Effectiveness of bird species identification using Birdnet: Case study at the La Mata coastal lagoon

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***Abstract*—Monitoring avian species is fundamental to detect any negative impact from human activity. In our case study, we focus in particular on the *La Mata* lagoon in Torrevieja (Alicante, Spain), aiming at the monitoring of two gull species that often share the same environment: *Larus Michahellis* (Yellow-Legged Gull), and *Ichthyaetus Audouinii* (Audouin's Gull). As of 2020, *Ichtyaetus Audouinii* has been included within the International Union for Conservation of Nature (IUCN) Red List, with the status of vulnerable as the global population has experienced a rapid decrease, which is expected to be approaching 40% between 2006-2030, and is projected to continue declining at a similar rate over the next three generations. Since conservation of these species requires informed, prompt and efficient decision-making, we propose constantly monitoring the ecosystem by deploying an AI-enabled IoT infrastructure to listen to bird sounds, and automatically identify bird species. To this end, we relied on the BirdNET artificial neural network for the acoustic analysis. However, using BirdNET models must be carefully planned to produce insightful data that can drive informed decisions. For this reason, we discuss our methodology and the logic behind tuning the most important parameters according to the proposed use case.**

I. Introduction

The Valencia region (south-eastern Spain) holds a network of wetlands which are important as wintering and breeding sites for a large number of waterbird species. These wetlands are protected as Important Bird Areas (IBAs) and RAMSAR [1] sites because of their waterbird populations of international relevance and they also hold many ecosystems protected under the European Habitats Directive (92/43/CEE). The Valencian weltands are also very extense, covering a surface of more than 44.000 ha. The large size of the area to be monitored poses significant challenges, and traditional techniques may be insufficient to meet the pressing conservation demands. In this context, the integration of Internet of Things (IoT) technologies has revolutionized conservation efforts by enabling more efficient, cost-effective and intelligent environmental monitoring. The deployment of various sensing devices facilitates the continuous collection of data that, when connected to the cloud, leverages AI-enabled big data analytics to provide a holistic view of the several phenomena occurring within these natural environments [2]. This technological breakthrough represents a paradigm shift in ecological monitoring and conservation strategies [3].

Fig. 1: Mature specimen of Yellow-Legged Gull. Source: Commonists, Wikimedia CC BY-SA 4.0.

Our case study is the *La Mata* lagoon, located in Torrevieja (Alicante, Valencia Region, Spain)[1]. This lagoon is part of a natural park that hosts numerous bird species requiring diligent monitoring to ensure the long-term viability of their populations, and to facilitate targeted interventions.

In particular, we focus on the relation between *Larus Michahellis* (Yellow-Legged Gull), see Figure 1, and *Ichthyaetus Audouinii* (Audouin's Gull), see Figure 2, as their populations overlap in the western Mediterranean area, and often feed on the same sources. The Yellow-legged gull has a large body size and an aggresive behaviour, making it a better competitor than the audouin's gull. Also, the Yellow-legged gull is known to predate on Audouin's gull's egges, nestlings and even adults [3] and it has a large local population of more than 1100 wintering individuals and more than 300 breeding pairs in 2022 [4]. The inclusion of *Audouin's Gull*, with the status of vulnerable, in the International Union for Conservation of Nature (IUCN) Red List [5] in 2020, has set off alarms as the global population has been decreasing at a rate close to 40% between 2006-2030, and this rate of decay is expected to be maintained in upcoming years.

Given the extensive size of the lagoon, relying solely on human observation for detecting various bird species is impractical. Therefore, the practical approach that must be adopted is to deploy advanced AI-enabled devices equipped with embedded microphones. Once deployed, these devices shall enable continuous, automated detection of bird species through continuous sound recording and sophisticated audio analysis. To achieve this goal, BirdNET [6] emerges as an optimal solution, as it offers a citizen science platform as

[1]https://parquesnaturales.gva.es/es/web/pn-lagunas-de-la-mata-torrevieja

Fig. 2: Mature specimen of Audouin's Gull. Source: Pixabay.

well as an analysis software for extremely large collections of audio. At its core, BirdNET relies on Convolutional Neural Networks (CNNs), which have been dominant in recent years for automated bird species recognition. The renowned BirdCLEF competition further corroborates the efficacy of these networks for classification problems [7]. BirdNET is particularly notable for its incremental inclusion of an increasing number of bird species, which enhances transfer learning opportunities. It supports fine-tuning and is compatible with various hardware models and operating systems, including Arduino microcontrollers, Raspberry Pi, and Nvidia Jetson Nano. Additionally, BirdNET is accessible on smartphones, offering a citizen science platform that is beneficial for biologists, conservationists, and bird enthusiasts. However, BirdNET's extensive training dataset, capable of identifying over 6,000 species (about 60% of all known bird species), presents challenges for deployment on resource-constrained embedded devices due to its size and complexity [8]. Consequently, benchmarking the model's quantization and testing hyper-parameter tuning becomes crucial for an effective deployment.

In this work, we start by benchmarking BirdNET-Analyzer v2.4 quantized at FP32, FP16 and INT8, and BirdNET-Lite. We aim to get insights on model initialization, first inference, warm-up, inference, and memory footprint. Subsequently, we test the models on a test dataset, to explore the best hyper-parameters configuration according to our use case. Indeed this establishes the foundation for future research aimed at optimizing BirdNET for our specific case study.

The remainder of this work is organized as follows: in section II, we present some related works on crowd-sourcing, conservation, ornithology, and acoustic monitoring via Deep Learning solutions. Then, in section III, we provide a brief overview of the target environment and case-study. Next, in section IV, we provide an overview on BirdNET. Section V is dedicated to model selection. A discussion about the test dataset is done in section VI, and hyper-parameter tuning is addressed in section VII. Finally, section VIII presents the main conclusions derived from this work, and discusses future lines of work.

II. Related works

The development of a web-based collection of bird sounds using citizen science platforms, such as Xeno-Canto [2] [9] and The Macaulay Library [3], had a cornerstone role in enabling modern machine learning models like BirdNET to be trained on top of vast amounts of data. Such large data collections were made possible by the implementation of user-friendly web interfaces for non-commercial, open databases easily accessible on the Internet, which in turn fostered citizen participation, thus enabling big open data repositories to be created [10]. In the realm of bird recordings sourced from citizen science projects, such as those mentioned above, the presence of unnamed background species presents a significant challenge to the reliability and accuracy of the recordings and their assigned labels. Typically, recordists are encouraged to document all species present in a recording. However, this is not always adhered to, resulting in incomplete species identification.

The reliability of the recordings, and the accuracy of the labels, can often be compromised, posing challenges for data quality in bird monitoring and research initiatives. Hence, ensuring a more comprehensive and consistent species identification in recordings could enhance the efficacy of both human and machine analyses in avian studies. In this regard, Raven PRO [4], by The Cornell Lab of Ornithology, qualifies as an essential tool to label and build reliable datasets for model training, labeling the data acquired with Autonomous Recording Units, or refining and correcting classifications made by BirdNET.

Recently, further valuable approaches include that of Gordillo et al. [11], who encouraged greater public participation in their research by producing real-time bird monitoring through the MK phone app which records, classifies, and updates posterior data used for predictions. Similarly, Lahua et al. [12] have made important findings towards the enhancement of CNNs for bird sound recognition by leveraging local data. Starting from a base model using a global dataset that covers 101 bird species, they improved performance in specific conditions, fine-tuning their model with locally sourced data. Their approach utilized data augmentation to effectively train with limited samples, demonstrating that even a small number of local samples (50-100 per class) significantly boosted classification accuracy, especially for recordings from the same region, assessing the importance of adapting models to their target environments. Open Sound Scape [13] provides an open-source Python toolkit for detecting and localizing biological sound in acoustic data. This open package of tools gives access to acoustic detection, classification and localization methods, being complemented with extensive documentation and tutorials that facilitate the adoption, learning, development, and usage of bioacoustics methods for ecology and conservation.

III. Overview of the Case Study

The lagoons of Torrevieja and La Mata (see Figure 3), located south of Alicante in the Valencia Region of Spain, cover approximately 1,400 and 700 hectares, respectively,

[2] www.xeno-canto.org

[3] https://www.macaulaylibrary.org

[4] https://www.ravensoundsoftware.com

Fig. 3: Satellite view of the two lagoons, La Mata (Green) and Torrevieja (Pink). Source: Google Earth.

