was evaluated using the mean Average Precision (mAP) metric at an Intersection over Union (IoU) threshold of 50% (mAP50) (Padilla et al., 2021). Initial experiments, represented by the purple lines in Supplementary Figure B.1 (*Base*, *Hyperparameter Exploration V1*, *Hyperparameter Exploration V2*, *AugmentedBG V1* and *AugmentedBG V2*), showed suboptimal performance, particularly due to a high number of FPs (Table B.1).

Given the complexity and small size of the dataset (Márquez-Rodríguez et al., 2025), the bounding boxes, which were initially designed to delimit both the frequency spectrum and the time window, were simplified (represented by the light orange line, *FullFrequencies*, in Figure B.1). This approach aimed to reduce the complexity of the task for the model, given the limited amount of data available.

To address the issue of the FPs, the ESC-50 dataset (Piczak, 2015-10-13), which is a large collection of 50 environmental sound classes, was introduced as background noise (negative samples). To prevent confusion, bird-related classes were removed only from ESC-50, but not from our primary dataset. When the dataset was fully included, the model primarily learned to recognize background sounds and failed to detect bird songs effectively (green line, *AllESC50*, in Figure B.1).

Subsequently, the ESC-50 dataset was reduced to comprise only 25% of the total training data. This adjustment led to significant improvements in the model's performance (dark orange line, *Best Model*, in Figure B.1). This balanced approach allowed the model to better differentiate between bird songs and background noises, improving detection accuracy while minimizing FPs.

The various model configurations employed during the experimentation are summarized in Table B.1, which also presents the performance metrics for each configuration. The *Best Model*, which employed synthetic background augmentation of noise and intensity changes and a reduced ESC50 dataset, achieved high mAP50 scores (0.29), along with balanced precision and recall. Other configurations, such as *AllESC50*, displayed lower performance metrics. On the other hand, the *Full Frequencies* model without the ESC50 dataset had the best performance during training, with an mAP50 score of 0.305. This highlights the importance of specific augmentation strategies and dataset choices in optimizing detection accuracy.

3.2. Selection of confidence score threshold for the bird song detector

To evaluate the confidence scores generated by the Bird Song Detector, we transformed confidence scores resulting from the output of the model into logit scores. This transformation allowed us to convert unitless confidence scores into a probability of detection, using a logistic regression (Wood and Kahl, 2024).

By converting the confidence scores into logit scores, we were able to assess the model's performance more accurately across various probability thresholds (Padilla et al., 2021; Wood and Kahl, 2024). This transformation helped identify the point at which the model's predictions were most reliable, ensuring that the selected threshold maximized True Positives while maintaining an acceptable level of False Positives. Through this method, we were able to ensure that the confidence scores reflected the actual likelihood of correct predictions, improving the interpretability and robustness of the model's output.

The conversion from confidence scores to logit scores is based on the logistic function:

$$\text{logit}(p) = \log\left(\frac{p}{1-p}\right)$$

where p represents the confidence score of the detector's prediction. This transformation helps to interpret the confidence scores probabilistically, providing a more nuanced understanding of the detector's performance characteristics.

We evaluated the Bird Song Detector using different probability thresholds (40%, 60%, 80%, and 95%) to find the optimal balance between maximizing True Positive (TP) and minimizing False Negatives (FN; see Table 1 and Fig. 7). This optimization process involved analyzing the trade-off between increasing TP detection (i.e., capturing more bird vocalizations) and keeping errors as low as possible due to FPs or

Table 1
Comparison of different probability thresholds for detection with their respective logit scores, confidence scores, and TP losses.

Probability threshold	Logit score	Confidence score	TP loss (%)
40%	−2.75	0.06	0.00
60%	−1.78	0.14	22.08
80%	−0.58	0.36	74.35
95%	1.30	0.79	99.03

