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University Degree in Audiovisual Systems
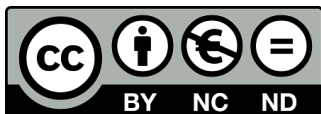Academic Year (e.g. 2014-2019)

Bachelor Thesis

"Violent event detection from acoustic signals"

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SUMMARY

Keywords:

DEDICATION

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1. INTRODUCTION

1.1. Context

Violence against women remains an invisible phenomenon, deeply within the victim's private life in most cases. It is based on deep social and cultural roots and it is undoubtedly linked to unbalanced relationships between men and women in different situations and contexts, such as economics, politics and religion. In order to prevent these conflicts, the related legislation has achieved important improvements for the last years. According to the results of most of the studies, victims can be usually defined as women who endured violence during their childhood and felt socially isolated. They are also characterized for a considerable economic dependency and a low educational level.

With the purpose of making a difference when identifying situations showing this kind of violence and applying the knowledge and technological advances acquired during this information era, machine learning and deep learning models can collect all the available data to protect eventual victims.

The main challenge is to get to know how the victim is feeling when she is under a threatening situation, for example, if she is scared or nervous, and combine this with other variables which may play an important role in the scene and might be helpful in making a decision about its characterization. There are several factors that can be considered to achieve this task. One of them is the audio, either the victim's voice or the environmental sounds.

Plenty of useful information can be extracted from the acoustic scene. The detection of audio events can be combined to understand what is happening in a certain moment. Once these data are collected, they can be classified in different categories and thus describe several aspects of the acoustic scene. Either based on an objective definition of gender violence or on an explanation previously obtained from a particular/specific victim, this acoustic knowledge can be interpreted as dangerous for the user.

1.2. Objectives

The utilization of learning models to extract useful information from data has become a very common practice in most of the fields. One type of habits that have gained a lot of popularity in the scientific community is the use of multimedia data. In many cases, the samples used to train the models consist in images that belong to a certain kind of problem, such as medical imaging or object recognition. This field is known as Computer Vision (CV). Many world well known architectures and enormous data bases have been born during the study of this kind of problems.

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In the same way, audio data have been used to get conclusions from a lot of real world problems. In order to tackle the task of violent event detection it is important to decide what perspective is going to be adopted when defining a violent event, whether an objective point of view or a more personalized standpoint according to the victim's criteria. Apart from this, it is also necessary to extract the required features, that is, the information from the audio signals that will allow us to train the models and get the results. However, the main work will be characterized by classifying a whole scene depending on the events this is built by. Once an action sound is categorized, it can be identified as violent by checking if it belongs to the violence definition previously defined.

The different acoustic scenes that may be considered for the problem can be composed by events of different nature or those that belong to just one class. This difference may cause that the techniques utilized to address the problem can differ. As a further approach, it is interesting to find a method that can distinguish among events that come from different sources of audio.

1.3. Regulatory framework

1.4. Socio-economic environment

2. STATE-OF-THE-ART

Since the main topic of this work, acoustic violent scene detection, has not been researched as such in the literature before, we decided to start our search by addressing close two topics that have been largely studied for the last years related to acoustics scenes and events also including some aspects on violence detection mainly aimed at the detection of violent scenes in movies.

2.1. Acoustic Scene Classification and Acoustic Event Detection and Classification

Acoustic Scene Classification (ASC) refers to the association of an audio sequence to a certain semantic label that describes the environment in which it took place [1]. With this idea in mind, the classification of acoustic scenarios has been tackled with two different kinds of concepts: soundscape cognition, i.e. understanding how the human being perceives the sounds subjectively from the physical environment that surrounds them [2], and Computational Acoustic Scenes Analysis (CASA), that is working on new computational methods that may help automatize this task through machine learning and processing signal techniques [3]. This notion can has many applications, such as content recognition –by allowing devices to obtain benefits and information from its situation [4]–, for medical usage [5], as a tool to aid musical recognition [6] or as a complement to Computer Vision (CV).

Simultaneously to these advances in the ASC, another related area has evolved during the last years: Acoustic Event Detection and Classification (AED/C). It can be described as the processing or treatment of sound signals in order to convert them into significant descriptions that match a listener's sensing of the events and sources composing the acoustic environment [7]. The detection part consists on identifying the events in a temporal stream of audio and labelling them. The result is usually accompanied by the time interval in which the occurrence is set. However, classification is a task that acts directly on the event that has been already isolated and has the purpose of designating a label or class to the sound [8]. These techniques also have plenty of applications, e.g., in the medical field [9], in biological topics such as bird noise detection [10], and for multimedia information retrieval from video sources in social media [11], etc.

2.1.1. Features and methods

As in many fields, the boundaries between features and methods used for audio tasks are becoming blurred since the recent rise of deep learning based methods. Classically, a problem is addressed with a pre-processing stage of the data and then the model or method is implemented. Right now, these two stages are sometimes maintained but also have been

mixed or changed depending on how the algorithm used works. In this chapter, we are going to try to explain these difference between features and methods and to separate them in order to ease its understanding.

Features

In every machine learning or pattern recognition task, for the system to be able to infer and extract conclusions from the input given, a pre-processing stage is necessary to make some transformations to the data so that they could be understood by the model. This stage is known as feature extraction and the goal is to convert the original information into a set of values or vectors that characterize the data regarding some desired properties [12].

There are several ways that allow us to perform this processing stage. The most common and basic one consists on extracting features that are closely related to the original signal which are called low-level descriptors (LLD) [13]. These are computed by performing some mathematical operations or formulas to the original data and can be considered rudimentary when comparing with other techniques. However, they are really extended and still in use nowadays [14].

In the audio field, there are two types in which all LLD can be grouped into. One of them is for the features that have been computed by considering the audio signal in its original form in the recording, i.e., in time-domain, that is the reason why they are known as time-domain audio features. The other case refers to those characteristics that are obtained from the signal after having been transformed into the frequency domain. These are commonly known as frequency-domain or spectral audio features. For the procedure of feature extraction, the signal is usually divided into frames that can be overlapped by using a sliding window, so the calculations are done per frame, obtaining a final matrix with size *number of frames × number of features* [12]. It must be taken into account that the goal of the whole system is going to be fundamental at the time of deciding which features must be computed. For example, not the same features are to be used for speech recognition than for musical information retrieval. In table 2.1, a summary of most used time and spectral features is included.

Then, a typical procedure would first divide the signal into frames and performed the desired mathematical and statistical transformations to obtain a LLD vector per sample in order to pass these input data to a statistical model that will be trained with the objective of summarizing the properties of the signals and develop a classification rule so as to be able to assign a faithful category to a new unlabelled observation [17].

In some cases, the mentioned descriptors, sometimes referred as manually-crafted features, are not enough to model data since they cannot achieve a meaningful enough representation of the original information for the system to learn from. Also, as mentioned above, the selection process of this type of features plays a significant role in the

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Feature	Description
Time	
Energy Entropy	It is useful to detect sudden changes from the energy of a signal. To calculate this value for a certain subframe, it is necessary to first compute the normalized energy of the subframe with respect to all the frames energy [15].
Short time energy	It is the energy for a short segment of signal. It is normally used in speech-related tasks in order to identify voiced form non-voiced fragments [16], among other things.
Zero Crossing Rate (ZCR)	This can be defined as the number of times the amplitude of the signal crosses the zero line per unit of time, i.e., changes from negative to positive. It is sometimes computed by the number of zero-crossings by the amount of samples in the frame [15].
Frequency	
Spectral Flux (SF)	It is computed to measure the spectral changes between two successive frames. To do so, the difference of their normalized squared spectra coefficients [15]. CPM: pero no dices respecto a qué está normalizado
Spectral Rolloff	This represents the skewness of the shape of the spectrum given the frequency below which a concrete percentage of the magnitude distribution of the frequency transform is concentrated [16].
Spectral Centroid (SC)	This is a measure related to the spectral position. It is defined as the center of gravity of the spectrum. [15].
MFCC	It is a feature that it is widely used because it gives good results in many tasks as for example, speech recognition since it interprets the frequency bands in a very similar way to human perception while doing a separation of the fine structure of the spectra (that corresponding with the harmonics) and the coarse (i.e. the filter representing the vocal tract). It is computed from the STFT.[16]. **A detailed explanation can be found in appendix ??**.

Table 2.1. EXAMPLES OF TIME AND SPECTRAL AUDIO
FEATURES.

final output so that the criteria of the designer could be considered a limitation for the classification task [18]. For this reason, a new strategy of addressing feature extraction

has appeared based on the idea of finding more specialized properties by using specific engineering algorithms that explores the given data in order to find non-human recognizable patterns. The techniques that allow to perform this task are usually called automated feature generation algorithms or machine-learnt features [19].

In order to compute these high-level features, there is not just one standardized machine model that allow to compute them all in a particular form. The calculation method, nevertheless, differs from one approach to another. One example could be the combination of low-level data with high-level semantic descriptors that consists on the inference of diverse musical dimensions by using support vector machines so as to find similarities among music genres. Particularly, they consider the output probabilities of the SVM classifier as a high-level feature space in which the distance between samples from different classes can be measured [20]. Some other application example could be building high-level feature detectors for image recognition by using unlabelled data to feed a Neural Network (NN) model [21].

Classification models

Several algorithms have been designed in order to perform a classification task by finding patterns from input data features. Next we will present briefly some of the most commonly used in the literature and then provide a more detailed description of those we have used in this project. In particular, the most basic methods to tackle the classification task are K-NN, SVM and also GMM [22].

In the case of K-Nearest Neighbour (K-NN), given a set of samples $x_1, ..., x_n$ that belong to a metric space X whose labels are $\theta_1, ..., \theta_n$ respectively, if a new sample x comes in, it will be categorized by following a majority vote process of the nearest neighbours considering a distance in the space X. A trade-off must exist in the choice of the number of nearest neighbours since on the one hand, it is desirable for it to be large so that the voting process has more participants and the probability of misclassification is minimized and on the other, a small value with respect to the total number of samples so the nearest points are close enough to the new observation [23].

Gaussian Mixture Models (GMM) are a class of soft clustering methods. They are commonly used to derive global statistical properties from the feature vectors of the sample data. Specifically, considering K clusters, they define a group of feature vectors from training data belonging to a certain category q and model them as a multivariate normal distribution $N(\mu_k, \Sigma_k)$ that is further weighted by the probability w_k of a particular of a certain observation to belong to cluster k. After learning a global model for the training data $M_q = w_k, \mu_k, \Sigma_k$, a new observation will be categorized by applying the maximum likelihood criterion [17].

However, the one that has been generally more successful is the Support Vector Machine (SVM) classifier . There are plenty of works in the literature that use this technique

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for audio classification tasks [24] [25] [1]. It is originally known to be a binary classifier but, nowadays, there have been some implementations that allow its use it in multiclass problems. This algorithm makes the classification by taking into account pairs of observations that are more likely to be misclassified and draws a hyperplane as the optimal boundary between the two classes [22]. Since this technique has been used for the experiments in this work, a more detailed explanation will be included in section 3.4.

Finally, we should mention all the techniques or algorithms that have been developed based under the idea of Artificial Neural Networks (ANN). This concept was inspired by human biology and how the neurons communicate among them in the brain in order to interpret the input or sensory data humans collect.

The ANN intention is exactly to transform input data into a desired output so that it performs a given task. A basic architecture is usually composed by an *input layer* of neurons, a certain number of *hidden layers* and an *output layer*. The model receives some input, typically a feature vector, and pass it trough the hidden layers in order to perform some transformations. The neurons of a layer are completely connected to the neurons of the next layer but neurons in the same layer are not usually connected. For this case, we can say that they are Fully-Connected (FC) layers. Finally, the output layer gives the final outcome of the network [26]. This is just the basic and initial nature of the idea but it was implemented in many different ways depending on the input data and the desired task.

One of the most explored implementations is the one related to Convolutional Neural Networks (CNN). This maintain the basic idea of receiving some inputs and apply a dot product operation to them before subject the data to a non-linear function but with the difference that input data are expected to be images [27]. The architecture of a Convolutional Network is based on the organization of the Visual Cortex in the human brain. This means that single neurons responds to some stimuli only in a certain region of the visual field, the Receptive Field. Then, a collection of these fields overlap with each other so as to cover the full visual space [28].

About the input data, it is introduced as a matrix instead of as a row vector. Then, the architecture of the layers adapt to the fact that input data are images. They do not consist of a single row of neurons, but they have a shape constituted by three dimensions: heigh, width and depth [27] . In this way, the net can capture the spatial and temporal relations present in an image by applying some filter functions. With this construction, the model can be trained with a smaller number of parameters and also reuse the weights.

A Convolutional Network can be described as a sequence of layers in which every layer converts a volume of activation results from the previous layer to another by computing a differentiable function. The architecture of a CNN is always composed by three type of distinguishable layers which are *Convolutional*, *Pooling* and *Fully-Connected*. A normal architecture will follow the next succession of layers [27]:

- INPUT: this represents the image at the entrance of the whole model. It commonly

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is a 3D matrix , one dimension per channel of colour, and contains the values of the original pixels.

- CONVOLUTIONAL: considering the neurons that are connected to a region of the input image, this layer computes their output by performing a dot product between the weights and the value of the pixels. The depth of the resulting data will coincide with the number of filters used.

