PERSA+: A Deep Learning Front-End for Context-Agnostic Audio Classification

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Abstract—Deep learning has been applied to diverse audio semantics tasks, enabling the construction of models that learn hierarchical levels of features from high-dimensional raw data, delivering state-of-the-art performance. But do these algorithms perform similarly in real-world conditions, or just at the benchmark, where their high learning capability assures the complete memorization of the employed datasets? This work presents a deep learning front-end, aiming at discarding detrimental information before entering the modeling stage, bringing the learning process closer to the point, anticipating the development of robust and context-agnostic classification algorithms.

Index Terms—audio classification, robust event detection, deep learning.

I. INTRODUCTION

Many contemporary audio applications rely on semantic audio analysis workflows that even run on mobile computing terminals [1]. Therefore, the improvement of audio classification algorithms has become a necessity. In recent years, Convolutional Neural Networks (CNNs) have set the standard on audio semantics, surpassing conventional methods which employed hand-crafted feature extraction as the front-end and a classifier as the back-end [2]. In the meantime, the process of temporal feature integration introduced additional engineering steps, attempting to capture the temporal dependency between successive feature observations, delivering performance improvements [3]. Now, CNNs have been applied to diverse machine learning (ML) tasks, delivering state-of-the-art performance, enabling the construction of models that learn hierarchical levels of features from high-dimensional data, i.e. spectrograms or even raw waveforms [4]. One question that arises, though, concerns the generalization of those algorithms, i.e. their ability to maintain robustness when encountering acoustic samples outside the deployed datasets [5].

The motivation behind this work emerged after the experimentation with a deep learning model on a speaker recognition problem and the empirical observation of a rather strange behavior. At some point, while developing the model, recognition accuracy reached a surprisingly high value (above 95% for a ten-speaker task), while, normally, we were straining to achieve a score of over 60%. Unfortunately, after investigating the situation, it turned out that this unforeseen performance leap occurred due to some abnormal data values: a bug in the audio processing library was producing artifacts on the produced spectrograms, and some time-frequency (tf) bins had the exact same -unique- values, based on the audio file they came from. These values were present in the high-frequency range of the spectrogram, forming a kind of a watermark. Therefore, any of the spectrogram slices that were used as input samples, contained a unique identifier. They were no more than 1% of the total values that each sample consists of. Nevertheless, the neural network was capable of focusing on these values to complete the assigned task with ease, ignoring all the rest, useful, data. Obviously, this did not solve the classification problem with success, because the data was unique for each file and not for each speaker. A train/test subset formation flaw via sample shuffling did the trick: the model just learned all the watermarks for each speaker, which were present in both train and test subsets. It became apparent that a deep learning model may be easily trained in an unwanted way, just by memorizing insignificant amounts of meaningless data. It should also be mentioned that these tf areas had extremely low power, below -90 dBFS, way under the dynamic range (DR) of an audible, recorded sound. Therefore, according to our judgment, careful data curation and targeted preprocessing should always accompany deep learning algorithms to force them to focus on the target patterns and not just learn some random values.

This work presents a preprocessing method aiming at discarding detrimental information before entering the modeler, anticipating the development of more robust and context-agnostic classification algorithms.

II. RELATED WORK

Hand-crafted feature extraction served the field of semantic audio analysis for many years [6]. Undoubtedly, deep learning brought higher accuracies, while the increased computational requirements are no more a barrier, as even the mobile computing devices offer enough computing power [7]. There is a variety of deep learning implementations for General Audio Detection and Classification, Environmental Sound Recognition, Keyword Spotting, Speech Emotion Recognition, and more. There is also a plethora of network architectures, including convolutional models [8], recurrent approaches [9], or even ensemble learning tactics [10]. That is, the emergence of more capable and efficient deep learning models for audio semantic analysis should not overlook the need for audio-specific pre- and post-
processing strategies, in applications where interpretability and generalization are crucial. In this direction, some considerations are expressed in the following paragraphs.

First, end-to-end learning has been adopted from the image analysis field and most of the early studies modified 2D topologies for image recognition, adapting them to audio classification tasks, without taking into consideration the particularities of semantic audio analysis [11]. Audio waveforms are usually converted to\(tf\) representations, such as spectrograms. Recently, many approaches are characterized as end-to-end and process\(1D\) data, employing filters with size and stride that are compatible to the window and the hop size that are used by the Short-Time Fourier Transform (STFT) [12]. Newer designs make use of smaller filters (e.g. 10 sample-long filters at 16kHz) [13].

The sample-level CNN is an excellent example of this approach, specifying filters with very small granularity in time for all convolutional layers, achieving decent performance [14].

Second, network architecture is always in the spotlight, as it may have an impact on the effectiveness of a deep learning model. U-Net [15] and Inception [16] are two examples of important milestones in the development of CNN classifiers, featuring a more complex architecture than the early approaches. SincNet is a network dedicated to audio semantic recognition that is based on parameterized sinc functions, which implement band-pass filters that only learn low and high cutoff frequencies [17]. Nevertheless, no noticeable gains have been observed when deploying these models [18], a consideration that is in accordance with the results of similar works that employed significantly larger datasets and flagship CNN architectures [19].

Third, there is evidence that CNNs are prone to overfitting and gaining a dataset bias [20]. Deep architectures require larger amounts of data for a meaningful training, in contrast to conventional learning models. For this reason, various data augmentation techniques are typically used. Furthermore, CNNs are subjected to data deformations, such as loudness variations, additive noise, etc. [21]. In past studies, the objective was to design robust and context-resistant techniques that could be used in real-world applications. Nowadays, the trend is to train the deep learning models with huge amounts of data to make the most of them. Approaches like MVA [22] and RASTA [23] that, for example, give noise robustness in Automatic Speech Recognition (ASR), are profound for sure. This is crucial since, in many applications, a trained ASR system needs to carry out recognition in a variety of everyday acoustic environments. It seems that this is not the case in the deep learning era. Many studies do not specify any pre-processing method to deal with inputs of different scaling or contexts, although it is obvious that data curation has a major impact on the performance of deep learning algorithms [24]-[25]. Ambiguous normalization strategies are deployed in many works [11], while there are cases where data normalization is based on the whole dataset, probably getting a hint of the test data [14].

For these reasons, we believe that state-of-the-art deep neural networks should be accompanied by well-defined pre-processing protocols so that the model adapts to the particularities and constraints of the audio domain. For instance, Pons et al. [26]-[27] have conducted exceptional research on deep network designs for audio analysis. They follow a two-part model decomposition with the front-end being the part of the model that interacts with the input signal to map it into a latent space, and the back-end predicting the output, given the representation obtained by the former. This approach is highly appreciated, as it can be considered more methodical, better facilitating the optimization of data pre-processing flows. Some works do indeed emphasize on data normalization, aiming at improving the robustness of the systems, deploying sophisticated front-ends along with context-adaptive recognition strategies [28]. A notable front-end of this kind is PCEN, which improves robustness to loudness variations [29]. This can be applied in far-field recording conditions, where signals are attenuated due to the distance. The key feature of PCEN is the use of dynamic compression that is based on automatic gain control, replacing the widely used static, log compression. On large evaluation sets that include noisy data and far-field recording cases, PCEN improves recognition performance [29]. Additionally, it can be implemented in real-time and be distributed across sensors, preserving the locality structure of harmonic patterns along the mel-frequency axis [30]. Nevertheless, there are occasions that PCEN does not manage to deliver the expected results, and a combination of methods is required for optimal operation [28].

These findings were taken into consideration for proposing a preprocessing protocol targeted to deep learning architectures, aiming at homogenizing data for eliminating the impact of the acoustic context on audio recognition and increasing the robustness of the models. That is, instead of augmenting data for simulating different versions of a particular acoustic event, we try to shape each single pattern to be as representative as possible.

### III. PER SAMPLE ENERGY NORMALIZATION

As highlighted, it is probable for a classification algorithm to perform worse outside in-vitro conditions [31]. A factor that may impact real-world performance can be the variations of the signal power [2]. We consistently try to avoid any input-gain bias to our algorithms -except when it is required- by excluding energy-based audio features in standard machine learning approaches [32]. This principle is followed on the CNNs as well, adopting the PER-Sample (PERSA) normalization strategy [2]. The latter ensures zero bias to input gain, eliminating this level of freedom. In brief, PERSA specifies the subtraction of the log-mean value on any 2-dimensional \(tf\)-sample, before entering the convolutional network. The length of the sample should be relatively large (i.e. from 500 ms to 5000 ms) for avoiding changes in the dynamics of the signal. Hopefully, sample lengths of the same magnitude are preferred in most deep learning audio recognition tasks.

### IV. CONTEXT-AGNOSTIC FRONT-END PROCESSING

The PERSA+ front-end comes as an extension of PERSA, expecting to favor performance on noisy recordings and bring consistency on diverse acoustic contexts. It is based on the hypothesis that: (a) parts of audio data that lay into the lower \(DR\) may not be crucial for audio classification and (b) it could be better for these parts not to be routed to the modeler because, instead of useful data, it is more probable to contain noise dis-
tributions that can be watermarked. The developed method was built on these assumptions, specifying noise injection to the data before entering the classification unit (both in train and test phases), expecting that it will handle noisy data more accurately but without compromising performance in high Signal-to-Noise Ratios (SNRs). PERSA+ specifies three core processing steps: (a) Noise Injection, (b) Log Compression, and (c) Mean Subtraction. Let us describe these in more detail.

Let the $k$-th sample of the signal have the form of a 2D two-dimensional $t f$ representation comprising of $L$ time frames and $M$ frequency bands, so as a $t f$ bin can be noted as $s[i, j]$ with $\{i \in Z \mid 0 \leq i < L\}$ and $\{j \in Z \mid j \in 0 \leq j < M\}$.

A. Noise Injection

First, a $t f$ representation of a randomly generated noise segment ($N$) is generated (i.e. pink noise). Let $p_r$ and $p_s$ denote the power of the signal and noise segments, respectively. The level of noise injected to $S_n$ is determined by the parameter $q$ (in dB).

$$S_n[i, j] = \left( S^2[i, j] + N^2[i, j] \right)^{1/2} \left( \frac{p_s}{p_n \cdot 10^{-q/10}} \right)$$ \hspace{1cm} (1)

B. Log Compression

Afterward, the log function with base 10 is applied to $S_n$: \hspace{1cm}

$$S_{ln}[i, j] = \log_{10} S_n[i, j]$$ \hspace{1cm} (2)

C. Mean Subtraction

Then, the mean value of the $t f$ slice is subtracted:

$$S_{persa+}[i, j] = S_{ln}[i, j] - \frac{1}{L \cdot M} \sum_{i} \sum_{j} S_{ln}[i, j]$$ \hspace{1cm} (3)

At this point, it should be noted that the final processing step could alternatively employ the division of each $t f$ bin by the mean energy of the whole sample, before applying the logarithmic function. The two approaches (log - mean subtraction vs. mean division - log) have the same impact on the shape of the final spectrotemporal sample with a slightly different offset. These two variations were tested and the former yields slightly better -and more consistent- results, directing the final decision. Finally, a small amount of random gain ($\pm 3\, dB$) is applied for differentiating similar $t f$ samples, making the data more meaningful for training.

It is obvious that PERSA+ depends on the parameter $q$. High values (e.g. $60\, dB$) virtually make no difference when compared to the standard method (PERSA), whereas lower values (e.g. $12\, dB$) significantly affect the input data, as a relatively high noise floor is set. This may bound the performance of the classification system, but with the promise for better performance under low SNR scenarios. All these concerns were taken into consideration for designing the appropriate experimental setup.

V. EXPERIMENTAL SETUP

A. Overview

The experimental setup employs the comparison of various audio preprocessing techniques, under typical classification tasks, while a special dataset has been developed to simulate low SNR conditions as well. A common 2D CNN, applied on mel-spectrogram audio representations, was selected as the core classification pipeline. Technically, Python was used for deploying the experimental setup with librosa [33] and Keras facilitating the feature extraction and deep learning procedures [34], respectively.