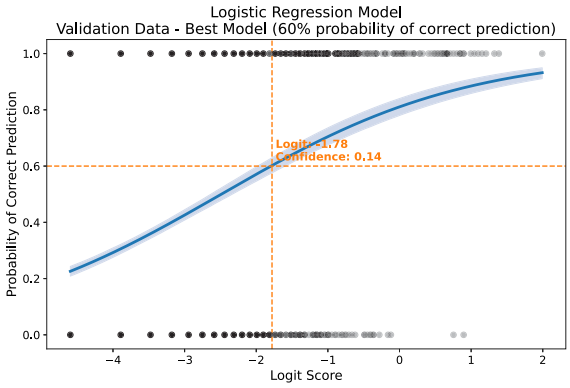


Fig. 7. Logistic regression model with a 60% probability threshold for accurate predictions. Each black dot (with some transparency to allow overlapping) represents a detection made by the Bird Song Detector. The confidence score of each detection is transformed into a logit score and plotted along the *X*-axis. A *Y*-axis value of 0 indicates an incorrect detection (i.e., it does not match an actual bird vocalization according to the ground truth). Conversely, a *Y*-axis value of 1 indicates that the detection was correct, based on the ground truth annotations provided by experts. The blue line represents the logistic regression model fitted to these data points. The shaded area surrounding the blue line represents the 90% confidence interval (CI) for the model's predictions, calculated with a bootstrapping method. The orange lines represent the intersection of the selected threshold (60%) with the blue logistic regression line, showing the corresponding logit score, which is approximately −1.78 (back-transformed into a confidence score of 0.14).

FNs. Higher probability thresholds tend to reduce the number of detections, including fewer FPs and TPs. After evaluation, we determined that the 60% threshold provided the best balance: it minimized the loss of TPs while keeping the FN rate at an acceptable level (see Fig. 7). The selected threshold (60%) corresponds to a logit score of −1.78. When transformed back into a confidence score, this results in a threshold of 0.14.

In practical terms, applying a confidence score threshold of 0.14 to our Bird Song Detector ensures that for any given prediction, the probability of it being correct is at least 60%, regardless of the original confidence score provided by the model.

Lower thresholds, such as 40%, result in a 0% loss of TPs but occur before the logistic regression model's effects begin to improve performance significantly (logit = −2.75, confidence = 0.06; Table 1). At this threshold, the model fails to utilize the logistic regression adjustments effectively, as evidenced by the extremely low confidence score.

On the other hand, higher thresholds, like 80% or 95%, lead to excessive losses of TPs (74.35% and 99.03%, respectively). These thresholds result in an impractical trade-off, where the reduction in FPs comes at the cost of almost complete loss of the TPs (which need to have a high probability threshold to be retained), significantly degrading the detector's performance.

In this case and for our case study, the 60% threshold is high enough to ensure that the logistic regression model's adjustments are actively enhancing detection performance, while also preserving a manageable amount of TPs. This threshold ensures that the model remains both reliable and practical for detecting bird songs, thereby offering an optimal balance between confidence and detection accuracy. For further experiments and results in the Bird Song Detector, a confidence score threshold of 0.15 will be used.

3.3. Bird Song Detector selection

The performance of the top models (*Best Model* and *Full Frequencies*) was compared using the same validation dataset. As explained above, we set confidence scores to ensure a 60% probability of correct predictions: 0.14 for the *Best Model* and 0.06 for the *Full Frequencies* model. Although both models display comparable performance across certain metrics, the *Best Model* outperforms *Full Frequencies*, notably in the number of predictions (315 vs. 59; Fig. 8). At a 60% of correct prediction rate, the *Best Model* not only generates significantly more predictions, but also maintains competitive performance metrics, including accuracy and F1-Score.

In the case of the *Full Frequencies* model, although higher precision is achieved, the limited number of predictions raises concerns about its robustness and generalizability. In contrast, the *Best Model*, with a greater number of predictions and balanced performance metrics, stands out as the more reliable choice for our ecological monitoring objectives, given its consistent performance across metrics.

The *Best Model* also demonstrates a better fit to the validation data and a lower prediction uncertainty, suggesting a stronger ability to generalize across the dataset and provide more reliable detections than the *Full Frequencies* model. This enhanced performance can be attributed to the model's specific augmentation strategy, which includes synthetic background noise, intensity variations, and the use of a reduced ESC50 dataset. These augmentation techniques likely contribute to the model's ability to make more confident predictions and improve overall reliability.

4. Results

4.1. Bird Song Detector performance

The Bird Song Detector built with the *Best Model* was evaluated on the test dataset, and its binary confusion matrix for these detections is shown in Fig. 9. This matrix shows that the detector was effective for identifying temporal windows containing bird vocalizations and had a relatively low proportion of FNs and FPs.

4.2. Bird Song Detector vs. BirdNET as a bird vocalization detector

The Bird Song Detector was compared against BirdNET, as a bird vocalization detector, in various configurations. Table 2 presents the confusion matrices for these configurations.

4.3. Bird species classification

To assess the impact of the Bird Song Detector on species classification, different classifiers were tested on both raw audio and pre-segmented audio from the detector. Table 3 summarizes the results.

Among the classifiers tested, fine-tuned BirdNET combined with the Bird Song Detector demonstrated the highest performance, achieving an accuracy of 0.30, a weighted F1-score of 0.28, and the best alignment between predictions and ground truth annotations (Idx Pred/Ann = 0.9183). Given its superior performance, a more detailed analysis of this classifier is presented, focusing on per-species performance metrics.