Fig. 4: Salt dunes, Torrevieja lagoon.

forming a combined perimeter of over 25 kilometers [14]. These lagoons constitute a vital biological reserve essential more than 120 avian species [15].

In this case study, we focus on the *La Mata* lagoon. This lagoon hosts the majority of aquatic bird species of conservation interest due to its abundant food resources and favorable salinity. In contrast, the adjacent *Laguna de Torrevieja* is characterized by a high salinity, and it supports a less diverse avian population. Not only the Torrevieja lagoon environment is naturally less favorable for wildlife, but the area is also more affected by human activity, being it the central site of the local saline economy which dates back to 1273. This economic activity has been pivotal to the region's development, with the salt mines becoming iconic landmarks (see Figure 4).

The pink hue of the Torrevieja lagoon, along with the salt dunes, attracts significant tourism. Representing the largest salt exploitation in Spain, the saline is situated within a delicate system where tourism, local economy, and community interests intersect [15]. Given the substantial size of the area, we aim to enhance our research by implementing IoT-based passive acoustic monitoring using the BirdNET model. This approach seeks to provide insights beyond those achievable through human observation alone.

IV. Overview of BirdNET

BirdNET is a research platform that seeks to support bird-related research and citizen science by providing a solution for the detection and classification of avian sounds using machine learning. Over time BirdNET has evolved from its initial version (1.0) [6], which served as a proof of concept, to more robust iterations such as BirdNET 2.0 up to v2.4[5], featuring an expanded dataset and improved model architecture. The BirdNET-Lite version[6] was designed for deployment on resource-constrained devices like the ones we plan to use; recent applications deem it still remains efficient; however, it is no longer maintained. The BirdNET repository provides useful scripts to process data leveraging BirdNET itself for the creation of datasets to be used for retraining. As a CNN derived from a family of residual networks (ResNets) [6], BirdNET-Analyzer processes audio recordings by performing preprocessing, feature extraction (using Mel-Frequency Cepstral Coefficients), computing Mel Spectrograms, and performing classification by outputting confidence scores for each species which are non-transferable [8]. By default, it will resample inputs to 48 kHz, and inference will be performed by the analyzer on the 3 central seconds of each file submitted [6]. Learning rate, batch size and dropout rate are typically the essential hyper-parameters for optimizing the model's performance for model retraining purposes, while confidence threshold, overlap and sensitivity are fundamental parameters for performing inference. Overlap, for instance, can be crucial to extract more features from a limited dataset; however, it does not necessarily lead to better feature extraction; in contrast, increasing overlap will bring up computational costs, memory usage and execution time, as illustrated in figures 7 and 8

BirdNET is designed for broad accessibility, offering mobile apps for iOS and Android, a user-friendly web interface on Mac and Windows, and a command line interface (CLI) for advanced users who need to process large datasets. It also provides APIs and scripts for integrating its functionalities into custom applications. Limitations include dependency on audio quality, potential gaps in species coverage, performance variation across species, and environmental variability affecting accuracy and detection distance [16]. Real-time processing on resource-constrained devices poses challenges, especially with higher overlap settings that increase computational costs. Additionally, BirdNET-Lite is no longer maintained, potentially limiting its utility for ongoing projects. Customizing hyperparameters for optimal performance requires significant machine-learning expertise, making it complex for some users. Despite these limitations, BirdNET remains a powerful tool for bird species identification through sounds. BirdNET's confidence scores, which range from 0 to 1, are unitless numeric expressions of BirdNET's confidence in its predictions, and should not be interpreted as probabilities. These scores necessitate species-specific evaluation, as cross-species

[5]https://github.com/kahst/BirdNETAnalyzer
[6]https://github.com/kahst/BirdNETLite

comparisons are invalid without individual validation [8]. Moreover, recording conditions, including equipment quality, environmental noise and detection distance, significantly influence the scores, highlighting the need for consistent recording setups [16]. For probabilistic interpretation, logistic regression can be employed to convert these scores into probabilities by relating prediction outcome to the probability that the prediction is correct [8]. Setting score thresholds should be based on precision and recall metrics tailored to specific research objectives, with manual reviews of high-score predictions aiding in threshold refinement [8].

V. Model selection

To orientate our choice across different configurations of the recently available analyzers, we conducted an essential TensorFlow Lite benchmarking analysis. In the analysis we evaluated specifics of the latest BirdNET-Analyzer v2.4 quantized at FP32, FP16, and INT8, as well as BirdNET-Lite. The evaluation was conducted using 20 warm-up runs and 100 total runs, with 4 threads, and it encompassed initialization time, inference time, and memory footprint metrics. The results are summarized in table I.

Notably, the FP16 configuration exhibited slower initialization and slower inference compared to FP32, contrary to typical expectations, favoring reduced precision for speed. BirdNET-Lite demonstrated the fastest first inference and inference average times, albeit with the highest initialization time. The INT8 configuration showed the lowest memory footprint, aligning with its reduced model size due to quantization. These findings underscore the importance of tailored benchmarking to assess model performance under specific hardware constraints, guiding optimizations for deployment on resource-limited devices.

VI. Bird sounds dataset

Initially, we assembled a balanced dataset from Xeno-Canto and the Macaulay Library including our target species *Yellow-Legged Gull* and *Audouin's Gull*. We ran the analyzer with default parameters and extracted 150 3-second segments for each class. Afterward, we tried retraining the model, only to find values indicating probable over-fitting, with AUPRC and AUROC metrics returning 1.0 as the best value, and 0.999999 as the worst. The metrics suggested an overly positive performance over those data, and it is, therefore, possible that most data available for those two classes on Xeno-Canto and the Macaulay Library have already been included in the test dataset, which has not been made public. This emerges as a critical aspect of these highly data-consuming analyzers, where in the absence of easily accessible testing data, evaluating the models can also become a critical and time-consuming activity. It is worth noting that *Yellow-Legged Gull* is by an order of magnitude more documented and widespread than Audouin's Gull; for this reason, for the former species, only a few samples dating more recently than our model were available, and nearly none for the latter. We therefore decided to leave retraining and fine-tuning to future research, using data sourced directly from the target environment as suggested by Lahua et al. [12]. We continued by assembling a multi-class dataset containing 76 species for testing hyperparameters impacts with unseen data. All samples used were retrieved from Xeno-Canto and were no older than 3 months. This choice was made to perform inference over data that are more recent than the analyzer version that we are testing, to simulate as much as possible a real-world application of the model. Although many limitations remain, this testing can be insightful of the model behavior with different tuning of the target hyper-parameters.

VII. Tuning of BirdNET for our use case

In this section we evaluate BirdNET Analyzer 2.4, quantized at FP32, on our test dataset, testing the different values of BirdNET hyperparameters used during inference. The choice to continue our evaluation over the Analyzer 2.4 is motivated by its internal design, which better aligns to our use-case. In particular, the analyzer offers the possibility to refine our detection procedure by means of species lists, either using a custom one, or generating a regional one from latitude and longitude coordinates using eBird distribution data[7]. The general insights provided here, complemented with further case-specific considerations, will guide future BirdNET applications in the context of the *La Mata* coastal lagoon case study.

A. Suggested Hyperparameter Tuning procedure

1) Batchsize: This parameter controls the inference batch-size, which is the number of audio samples processed simultaneously by the neural network. Larger batch sizes have been proven efficient with regard to inference time at the expenses of memory usage [17].

Tuning the batch size allows to balance computational efficiency and memory usage. An optimal batch size maximizes resource utilization within the hardware's memory limits, while higher batch size values will speed up inference times at the expense of memory usage.

In this step we test impact of different batch sizes on time and memory usage of the BirdNET-Analyzer. By systematically testing batch sizes of 1, 16, 32, 64, and 128, it was found that larger batch size values generally improved the inference time, while memory usage increased significantly (see figures 5 and 6).

Specifically, peak memory usage values recorded were 466.17 MB for batch size 1, 785.94 MB for batch size 16, 1143.23 MB for batch size 32, 1778.85 MB for batch size 64, and 1876.52 MB for batch size 128.

These results confirmed our expectations, highlighting the trade-off between the time advantage of processing larger data batches, and the available system memory.

2) Overlap: We evaluated the analyzer's inference on the test dataset, and the results demonstrated that the overlap parameter, which controls the overlap of subsequent audio segments used in inference, significantly affects both memory

[7]https://ebird.org/home

TABLE I: TensorFlow Models' benchmarking results (lite, v2.4 FP32, FP16, INT8).