- POOL: this performs a fixed operation that consists of a downsampling of the spatial dimension. It typically reduces by half the height and the width of the input image.

- FC: this is the final layer which gives the output of the whole net. It is a vector-shape layer and is completely connected to the previous layer. In a classification task the number of neurons matches the amount of classes of the problem.

Note that this list represents the order of the layers in the architecture, however, the number of layers of each type vary depending on how the model is designed and how deep it is desired to be. For example, some examples of deep architectures can be found later in section 3.2.1, in table 3.2.

With this building, a Convolutional Network passes the information of the pixels layer by layer while reducing the input images in a way that is much easier to process. This is performed without missing any feature since all of them are essential to compute a good prediction outcome.

In the convolutional layer, a convolution operation is performed for each small region of the input image. The element that carries out this operation is called *kernel* or *filter*. This partial region that the kernel covers in the input data is set by deciding the height and the width as a designing parameter. About the depth, it must match the depth of the input data so the filter can slide trough the image along its 2D and obtaining the results of the convolution operation by computing between the pixels inside the region and the values of the filter. An example can be observed in figure 2.1. For each filter, a 2D activation map is obtained after subjected the result of the convolution to a non-linear operation as the Rectified Linear Unit (ReLU) function. Finally, we will pack all these in a unique volume that will consists in the output of the convolutional layer [27]. For example, if we have a number of 64 filters, we will get then a group of 64 2D activation maps that will be the input of the next layer. Traditionally, it was the first convolutional layer the one that was responsible of capturing low-level features related to edges or colours in the image. The upper layers were the ones in charge of extracting high-level features so the network was able to understand the image similar to how the humans do [28].

We have included how the input interacts with the convolutional layer and also introduced the concept of depth of the resulting volume. However, it is needed to explain the how the total size of this output is computed and what it depends on. There are three main parameters that play a role in this decision: *depth*, *stride* and the *zero-padding* [27].
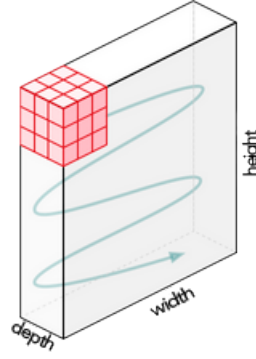
Fig. 2.1. Movement of the kernel represented as a red block along the width and the height of the original input image. It is clear that it occupies the whole depth of the input image. The arrow indicates an approximation of the movement that the filter follows [28].

- DEPTH: it is a hyperparameter that corresponds to the amount of kernels used in the convolutional layer when learning from the input. The set of neurons that extent through the depth dimension operating in the same region is called depth column. This is the previous mentioned red block shown in figure 2.1.

- STRIDE: this indicates the displacement of the sliding filter along the image. If it has a value of 1 (non-strided), this means that the kernel will shift a position of one pixel along the width. When it is set to 2, then it moves two pixels. It rarely has values greater than 2. The moving process consists on the filter going from right to left with a hop determined by the stride value. When the right margin is reached, then it jumps to the beginning of the next row from the left margin and repeats the process in the same way until the image is completed [28]. The bigger the stride, the smaller the size of the output volume.

- ZERO-PADDING: this is also called just *padding*. It consists on adding zeros to the borders of the image. What is a hyperparameter in design is the size of this padding. This allows to control the width and height of the output volume so we can keep it the same through the different layers. When it is indicate a "valid padding", it means that no padding is added and the output size will be reduced. If we indicate "same padding", then it has a value of 1 and means that the resulting volume will have the size of the input [29].

As shown below, the total size of the obtained volume, D, can be computed as function of the input size, W, the spatial 2D dimensions of the convolutional filter, F, the stride of the filters shifting, S, and the amount of padding in the zero-padding, P [27].

$$D = \frac{W - F + 2P}{S} + 1$$

The convolutional layers can be grouped all together, one after another, but they are usually interpolated by what it has been previously defined as *pooling* layer. This habit

has the objective of reducing the the width and the height of the resulting volumes in a progressive manner in order to decrease the total number of training parameters and control the computational cost, and, therefore to avoid overfitting [27] . There can be performed two types of pooling operation: the max-pooling or the average-pooling. The former just returns the maximum value from the portion of the image where the filter is placed. The latter, computes the average of all the values in this portion [28]. The pooling layer acts in an independent way on every input depth level.

Two hyperparameters are needed in order to configure the spatial portion in which the pooling is computed: the filter size, related to length of height and width, and the stride. However, for this operation zero parameters are introduce since it consists on a fixed operation over the input data. In figure 2.2, it is shown how the max-pooling operation is performed [27].
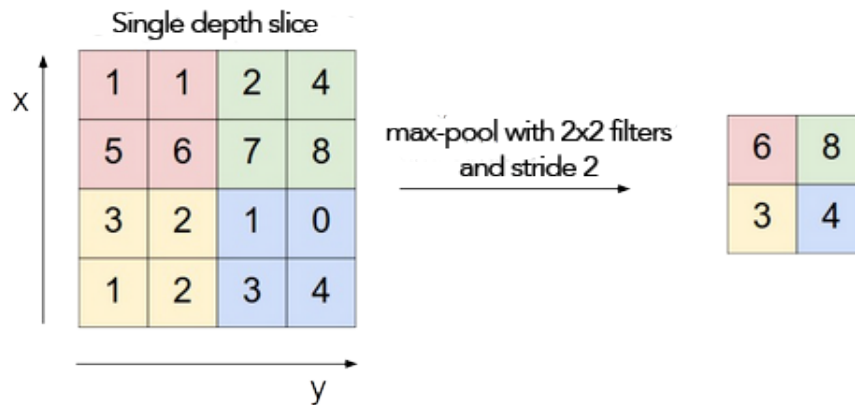
Fig. 2.2. Max-pooling operation with a filter size of 2 and a stride of 2 for a single depth filter. Each colour represents a the action portion for each operation [27]

Together a convolutional layer and a pooling layer constitute a complete layer structure typical in a Convolutional Network. The number of these complete layers can vary depending on the design and the task needs. These represent the main core of the network before passing to the last layers and calculating the final output [28].

For the final step, a common way of acting is to apply some non-linear activations in order to learn from the high-level features resulted from the output volume of the last convolutional layer. This takes place in the Fully-Connected layers ending the model. This part has the shape of a Fully-Connected layer, as the one described in the basic model of ANN. To make the weights from the convolutional layers available to feed this last part of the model, it is necessary to flatten the output volume and obtain a column vector. The learning process is possible due to a backpropagation operation performed in every epoch of training. As a total output, the values that represent the classification of the different samples into one or another category are obtained [28]. A common classification technique is the one called *Softmax*. This normalizes the result of the previous FC layer into a vector whose values follow a distribution that total sum results in 1. This type of output is called *soft predictions* and represent the probability for each sample of belonging

to a category in the classification [30]. However, there exists other activation functions that can compute the classification output in other ways.

In figure 2.3 an scheme of a common Convolutional Neural Networks is shown. This takes an input image, compute the features along three groups of convolutional layer plus max-pooling and, finally, includes three Fully-Connected layers, being the last one a softmax function layer with as many neurons as classes that gives the soft predictions for this image of belonging to each class.
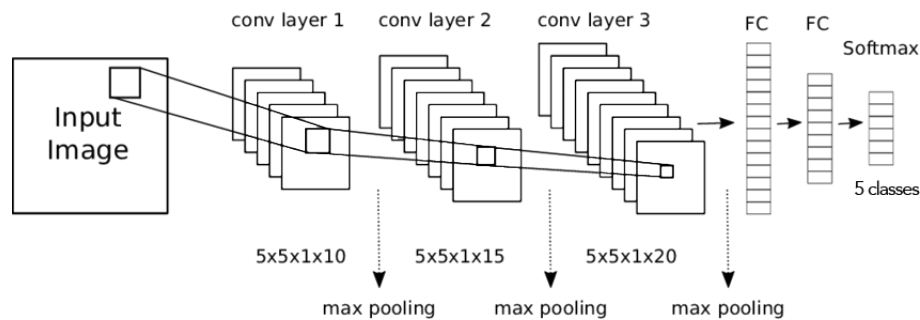
Fig. 2.3. Representation of a typical CNN model [31]

Convolutional Neural Networks (CNN) were originally designed to work with images but they have been applied to other fields as audio. An image can be defined as a matrix of values, i.e. pixels, in two or three dimensions, so the only prerequisite to use a CNN is to have the input data in this form. For audio researching, it has been commonly used the log-scaled mel spectrogram, that is a way of representing audio in a scale different than frequency that is more similar to humans perception. It has been used in plenty of works with CNN and also combined with other techniques [32] [33] [34].

2.1.2. Features and methods

In the literature, numerous articles have been published related to ASC field. These can be sorted into two different trends based on how the problem is addressed. One of them considers the scene as a single instance with the purpose of representing it through a long-term statistical distribution that models a set of low-level features [17]. An acoustic event can be characterized in different ways for this type of method. In previous works, feature extraction methods imported from the field of speech recognition played a main role in this field too, such as the fundamental frequency (F0), the F0 envelope and the probability of voicing. Apart from these, also spectral features, as Mel-Spectrum bins, Zero Crossing Rate (ZCR) and Spectral Flux (SF), and energy features, such as the energy in bands or the logarithmic-energy [25] had an important function on this task. However, the best results have been achieved with the so-called Mel-frequency Cepstrum Coefficients (MFCC), defined as a cepstral feature, **which will be explained further on. CPM: sí, referencia dónde lo has puesto**. This kind of characteristics extracted from the audio can be called low-level descriptors and they are usually combined with algorithms and methods to address the classification task. In this "bag-of-frames" approach, in which

Explain more MFCC? CPM: acuérdate de esto.

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the scene is considered as a single object, a typical technique was to model the samples features into global statistical characteristics from the local descriptors by using Gaussian Mixture Models (GMM) [35].

There is another path to dig for Acoustic Scene Classification, which consists on including a representation of data prior to the classification, which transforms the scene by using a set of high level features normally obtained with a vocabulary or dictionary formed by acoustic atoms. These are usually a depiction of events or streams within the scene and do not need to be known a priori [17]. Apart from the typical well-known audio features, the ones named above as low-level descriptors, there exists other acoustic characteristics which may seem to be hidden in the data but can be found by using unsupervised-learning methods. This is the way to act when dealing with the above mentioned acoustic atoms.

One of the approaches that can be found in the literature about this idea is based on the use of a previously learned over-complete dictionary that is utilized to sparsely decompose the spectrogram of audio. This dictionary will be used by an encoder with the purpose of mapping new input data to real similar versions of their own sparse representation in a fast and efficient way. Finally, the obtained codes will feed a Support Vector Machine (SVM) classifier, used for the task of music genre prediction [36].

Another job done in the sparse-feature representation framework presents a way of mixing high feature learning techniques with a pooling method for the objective of music information retrieval and annotation. After some preprocessing of the audio signals data, three feature-learning algorithms are trained finding that sparse restricted Boltzmann machine (sparse-RBM) gets better results than K-means and Sparse Coding. Once the features are obtained, an extra step takes place before performing the classification task, the one called pooling and aggregation. The goal of this procedure is to achieve a feature representation for a long sequence such as a song. Since when joining short-term features that belong to small segments inside the song may result in a loss of their local meaning, a max-pooling operation is computed over each subsegment in order to just consider the maximum value for each feature dimension. After that, these are aggregated by computing the average. The max-pooling contribution resides on reducing the smoothing effect when averaging the values [37]. This approach is feasible because of the homogeneity in music data. However, this technique could be slightly risky when dealing with acoustic scenes. For this case, a modified version of this method has been proposed. Taking into account that the presence of events is less frequent, instead of considering the whole long sequence to apply the max-pooling for, it will just be used in those segments that had been already detected as significant events by establishing a threshold value and setting an onset and offset that allow to know the start and end time [38]. **The representation of the audio event in a feature space explained in this case is the one that better fits our approach (3.3) until now.**

The classification of acoustic scenes can be linked to event detection. The working method used for this task is really similar to the one used for ASC. Thus, it is not sur-

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prising that most of the works found in the literature address this task with the use of MFCC as features and with techniques such as HMM or GMM. For the purpose of finding the desired events, the whole detection process can be split into two parts. Firstly, a classification of already isolated events should be executed in order to build a vocabulary of acoustic actions. In this case, the data used belong to short-term sequences that must strongly show the semantic meaning of the corresponding event. This is important because there may be more acoustic representations in the same short segment than the one to be detected, but this must stand out among the others. Consecutively, for the detection part, the input data will be composed by long tracks so that time allocation of the events will be implemented. Therefore, after obtaining the different short segments from dividing the long sequence up, they will be classified considering the results from the first step [39].

A novel type of feature has been used in the last years that differs from the already explained low-level and high-level ones: Deep Neural Networks (DNN) have grown increasingly for plenty of classification tasks and so in the multimedia area. The problem with this type of systems is the huge amount of data that is needed to make them work properly, which can be translated in a lack of labelled data. One of the habits that has been currently resorted by the researchers consists of learning what is called deep data *embeddings* from extensive collections of, ir our case, audio and use them so as to perform **shallow classifications by using simpler datasets**. There have been implemented some models about this topic, such as Look, Listen and Learn (L^3) [40] net that uses as input for the the embedding extractor the linear-frequency log-magnitude spectrogram of 60 million audio samples, the system called SoundNet [41] that has been designed to obtain embeddings from training a deep audio classifier in order to predict the output o a deep image classifier and the VGGish network, designed by Google researchers. This last case is the one we used in this work and it will be explained in more detail in section 3.2.

2.1.3. Transfer learning

All these models previously mentioned allow us to use complex extractors trained with huge collections of data and apply them to models considerably much less complicated to address other type of problems. This is possible due to a kind of techniques commonly known as transfer learning and domain adaptation.

The typical consideration in plenty of machine learning tasks consists on extracting the training and testing subsets of data from the same feature space and same distribution. When one of these initial assumptions change, it is necessary to rebuild the whole model from the initial point, including new training data, which means a lot of computational cost and loss of efficiency [42]. Its working manner can be explained as an analogy of how humans transforms their ability on a certain task to obtain knowledge for other purpose. An example could be how musicians apply their previous experience to get to know faster how to play another instrument.

Go deeper? HMM, GMM, MFCC

CPM: esto está muy bien.

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The first work in which this topic has been treated widely was in 1995 in the workshop *Learning to Learn* [43] and since then many approaches have arisen and renamed the same idea as knowledge consolidation or inductive transfer. However, it was 10 ten years later, in 2005, when the first idea of the ability of a system to identify and apply learned skills previously to completely new problems appeared from the hand of the Broad Agency Announcement (BAA) 05-29 of Defense Advanced Research Projects Agency (DARPA)'s Information Processing Technology Office (IPTO) [42]. This can be expressed as a relation between a *source* task, where the abilities are learned, and *target* task, the novel problem that needs to be resolved. As a difference with other similar methods, in this concept of transfer learning the roles of these two are not equal since the weight of the target is much heavier. In figure 2.4 it is shown the difference between a common machine learning approach and the use of transfer learning.
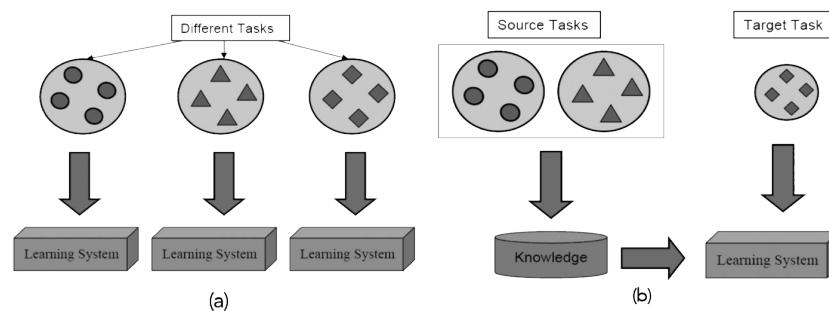
Fig. 2.4. Difference between traditional machine learning (a) process and feature learning (b) [42]

The same idea can be understood from a mathematical point of view as the analysis of the relationship between the two different spaces from types of targets [42].

Considering a *domain D* that is composed by a feature space denoted by X and a marginal probability named $P(X)$, where $X = \{x_1, ..., x_n\} \in \chi$. The whole domain can be expressed as $D = \{\chi P(X)\}$ where x_{ith} is a certain vector inside the feature space.

In the same way, a *task* can be defined as T formed by a label space γ and an objective predictive function η. The task formulation is $T = \{\gamma, \eta\}\}$. This predictive function cannot be observed, however the intention is to learn it from the training data, that is composed by pairs of the form $\{x_i, y_i\}$, $x_i \in X$ and $y_i \in \gamma$.

The predictive function η can be used to predict a corresponding label of a new sample x. From a probabilistic perspective, this new label can be expressed as $P(y|x)$. So, the task T can be defined as $T = \{y, P(Y|X)\}$, in which $Y = \{y_1, ..., y_n\} \in \gamma$. For each vector x_i, the function η finds a prediction y_i.

Once these parameters have been defined, considering the source domain D_S, task of source domain T_s, the target domain as D_T and its respective task as T_T, the transfer learning has the purpose of obtain the condition distribution in the target domain $P(Y_T|X_T)$ with the information extracted from D_S and T_S where $D_S \neq D_T$ or $T_S \neq T_T$ [44].

CPM: no entiendo esta notación, ¿está bien transcrita?

CPM: ¿es necesaria la th?. Yo diría where x_i is

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2.2. Violent Event Detection

All the multimedia information available can be applied to many fields and with different connotations. One of the variants that has appeared in the acoustic scenes and events field is the one applied to violence detection. For this case, an essential point before addressing any problem is to decide what kind of definition the word 'violence' is going to adopt since it is a subjective concept. An objective perspective has been given by the World Health Organization as "The intentional use of physical force or power, threatened or actual, against oneself, another person, or against a group or community, that either results in or has a high likelihood of resulting in injury, death, psychological harm, maldevelopment or deprivation" [45]. There are other definitions found in different works as "physical violence or accident resulting in human injury or pain" [46] or "any situation or action that may cause physical or mental harm to one or more persons" [15].

Recent studies have treated this problem in different ways due to all types of conditions that this may take place in. During the last years, the possibility of creating and providing audiovisual content has grown widely, which has led to an enormous variety of topics in which, some of them, could be considered inappropriate for certain audiences. This is the reason why there have just been done works related to the field of video content analysis and detection of violence.

In some cases, audio and image features have been combined to address these problem [47]. However, it has been found that sound information could be really useful and a more efficient way of working compared to image, since it is easier to process and the cost is lower. Related works have utilized audio features in the time-domain and in the frequency-domain, similar to the ones explained for ASC, then combined with a normal SVM classifier [15]. Other researches have tried more complicated models with the intention of improving the classification task. It is the case of using DNN, fed with both image and audio data, which performs the task more efficiently [48]. Violence detection has also been used for other applications such as video surveillance. For example, one of the scenarios for this purpose consists on preventing violent acts inside elevators [49]. For this case, the considered dangerous situations are composed of anti-social actions that are likely to happen in this kind of places, concretely, urinating, vandalism and attacks on vulnerable victims, such as women, children or elderly. The framework proposed is based on audio-visual data, but the master classifier is driven by audio, due to the possible subtleness of the scenes that are desired to detect. So, first the audio incident detector triggers the process when a non-silent event takes place. Then, the image processing begins in order to extract information related to who is involved in the action and how aggressive is it. Another utilization of the surveillance approach is its use for the evolution of smart cities [16]. For this goal, since the system will be implemented in real-life environments, one of the advantages about working with data coming from sounds is the respect for privacy, that, otherwise, using video recordings would be violated.

The difference in these two applications, apart from the task they are addressing,

resides on the data they are working with. For violent content analysis, the data usually comes from fictional audio sources as movies or video-games. However, for real-environment systems, the data is extracted straight from actual day-to-day life situations. In this second case, some disadvantages can be appreciated. For example, the signals are not preprocessed, which means the original properties of the sound are not modified so the processing part before classification becomes tougher. Also, the presence of background noise is more common and loudness of some events, as speech, may vary with time [50].

2.2.1. Gender-based violence

Throughout history, women have been subjected to abuse and suffering in many different situations even though in those that were considered as their close familiar environments. They have been bashed, sexually harmed and psychologically misstreated by those who were supposed to be one of their closest intimates [51].

In the same way, in the recent times, late studies have shown that 35% of women from all over the world have been victims of physical or sexual damage [52], and 43% of women from Europe have declared going through some psychological or mental violence at least once in their lives [53]. In this context, it is necessary to define the concept of gender-based violence, which can be described as the set of harmful behaviours that are focused on women and girls just because of their sex, such as female children and wife abuse, sexual assault, dowry-related murder and marital rape, among others. Particularly, violence against women involves any act of verbal or physical force, extortion or lethal denial which has a woman or girl as a target and provokes the physical or psychological hurt, humiliation or irrational privation of liberty and contributes to continue women subordination [54]. Within this definition, it can be considered that most of the times that these violent situations take place, they are originated due to persons that are supposed to be part of the victims' closest circle of trust, i.e., their husbands or boyfriends. This is called Intimate Partner Violence (IPV) and it is recognized as a public health problem affecting women across their life span resulting in different undesirable unhealthy outcomes, such as depression, chronic pain and even dead [55].

2.2.2. Our point of view

As a contribution to the EMPATIA-TC project developed by Universidad Carlos III de Madrid, the main goal in this work is to make progress in detecting gender-based violence situations, specifically applied to day-to-day scenes, in which IPV is likely to be present. One of the parts from the proposed system is composed by wearable devices that the victim can carry to collect diverse types of information and process them to obtain conclusions and increase the efficiency. Among these accessories, we can find a pendant that senses the user's voice and the surrounding audio to analyse what is happening at a given moment. For our purpose, the interesting part resides on achieving auditory data

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so as to detect violent incidents that consists of sounds already known for characterizing these episodes considered dangerous by the victim.

The definition that is assigned to violence is really important in order to define which audio events should be taken into account. However, considering the subjectiveness of this concept, categorizing violence for every type of user is an extremely difficult task. For this reason, the final idea to answer this question is to make the victim able to decide which kind of hearing events the system must be aware of. In the complete project, this can be carried out by a phone user interface which displays a list of sound events and she has the labour of picking up those that are violent according to her criteria. Since the development of this tool is out of the scope of this work, we have decided to implement a simpler mechanism which will be explained in subsection 3.3.1.

2.3. Databases

A main objective was to find a database that allows for building a system with the desired characteristics, so a rich variety of acoustic events is needed with an essential big representation of violent sounds. In the table 2.2 is represented a relation of the different databases that have been considered for the realization of this work.

The last three options shown in table 2.2 are the ones that better suit the problem of this project. *VSD Benchmark* was the first option we chose. Within the two ways of working given, the movies and the YouTube videos, the former was the easiest to use since the annotation specified exactly what kind of violent events were present in the scene and the onset and offset time stamps within the whole film. However, this data is copyright restricted and it was necessary to pay for the contents. The latter was accessible but just indicated the presence of violence, without determining the type of event. Another choice was the *Freesound dataset* because it contains all types of videos so we could extract those classes that are more interesting for us. However, it is still under an annotation process and it is not ready to download yet. As a final conclusion, we decided to go for *AudioSet*, which **will be explained further on. CPM: recuerda poner la sección específica.**.

Name	Description	Considerations
URBAN-SED [32]	10,000 soundscapes with sound events. Every soundscape contains 1 to 9 sound events with strong annotations.	Events are completely specified but it just contains three interesting types of classes.
UPC-TALP [56]	It belongs to CHIL project, for the AED task. Isolated acoustic events that occur in a meeting room environment.	Payment is needed to achieve the data and the classes are a little out of our topic.
MIVIA: Audio Events Data Set for Surveillance Applications [57]	6,000 events with background noise.	The classes included belong to our topic, but they are just three: glass breaking, gun shots and screams.
TUT rare sound events [58]	Source files for creating mixtures of rare sound events (classes baby cry, gun shot, glass break) with background audio.	Similar problem to MIVIA: just from three interesting classes.
IEEE AASP Challenge [59]	Composed by ASC and AED. It is formed by two subtasks: OL (Office-live) and OS (Office Synthetic)	Labels for both subtasks are out of our scope since they are likely to happen in an office environment: keyboard clicks, hitting table, etc.
TUT-SED Synthetic 2016 [60]	Isolated sound event samples were selected from commercial sound effects	The variety of classes is large enough but for our purpose just four of them are useful.
VSD benchmark [61]	Violent events from 32 Hollywood movies and 86 YouTube web videos, together with high-level audio and video concepts.	Payment is needed to purchase the movies and the videos do not specify the type of violent event
AudioSet [62]	An ontology of 632 audio event classes and a collection of 2,084,320 human labeled 10-seconds sound clips from YouTube videos.	Our final choice. Plenty of the videos have more than one audio label but we were able to adapt the data to the problem because of the huge amount of clips.
Freesound dataset (FSD) [63]	Filling AudioSet ontology with 297,144 audio samples from Freesound.	This may seem a very good option as well but it is not available as of today.

Table 2.2. TABLE OF STUDIED DATABASES

3. METHODS

3.1. Database: AudioSet

3.1.1. What is AudioSet

Audio Set can be described as a large-scale sound dataset with the goal of putting the availability of audio and image data on the same level. It is composed by a huge variety of manually-annotated audio events and is organized by following an ontology formed by 632 different audio classes. The data has been extracted from YouTube videos and the labelling process has been based on diverse factors such as metadata, context and content analysis. It has been developed by Google with the purpose of producing an audio event recognizer that can be applied to plenty of acoustic situations coming from the real world [62].

3.1.2. Ontology

In order to put this dataset together the events have been organized in an abstract hierarchy. This is composed by higher-level classes which describe a certain type of sound and also acts as parents of other labels that refer to more specific events. With this purpose, the relationship among different classes needed to be non-exclusive, so labelling similar audio events may result into a more general class, the parent, if there existed ambiguity. This is also helpful for labellers due to group the clips in an easier and faster way.

The Audio Set Ontology was collected considering some fundamental guidelines explained below:

- A complete collection of all desirable labels was prepared so that it can be used to define sound events from real-world aural data.

- When labelling an audio event the result must match the criteria of a common listener.

- Different categories should be easy to distinguish by an ordinary listener. In the case that two different labels do not satisfy this requirement, these should be merged. With this condition, the plethora of possible labels remains limited.

- The distinction of two different classes must be done by relying just on the audio, it cannot be accompanied by image or visual information.

- The hierarchy should not be very deep by keeping the number of children per parent class to no more than 10. This also eases the annotation labour.

It is easy that an ontology of this volume gets leaned or biased towards a particular direction due to several factors, such as the subjectiveness of its creators or the selection of the initial set of classes used when starting to work. With the intention of generating a primary list that covers a wide range of audio events in an objective way, the researchers decided to apply an impartial, web-scale text analysis from the very beginning. They agreed on detecting hyponyms of the word "sound" by utilizing a modified version of the famous technique called *Hearst patterns* [64], a method proposed to automatically acquire hyponymy lexical relations from unrestricted text. As a result, an enormous collection of terms came up. This was filtered by considering how well these terms represented audio, i.e. by combining together the global frequency of occurrence and how exclusively these are recognized as hyponyms of "sound" instead of other terms. As an output of the final process, a list of 3000 terms was obtained.

With respect to the hierarchical relation among categories, it was constructed by the authors with the main intention that this satisfied their human comprehension of the sounds. Event though this is a subjective manner, it also makes sense since this is how the hierarchy best performs its labour on helping human labelling. After all the organization process, the model is not based on a strict behaviour as a singular node can appear in many different locations, i.e., a single node can be child of different parent nodes. As we said before, the final result is composed by 632 audio event labels and, in the hierarchy, there is no sample deeper than 6 levels. Figure 3.1 shows the nodes that belong to the two top layers of the ontology.

Human sounds
— Human voice
— Whistling
— Respiratory sounds
— Human locomotion
— Digestive
— Hands
— Heart sounds, heartbeat
— Otoacoustic emission
— Human group actions

Source-ambiguous sounds
— Generic impact sounds
— Surface contact
— Deformable shell
— Onomatopoeia
— Silence
— Other sourceless

Animal
— Domestic animals, pets
— Livestock, farm animals, working animals
— Wild animals

Sounds of things
— Vehicle
— Engine
— Domestic sounds, home sounds
— Bell
— Alarm
— Mechanisms
— Tools
— Explosion
— Wood
— Glass
— Liquid
— Miscellaneous sources
— Specific impact sounds

Music
— Musical instrument
— Music genre
— Musical concepts
— Music role
— Music mood

Natural sounds
— Wind
— Thunderstorm
— Water
— Fire

Channel, environment and background
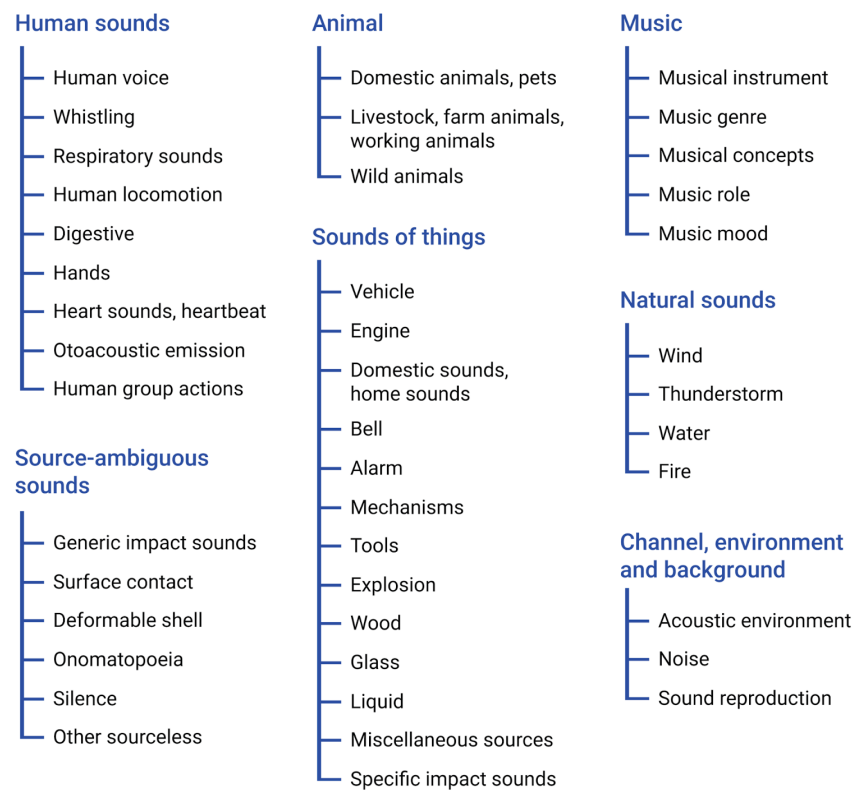— Acoustic environment
— Noise
— Sound reproduction

Fig. 3.1. First two layers of Audio Set Ontology [62]

This whole structure is offered to any user as a file in JSON format. A couple of fields have been included for each label in order to describe its meaning and make clear its position within the hierarchy. A description for all of these can be found in table 3.1.

ID	This field includes the Knowledge Graph Machine ID (MID) that best describes the sound or its source. It is used as a primary identifier for the class.
Display name	Short name formed by one or two words that identifies the audio class. It sometimes includes a small alternative separated by a comma so it does not feel ambiguous.
Description	One or two explaining sentences so the meaning of the category is more defined. These can be extracted from Wikipedia or WordNet.
Examples	At least one example of the label is provided as a URL of a YouTube video.
Children	An array filled by the Machine ID (MID)s from all immediate children of the class.
Restrictions	It specifies if the category in question either has been discarded or there are no audio clips under it.

Table 3.1. FIELDS PER CATEGORY IN THE ONTOLOGY.

For the field *ID*, the identifiers are known as Machine ID (MID) and belong to the *Knowledge Graph* designed by Google [65]. This is a knowledge base that Google services use to improve the quality of its search results and it is composed with information extracted from a wide variety of sources. The MIDs are the identifiers of the different elements that belong to this huge dictionary. For instance, the MID of the word "Speech" is "/m/09x0r". Another field that deserves a special explanation is the one corresponding to *Restrictions*. Within all the categories of sound events, there are two flags that indicate an exclusive behaviour that differ from a typical label: "blacklisted" and "abstract". The former refers to a class that has been hidden from labellers due to its confusing meaning. The latter has been used for those classes that are just utilized as intermediate nodes in order to provide a better grouping inside the organization, and are not expected to be used in the implementation tasks. In total, out of the 632 categories, 56 have been categorized as "blacklisted" and 22, as "abstract".

3.1.3. Data

The different YouTube videos that constitute the dataset are included in a .csv file in which each row comprises the video identifier, the start and end time of the audio event within the video and the ontology labels that the certain clip belongs to. All the video

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segments have a length of 10 seconds maximum, except from those that the original video is shorter, then the whole thing will be considered as the an audio event.

The final release of the dataset is composed by 1,789,621 segments, with a duration of 4,971 hours of video and audio. After executing the selection process in which the different labels were populated with the final corresponding segments, a total of 527 classes were gathered, out of which 485 counted with at least 100 samples.

3.1.4. Data access

The data can be obtained through the website [66] in two different formats:

- Files in .csv format that include for each video segment its YouTube video ID, start time, end time and the one or more labels it belongs to.

- Instead of the audio files themselves, they provide already extracted audio features for each segment in compressed files that can be easily downloaded.

For our purpose, we worked with the dataset in both different ways. However, we got further with the already extracted features. These are obtained by using a model called *VGGish* [67] which has been pre trained on a preliminary version of the database YouTube-8M [68]. The features are available to the user in TensorFlow (TF) [69] record files and the code for the VGGish model is also included in a public repository.

3.2. Feature extractor

In order to best describe the just mentioned VGGish mode, it is necessary to first explain the original network it was based in .

3.2.1. Visual Geometry Group (VGG) model

Convolutional Neural Networks (CNN) are usually able to achieve really good results and even improve human skills on Computer Vision tasks, for example, on recognizing object in an image. With the exponential growth of the research works on this field, some challenges have appeared so as to promote the creation of new systems and test their efficiency and results. This is the case of the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), based on the database of the same name, ImageNet. As a solution for the proposed exercise, the investigators from the Visual Geometry Group (VGG) in the University of Oxford implemented a new system achieving the first position and winning the challenge in 2014 [70]. The work they proposed consists of a study of the depth in a Convolutional Network architecture and how this can affect to the accuracy on the goal of large-scale image recognition [71]. To try this, it was necessary to increase the number of

Include any explanation about ratings? CPM: no sé a qué te refieres...

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layers in the network, which was viable due to use a small size of convolutional filters in all of them.

For the training step of their system, they used an input image with standard size of 224×224 in RGB format. The principles to build the architecture are detailed below:

- The input image crosses a bunch of convolutional layers in which the kernel has a size of 3×3.

- The convolutional stride has a value of 1 pixel.

- The padding is fixed to 1 pixel, so the dimensions of the input do not change during the convolution.

- Max-pooling is also included with a window size of 2×2 and a stride value of 2 pixels.

- Two Fully-Connected (FC) layers with 4096 channels after all the Convolutional Network layers.

- One FC layer with 1000 channels to perform the ILSVRC classification.

- A soft-max layer is employed for the final layer.

- All hidden Convolutional Network layers use the non-linear function ReLU as **activation function**.

All the designs that the creators came up with are based on these initial guidelines, except from just one case where Local Response Normalisation (LRN) is applied. They just differ from each other on the number of layers, starting with 11 the first approach and ending with 19 the last one. The different architectures are specified in the table 3.2 and are ordered from A to E.

3.2.2. VGGish model

The model we used in our project for feature extraction presents a configuration with principles similar to the ones explained in the previous subsection 3.2.1 but with slight changes that their developers have included in order to adapt it to the audio approach.

The architecture is based in the configuration A from table 3.2 with 11 weights. The differences respect to the original network are listed below:

- The input size was changed from 224×224 to 96×64 because of the log-mel spectrogram audio inputs.

- They built the implementation with just four groups of convolutional and max-pool layers so the fifth one was dropped.

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ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Table 3.2. VGG CONVNET CONFIGURATIONS.

- For the last FC layer, they decided to build it just with 128 channels since it is the layer that compacts the final embedding and defines its dimensions.

- Also the final *Softmax* layer is not used.

Figure 3.2 shows how the configuration of the final VGGish model looks.

Input stage

Before passing the data through the whole CNN, a preprocessing stage have been included by the developers in which the input audio will suffer some transformations.

1. In the first place, after loading the input audio, the sample rate and the number of channels are checked to be 16 kHz and monochannel, otherwise the file is transformed to satisfy these conditions.
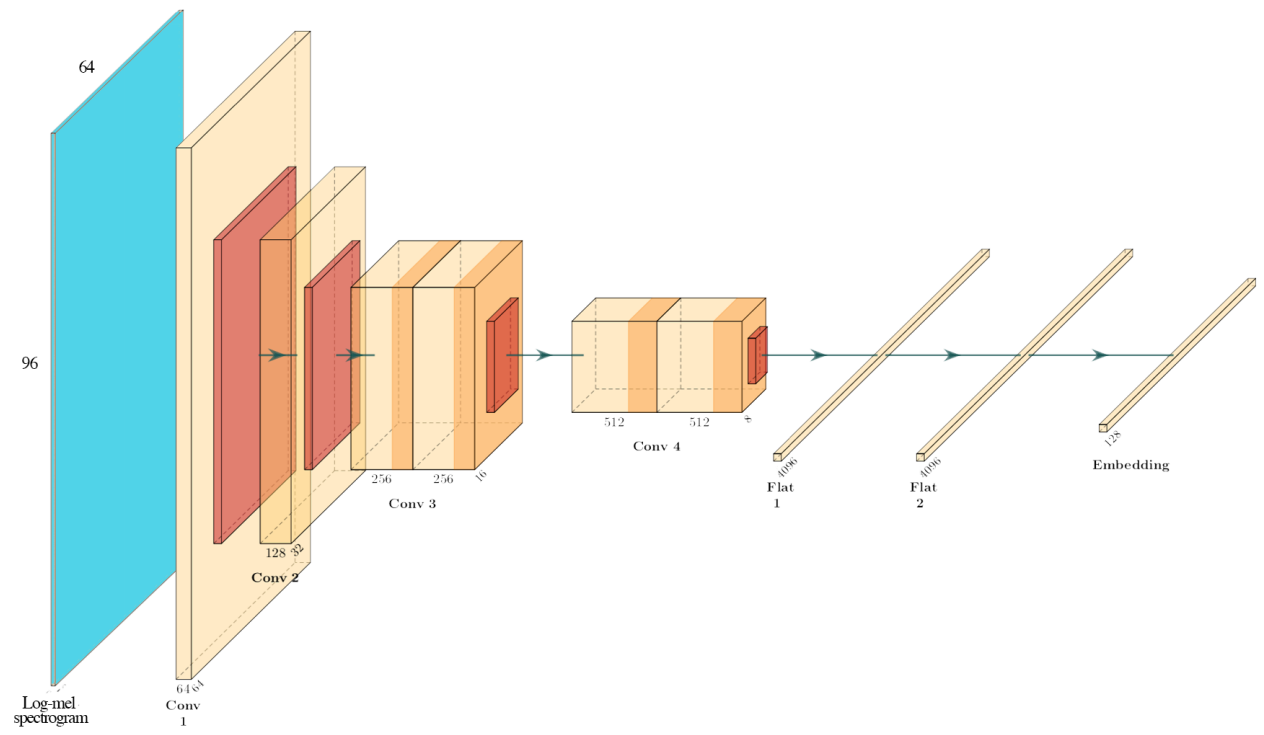
Fig. 3.2. VGGish architecture

2. When the data is ready, the next step is computing the spectrogram. For this, it is necessary to calculate first the Short-Time Fourier Transform (STFT) of the signal. The operation is performed by using a sliding Hanning window of 25 ms with a hop size of 10 ms. As a result, just the magnitudes that correspond to the positive frequencies are retained, since the ones corresponding to the negative part of the spectrogram are redundant.