Fig. 10 provides the species-specific normalized confusion matrix, offering a visual representation of misclassifications and correct predictions. Darker cells along the diagonal indicate TPs, while off-diagonal cells correspond to FPs and FNs, illustrating common misclassification patterns.

Additionally, to better understand the classification behavior, Table B.2 presents the classification report for the Bird Song Detector and fine-tuned BirdNET, showing precision, recall, and F1-score for each species. This allows for an assessment of which species were more accurately identified and which ones posed challenges for classification.

Table 2
Comparison of confusion matrices for different models used as **bird vocalization detectors**, including various configurations of BirdNET (fine-tuned and non fine-tuned, with different confidence thresholds and species lists) and Bird Song Detector model. All models are evaluated solely in terms of detection performance, that is, their ability to distinguish between segments with bird vocalizations and background noise, independently of species classification. The table shows the number of TPs, FPs and FNs for each configuration. The last two rows highlight relative changes in performance when comparing the Bird Song Detector to fine-tuned BirdNET at confidence thresholds of 0.6 (blue) and 0.1 (orange). Bold values indicate improvements made by Bird Song Detector.

Model	Fine-tuned	Confidence score threshold	Species list	Prediction: Bird		Prediction: Background	
				GT: Bird (TP)	GT: Background (FP)	GT: Bird (FN)	GT: Background (TN)
BirdNET	✗	0.6	Full list	39	0	158	–
BirdNET	✗	0.6	Expert list	48	1	179	–
BirdNET	✓	0.6	Classifier classes	98	6	211	–
BirdNET	✓	0.1	Classifier classes	245	63	135	–
Bird Song Detector	–	0.15	–	196	9	70	–
Comparison with 0.6 confidence threshold				***+100%***	*+50%*	***−67%***	–
Comparison with 0.1 confidence threshold				*−20%*	***−86%***	***−48%***	–

Table 3
Comparison of classifier performance with and without the Bird Song Detector. Shown metrics are Accuracy (Acc.), macro and weighted average (Avg) precision (Prec.), recall (Rec.), F1-score (F1), and an index calculated based on the number of predictions relative to the total number of annotations (Idx Pred/Ann). Shaded rows indicate improvement when using Bird Song Detector. All metrics are better at higher values, except for Idx Pred/Ann, which is optimal when closer to 1.

Classifier	Bird Song Detector	Acc.	Macro Avg			Weighted Avg			Idx Pred/Ann
			Prec.	Rec.	F1	Prec.	Rec.	F1	
BirdNET fine-tuned	✗	0.21	0.12	0.14	0.11	0.18	0.21	0.17	1.8046
BirdNET fine-tuned	✓	0.30	0.21	0.14	0.13	0.37	0.30	0.28	0.9183
Random Forest	✗	0.19	0.10	0.10	0.08	0.19	0.19	0.15	0.9059
Random Forest	✓	0.29	0.11	0.12	0.10	0.24	0.29	0.23	0.5435
ResNet50	✗	0.02	0.00	0.03	0.00	0.00	0.02	0.00	3.2682
ResNet50	✓	0.08	0.01	0.05	0.01	0.01	0.08	0.02	0.6306
MobileNetV2	✗	0.02	0.01	0.04	0.01	0.01	0.02	0.01	3.2682
MobileNetV2	✓	0.08	0.01	0.04	0.01	0.02	0.08	0.02	0.6306

5. Discussion

This study presents the methodological development and evaluation of a two-stage pipeline designed to enhance bird species identification in PAM. The results demonstrate that incorporating a Bird Song Detector significantly enhances bird identification in audio recordings. By segmenting recordings and isolating relevant audio regions, the detector effectively reduces FNs while keeping FPs to a minimum. This pre-filtering process ensures that classifiers operate on cleaner, more focused segments, reducing the risk of misclassification due to background noise or overlapping sounds.

Evaluation of Detectors. Most publicly available ecoacoustic algorithms (Kahl, 2021; Google Research, 2024) focus primarily on bird species classification rather than the detection of vocalizations. However, general species classification models often struggle in PAM programs deployed in real-world scenarios, as it is already a known case for BirdNET (Pérez-Granados, 2023; Funosas et al., 2024). Our results confirm that relying solely on BirdNET for binary bird detection leads to high FN and FP rates, which limits its ability to detect bird presence.

Selecting an appropriate confidence threshold for the Bird Song Detector is key to balance recall and precision. As shown, increasing the threshold reduces FPs but also results in substantial TP losses—up to 99% at the highest setting. We found that a threshold of 0.15 offered the best compromise, maintaining reasonable recall while limiting the number of non-informative detections processed downstream. This balance is critical in real-world deployments, where excessively low thresholds would flood subsequent stages with noise, while overly conservative thresholds risk missing important vocalizations. The chosen threshold of 0.15 minimizes FN rates without overwhelming the classifier with FP detections, thus optimizing overall system efficiency and ecological reliability.

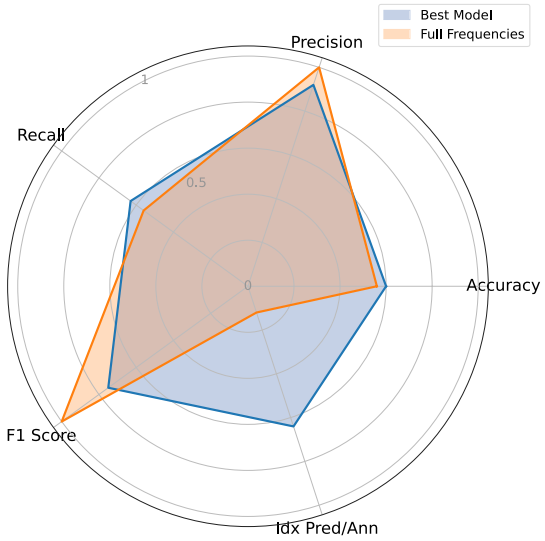
Fine-tuned BirdNET, when used as a detector with a 0.6 confidence score threshold, failed to detect 68% of positive samples, meaning a large portion of bird vocalizations were missed. Lowering the confidence threshold to 0.1 improved recall, reducing FNs to 36%, but at the cost of 20% FPs, a 950% rise in FPs. In contrast, the Bird Song Detector achieved a more balanced trade-off, reducing FNs to 26% while keeping FPs below 5%. This demonstrates its effectiveness in distinguishing bird vocalizations from background noise while maintaining high precision.

Threshold Optimization and Error Analysis. Compared to BirdNET at 0.6 confidence, the Bird Song Detector significantly improved detection performance. Specifically, FNs decreased by 67% (from 211 to 70), ensuring that far more bird vocalizations were correctly identified. While this came with a 50% increase in FPs (from 6 to 9), the absolute increase was only three additional FPs. Considering that this evaluation was conducted on the test subset, which comprised approximately 100 to 200 min of annotated audio, where the potential for false detections is virtually limitless, an increase of three FPs has a negligible impact on overall performance while higher numbers like 63 would create excessive noise in PAM applications.

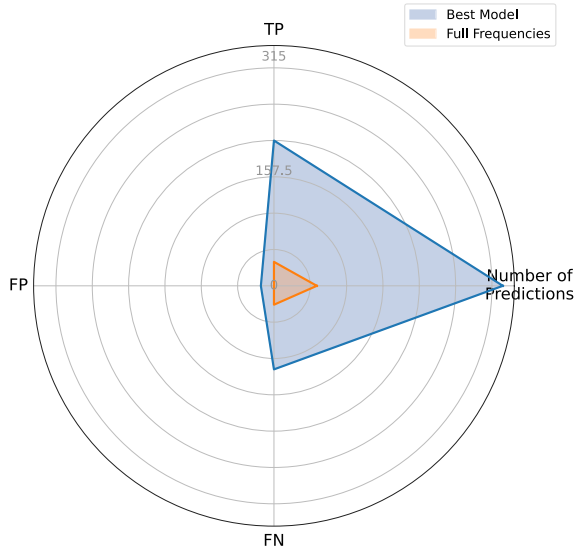
Upon reviewing the Bird Song Detector's FPs, we found that some errors were due to anthropogenic noises, such as repetitive fence hits, which may share frequency patterns or temporal structures with bird vocalizations. This highlights an ongoing challenge in field recordings, where separating natural and human-made sounds can be difficult. Further refinements, such as incorporating additional non-bird training data or adaptive thresholding strategies, could help reduce these misclassifications.

On the other hand, when compared to BirdNET at the lower 0.1 confidence score threshold, which is BirdNET's default confidence score threshold setting, the Bird Song Detector further reduced FNs by 48% and FPs by 86%, though it resulted in a 20% decrease in TPs. Despite this slight reduction, the overall improvement in FN minimization and precision suggests that the Bird Song Detector provides a more reliable balance between sensitivity and accuracy. This is particularly relevant in ecological studies, where minimizing FNs is often more critical than reducing FPs, as missed vocalizations can lead to an underestimation of species presence and activity.