B. Datasets

The performance of the competitive methods was mainly evaluated on a 3-class classification task, according to the Speech/Music/Other (SMO) taxonomy. The LVLib-v1 dataset was deployed as a baseline. To conduct additional experiments, the LVLib-v3 was also employed. This dataset was generated after applying random gain ($[0, -10, -20, -30\, dBFS]$) on LVLib-v1, for each fold and class, respecting a 3-fold setup. Following a similar philosophy, the LVLib-v4 brings further signal degradations. In specific, audio waveforms are contaminated with additive interference signals. The interference follows the SMO taxonomy and was added according to a specific protocol: 1st fold - Music is contaminated with Speech. Speech with Music and Other with machinery noise, 2nd fold - Music is contaminated with Other, Speech with machinery noise and Other with Music, 3rd fold - Music is contaminated with machinery noise, Speech with Other and Other with Music. The SNR of the additive noise follows a Gaussian distribution ($9 \pm 3\, dB$). When LVLib-v4 is used, the algorithms are trained on LVLib-v3 with the test fold substituted by the corresponding fold of LVLib-v4. Moreover, a combination of LVLib-v1 and v4 sets was used, simulating mixed conditions. All LVLib datasets are publicly available at m3c_web_auth_gr/research/datasets/. A 3-fold data splitting is recommended, facilitating the direct comparisons between the results of different studies. One more task was conducted on a 10-class ESR taxonomy, using the well-known UrbanSound8k dataset [35].

C. Competing Front-ends

Five different front-ends were tested: log-compression (LOG), log-compression with amplitude augmentation (LOG-AU), log-compression with thresholding (LOG-T), PERSA, PERSA+, and PCEN. The LOG method employs the log transformation of the spectrogram power. LOG-AU additionally brings magnitude augmentations for overcoming any level bias on the classifier. That is, random gain is applied before the data entering the back-end, according to a uniform distribution with the $a$ and $b$ parameters set to $-30$ and $30\, dB$. Next, LOG-T specifies a per-sample maximum normalization with logarithmic compression, compressing the DR of the signal, as denoted by the following equation:

$$S_{log-t} = \log_{10} \left( S + 10^{c/20} \right)$$ \hspace{1cm} (4)

where parameter $c$ corresponds to the desirable DR (in dB). Finally, The PCEN front-end was deployed using the default librosa setup [33].

D. Backend

Based on former results, the simple VGG-like architectures show adequate performance in all circumstances [18]. Therefore, a decision to use a lightweight backend of this type with
roughly 100k parameters was made. It consists of four successive CPD blocks (comprised of successive Convolutional, Pooling, and Dropout layers), a Global Average Pooling, two Fully Connected, and an intermediate Dropout layer. Filter-size was set to 3x3 globally, while the number of filters was set to 16, 32, 64, and 128 for the four convolutional layers. The pooling size was set to 2x2 for all layers of this kind. The fully connected layers had 32 and [number of classes] neurons respectively. The rest of the parameters are the ReLU as the activation function for all intermediate layers, SoftMax for the output layer, Categorical Cross-Entropy as the loss function, and Adam as the optimizer. The dropout rate was set to 20%.

VI. RESULTS

First, for the PERSA+ and LOG-T algorithms a hyperparameter optimization procedure was carried out. Figure 1 demonstrates the performance of the two methods on LVLib-v3, with respect to the $q$ and $c$ parameters. The values of 9 dB and 30 dB were selected respectively, aiming at maximizing the effect of the methods, without causing significant performance degradation on clean data. Table I presents the accuracy of PERSA+ when deployed on LVLib-v4, under variable SNR versus different $q$ values. The relation between the SNR and $q$ parameters in terms of classification performance underpin the impact of the noise injection strategy when dealing with noisy data. Table II shows the scores for the competitive methods on three different tasks. All methods perform well on the LVLib-v1 dataset (85.9 ± 0.9%), with these that theoretically are more robust (LOG-T, PCEN, PERSA+) having slightly lower ratings (85.2 ± 0.6%) than the “standard” ones (LOG, LOG-AU, PERSA - 86.6 ± 0.7%). On the LVLib-v3, which employs input-gain variations, the LOG and LOG-AU methods fail with a performance reduction of about 6.5% and 4.5%, respectively, whereas all other approaches keep their ratings (mean performance drop of 0.2%). On the LVLib-v4, which has noisy data, the PERSA+ shines. A wide performance gap is evident between the first the rest of the methods, with the scores being 75.8%, 73.3%, 73.9% for the PERSA+, LOG-T, and PCEN front-ends, respectively.

