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Acoustic Event-Based Prestressing Concrete Wire Breakage Detection

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Abstract

The integrity of concrete bridges, essential for public safety and infrastructure longevity, can be risked by the breakage of prestressed wires, potentially leading to catastrophic failures. In response to this challenge, this study introduces a novel approach to detect prestressed wire breakage by employing dynamic signal representations: the Short-Time Fourier Transform (STFT, a technique for time-frequency analysis) and Mel-frequency cepstrum coefficients (MFCCs, capturing the timbral aspects of sounds). Acoustic emission signals from two Italian bridges were collected and processed to extract relevant features using STFT and MFCCs. The study employs a multilayer perceptron (MLP) classifier enhanced with the MixUp data augmentation technique—a method that blends samples to enhance training data diversity and volume—addressing the challenge of limited data and improving model robustness. The promising results achieved by the MLP classifier in detecting prestressed wire breakages underscore its efficacy. These results highlight the method's potential, specifically using MFCC, for integration into real-time bridge monitoring systems, offering an efficient solution for enhancing infrastructure safety.

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Keywords: acoustic emission; real-time monitoring; dynamic signal representations; multilayer perceptron; data augmentation

Nomenclature

AEC	Acoustic Event Classification
AE	Acoustic Emission
ANN	Artificial Neural Network
STFT	Short-time Fourier Transform
MFCC	Mel-frequency cepstrum coefficients
DFT	Discrete Fourier Transform

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DCT	Discrete Cosine Transform
MLP	Multi Layer Perceptron
MCC	Matthews Correlation Coefficient

1. Introduction

Bridges have a crucial role in transportation networks, impacting economic and social development. The bridges' integrity became a critical problem as they aged. The recent dramatic incidents on the Polcevera bridge in Genova, Italy, underscore the need for better monitoring and maintenance, specifically in detecting prestressing cable degradation. The corrosion of prestressing cables, driven by several factors, poses a significant challenge due to their inaccessibility and the potential for catastrophic failure. Moreover, conventional inspection methods, such as visual inspections and radiography, are often costly, time-consuming, and need more detailed investigation.

To address this challenge, a novel approach is proposed using "Acoustic Event Classification" (AEC) for detecting wire breakage in prestressed concrete bridges. AEC, powered by artificial neural network (ANN) and employing dynamic signal representations has demonstrated success in various fields (Mesaros et al., 2021; Sigtia et al., 2016) but has yet to be applied to this specific context. The proposed method accounts for the unique characteristics of wire breakage signals. This study contributes a tailored solution, mainly adopted and optimized for wire breakage detection, considering the advantages of AEC, employing Short-time Fourier Transform (STFT) and Mel-frequency cepstrum coefficients (MFCC). A Data augmentation technique, MixUp, is applied to enhance model generalization ability, making it more robust to real-world case scenarios (Farhadi et al., 2024). This method offers continuous, automated, and non-invasive monitoring, capable of detecting even single wire breakages, which is critical for identifying localized corrosion. Compared to traditional inspection methods such as radiography (Khedmatgozar Dolati et al., 2023), or fiber optics (Hampshire and Adeli, 2000), it provides a cost-effective and sensitive bridge safety and longevity solution, addressing a significant infrastructure challenge. The main goal of this research is to develop an automated monitoring system capable of detecting wire breakages in bridges, enabling timely maintenance actions to ensure their ongoing safety.

2. Acoustic Emission and Experimental Context

This research focuses on harnessing the acoustic emission (AE) technique to acquire signals ranging from 20 kHz to 500 kHz. The importance of studying signals in this range is its ability to isolate the event from the structural operational and ambient background noise. These ultrasonic signals, detected by piezoelectric sensors, originate from the rapid release of energy within the structure, providing valuable insights into the integrity of bridge components. The lifecycle of an AE signal involves initiation at a structural weak point, rapid propagation through the material, and eventual equilibrium. This process generates elastic waves characterized by an initial amplitude increase followed by an exponential decay. Ultimately, these waves travel through the material and reach the surface of the structural component, where piezoelectric sensors detect them. It is important to note that AE events often consist of multiple wave types, including longitudinal and transverse waves and surface waves resulting from reflections and superposition (RILEM Technical Committee (Masayasu Ohtsu)**, 2010).

This study focuses on two bridges in Italy: the Alveo Vecchio and Ansa del Tevere. These sites were chosen as they are representative of typical Italian highway bridges, providing a robust setting for AE signal collection. The Alveo Vecchio bridge, located on the Napoli-Canosa highway in Italy, was selected to collect real-world data. Another experimental test was conducted on the Ansa del Tevere bridge in Roma, Italy, enhancing the diversity and robustness of the collected AE signal dataset. This strategic selection ensured the acquisition of a comprehensive dataset of AE signals triggered by wire breakages in prestressed concrete beams, forming the foundation for developing and testing the proposed model for wire breakage detection.

3. Methodology

3.1. Feature Extraction Using STFT

The STFT is a widely used signal processing technique for analyzing the time-frequency characteristics of signals. Mathematically, the STFT involves applying the Discrete Fourier Transform (DFT) to short segments of the signal after applying a window function to each segment. This process yields a spectrogram, which represents the signal's frequency content over time. This is essential to avoid discontinuities at frame boundaries and having a smoother representation.

3.2. Feature Extraction Using MFCC

This section MFCCs play a key role in AEC analysis due to their efficiency in representing signal spectra. The extraction of MFCCs involves several steps, outlines in key studies (Logan, 2000; Beigi, 2011). Initially, AE signals, which vary over time, are divided into short segments, or frames, using windowing functions, such as the Hamming function. This step ensures frame stability and enhances signal harmonics. Then, the Discrete Fourier Transform (DFT) is applied to each frame, leading to the amplitude spectrum log, capturing perceived loudness. The computed frequency content transforms the Mel spectrum via a Mel-filter bank. This transformation is crucial for capturing spectral characteristics relevant to wire breakage detection. Lastly, the inverse Discrete Cosine Transform (DCT-III) is employed on the Mel frequency coefficients, generating cepstral coefficients (Fig. 1). These coefficients represent the signal's energy content and exhibit robustness against noise and spectral estimation errors (Balsamo et al., 2014). This MFCC extraction process forms the foundation for subsequent wire breakage detection methodologies (section 3.3).

3.3. Data Augmentation and Network Architecture

In the context of training an Artificial Neural Network (ANN), the challenge arises from the large number of parameters, such as weights and biases. A substantial volume of training data for each class is necessary to build a generalized model capable of adapting to various scenarios (Zhang et al., 2021). This data must be comprehensive enough to encompass the diverse acoustic characteristics of the model's complexity. Furthermore, the challenge of AEC lies in the limitation of available sound combinations, some of which may be absent or inadequately represented in the recorded data. This scarcity of diverse data poses a significant hurdle to achieving model generalization. While several methods exist to enhance model performance on test datasets, data augmentation (DA) has a key role in artificially expanding the training dataset for machine learning algorithms. In principle, effective DA holds the potential to bridge the performance gap between train and test datasets, a crucial objective as demonstrated by Chun et al. (2022). In AEC domain, a spectrum of DA techniques exists, ranging from fundamental approaches like time stretching and dynamic range compression to more intricate methods like MixUp (Zhang et al., 2017) and block mixing, as explained in Mesaros et al. (2021). In this research, the MixUp strategies is employed to address the limited dataset and improve the model performance.

In this approach, DA plays an essential role in enhancing the employed multilayer perceptron (MLP) architecture which is designed for binary classification. In the proposed model, the input layer receives STFT and MFCCs as widely recognized and effective representation methods in AEC. Moreover, the output layer categorizes the signals into two distinct groups: wire breakage and environmental noise. The core purpose of the proposed model is to provide binary predictions, where '1' denotes wire breakage, and '0' indicates environmental noise. At this stage, the MLP model reveals its effectiveness. The "cross-entropy" error function for the binary classification task was employed to minimize an error function. This choice is well-established in the machine learning field, known for speeding up training and improving the model's ability to generalize (MacKay, 2019). The introduced data augmentation and the MLP model come together to form an efficient system in the domain of wire breakage detection in the context of structural health monitoring. This combination provides the capability to accurately identify and classify the wire breakage events in the prestressed concrete beams.

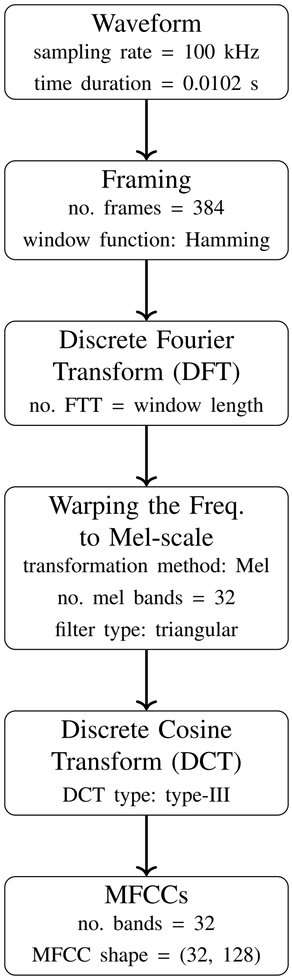


Fig. 1: Process to extract MFCC features

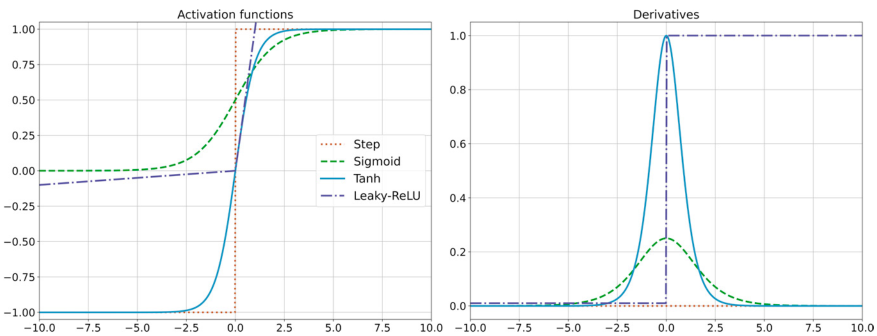


Fig. 2: Activations functions and their derivatives

Moreover, it is worth noting that activation functions play a crucial role in neural networks by determining the output of neural processing units 2. These functions and their derivatives are crucial for the backpropagation process, allowing the model to adjust its parameters correctly during training.

4. Results and Analysis

4.1. Dataset and Implementation

This is the first study to classify wire breakage events for structural health monitoring using acoustic emission signals; therefore, the development of a dataset that is both representative and comprehensive is vital. The primary dataset, carefully collected from the Alveo Vecchio bridge, comprises 244 acoustic signals, including 128 wire cut signals and 116 environmental noise signals. Precise measurement leads to the recording of strong label signals, which eases the augmentation process and minimizes real-time detection errors. Multiple recording channels were used to capture sound events from different positions, further enhancing model performance. To prepare the dataset for analysis, a preprocessing phase was involved. Signals were time-stretched to modulate their frequency range from ultrasonic to audible frequencies, allowing for the consistent application of the Mel-spectrum representation. This transformation resulted in a final sampling rate of 100 kHz, spanning frequencies from 0 to 50 kHz. Distinguishing wire breakage signals from environmental noise based on characteristic parameters like amplitude and energy can be challenging. However, these signals exhibit unique patterns and frequency components that can be harnessed through advanced signal processing techniques, such as STFT and MFCC analysis.

To facilitate further analysis, signals were transformed into STFT and MFCCs using Python. The FFT length was chosen, aligning with the window length for high-resolution and informative representation. This study employed 32 filter banks with 256-FFT points, resulting in 384 compact frames. The FFT length selection was guided by the signal's sampling rate and desired frequency resolution, ensuring a suitable representation of the signal's characteristics. These representations were valuable inputs for subsequent analysis, distinguishing wire breakage from environmental noise signals. The proposed approach initially trained the model on data from the Alveo Vecchio bridge, consisting of 244 signals (128 wire breakage events and 116 environmental noise events), with an 80-20% train-test split. To boost sample size and model performance, data augmentation (DA) was applied to training sets, maintaining the same ratio. This led to a total of 2706 events (1374 wire breakage and 1332 environmental noise events). Table 1 shows the distribution of original and augmented datasets used for training and testing on the Alveo Vecchio bridge. Additionally, the models' performance on the Ansa del Tevere bridge dataset was assessed, an unseen test dataset representing a different structure.

Table 1: Distribution of original and augmented dataset for training and testing - Alveo Vecchio bridge

Data type	**Number of Samples**	**Percentage**
Original (total)	244	-
Original (wire breakage)	128	52.50%
Original (environmental noise)	116	47.50%
Original (training set)	195	80.00%
Original (test set)	49	20.00%
Augmented (total)	2706	-
Augmented (wire breakage)	1374	55.00%
Augmented (environmental noise)	1332	45.00%

4.2. Model Training and Configuration

Extracted STFT and MFCCs were standardized with a constant size to optimize the training process of MLP models (Gao et al., 2019). The model configuration involved the RandomizedSearch CV method to select specific hyperparameters for this particular task shown in Table 2. Given the computational demand for training ANN models, various strategies were applied to enhance the model performance. These included using MFCCs for feature extraction reducing the data dimensionality while preserving essential information. DA techniques were applied to strengthen the training dataset further, ensuring that our model had diverse examples to learn from. Glorot initialization was leveraged for weight initialization, a method known for mitigating gradient-related problems. Regularization techniques, including batch normalization and dropout, were incorporated to prevent overfitting, thereby improving the model's generalization ability. The optimization process was expedited through the use of the Nadam optimizer, known for its efficiency in terms of convergence. Cross-validation with a stratified shuffle technique (n=10, validation size=0.1,

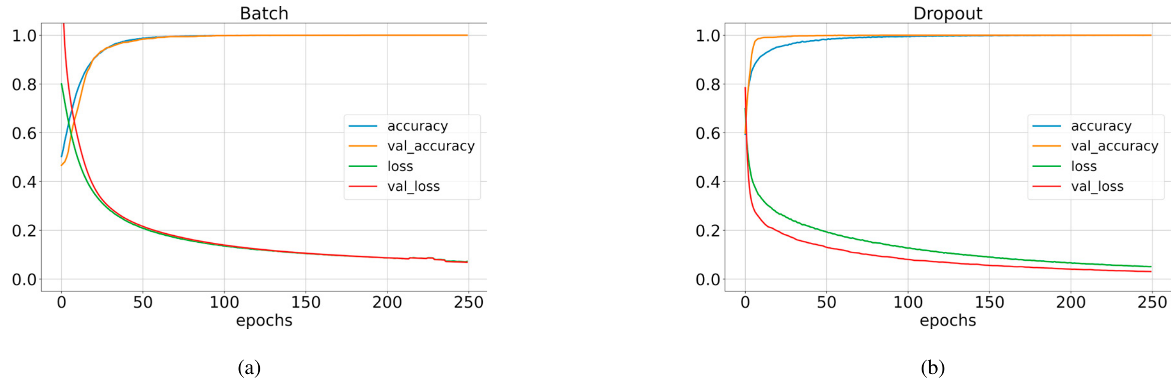


Fig. 3: Learning curves depicting model performance on the MFCC dataset using batch normalization (a) and dropout (b)

metric=loss) was employed to ensure unbiased model evaluation and minimize the risk of information leaking. This approach resulted in a robust model training and configuration process.

Table 2: Optimized hyperparameters

Hyperparameter	Selected Parameters
Number of hidden layers	5
Number of epochs	250
Activation Function	leaky-relu
Learning Rate	9.5E-7
Optimizers	Nadam
Initializer	Glorot
Number of neurons (1st layer)	900
Number of neurons (Hidden layers)	90

4.3. *Performance Evaluation Criteria*

A range of measurement metrics were employed to evaluate the deep learning models. