

Proceedings

# Analysis of the Noise Impact of the Airport of Barcelona to the Llobregat Delta Natural Environment during the 2021 Lockdown Period <sup>†</sup>

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**Abstract:** The noise caused by airports and its impact on human health, together with train, road traffic, leisure and wind noise has been widely analyzed, even in the reports published in 2019 by the WHO. Noise effect has also been studied in the literature on other species, such as birds and amphibians. In this work, we focus on a natural environment of special singularity due to its location: the natural space of the Delta del Llobregat, next to the city of Barcelona. Placed in an area close to the Port of Barcelona, and right on the way out of the planes taking off at Barcelona airport. In this paper, we present a first analysis of the typology of the sounds found in the natural environment of the Delta del Llobregat after conducting a simultaneous recording campaign at three separate spots of biological interest, determined by the park's curators. We identify the interfering sounds, as well as the amount of wildlife sounds in relation to the noises caused by the airport activity. The recordings and posterior analysis were made on 5 March 2021, when airport activity was still greatly diminished by the mobility restrictions. Also, we apply machine learning techniques to classify the acoustic events produced by both airport activity and wildlife aiming to build an automatic system that would allow to gather labelled data in future works.

**Keywords:** soundscape; airport; acoustic event detection; citizen science

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## 1. Introduction

The effect of aircraft noise on humans, among other noise polluters, has been widely studied and analyzed over the last few decades [1]. Fewer studies have also analyzed the impact of those sounds on wildlife (e.g., birds or amphibians), and despite the well-known consequences that noise can have on animals such as reproductive or long-term survival problems, there are still natural parks over-exposed to sounds produced by humans [2]. In this work, we aim to collect audio files and analyze the soundscape of the *Delta del Llobregat* natural park, which is a Protected Area (PA) located next to the city center of Barcelona. Concretely, the selected location is surrounded by the Port of Barcelona and the *Josep Tarradellas Barcelona-El Prat* airport in Spain. Using acoustic data gathered at three spots of biological interest inside the natural park, we aim to train a machine learning model able to classify real-world acoustic events that would allow researchers to easily obtain more data to find patterns in the behaviour of wildlife in the selected areas.

Similar works have been conducted in other natural parks located close to noisy areas such as airports. For example, in ref. [3], the overlap between natural areas and Brazilian airports is studied. Moreover, the legislation of different countries regarding the location of airports near protected areas are analyzed, and measures to mitigate the impact of aircrafts to wildlife are proposed. Another example can be found on ref. [2]. In that work, A.L. Radle focuses on the impact of noise to wildlife on different ecosystems (e.g., terrestrial wildlife, marine wildlife or noise in national parks). Similarly, in ref. [4], C. Iglesias-Merchan et al.

evaluate the impact of aircraft noise in a protected area in the Central Mountains of Spain. Finally, on ref. [5], mist-nets and sound automatic recording units are used to classify bird species near natural areas close to different Brazilian airports. They evaluate several biodiversity indexes and identify airport avoider bird species and airport adapter bird species. Results show that, in quieter locations, the abundance of different bird species is, indeed, richer.

The work presented in this paper exposes the results of a manually labelled recording campaign carried out in the Delta del Llobregat protected area. Concretely, three simultaneous recordings of 2 h of duration have resulted in acoustic events from 14 different categories: some of them produced by humans and some others produced by the environment wildlife. Then, the classification results of three different machine learning algorithms trained and tested over the collected dataset are compared. The reason to apply machine learning techniques over the recorded data comes from the idea that automatically classifying the acoustic events present on the soundscape of the selected location would allow to automatically have more data that could be used to analyze over time the impact of the airport sound over the bird species inhabiting the protected area.

The remainder of this paper is organized as follows: first, Section 2 explains the methodology carried out to gather data in three different spots. Section 3 details the analysis conducted to the designed dataset after labelling it. Then, Section 4 reports the classification algorithms trained with our data and compares their results. Finally, Section 5 closes the paper and proposes some future work.

## 2. Airport Recording Campaign

Once the recording points were decided, and having requested prior permission from the consortium for protection and management of the natural spaces of the Delta del Llobregat, we planned a recording campaign for 5 March 2021. At that date, due to the COVID-19 pandemic, take-offs and landings of flights were happening more or less with a frequency of a flight every 15 or 20 min.

The recording equipment required was: (i) tripod, (ii) Zoom H5 Recorder, (iii) pen and writing support and (iv) data collection sheet (see Figure 1). The three recorders were synchronized with 3 hand claps. Later on, the three recorders were separated and placed at their final designed locations, and after finishing the recording setup, all the technicians started the annotations in the data collection sheets. At the end of the recordings, another synchronization was conducted, to be able to adjust the data stamp if the three clocks were not precisely synchronous. The three recordings lasted for 2 h, starting at 16:20 in the afternoon. The distance between the three chosen locations was around 500 m.



Figure 1. Locations of the three recordings in Delta del Llobregat.

## 3. Data Analysis

After the recording campaign, an exhaustive analysis was conducted over the data. Firstly, a manual labelling process was carried out using Audacity (open-source software for audio and recordings treatment that can be downloaded for free at <https://www.audacityteam.org/>).

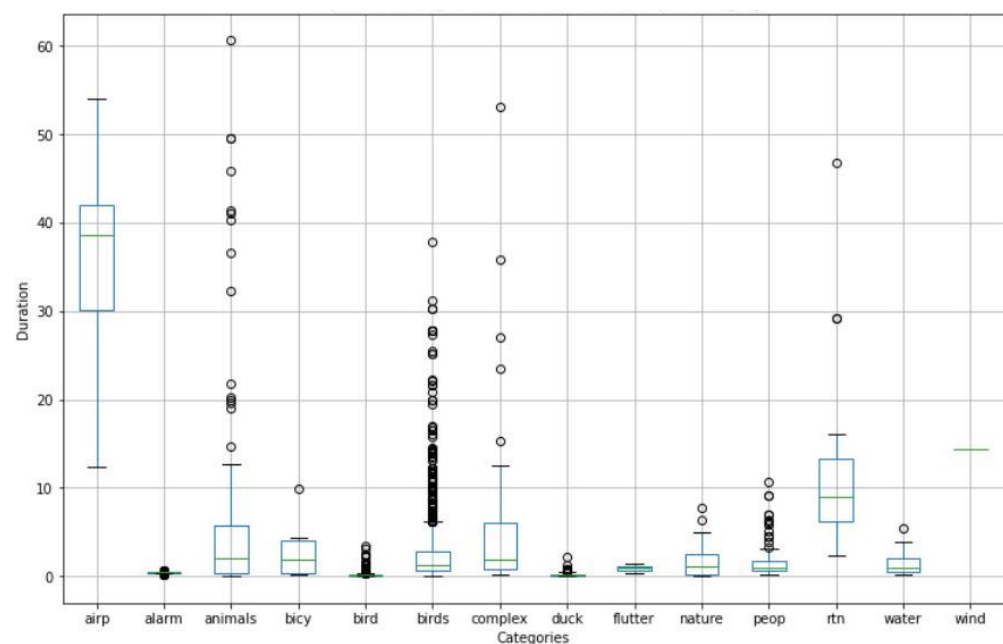
[audacityteam.org/](https://audacityteam.org/) (accessed on )). The volume of the acoustic events detected is the one represented in Table 1.

**Table 1.** Number of events for each of the categories of the labelled dataset.

Category	Description	Number of Events
1-airp	Airplanes taking off or landing	33
2-alarm	Alarms from the airport or surrounding states	81
3-animals	Sounds produced by animals	188
4-bicy	Bicycles	6
5-bird	Single bird vocalizations	5726
6-birds	Multiple bird vocalizations	1493
7-complex	Unidentified sounds	79
8-duck	Duck vocalizations	1437
9-flutter	Ducks moving their wings	2
10-nature	Leaves from trees moved by the wind	19
11-peop	People talking	91
12-rtn	Road traffic noise	32
13-water	Water sound	13
14-wind	Wind sound	2

Regarding the feature extraction process, the following parameters were obtained for each of the acoustic events: (1) Mel Frequency Cepstral Coefficients (MFCC), which represent the short-term power spectrum of a sound [6], (2) the Spectral Centroid, used in digital signal processing to characterise a spectrum, (3) the Spectral Roll-Off, and (4) the Zero Crossing Rate.

As shown on Figure 2, not all the categories have the same duration. Therefore, the average length of all the categories was used to split the events into windows of the same duration (0.94 s). Considering those divisions, the dataset was created in a way that all the audio slices belonging to the same acoustic event (e.g., an aircraft passing by), were placed only on the training set or the testing set. Finally, the 80% of the audio fragments were used for training and the remaining 20% were used for testing.



**Figure 2.** Boxplot of average duration time of events per category.

#### 4. Classification Algorithm

Several machine learning algorithms have been tested to automate the acoustical detection of events. The accuracy given for each model is evidenced on Table 2.

**Table 2.** Accuracy value for the tested algorithms.

Algorithms	Accuracy
k-NN	53.5%
Decision Tree	51.3%
Random Forest + Bagging	68.8%
SVM (kernel: polynomial)	38.6%
SVM (kernel: sigmoid)	15.0%
SVM (kernel: RBF)	83.2%

##### 4.1. k-Nearest Neighbor

k-NN has given efficient results for acoustic event detection in other fields [7,8]. A grid search was performed to check what number of neighbors results in the best accuracy value. Finally, the best result (accuracy value of 53.5%) was obtained when using a value of  $k = 6$ .

Usually, the sounds produced by airplanes (*airp* category) are confused with *complex* sounds. As the *complex* category contains acoustic information that we could not identify in the labelling process, it is possible that some of the windows from that category contain fragments of airplane sounds. Also, some *alarm* events are confused with the *rtn* category. Since transit sound is continuous in background on almost all of the recordings, some events catalogued as *alarm* could contain also *rtn* background noise. Finally, the algorithm tends to confuse the categories *bird* and *birds*, which means that it is unable to differentiate the number of birds present on a concrete window.

##### 4.2. Decision Tree

The model created with a decision tree is designed with a maximum profundity (largest way from the root node to the leaf node) of 6, since it is the one that results in a higher accuracy (of 51.3%). Again, maximum profundity was chosen after conducting a grid search.

In this case, the decision tree model shows that categories *airp* and *peop* have clear patterns, and hence there is no confusion identified on these events. Alternatively, all the categories related to animals (*animals*, *bird*, *birds*, *duck*) are often confused. Also, the fragments belonging to categories with the poorest samples (*alarm*, *bicy*, *complex*, *flutter*, *nature*, *transit*, *water or wind*) are the ones that result in the worst classification results.

##### 4.3. Random Forest

Random Forest has already been used in other research projects of acoustic events detection and classification [9]. To design our concrete model, we have conducted a grid search varying the maximum depths parameter. We found that the best performance of the model was achieved for  $\text{max\_depth} = 48$ , with an accuracy of 68.6%. Then, Bagging, Boosting and Voting methods were applied to try to increase the accuracy of the model, and after applying Bagging the accuracy raised to 68.8%.

The accuracy obtained in this algorithm is the best one so far, but it is also important to study the weaknesses of the model by means of analyzing the events that it confuses the most. With this classifier, the algorithm confuses sporadic events of all the categories. However, some patterns can be identified again. The algorithm tends to confuse the *rtn* and *airp* categories, and the *bird* with *birds*, which proves that it is not able to identify the number of birds vocalizing simultaneously. Something remarkable that has not happened on other algorithms is that some *birds* events are confused with the *peop* category, showing that it confuses bird vocalizations with human voice. The reason behind this confusion

may be that there are some similarities between bird vocalizations and human sounds, as stated in some studies [10].

#### 4.4. Support Vector Machine

One of the most widely used methods for the classification of sound events is the Support Vector Machine (SVM). In this work, the Radial Basis Function (RBF) kernel [11] has proven to be the one that obtains the best classification results out of 4 (linear, sigmoid, polynomial and RBF). The linear kernel never converged and therefore, there are no results to present. When using the sigmoid kernel, the classifier was able to identify correctly only the following categories: *animals*, *bird* and *duck*, and obtained poor results for the other ones. With the polynomial kernel, the classifier tended to classify events from other categories as *bird*. Finally, RBF kernel obtained the best results among all the classifiers presented in this work. The obtained confusion matrix of the algorithm when using the RBF kernel can be seen on Figure 3. This kernel results in an accuracy of 83.2%. On the confusion matrix, it can be seen how the system is able to classify the categories: *airp*, *animals*, *bird*, *birds*, and *duck*, respectively.

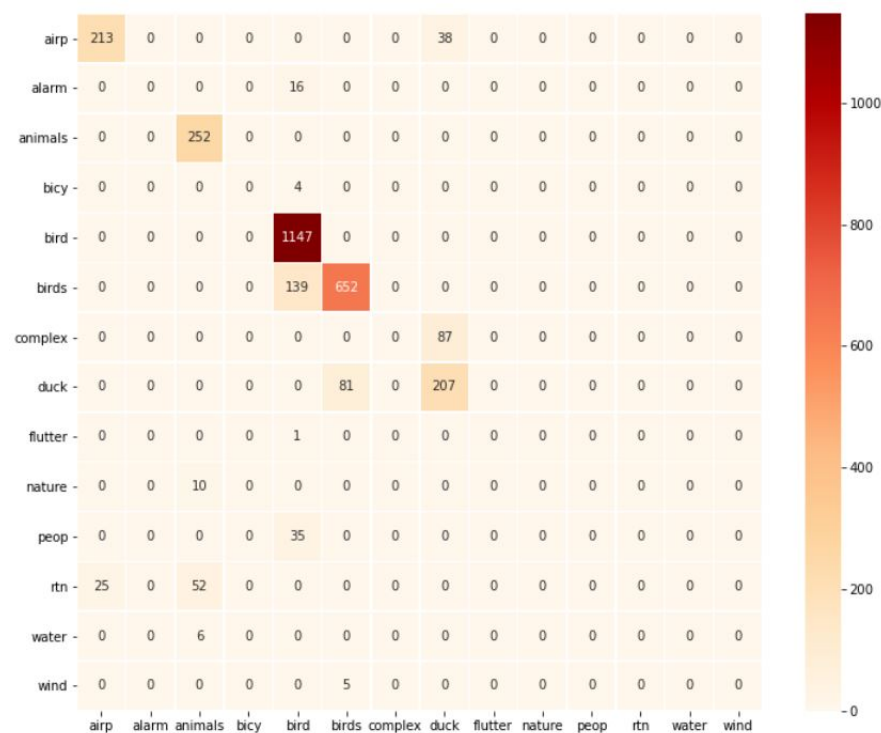


Figure 3. Confusion matrix of the SVM algorithm.

### 5. Conclusions

After analyzing the machine learning results, it has been detected that, in general, all of the implemented algorithms have confusion patterns over different classes. The main reason for it might be the lack of data from some of the categories in the training set. The most common confusion happens between the *bird* and *birds* categories, which may be caused by the splitting of different windows of the same acoustic event in different fragments, and due to the similarity of the spectrum of both signals. As the window is usually shorter than the duration of the *birds* event, it may have happened that some of the windows of the labelled event contained only information of a single vocalization. This fact was not considered when dataset was created.

To improve the current results, in future work, a wider recording campaign should be done. This would probably allow the algorithms to create more accurate patterns for detection, hence resulting in a more efficient model with better classification results.

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## Abbreviations

The following abbreviations are used in this manuscript:

KNN	K-Nearest Neighbor
LD	Linear dichroism
MFCC	Mel Frequency Cepstral Coefficients
PA	Protected Area
RBF	Radial Basis Function
SVM	Support Vector Machine
WHO	World Health Organisation

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