3. Transforming the spectrogram to Mel scale is what follows. To do so, they compute all mel frequency bins that are going to modify the values of the spectrogram in frequency domain by following a hertz to mel conversion formula . The result is a mel spectrogram from 125 Hz to 7,500 Hz divided in 64 bins.

4. Then, the log-mel spectrogram is calculated by doing the logarithm of the previous result plus a small offset value **to avoid the logarithm of** 0.

5. As a final step, they compute a framing operation over the log-mel spectrogram. The resulting are non-overlapping examples of 0.96 seconds, in which 64 mel bands and 96 frames are contained, each frame with a duration of 10 ms.

Therefore, the result obtained is an ensemble of 10 frames, approximately one per second, each of them with size 96×64, i.e, 96 frames and 64 mel bands.

CPM: a lo largo de la memoria se habla un montón del espectrograma así que parece bueno que haya un

Embedding stage

Once the initial processing part is done and the log-mel spectrogram matrix is computed and divided into the desired number of frames, it is used as input data for the VGGish CNN. After all the computations inside the network, each example is converted into an embedding of size 128 giving a result of one of these per second of the original audio file. It is worth mentioning that in this part, a pre trained checkpoint file is loaded.

Postprocessing stage

As final step, they performed some post-processing of the resulting embeddings. A Principal Components Analysis (PCA) transformation is done joint with a whitening process. Also, a quantization to 8 bit for each embedding element. All these actions are computed with the purpose of making the final output compatible with the embeddings obtained from the YouTube-8M database.

3.2.3. Why VGGish

For our goal, one of the toughest tasks consisted on the selection of data that properly adapted to our problem and its preparation so as to obtain features that allowed us to characterize every acoustic event from a violent point of view. Since our first efforts of finding an available dataset containing enough violent scenes was driving us to a dead end, we decided to take advantage a huge database which let us rethink the standpoint about how we were going to address the problem. As it was mentioned in subsection 2.2.2, one of the main questions was how to define the term violence for each victim depending on how her certain situation. After finding the Audio Set database, previously explained in section 3.1, with all its variety of samples, we had a wide range of audio data to work with. This is how we came up with the system explained below in 3.3.1.

At this point, not only we had an idea but we had already found a data resource to start with. However, the issue was related to what kind of features could be extracted in order to categorize events from different nature with a unique violent label. An acceptable conception of the term violence could be expected to cover all kinds of short high gain events such as hits, smashes, gunshots, yells, etc. Also, we would like to introduce sounds that were likely to happen in a domestic environment within a **tense** atmosphere as children crying, dog barking or glass breaking. However, we also wanted to take into account the possibility of including other cases not usually consider violent a priori. For example, the sound of keys jangling or the noise produces by a shaver machine. These situations may be too particular and just would be present in few uses, but this is how we understand the problem given the advice of the social sciences experts in the UC3M4Safety team.

So, our first intention was to apply some audio processing techniques to extract low-level features, as the ones previously explained in 2.1.2. Even though there are plenty of

previous works and a lot of tools to work in this way, it was not sure which path should we take in order to decide what features better fitted our task. Apart from this, since the database had such a big volume it would have supposed an enormous cost of time to compute features every time we wanted to try new type of categories. Moving on, by following the advances on finding new level features already mentioned in 2.1.2, we decided to investigate new methods of extraction based on the use of Neural Network models. Nevertheless, even thought the features obtained in this case had been more appropriated, the time consumption of training a big model was one of the aspects that did not totally convince us.

The previous selection of Audio Set as our dataset allowed us to get to know the VGGish model proposed by Google researchers for feature extraction. This system loads the parameters already learnt from training with another huge dataset as YouTube-8M. This is possible due to apply transfer learning idea, explained above in subsection 2.1.3, that consists of leveraging features or weights extracted from certain models and use them in simpler ways for different tasks [43], so all the computational cost and training time is not a problem any longer. Finally, we decided to put in practice this pre trained embedding extractor by loading the given parameters so as to obtain our final input representations.

3.3. Our approach

In order to start describing our approach, we will first explained in 3.3.1 how we obtained the input data to work with by using the resources previously explained in 3.1 and 3.2, and now we will move to the implementation of the whole model in section **??**.

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3.3.1. Input data

Different phases took place when trying to obtain all the necessary data from the YouTube videos specified in the database. We will explain them from the first step of deciding which classes better fit our problem to the last part in which the desired embeddings are achieved.

Violent classes

In subsection 2.2.2 we mentioned our idea about giving the victim a choice of defining her own perception of violence, so the final implementation can adapt to her situation in a better way. To do so, we have taken advantage of the ontology provided by the Audio Set creators we explained in subsection 3.1.2.

Our system has been implemented based on the idea of using the parent-children relationship among the different nodes to ease the process of selecting among the 632 classes. It must go through all the branches so as to offer the victim the possibility of choosing

any of the audio event categories. However, instead of consider each label individually, this starts the way from the parent classes down to the children ones.

Let's say we begin from the class "Human sounds" that is the top level of all sounds emitted by humans contained in the dataset. The system will ask the user if she wants to advance in that direction, i.e., to go across the branches that belong to that part of the tree. If the answer is positive, it would go for the next class, that in this case it would be "Human Speech". It will advance this way until there were no children nodes in the actual class. When this happens, the user will be asked to add the label to the record of *violent classes*, that will be saved in a text file so they can be read by other parts of the model further on. If the user does not want to go deeper, she will be asked to add the current class to the record. If the answer is "No", then they system will jump to the next sibling category. The corresponding flowchart is shown in figure 3.3.
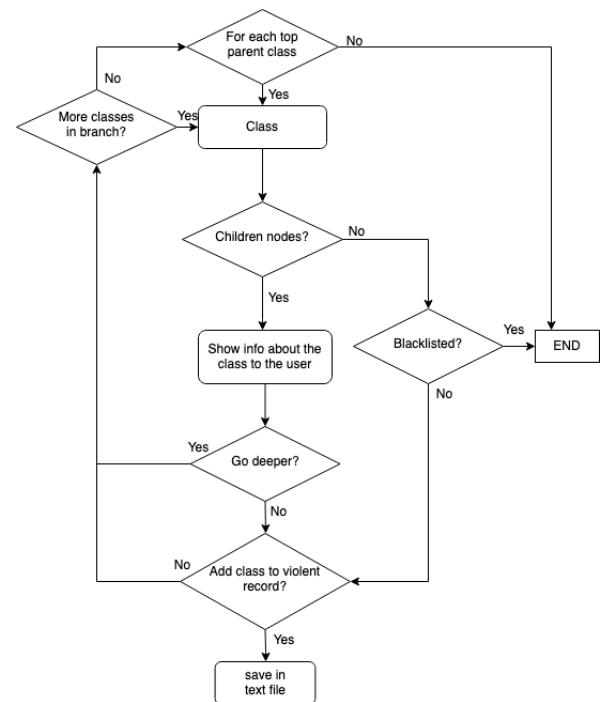
This way of flowing through the different classes allows to skip those parts that are not related to our problem. For example, as we can see in figure 3.1, one of the top parent labels is "Natural sounds", that relates to sounds from weather phenomena. In most of the cases these classes will not be selected so the whole branch can be skipped.

Fig. 3.3. Flowchart about selecting violent classes

Downloading videos

The following step consists in achieving audio files that belong to the chosen labels. For this purpose, we have made use of the .csv files that were explained in subsection 3.1.4. For each included video, we took its ID and build the corresponding YouTube URL. Once downloaded, we trimmed the file considering the onset and offset and, finally, converted it to audio format (.wav). In our script, we can pass as a parameter the identifier of the desired classes in comma-separated format and either the number of videos per class for a balanced set or a total number of downloads for an unbalanced set. However, there might be some errors when obtaining all the data: the two most common cases are due to lack of enough videos of the desired type in the dataset or because the video is not available anymore on YouTube. When this happens, a message is shown to the user.

It it also worth mentioning that throughout the developing of this downloading task, a script has been coded to achieve the whole dataset in both formats, video and audio, for future works. We are not going to specify anything else since this feature was not finally

used.

3.3.2. Extracting embeddings

At this point, all the desired data has been already downloaded to extract the embedded features that will be used to train the model. For this part, we have used the VGGish network explained in subsection 3.2.2. Since the audio files duration is usually 10 s, and the embedding extractor gives as a result a vector of size 1×128 for each second, we will obtain a 10×128 feature matrix composed by values within the range 0 - 255. Therefore, our input feature matrix will have a size of $(number of audios) \times 10 \times 128$. The corresponding labels will be stored in a vector of size $(number of samples)$.

There are some points about the data obtained in this step that should be commented. One of them is about the length of the audio files. As it was previously indicated in 3.1.3, most of them last 10 s because the creators decided to set this duration for the audio events, but this can change if the video is originally shorter. For these situations, since the model is configured to have an input of 10×128, the embedding matrix of the shorter clip must be padded with zero-rows to achieve the required dimensions. Even though this does not happen very often, there might be some silent segments that will be labelled with the category of the rest of the audio.

Reference from cases in which the matrix is 2D

The other case is related to what was explained in 3.1.4. For the recent explanation of how to extract the input features from the audio files we have utilized the first manner of accessing the data, i.e., by reading the text files with the videos information before downloading. There is a second option of using the already extracted embedding features. However, these do not look exactly the same when comparing them to the ones obtained from our own extractor. This difference is due to the implementation of the given code differs from their internal production system in computing issues such as underlying libraries in the installation of VGGish and hardware **equipment**. In spite of this, the result in classification tasks are expected to be equivalent. In order to prove this assumption, we decided to try a small system with both kinds of data. The reason for this check is that although the development of the methodologies could be made by using the first and faster manner of accessing the data, for the real implementation in the pendant device within the EMPATIA project (out of the scope of this project) only the second way will be feasible.

Include json format of tfrecord files

3.3.3. Assessing the differences between the two types of data access

In order to check what is explained above we have decided to run a little experiment in which a toy classification is performed. Also, we wanted to visualize the different features to check if we could appreciate common patterns by using the t-distributed Stochastic Neighbor Embedding (t-SNE) algorithm, which will be explained later in this section.

Our first step consisted in determining a subset extracted from the original dataset.

We thought about choosing for this small application a subset composed by three classes that could be considered violent and other three that were non-violent. Apart from this, we paid attention to the number of samples per category to pick some classes over others. Finally, we ended up picking up the labels detailed in table 3.3 and a number of 80 samples for each of them, which led us to a total of 480.

Class	Description
Screaming	A sharp, high-pitched human vocalization; often an instinctive action indicating fear, pain, surprise, joy, anger, etc. Verbal content is absent or overwhelmed, unlike Shout and Yell.
Crying, sobbing	Sound associated with the shedding of tears in response to an emotional state, arising from slow but erratic inhalation, occasional instances of breath holding and muscular tremor.
Gunshot, gunfire	The sound of the discharge of a firearm, or multiple such discharges.
Animal	All sound produced by the bodies and actions of non-human animals.
Engine	The sound of a machine designed to produce mechanical energy. Combustion engines burn a fuel to create heat, which then creates a force. Electric motors convert electrical energy into mechanical motion. Other classes of engines include pneumatic motors and clockwork motors.
Printer	Sounds of a computer peripheral which makes a persistent human readable representation of graphics or text on paper or similar physical media.

Table 3.3. CHOSEN CLASSES FOR A SMALL CLASSIFICATION.
SCREAMING, *CRYING, SOBBING* AND *GUNSHOT, GUNFIRE* ARE
CONSIDERED AS THE VIOLENT ONES.

For the classification task, we decided to create a small CNN composed by few layers. Since our input data are matrices of shape 10×128, these were treated as images so the model was built with layers that perform spatial convolution [72]. The architecture is detailed in figure 3.5. We used a small kernel size of 3×3, zero padding so as not to the shape of the output and a activation of function ReLU. Two dense layers are added at the end, first one with also ReLU as activation function and the second one with *softmax* to perform the classification, and as many filters as the number of classes.

In order to measure the results, since our subset is balanced, we could have evaluated our model by computing the accuracy and the confusion matrix. More information about these metrics can be found in the appendix 4.3. In figure 3.4, the four confusion matrices

corresponding to the training and test phases for both types of data are shown. Also, in table 3.4 are included the accuracy for each case. The results are more accurate when training with the embeddings extracted directly from the audio files we downloaded. When obtaining them from the TensorFlow files, they value of the metrics indicate a worse performance. However, we opted for this second manner because the performance difference is not too big and it requires much less computational cost and time loss.

(a) Confusion matrices when embeddings are extracted from audio files

(b) Confusion matrices when embeddings are taken from *.tfrecord* files
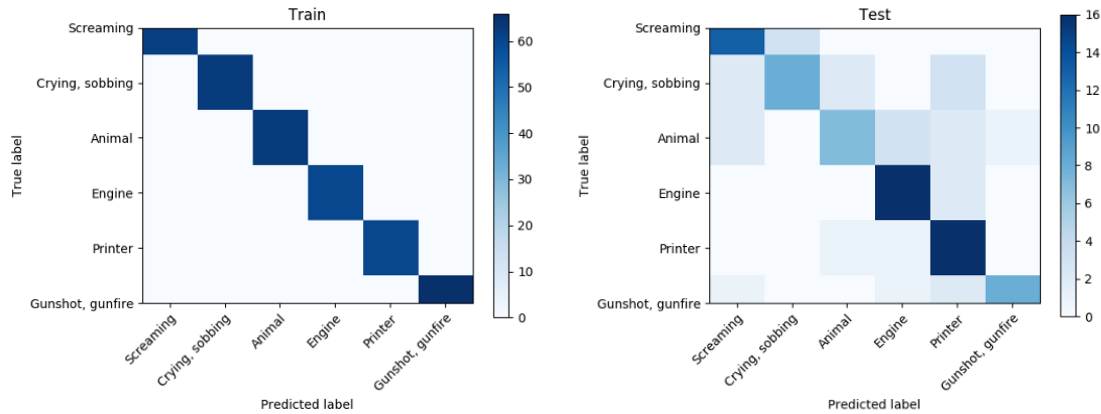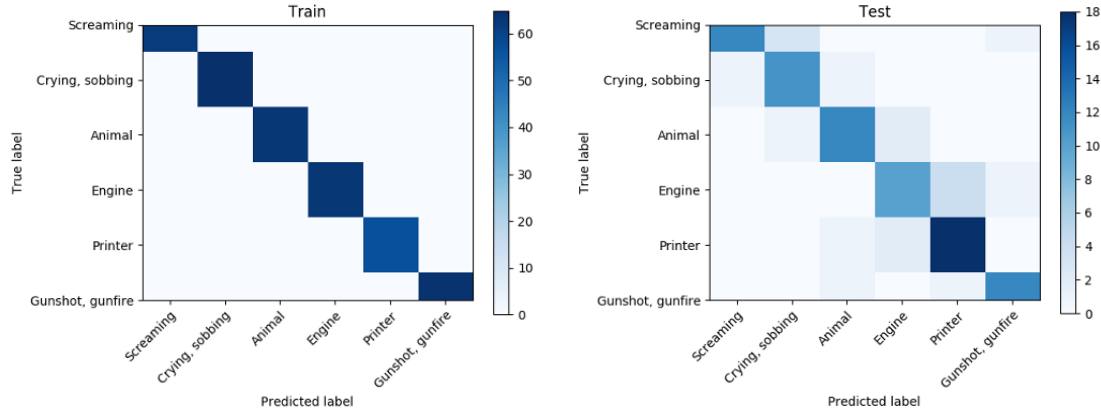
Fig. 3.4. Confusion matrices

format / subset	**Train**	**Test**
Audio file	0.98	0.63
.tfrecord	1.0	0.72

Table 3.4. ACCURACY VALUES FOR AUDIO AND *.TFRECORD*
FILES

For the training phases, it can be appreciated that there may be an over-fitting since the accuracy is perfect. This means that the NN stop improving its capacity of learning how to solve the problem in a certain moment of the training task. Instead,

it does learn some behaviour pattern that the training data follows. This impacts negatively in the model since the new data that the system will have to learn from will look different and will not follow these same rules [73]. CPM: no le daría más importancia a esto.. In spite of this result, we did not give it so much importance since we just wanted to do a quick check of the similarity between the two types of data which can be appreciated due to the similarity of both metrics results.

Dimensionality reduction for visualization

Apart from the classification exercise, we wanted to see if by plotting the data samples we were able to identify or appreciate some common patterns. In our problem, each of our samples is characterized by a matrix of features with 128 columns, which means that we were working with data belonging to a high-dimensional space. Visualizing this type of data has always been a case of study for many different fields. Plenty of methods have been published so as to find a solution for this task. Some of the most accepted methods consists on reducing the dimensionality of the data so this can be transformed from the high-dimensional space to a lower one and can be visualize in a common scatter plot of 2D or 3D. In particular, these techniques rely on the idea that within a multivariate sample denoted as $x_i = [x_{i1}, ..., x_{in}]^T$ and considered to be a point that corresponds to a $n - dimensionality$ space, a $d - dimensionality$ space can be found, so that $d < n$. If this is possible, then the observations can be transformed to this lower dimensional space d without any loses [74].

One of the most common and well-known dimensionality reduction methods is the one known as Principal Components Analysis (PCA). This follows the idea previously explained. It specifically aims at extracting the *important* information from the original data and transform them into a set formed by orthogonal variables which are actually known as principal components. This is done by multiplying the matrix data X by a projection matrix Q that contains the coefficients of the linear combinations that allow the conversion. The projections must be orthogonal to each other and they represent the data maximum variance in descending order, being the first component the one with largest variance [75]. In fact, each of the projections correspond to an eigenvector in descending order following the value of the eigenvalue. So, the first component will be the eigenvector with the highest eigenvalue. It has been proved to be one of the most reduction dimensionality techniques
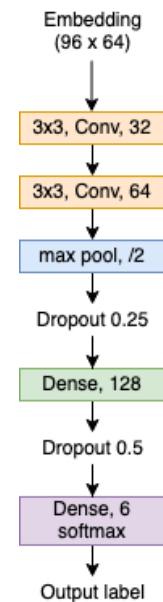

Fig. 3.5. Architecture to see how the different embeddings work

nowadays. Its use is completely accepted and it is implemented in many famous software libraries. However, it presents some limitations. One of them consists on just considering linear combinations of the original data. When the relation is non-linear, a dimensionality reduction with this technique may result in a loss of information [76].

When the relation between the different subspaces cannot defined as linear, there have been developed other methods with such as t-distributed Stochastic Neighbor Embedding (t-SNE). This algorithm appears as an extension of the previously developed Stochastic Neighbor Embedding (SNE) [77]. Both are based on the same idea of a new way of measuring the similarity between samples. Instead of comparing two observations, let's call them x_i and y_j, by computing the euclidean between them, this is done by calculating the conditional probability $p_{j|i}$ of x_j being picked as a neighbour of x_i considering that the samples belong to a Gaussian distribution centered at x_i. Its depends on how far the samples are from each other, i.e., it is high when they are close and minimum when there are totally separated [78]. Apart from this, two analogous observations are created in the subspace of lower-dimensionality, y_i and y_j, and conditional probability $q_{j|i}$ is computed in this situation. It is important that, for y_i and y_j to be faithful representations of x_i and x_j, both conditional probabilities must be equal.

In order to calculate the probabilities, a crucial factor is the variance of the Gaussian distribution. There is not a unique valid choice for this parameter, so t-SNE performs a binary search so as to find the optimal one [76]. This is also influenced by what is called the perplexity. This can be defined as an assumption of the number of adjacent neighbours for each point. It is a value that is fixed by the user, but it usually belong within a range from 5 to 50 [78].

There are several considerations that should be known before looking at a representation of data from this algorithm [79]. Actually, it is not an easy task to understand this kind of plots, since the distance between points in the new subspace are not related to the real euclidean distance, which has been denoted as "The Crowding Problem" [78]. This means that the groups cannot be interpreted as real collections of data in the the original dimension. However, in order not to misunderstand the data distribution, a couple of visualizations varying the parameters usually tends to be done so that the conclusions can be based on more than one result. In figure 3.6 we show ten t-SNE outputs, five for each type of data for diverse values of perplexity from 2 to 50.

The selection of the perplexity value depends on the number of observations per class [79]. Since our subset has 80 samples for each category, we can consider that a proper value is 20 or 30. As we can see, a boundary cannot be extracted among the different labels, but we can see some grouping patterns in the data that correspond to the original labelling and helps us to confirm the similarity of the two different given types. It is true that this method should never be used as an algorithm for clustering itself, but it is a good resource as a backing strategy to other results, as in this case.

CPM: aumentar las figuras para que se puedan leer las leyendas.
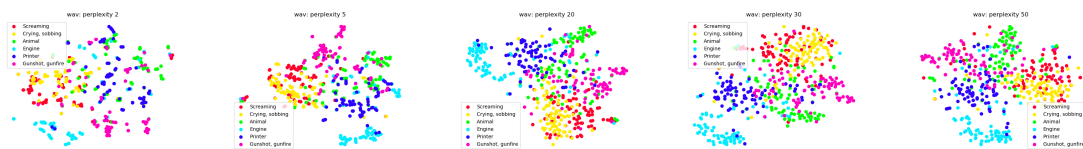
(a) From audio files
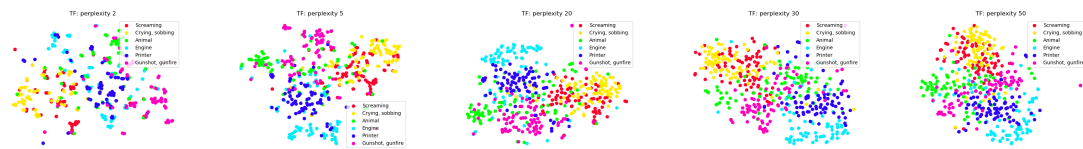
(b) From *.tfrecord* files

Fig. 3.6. t-SNE results from both formats with a legend that shows the labels of the data in the original 128D space

3.4. Models

3.4.1. Support Vector Machine (SVM)

Adapt...

Considering instances of data with their respective ground-truth labels, this classifier finds the frontier defined as a hyperplane that maximizes the distance between the two observations closest to each other that belong to different classes and are more likely to be misclassified. These two points are called support vectors [22]. This type of method is characterized for being a binary classifier. However, its implementation has been transported to multiclass problems by combining various SVMs in order to stablish a decision criterion so the whole system can chose among Q categories. This can be done by following either one-versus-all or one-versus-one approach. The former addresses the problem training Q classifiers so as to differentiate between data from one class and data from the other $Q - 1$ classes. The latter treats the problem by training $Q(Q - 1)/2$ SVMs to distinguish among all possible combinations of categories. In any of the approaches, the classification of a certain observation is performed by computing the distance between the sample data and the hyperplane that defines the frontier [1]. The one-versus-one is the one implemented by C-Support Vector Classification (SVC) from Scikit-learn library and is the one we will use in one of the experiments explained in section **??**. In figure 3.7 it is shown a representation of the decision boundaries that could designed by other type of methods against the hyperplane a SVM classifier would draw.

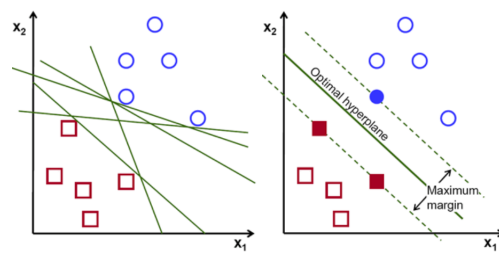Add requi- sites for sklearn algo- rithm and details about imple- men-

34

Fig. 3.7. Visualization of a hyperplane set by SVM and other decision boundaries [80]

4. EXPERIMENTS

In this chapter we are going to explain the final models of the work and the preparation of the input data to feed these models. For the different solutions, we have used the algorithms previously explained in the models section 3.4. Below, it can be found a list which includes the 6 implementations:

- SVM classifier for multiclass classification

- SVM multiclass + SVM for a final binary classification

- LSTM for multiclass classification

- LSTM multiclass + SVM for a final binary classification

- CNN for multiclass classification

- CNN multiclass + SVM for a final binary classification

4.1. Input data preparation

For the proposed experiments, we have decided to build a small dataset formed by embeddings extracted form the *.tfrecord* files that belong to 14 classes: half of them *violent* and the other half, *non-violent*. To find these, we first did a run on the simple user-interaction program that is explained in 3.3.1. **Putting ourselves in a gender-based violence victim's skin**, a total of 28 classes were selected . From this set, we picked 7 as the violent classes. The other 7 were chosen just by looking at the ontology.

It is important to mention that this small dataset is composed by samples with just one label assigned. As explained before in 3.1, the database is unbalanced. Some of the most appropriated classes to be considered violence are really little populated. When doing the selection of categories, apart from paying attention to the own meaning of the class, we also checked the number of samples. For the non-violent type, this was not a problem, since we took some of the most-populated labels. However, in the violent case, we had to deal with the condition of representing violence and also having enough observations. So, due to these limitations, we could not obtain a set naturally balanced. In table 4.1, it is shown the 14 labels that were selected divided in violent and non-violent. In figure 4.1, a bar plot shows the number of samples obtained per class right after the selection.

Some initial preprocessing were performed before passing the data to the different models. As mentioned in 3.3.2, we had to deal with the zero-filling problem, which means that some of the rows of the embeddings matrices are completely zero because of

Include description of classes?

Violent	Non-violent
Baby cry, infant cry	Printer
Slap, smack	Music
Screaming	Speech
Machine gun	Vehicle
Breaking	Animal
Slam	Dishes, pots, and pans
Yell	Wind

Table 4.1. RELATION OF *VIOLENT* AND *NON-VIOLENT* SELECTED CLASSES

the duration of the original video is less than 10s. As a solution, we decided to substitute the zero numbers in all the data with the machine epsilon[1] value.

However, in the two models that use SVM for the multiclass classification a different solution was proposed. As it was explained in subsection **??**, this algorithm needs the input data matrix to be in the form [*number of samples* × *number of features*], which differs from the originally shape of our data, [*number of samples* × *number of seconds* × *number of features*]. For this reason, we decided to reshape our data to the required form which resulted in a matrix of shape [(*number of samples* × *number of seconds*) × *number of features*]. With this conversion, instead of classifying full audio instances, the samples became the seconds of those instances. In order to remove zero data, we first checked the amount of zero-rows in every class. Since it was not very meaningful, we took them out of the dataset.

Once we had our data with all non-zero values, we needed to convert the set to balanced. First, for the classification task, we divided our data in train, validation and test subsets, using a 20% for last one. Then, we decided to take out of the set half of the samples from the most populated classes [2] from the train and validation sets, and generate new data for those with less observations by applying the data augmentation technique explained in subsection **??**. **This technique deduces a distribution for the given observations and generate synthetic samples within the distribution of each class until even the most populated category.** Just the train and validation set were subjected to this conversion, leaving the test set with the original embeddings. In figure 4.2, the subfigure (a) shows the distribution of data per class in the dataset for the case of the models that use SVM multiclass classifier. In subfigure (b), it is shown the distribution for the other four cases.

---

[1]The machine epsilon value is considered the smallest value that satisfies $1 + \epsilon_{match} > 1$. It consists on the difference between one and the next closest number that is representable as a machine value [81]

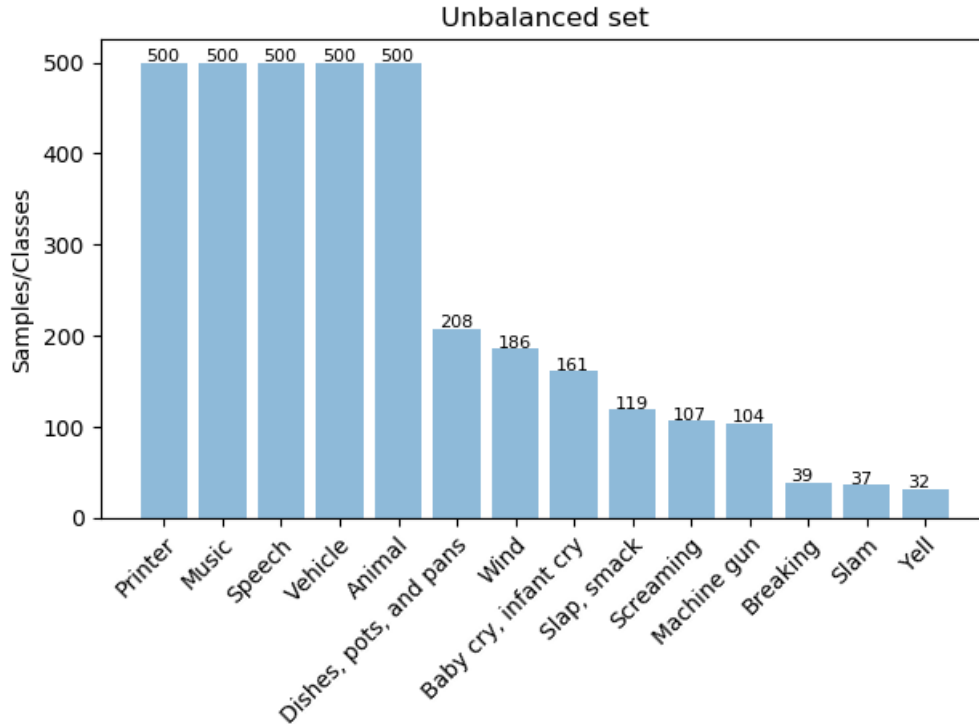[2]*Speech*, *Music*, *Vehicle* and *Animal*

Fig. 4.1. Bar plot that shows the number of samples for each of the selected classes. Clearly, the violent categories are much less populated than the others, that did not have to much any semantic criteria

After these sets are obtained, the data augmentation technique SMOTE is applied. Finally, the shape input data for each of the experiments is shown in table 4.2

	SVM multi and SVM + SVM binary	**LSTM multi and LSTM + SVM binary**	**CNN multi and CNN + SVM binary**
Train and validation	17645 (1993 per class)	2800 (200 per class)	2800 (200 per class)
Test	6898	699	699

Table 4.2. TRAIN, VALIDATION AND TEST SET FOR DIFFERENT EXPERIMENTS

4.2. Implementations and results

For all the experiments, as mentioned above, the dataset was split by selecting a 20% of the data for the testing procedure. The other part was divided into train and validation subsets with a k-Fold Cross Validation technique, with 10 folds, which can also be called 10-fold cross-validation. A more detailed explanation about this resampling technique can be found in appendix 4.4. The average and standard deviation of the results for the different folds were obtained for training and validation. Then, a final measurement was
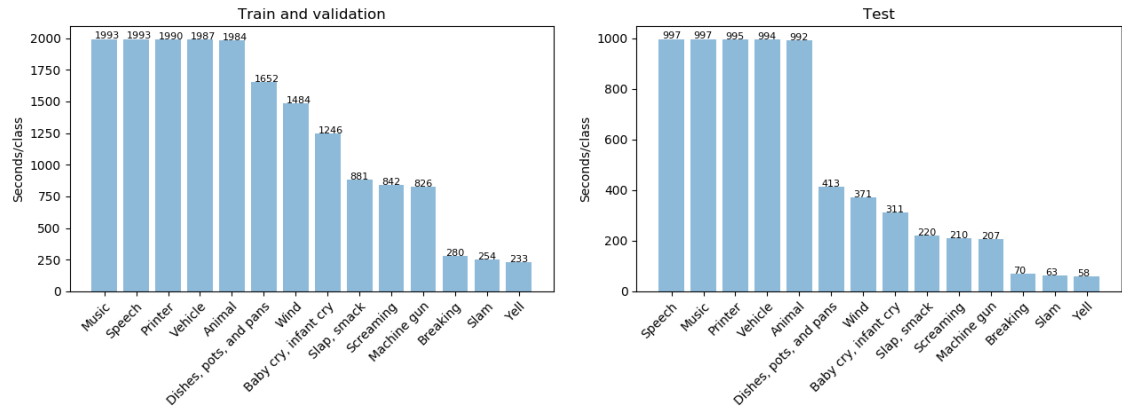
(a) This is the resulting subsets after downsampling the most populated classes and removing the zero-rows for the experiments that involve a SVM classifier
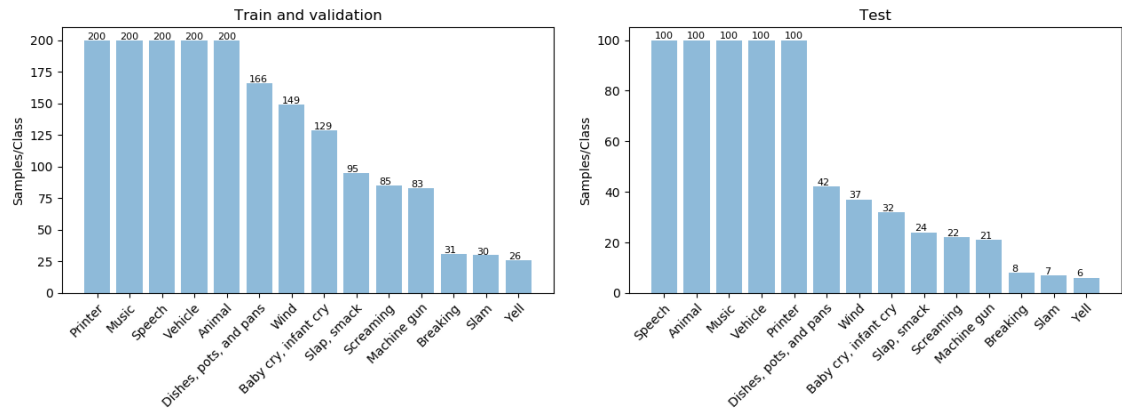
(b) This is the resulting sets after downsampling the train and validation sets. The test set remains the same after the split

Fig. 4.2. Number of observations for train, validation and test subsets used in the different experiments

performed for the test set. The way of checking the model performance was by finding the accuracy and confusion matrix, whose explanation can be found in appendix 4.3. For the cross-validation procedure, a matrix with the average values[3] was obtained and also one for the standard deviation[4] so the estimation of the model is represented for the corresponding subsets.

---

[3]In the average matrices, the results for each cell are shown just with one decimal in order to make a better and more comfortable visualization. However, the colour bar on the right of the plots must be taking into account since there might be some cells in which the value is 0.0 but it is actually greater.

[4]In the standard deviation matrices the results are shown multiplied by 10^2 in order to see the value in the different cells of the matrix
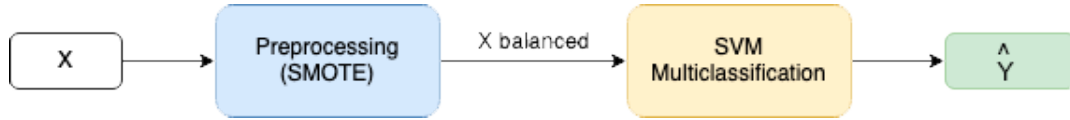
Fig. 4.3. SVM multiclass classifier whole model. *X* is the input data that can be from train, validation or test set. $\hat{Y}$ is the predicting labels for *X*.

4.2.1. Implementation 1: SVM classifier for a multiclass classification

Our first experiment consists of a SVM classifier that is used for a multiclass classification. In this case, we wanted to check the results of the performance of one of the most employed techniques in this filed different from NN. It is true that this method is originally designed for binary problems but, as explained in 3.4.1, we took advantage fo the multiclass algorithm. To define our model, we used mainly the default parameters. These includes of using a RBF as a kernel. In this work, we have not investigated which type kernel could better fit our problem, however we found in the literature that the default option of RBF is the most appropriated for real world applications [82].

In figure 4.3, a block diagram representation of the whole model is included. For this algorithm, the predicting labels $\hat{Y}$, are hard values, i.e. they correspond directly to the estimated label.

Below, we can find the results for the different sets. In figure 4.4, the confusion matrices for the train and validation sets are shown. In figure 4.5, the confusion matrix for the evaluation on the test set is included. Finally, in the bar plot of figure 4.6, the accuracy values for the three sets are represented. For this case, the standard deviation is not shown for train and validation because it is zero when considering two decimals.
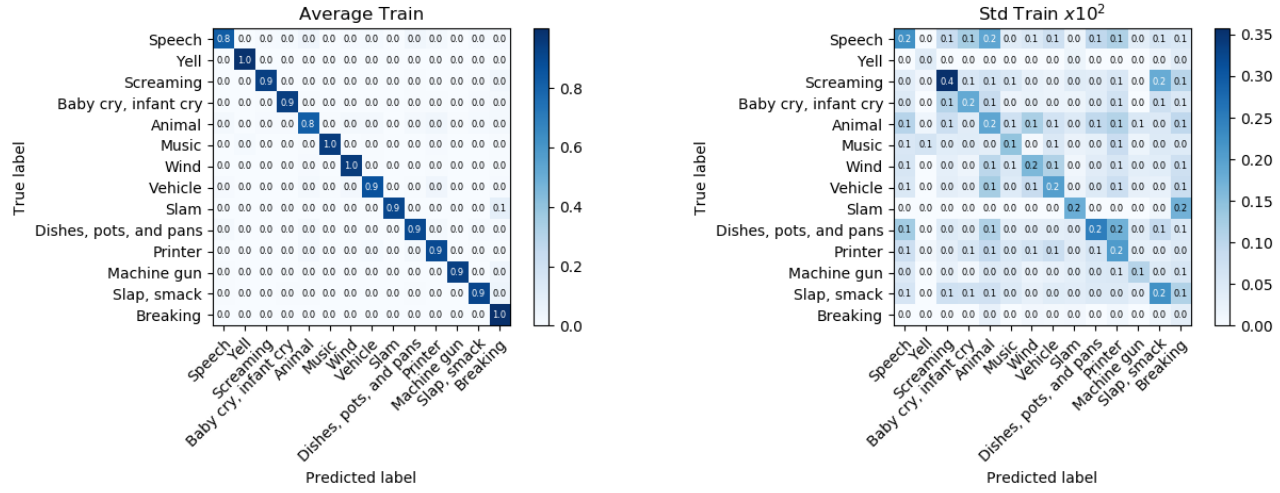
(a) Average and standard deviation for the train set
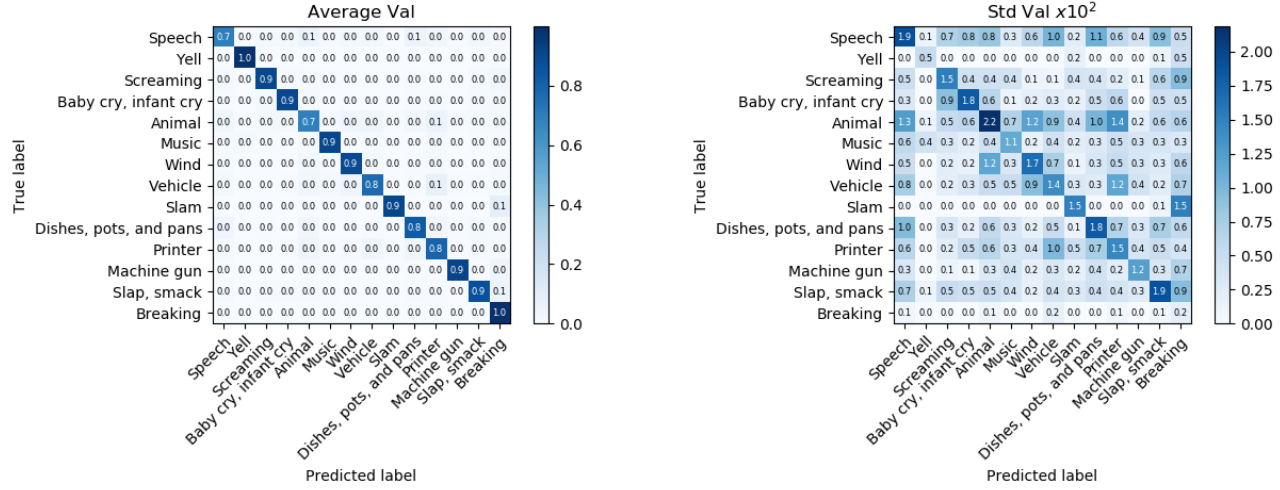
(b) Average and standard deviation for the validation set

Fig. 4.4. Confusion matrices for SVM multiclass classification for train and validation sets
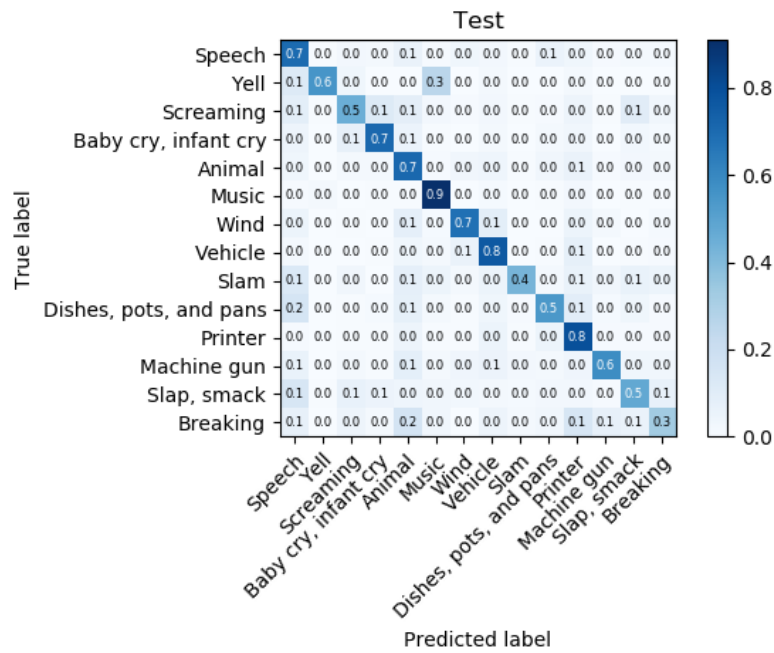
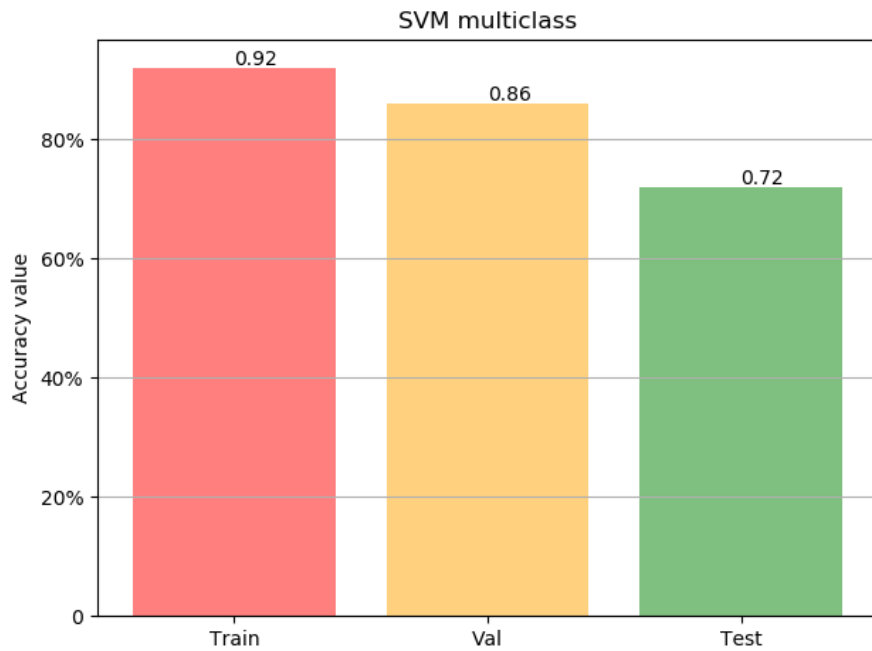Fig. 4.5. Confusion matrix for the test set for the SVM multiclass classification

Fig. 4.6. Accuracy values for the three sets for the SVM multiclass classification

ACRONYMS

.csv Comma-separated values. 21, 22, 28

.wav Waveform Audio File Format. 28

AED Acoustic Event Detection. 18

AED/C Acoustic Event Detection and Classification. vii, 3

ANN Artificial Neural Networks. 7, 10

ASC Acoustic Scene Classification. vii, 3, 11, 12, 15

BAA Broad Agency Announcement. 14

CASA Computational Acoustic Scenes Analysis. 3

CHIL Computers in the Human Interaction Loop. 18

CNN Convolutional Neural Networks. 7, 11, 22, 24, 26, 30, 36, 38

ConvNet Convolutional Network. 7, 8, 10, 22, 23

CV Computer Vision. 1, 3, 22

D Dimensions. 8, 9

DARPA Defense Advanced Research Projects Agency. 14

DNN Deep Neural Networks. 13, 15

F0 fundamental frequency. 11

FC Fully-Connected. 7, 8, 10, 11, 23, 24

GMM Gaussian Mixture Models. 6, 12, 13

HMM Hidden Markov Models. 13

ILSVRC ImageNet Large Scale Visual Recognition Challenge. 22, 23

IPTO Information Processing Technology Office. 14

IPV Intimate Partner Violence. 16

K-NN K-Nearest Neighbour. 6

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APPENDIX X

4.3. Metrics

A fundamental part of a machine learning project consists of checking the performance. There are plenty of metrics to carry out this evaluation and the results will look in one way or another depending on the method utilized. The following two are the most used in this project

4.3.1. Classification Accuracy

This is a technique commonly used and it is usually referred to as just accuracy. It can be defined as the relation between the amount of right predictions and the total number on input instances [83].

$$acc = \frac{Number\ of\ incorrect\ predictions}{Number\ of\ total\ input\ instances}$$

This metric best works when dealing with a balanced dataset, i.e., the same of number of samples per class. If the problem is addressed with unbalanced data, then the accuracy value could be a higher value due to predict all the instances belong to the major class. For example, if 90% of the data are part of the same class A and all the predictions results are this class, then the accuracy value will be 90%, which apparently is a satisfying output, even though we are misclassifying all the samples from class B [84].

4.3.2. Confusion matrix

As it own name describes, the output of this type of metric consists of a matrix which shows a complete evaluation of the model. By definition, an entry i, j of the matrix denotes the amount of observations that belong to group i but are predicted as group j [83]. For example, considering a binary classification problem in which there are two classes, YES

n = 165	Predicted: NO	Predicted: YES
Label: NO	50	10
Label: YES	5	100

Fig. 4.7. Example of confusion matrix

and NO, for a test set composed by 165 samples, the matrix included in figure 4.7 is obtained.

There are four groups that can be extracted from this matrix: True positives, the samples that are predicted as YES and that is in fact their true label, True Negatives, those cases that were predicted as NO and they are originally labelled as NO, False Positives, in which the predicted label is YES but they are actually negative, and False Negatives, those in which the predicted label is NO when their original label is YES.

This metric an the one explained before, accuracy, can be related by taking the diagonal of the matrix and computing the next operation:

$$acc = \frac{TruePositives + FalseNegatives}{Total\ number\ of\ samples} = \frac{100 + 50}{165} = 0.91$$

When the classification task consists on more than two classes, a multiclass problem, a similar definition of the confusion matrix can be extended from the binary problem. Considering a certain observation C_k, the True positive part of the matrix is placed in the exact point where the column and the row of this certain observation are crossed, i.e, when the predicted label is equal to the true label. The False positives samples are placed along the column C_k for all the rows $C_0, ..., C_{k-1}, Ck + 1, ..., C_n$ which refers to all the samples that have been misclassified with the class C_k. The False negatives are, however, all the samples that originally are labelled with C_k tag but have been wrongly categorized with $C_0, ..., C_{k-1}, Ck + 1, ..., C_n$ classes. Finally, the True negative samples are distributed across all the other positions in the matrix. In figure 4.8, a good example for this explanation is shown.
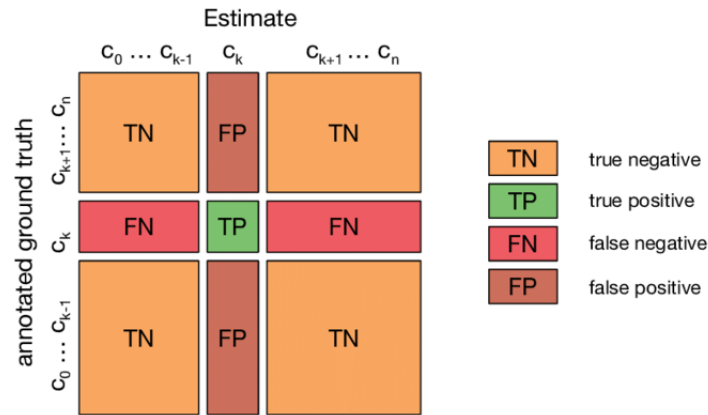

Fig. 4.8. Confusion matrix for a multiclass classification [85]

4.4. k-Fold Cross Validation

The cross-validation technique consists in a resampling practice that is commonly used in order to evaluate machine learning algorithms when the dataset is not very large. It just depends on the parameter k which represents the amount of folds or groups the data is

going to be split into. This is the reason of the k-fold prefix. When the method is referred to in a situation in which the parameter is already fixed, for example, if $k = 5$, it can becomes named as 5-fold cross-validation.

The purpose of this procedure is to check the performance of a machine learning model on unseen data. This is for not evaluating with the data used for the training process. It is really used nowadays and allows to obtain a less biased estimation than if using other kind of techniques as just a simple train and test split [86]. The steps followed by the method are listed below [87].

1. The data is split in a random way into k folds. The value of this parameter can be chosen previously by running the algorithm for different options and picking the one with the best performance. However, a not very high value is usually chosen, keeping it in a range between 5 and 10.

2. Fit the model by using the data in the $k - 1$ folds as train set, and the other part in the k fold for the validation process. Collect the results for this configuration.

3. The process must be repeated until all folds have been used as the validation set. Then, the average and standard deviation of all the results can be computed as the metric of the model.

Sometimes, instead of dividing the whole set of data in k folds, it is first done a split into train and test sets. Then, the test set is excluded for a final measure and the train is split again with the k-Fold Cross Validation procedure. The concept of the technique is shown in figure 4.9.
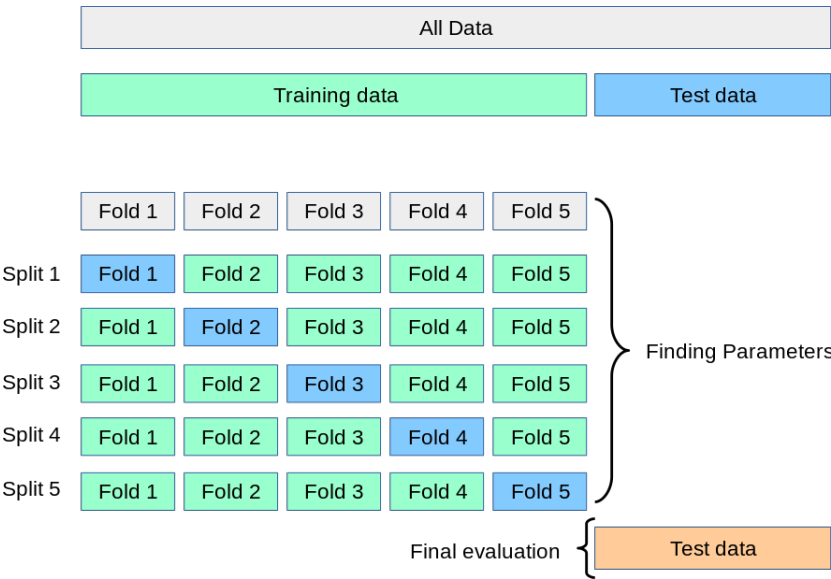

Fig. 4.9. K-fold cross-validation scheme. The data is first split into train and test, and then the train is split again with this method [88]