Model	Init Time (ms)	First Inference (µs)	Warmup Avg (µs)	Inference Avg (µs)	Memory Footprint (MB)
BirdNET-Analyzer v2.4 FP32	39.928	48506	36046.3	33681.3	137.391
BirdNET-Analyzer v2.4 FP16	121.221	101113	37431.3	32009.2	251.695
BirdNET-Analyzer v2.4 INT8	33.929	47107	32756.6	31230.3	116.977
BirdNET-Lite	133.866	26410	13430.2	11846.8	144.223

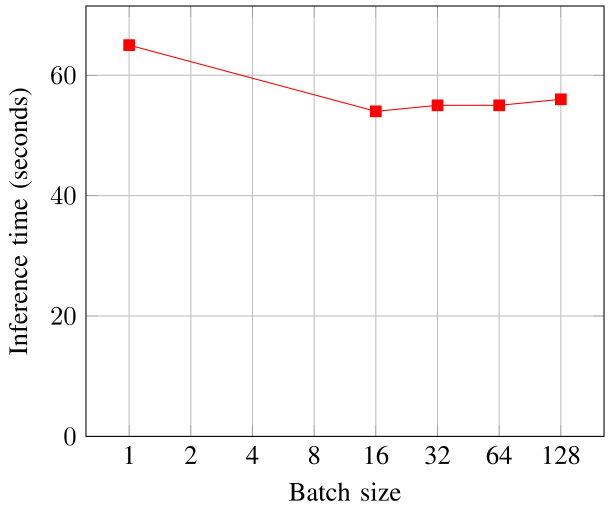

Fig. 5: Inference time when varying the Batchsize.

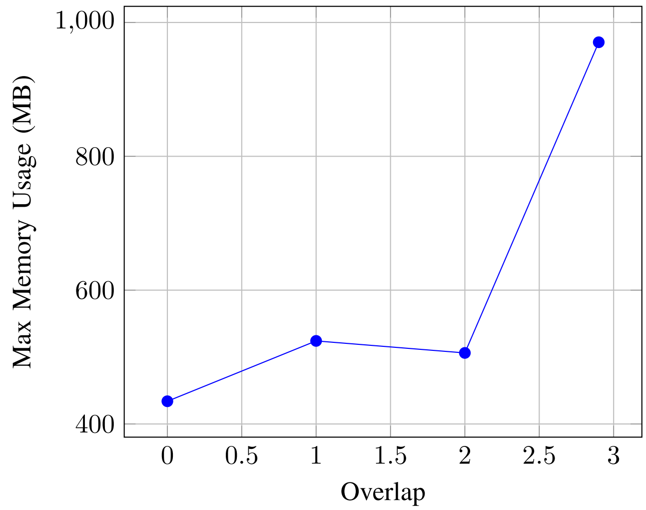

Fig. 7: Memory Usage in MB when varying the Overlap.

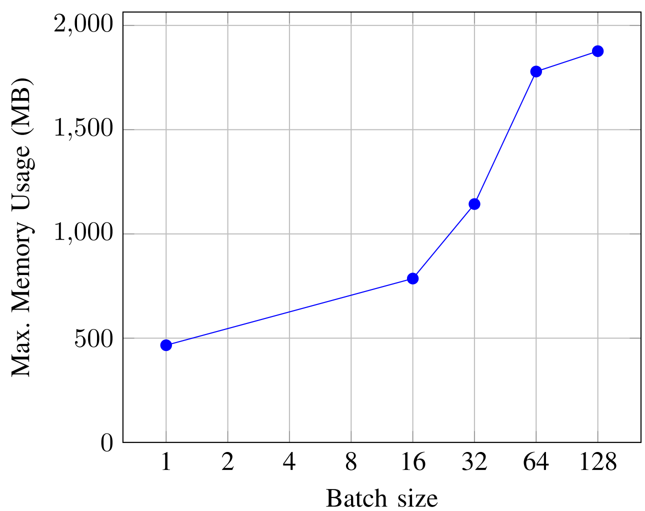

Fig. 6: Memory Usage in MB when varying the Batchsize.

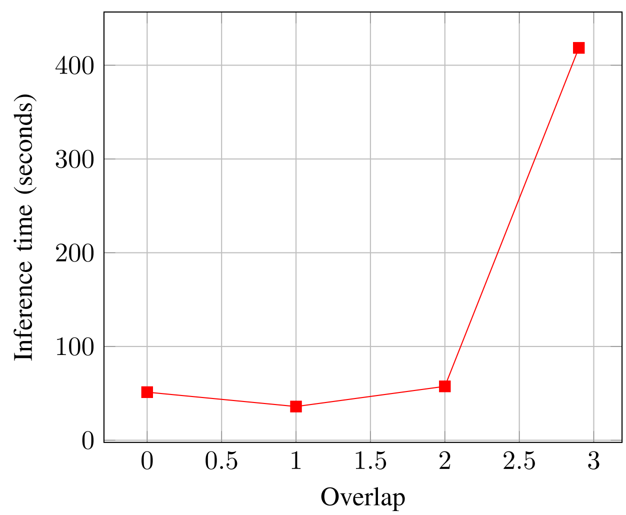

Fig. 8: Inference time when varying the Overlap.

usage and processing time. A moderate overlap value (1.0) optimized performance by reducing processing time with only a slight increase in memory usage. However, the maximum overlap value (2.9) degraded performance considerably, leading to higher memory consumption and longer processing times. Optimal overlap values vary across different acoustic domains: low values perform well in environments with few vocalizations, while denser acoustic scenes benefit from higher overlap. Therefore, selecting the appropriate overlap value for the target environment is crucial for balancing resource consumption, processing efficiency, and detection quality [6].

3) Sensitivity: This parameter controls the threshold at which bird sounds are detected and identified from audio recordings using a sigmoid activation function; in particular, it manages the trade-off between detecting more bird vocalizations, including faint or distant calls and minimizing false positives that might arise from background noise or non-bird sounds. By lowering the sensitivity, we will reduce the system's responsiveness to marginal sounds, thus lowering the occurrence of false positives; yet, this may cause us to

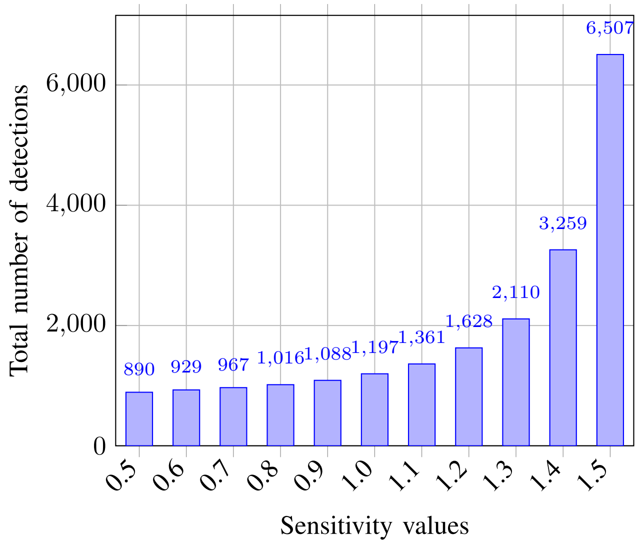

Fig. 9: Total number of detections when varying the sensitivity threshold.

potentially miss some bird calls, especially those that are faint or distant. A practical application of this parameter involves adjusting it according to the specific acoustic environment. In Figure 9 it can be seen that detections increment proportionally to the increase in sensitivity. Notably, the largest number of detections obtained corresponds to multiple detections inferred over single 3-second audio segments; this indicates that, at higher sensitivity values, the analyzer becomes more likely to report background species. In the context of this research, our testing has been conducted using the Analyzer v2.4 at FP32 quantization. This version qualifies as the one with the highest specificity to the other quantizations, and also compared to the lite version. Given that specificity and sensitivity are inversely proportional, the suggested approach for our use case is to work with default or even lower sensitivity values. This approach will minimize the number of false positives, allowing us to focus on the detections that are most reliable.

4) MinConfidence Threshold: The Minimum Confidence threshold parameter is used to filter out detections according to a confidence score of choice. Since the performance of the BirdNET analyzer can vary greatly across species, acoustic domains, and even recording devices [18], [16], a necessary practice will be to manually inspect and validate BirdNET detections, and to assess an optimal minimum confidence threshold tuning according to the aforementioned variables.

B. Results and discussion

The evaluation of the BirdNET Analyzer 2.4 FP32 library across various hyperparameters yielded several findings regarding inference time, memory usage, and detection capabilities.