Beyond improving bird presence detection, the Bird Song Detector enhances species classification by ensuring that only relevant audio



(a) Comparison between models used for the Detector according to different metrics: Accuracy, Precision, Recall, F1 Score, and an index calculated based on the number of predictions relative to the total number of annotations (Idx Pred/Annn).



(b) Detailed Breakdown of Predictions. This plot illustrates the integer values of TP, FN, FP, and the total Number of Predictions.

Fig. 8. Spider web plots comparing model performance metrics. The blue area represents the *Best Model*, while the orange area indicates the *Full Frequencies* model.

segments are analyzed. Unlike BirdNET, which operates on fixed 3-s windows regardless of whether they contain a vocalization, our detector selects only segments where bird sounds have been detected. This targeted segmentation reduces background noise and mitigates the effects of overlapping calls, two major obstacles in species identification. As a result, downstream classifiers operate with a higher signal-to-noise ratio, leading to greater classification accuracy and a more efficient analysis of bioacoustic data.

Comparison of Classifiers and Deep Learning Models. The Bird Song Detector significantly improved classification accuracy across all

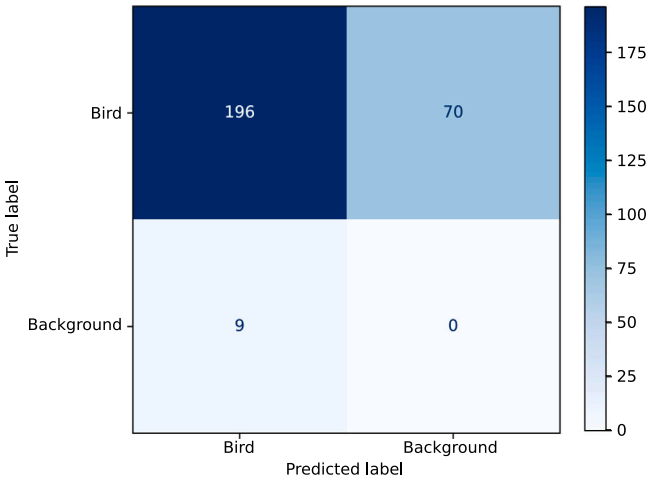


Fig. 9. Binary confusion matrix for the Bird Song Detector on the test dataset with a confidence threshold of 0.15.

models. Without it, classifiers exhibited higher FP rates and greater misclassification errors, as they processed unfiltered, noisy audio segments. The reduction in Idx Pred/Ann indicates that the Bird Song Detector provided cleaner, more structured data, improving the alignment between predictions and ground truth annotations.

The shown improvements underscore the importance of pre-filtering irrelevant audio segments before classification, as it reduces false detections and improves prediction reliability. The Random Forest classifier also demonstrated notable gains, increasing its accuracy from 0.19 to 0.29 when paired with the Bird Song Detector, suggesting that traditional machine learning models can remain competitive in bioacoustic classification when leveraging BirdNET embeddings (Ghani et al., 2023).

However, despite these improvements, classification performance in this study remained lower than the results reported in the original BirdNET research (Kahl et al., 2021). BirdNET was originally evaluated on clean, single-species recordings, achieving a mean average precision of 0.791, an F0.5 score of 0.414 for annotated soundscapes, and an average correlation of 0.251 with hotspot observations (areas with high species diversity). However, in real-world PAM applications, these conditions do not hold, leading to a notable decline in performance (Kahl et al., 2021; Pérez-Granados, 2023). Our findings align with these observations, species classification accuracy remained moderate even after fine-tuning BirdNET and applying the Bird Song Detector. Background noise, species imbalances in training data, and acoustic similarities among certain species contributed to misclassifications, highlighting the ongoing challenges of automated species identification in PAM programs.

Several species exhibited particularly low precision, recall, and F1-scores, reflecting a failure to correctly classify them. These misclassifications are likely due to class imbalance, species similarity, and dataset limitations. The Bird Song Detector improves classification by filtering out non-bird segments, but it does not eliminate the fundamental challenge of uneven species representation in training data, which remains a limiting factor in overall classification performance.

Despite overall improvements, deep learning models such as ResNet50 and MobileNetV2 performed poorly in both approaches. Their baseline accuracy was extremely low (0.02), and they exhibited high FP rates. Without the Bird Song Detector, these models had very high Idx Pred/Ann values (3.2682), meaning they overpredicted species occurrences far beyond the actual number of vocalizations. Although applying the Bird Song Detector reduced this metric to 0.6306, their classification performance remained inadequate, with weighted F1-scores below 0.02.

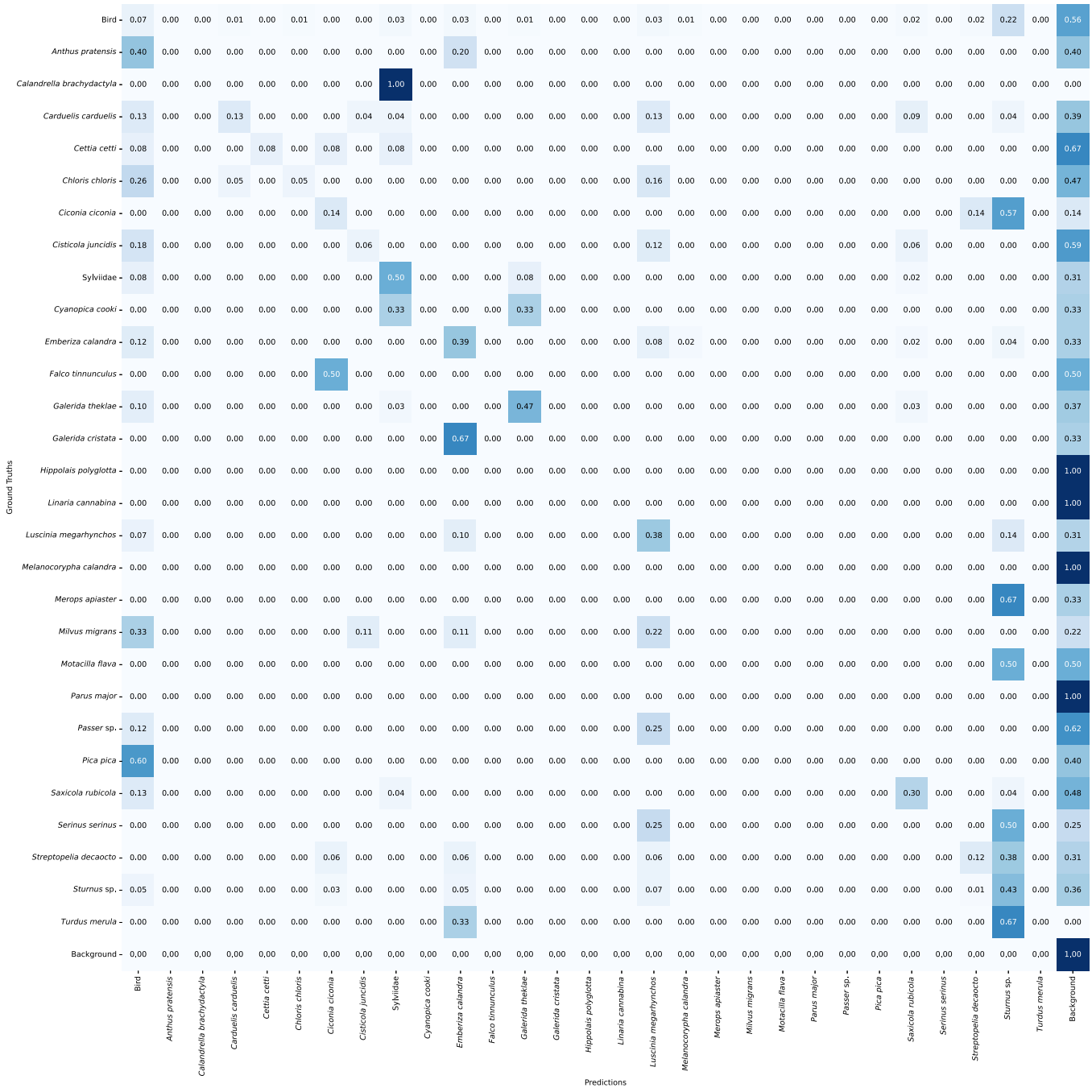


Fig. 10. Species-specific normalized confusion matrix showing the performance of the BirdNET classifier on predicted segments from the test dataset, processed by the Bird Song Detector. The values are normalized by rows, with *Y*-axis labels representing the ground truth species and *X*-axis labels representing the predicted classes. Darker cells indicate higher correct prediction ratios. The main diagonal (highlighted in bold) corresponds to TP ratios for each species, where predicted labels match the ground truth. Off-diagonal cells represent FPs, where the prediction is incorrect. The "Bird" category includes species not present in the classifier's training data. In such cases, predictions were assigned to the "Bird" class, as no better classification could be made.

These findings suggest that deep learning models pre-trained on image datasets (e.g., *ImageNet*) do not generalize well to bioacoustic classification tasks. Unlike images, bird vocalizations are temporal and frequency-dependent, requiring models to extract patterns across time and frequency domains. The poor performance of *ResNet50* and *MobileNetV2* suggests that models optimized for visual features fail to capture the nuances of bioacoustic signals. Future adaptations for deep learning in this field should explore pretraining on bioacoustic datasets rather than visual datasets like *ImageNet* or using spectrogram-specific architectures designed for temporal pattern recognition (Ghani et al., 2023; Xiao et al., 2022; Xie et al., 2022; Gong et al., 2021).

The reduction in Idx Pred/Ann after applying the Bird Song Detector further reinforces the importance of pre-filtering noisy audio segments, even for deep learning architectures. However, the failure of *ResNet50* and *MobileNetV2* to achieve meaningful classification — despite cleaner input data — suggests that architectural modifications, domain-specific pretraining, and tailored feature extraction methods are necessary for deep learning to be effective in species classification.

Limitations Due to Class Imbalance. One limitation of our dataset is the imbalance in the number of annotated vocalizations per species. This imbalance mirrors natural patterns in animal abundance, behavior, and detectability — a well-documented issue in ecological monitoring

studies (Cui et al., 2019; Beery et al., 2018; MacKenzie et al., 2002). While this poses a challenge for classification performance, it also reflects the operational conditions of real-world PAM applications, reinforcing the need for methods that can handle such skewed data distributions.

This class imbalance was also evident during dataset splitting and model evaluation. Some species had a disproportionately larger number of training samples than others, while others, such as *Falco tinnunculus* and *Milvus migrans*, were extremely underrepresented. The poor performance of the model was likely due to this imbalance, as classifiers tend to overfit to these dominant classes while performing poorly on underrepresented ones (Johnson and Khoshgoftaar, 2019; Cui et al., 2019; Pantazis et al., 2024). Although BirdNET's built-in oversampling was supplemented with *mixup* augmentation, these techniques were not sufficient to counteract imbalance effect—particularly for underrepresented species. Combining diverse augmentation methods has shown promising results in recent work for improving species-level recall in imbalanced datasets (Kumar et al., 2024).

Prior to this upsampling, 17 species had fewer than 10 instances, and their classification results were generally poor, with most having an F1-score of 0.00. In contrast, only three species had more than 50 instances, and they exhibited relatively higher F1-scores, with *Sturnus* achieving 0.42 and *Emberiza calandra* reaching 0.46. Class frequency and recall appear highly correlated. A clear example is *Anthus pratensis*, which had 42 instances in the test set and achieved a recall of 1.00 but a low precision of 0.16, indicating that the model predicts this class frequently. Conversely, species like *Cettia cetti* and *Galerida cristata* have moderate recall values (0.13 and 0.47, respectively), showing some predictive ability but still suffering from low precision. This suggests that the model frequently predicted this species, even when incorrect, due to its prevalence in the training data. Conversely, species like *Falco tinnunculus* (n = 2) or *Milvus migrans* (n = 9) had zero recall and precision, indicating that the model was completely unable to recognize them. These bird species normally fly over large altitude and far away from the recorders, so getting more vocalizations that could be labeled and used to train the models would require a more focused sampling. The model likely overfits to the more frequently occurring classes while underperforms on rare species. This issue is further exacerbated by the presence of species with very small sample sizes, leading to cases where the model never correctly identifies them.

This variation in classification accuracy across species suggests that more balanced training datasets are needed to improve generalization and adaptive thresholding techniques, where confidence scores are dynamically adjusted per species, which could enhance performance (Pérez-Granados, 2023; Wood and Kahl, 2024). Despite these challenges, the Bird Song Detector mitigates some imbalanced effects by ensuring classifiers only process relevant bird vocalizations, reducing misclassifications from overwhelming background noise.

The Bird Song Detector helps mitigate data imbalance by ensuring that classifiers only process relevant audio segments of any bird vocalization, reducing misclassification errors caused by excessive background noise. However, even with this improvement, classification performance is still constrained by the lack of diverse and representative training data. Addressing this limitation would require curated datasets with balanced species representation and adaptive thresholding techniques to optimize classification confidence based on species prevalence.

Data Bias in Public Bird Sound Resources. Additionally, BirdNET's performance is still influenced by biases in its training data. The public datasets used for BirdNET training (e.g., Xeno-canto Foundation, 2024; Macaulay Library, 2024) are dominated by high-quality focal recordings, which lack overlapping sounds and real-world acoustic complexity. This makes BirdNET less effective in identifying species in dense, multi-species environments, such as Doñana National Park.

Ecological Implications and Future Applications. Although the conservation challenges of Doñana are multiple and require complex solutions from the different social agents involved, we believe that the practical implications of our research for ecological monitoring and conservation of bird populations are significant. Indeed, the integration of Deep Learning models applied to PAM allows for the cost-effective and scalable monitoring of bird diversity, which is essential for tracking bird-species trends over large protected areas. Managers of Doñana can use information from automatic sound classification of bird species to assess the health status of the different habitats present in the area (as many bird species serve as indicators of environmental changes), effectively combining them with direct census monitoring and other methods. This information helps to design conservation measures trying to mitigate bird species diversity loss. While the current work is based on a subset of annotated data, full-scale deployment of this pipeline across the entire dataset from Doñana National Park is ongoing. For this reason, winter migratory species may not be represented in the annotated subset used here. However, future analyses will incorporate these additional recordings. At last, the main aim of the BIRDeep project is to enable a real-time tracking of avian diversity to have accurate information on bird diversity in large, protected areas such as Doñana National Park.

6. Conclusions

We have demonstrated the feasibility and advantages of integrating a Bird Song Detector with fine-tuned classifiers for detecting and classifying bird vocalizations in the soundscapes of Doñana National Park. The proposed pipeline enhances both detection and classification accuracy by isolating relevant audio segments before species identification. This approach mitigates many of the challenges faced by traditional classification models, particularly in complex acoustic environments.

The Bird Song Detector plays a crucial role in improving model reliability by significantly reducing FNs while maintaining a manageable FP rate. This ensures that classifiers process only the most relevant segments, leading to more accurate species predictions. However, persistent challenges, such as species misclassification due to class imbalance and the presence of anthropogenic noise, highlight the need for further refinements. Addressing these limitations will require expanding annotated datasets, incorporating adaptive thresholding strategies, and improving classifier fine-tuning for underrepresented species.

Another key challenge lies in the biases present in public-access bioacoustic datasets, which primarily contain clean, focal recordings with minimal background noise. These datasets do not fully represent real-world soundscapes, affecting model generalization in environments like Doñana, where overlapping bird calls and non-bird sounds are common. Future work should focus on developing datasets that better capture the complexity of natural soundscapes and on training models to differentiate between species in multi-species recordings.

Future research should explore the integration of more advanced bioacoustic deep learning architectures, as models pretrained on image datasets like *ImageNet* may not fully capture the temporal and spectral characteristics of bird vocalizations. Additionally, refining detection models to better distinguish between bird sounds and anthropogenic noise will further enhance the applicability of this approach in real-world conservation settings.

By providing a structured and scalable method for bird vocalization analysis, the proposed pipeline represents a significant step towards improving automated biodiversity monitoring. With continued advancements in data quality and model adaptation, this framework has the potential to be deployed in diverse ecological contexts, facilitating more precise and efficient monitoring of avian populations and applying bird identification for conservation and management.

CRediT authorship contribution statement

Alba Márquez-Rodríguez: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Miguel Ángel Mohedano-Munoz:** Writing – review & editing, Validation, Supervision, Resources, Investigation, Data curation, Conceptualization. **Manuel J. Marín-Jiménez:** Writing – review & editing, Validation, Supervision, Investigation, Conceptualization. **Eduardo Santamaría-García:** Visualization, Resources, Investigation. **Giulia Bastianelli:** Resources, Investigation. **Pedro Jordano:** Writing – review & editing, Supervision. **Irene Mendoza:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Investigation, Funding acquisition, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to enhance the writing quality and facilitate language translation. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This study has received financial support from the BIRDeep project TED2021-129871A-I00, which is funded by MICIU/AEI/10.13039/501100011033/ and the European Union NextGenerationEU/PRTR, as well as grants PID2020-115129RJ-I00 and PTA2021-020336-I from MCIN/AEI/10.13039/501100011033/. AMR has been awarded a fellowship of the CSIC JAE Intro 2023 program (ref. JAEINT23_EX_0243). Logistic and technical support for the installation of the recorders and fieldwork assistance were provided by the ICTS-Doñana (ICTS Doñana, 2025).

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ecoinf.2025.103254.

Data availability

The dataset mentioned in this work (Márquez-Rodríguez et al., 2025), which includes annotated audio split into train-validation-test sets and the best data augmentations used during experimentation, is freely available at: https://huggingface.co/datasets/GrunCrow/BIRDeep_AudioAnnotations, DOI:10.57967/hf/4821. Metadata follow the Darwin-Core standard (Wieczorek et al., 2012). All code used in this study is available at: https://github.com/GrunCrow/BIRDeep_BirdSongDetector_NeuralNetworks, DOI:10.5281/zenodo.14940479. The GitHub repository for the Bird Song Detector, which includes the interface, scripts, and trained models, is accessible at: https://github.com/GrunCrow/Bird-Song-Detector,DOI:10.5281/zenodo.15019122.

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