Table III depicts performance ratings for all methods on two additional tasks. The proposed method prevails on the LVLib-v1 and v4 combination, while shows slightly lower accuracy on UrbanSound8k than the best performing method (PERSA) of about 1%. In short, PERSA+ does indeed manage to handle low SNR scenarios better than all competitive methods, without compromising performance on normal conditions.

VII. CONCLUSION

In general, experimental results prove that PERSA+ verifies its design assumptions, matching the performance of PCEN. The proposed front-end layer favors robustness and universality. At this point, it should be stated what exactly PERSA+ is meant to do: (a) it can simulate noisy conditions that are closer to real-world scenarios, (b) it can lead to more representative results for the classification algorithms and unveils their true potential to perform equally in different contexts, (c) it can be used for avoiding misleading performance ratings that may be the outcome of overfitting, (d) it can be used for rapid experimentation on small datasets as it performs consistently across different classification tasks, (e) it delivers higher classification accuracy on noisy data, with minimum losses on clean data, and (f) it is probable to perform slightly worse on most occasions, especially on the test bench.

Summing up, a neat front-end for audio classification was presented, while a solid evaluation was executed. Positive results were observed and the method seems potent. Nevertheless, further tests have to be made on more benchmark datasets. The keyword-spotting task is mainly under consideration for a more complete evaluation, while further modifications and improvements, like the deployment of alternative $t$f representations, time-domain operation, and signal and noise weighting are under investigation.

![Table I](image1)

| Table I | Classification accuracy (%) for the PERSA+ front-end with respect to parameter $q$ and noise conditions. |
|---------|--------------------------------------------------------------------------------------------------|
| $q$     | SNR  |
|---------|------|
| 8       | 90.6 ± 1 | 89.8 ± 1 | 89.4 ± 1 |
| 12      | 87.8 ± 1 | 87.2 ± 1 | 86.8 ± 1 |
| 16      | 85.8 ± 1 | 85.2 ± 1 | 84.8 ± 1 |

Values above -1% of the higher value for each column are highlighted.

![Table II](image2)

| Table II | Front-end performance across the LVLib SMO datasets |
|---------|-----------------------------------------------------|
|               | LVLib-v1 baseline | LVLib-v3 random gain | LVLib-v4 random noise |
| LOG          | 86.2 ± 1.0       | 79.8 ± 1.0           | 58.9 ± 9.9           |
| LOG-AU       | 85.9 ± 1.5       | 81.4 ± 1.0           | 61.0 ± 8.6           |
| LOG-T        | 85.3 ± 5.0       | 85.2 ± 5.1           | 72.3 ± 2.1           |
| PERSA        | 87.6 ± 1.1       | 86.4 ± 3.9           | 73.3 ± 5.4           |
| PERSA+       | 85.9 ± 5.8       | 85.7 ± 4.9           | 75.8 ± 5.4           |
| PCEN         | 84.4 ± 6.4       | 85.1 ± 6.5           | 73.9 ± 2.4           |

Values above -1% of the highest value in each column are highlighted.

![Table III](image3)

| Table III | Front-end performance on additional tasks |
|---------|------------------------------------------|
|               | LVLib-v1+v4 | UrbanSound8k |
| LOG          | 69.9 ± 0.7  | 71.1 ± 1.0   |
| LOG-AU       | 71.1 ± 1.6  | 71.9 ± 5.2   |
| LOG-T        | 78.0 ± 2.8  | 69.7 ± 5.1   |
| PERSA        | 79.8 ± 1.1  | 72.2 ± 5.9   |
| PERSA+       | 81.8 ± 3.1  | 71.4 ± 4.6   |
| PCEN         | 79.5 ± 3.1  | 71.8 ± 2.5   |

Values above -1% of the highest value in each column are highlighted.
REFERENCES

[1] N. Lane, S. Bhattacharya, A. Mathur, P. Georgiev, C. Forlivesi, F. Kawar, “Squeezing deep learning into mobile and embedded devices”, IEEE Pervasive Computing, vol. 16(3), pp. 82-88 (2017).

[2] L. Vrysis, N. Tsipas, I. Thoidis, C. Dimoula, “1D/2D Deep CNNs vs. Temporal Feature Integration for General Audio Classification”, Journal of the Audio Engineering Society, vol. 68(1/2), pp. 66-77 (2020).

[3] A. Meng, P. Ahrendt, J. Larsen, L. Hansen, “Temporal feature integration for music genre classification”, IEEE Transactions on Audio, Speech, and Language Processing, 15(5), pp. 1654-1664, 2007.

[4] H. Purwins, B. Li, T. Virtanen, J. Schlüter, S. Chang, T. Sainath, “Deep learning for audio signal processing”, IEEE Journal of Selected Topics in Signal Processing, vol. 13(2), pp. 206-219 (2019).

[5] T. Tommyasi, N. Patricia, B. Caputo, T. Tuyteliers, “A deeper look at dataset bias”, In domain adaptation in computer vision applications, Springer, Cham, pp. 37-55 (2017).

[6] L. Vrysis, N. Tsipas, C. Dimoula, G. Papanikolaou, “Crowdsourcing Audio Semantics by Means of Hybrid Bimodal Segmentation with Hierarchical Classification”, Journal of the Audio Engineering Society, vol. 64(12), pp. 1042-1054 (2016).

[7] L. Vrysis, N. Tsipas, C. Dimoula, G. Papanikolaou, “Mobile audio intelligence: From real-time segmentation to crowdsourced semantics”, In Audio Mostly 2015, p. 37 (2015).

[8] J. Salamon, J. Bello, “Deep convolutional neural networks and data augmentation for environmental sound classification”, IEEE Signal Processing Letters, vol. 24(3), pp. 279-283 (2017).

[9] N. Tsipas, L. Vrysis, K. Konstantoudakis, C. Dimoula, “Semi-supervised audio-driven TV-news speaker diarization using deep neural embeddings”, The Journal of the Acoustical Society of America, vol. 148(6), pp. 3751-3761 (2020).

[10] S. Abdoli, P. Cardinal, A. Koerich, “End-to-end environmental sound classification using a 1d convolutional neural network”, Expert Systems with Applications, vol. 136, pp. 252-263 (2019).

[11] H. Fayek, M. Lech, L. Cavedon, “Evaluating deep learning architectures for Speech Emotion Recognition”, Neural Networks, vol. 92, pp. 60-68 (2017).

[12] W. Dai, C. Dai, S. Qu, J. Li, S. Das, “Very deep convolutional neural networks for raw waveforms”, In International Conference on Acoustics, Speech and Signal Processing, IEEE, pp. 421-425 (2017).

[13] D. Palaz, M. Magimai-Doss, R. Collobert, “Analysis of CNN-based speech recognition system using raw speech as input”, In 16th Annual Conference of the International Speech Communication Association, pp. 402-405 (2015).

[14] J. Lee, J. Park, K. Kim, J. Nam, “SampleCNN: End-to-end deep convolutional neural networks using very small filters for music classification”, Applied Sciences, vol. 8(1), pp. 150 (2018).

[15] O. Ronneberger, P. Fischer, T. Brox, “U-net: Convolutional networks for biomedical image segmentation”. In International Conference on Medical image computing and computer-assisted intervention”, pp. 234-241 (2015).

[16] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, Z. Wojna, “Rethinking the inception architecture for computer vision”, In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 2818-2826 (2016).

[17] M. Ravanelli, Y. Bengio, “Speaker recognition from raw waveform with sincnet”. In Spoken Language Technology Workshop, IEEE, pp. 1021-1028 (2018).

[18] L. Vrysis, N. Tsipas, C. Dimoula, G. Papanikolaou, “Experimenting with 1D CNN Architectures for Generic Audio Classification”, In Audio Engineering Society Convention 148, (2020).

[19] S. Hershey, S. Chaudhuri, D. Ellis, ..., M. Slaney, “CNN architectures for large-scale audio classification”, In International Conference on Acoustics, Speech and Signal Processing, IEEE, pp. 131-135 (2017).

[20] I. Model, L. Shamir, “Comparison of Data Set Bias in Object Recognition Benchmarks”, IEEE Access, vol. 3(1), pp. 1953-1962 (2015).

[21] S. Dodge, L. Karam, “Understanding how image quality affects deep neural networks”, In 8th international conference on quality of multimedia experience, IEEE, pp. 1-6 (2016).

[22] C. Chen, J. Bilmes, “MVA processing of speech features”, IEEE Transactions on Audio, Speech, and Language Processing, vol. 15(1), pp. 257-270 (2006).

[23] H. Hermansky, N. Morgan, “RASTA processing of speech”, IEEE transactions on speech and audio processing, vol. 2(4), pp. 578-589 (1994).

[24] Y. Aytar, C. Vondrick, A. Torralba, “Soundnet: Learning sound representations from unlabeled video”, In Advances in neural information processing systems, pp. 892 (2016).

[25] S. Dieleman, B. Schrauwen, “End-to-end learning for music audio”, In International Conference on Acoustics, Speech and Signal Processing, IEEE, pp. 6964-6968 (2014).

[26] J. Pons, O. Nieto, M. Prockup, E. Schmidt, A. Ehmman, X. Serra, “End-to-end learning for music audio tagging at scale”, In 19th International Society for Music Information Retrieval Conference, p. 637-644 (2018).

[27] J. Pons, X. Serra, “Randomly weighted CNNs for (music) audio classification”, In International Conference on Acoustics, Speech and Signal Processing, IEEE, pp. 336-340 (2019).

[28] V. Lostanlen, J. Salamon, A. Farnsworth, J. Bello, “Robust sound event detection in bioacoustic sensor networks”. PloS one, vol. 14(10), (2019).

[29] Y. Wang, P. Getreuer, T. Hughes, R. Lyon, R. Saurous, “Trainable frontend for robust and far-field keyword spotting”, In International Conference on Acoustics, Speech and Signal Processing, IEEE, pp. 5670-5674 (2017).

[30] V. Lostanlen, J. Salamon, M. Cartwright, B. McFee, A. Farnsworth, J. Kelling, J. Bello. “Per-channel energy normalization: Why and how”, IEEE Signal Processing Letters, vol. 26(1), pp. 39-43 (2018).

[31] B. Kadioglu, M. Horgan, X. Liu, J. Pons, D. Darcy, V. Kumar, “An Empirical Study of Conv-Tasnet”, In International Conference on Acoustics, Speech and Signal Processing, IEEE, pp. 7264-7268 (2020).

[32] L. Vrysis, L. Hadjileontiadis, I. Thoidis, C. Dimoula, G. Papanikolaou, “Enhanced Temporal Feature Integration in Audio Semantics via Alpha-Stable Modeling”, Journal of the Audio Engineering Society, vol. 69(4), pp. 227-237 (2021).

[33] B. McFee, C. Raffel, D. Liang, D. Ellis, M. McVicar, E. Battenberg, O. Nieto, “librosa: Audio and music signal analysis in python”, In Proceedings of the 14th python in science conference, vol. 8 (2015).

[34] F. Chollet, “Deep learning with python”, Manning Publications Co, (2017).

[35] J. Salamon, C. Jacoby, J. Bello, “A dataset and taxonomy for urban sound research”, In 22nd ACM international conference on Multimedia, pp. 1041-1044, (2014).