Increasing *Batchsize*, as expected, led to improvements in inference time (see Figure 5), but only up to the value of 16, whereas the trend was inverted for higher values. Slightly increasing the *Batchsize* reduced the time taken for processing, but the alleged benefit was also accompanied by a significant increase in memory usage (see Figure 6). These findings are consistent with the established understanding [17] that larger batch sizes enhance computational efficiency, but at the cost of higher memory demands. The observed trade-off between speed and resource consumption underscores the need for careful tuning so as to maximize performance within hardware limitations.

Overlap: The overlap parameter exerted a substantial influence on both memory usage and processing time. Unexpectedly, a moderate overlap value (1.0) reduced processing time, while memory usage peaked more than with higher values. On the other hand, as expected, higher overlap values (2.9) significantly increased memory consumption (see Figure 7) and extended processing times (see Figure 8). This suggests that excessive overlap introduces redundancy, leading to resource inefficiencies, although it can be beneficial in the presence of long bird vocalizations. The results validate the necessity of fine-tuning the overlap parameter to enhance detection accuracy without overburdening system resources.

Sensitivity: Increasing the sensitivity value resulted in a proportional rise in the number of detections (see Figure 9). Notably, the same audio segments were marked with multiple detections, suggesting that, at higher sensitivity levels, the analyzer is more likely to report background species. This outcome aligns with the known trade-off between sensitivity and specificity, where higher sensitivity captures more faint or distant calls, but also increases the risk of false positives. For our use case, where specificity is critical, the results suggest that default or lower sensitivity settings are preferable to minimize false detections, while maximizing reliability; this differs from scenarios where rare species are to be detected, in which case high sensitivities allow detections to increase.

The observed results regarding the trade-offs associated with different parameter settings have in general been consistent with expectations, except for a few cases. For instance, while larger batch sizes were anticipated to enhance processing efficiency, the impact on time was not as high as expected, whereas the accompanying memory overhead was substantial. Similarly, while higher overlap values were presumed to improve detection granularity, they also introduced exponential inefficiencies that were not fully anticipated, with values above (2.0) returning unexpectedly high memory usage and inference time (see Figs.7 and 8).

These insights underscore the complexity of balancing multiple hyperparameters to achieve optimal performance tailored to specific use cases. Despite this complexity, the findings offer valuable guidelines for configuring the BirdNET Analyzer 2.4 library. By focusing on the most critical hyperparameters, it is possible to balance inference time and memory usage, ensuring optimal performance in practical applications.

VIII. Conclusions and Future Work

This paper developed a comprehensive framework for our case study, emphasizing the critical need for conservation efforts and the opportunities provided by IoT technologies. When combined with advanced Machine Learning tools, these innovations enable new possibilities at the intersection of environmental science, computer science, and citizen science, the latter playing a key role in driving successful outcomes.

Carrying out this research highlighted the importance of assessing and bench-marking AI models, since, for each particular use case, choosing the most optimal strategies and configurations can lead to more reliable results. Dealing with such complex models, which require enormous datasets for training, makes clear how critical the scarcity of unknown data is. In fact, when there is little to null availability of new data for specific species across repositories, as occurred in this research work, even standard procedures such as evaluating accuracy, and comparing base models to fine-tuned ones, becomes a hard task.

Despite the challenges met, results about the model's inference performance across variable hyper-parameters tuning have proven useful and led to both expected and unexpected findings. In this paper we have laid the basis for further model evaluation and selection for specific use cases. By bench-marking different versions of the target model we orientated ourselves towards the most promising version and followed up by testing memory usage behaviour and inference time of Batch Size and Overlap hyper-parameters. The complexity of balancing different hyperparameters remains a crucial aspect to address, particularly in a field where each case study will introduce its own challenges by means of variables such as target species and populations, environment, and available hardware.

Future work will build upon the results of this research and further assess BirdNET reliability and accuracy in processing large and varied datasets coming from Autonomous Recording Units (ARU) deployed in the Laguna de La Mata. Leveraging BirdNET can be greatly beneficial to complement time consuming tasks such as manual labeling and validation [19], as long as it is used attentively, and with proper adjustments made in the context of meeting specific application requirements. In addition, we also plan to systematic augmentation of audio data, and to analyze dependence on microphone characteristics.

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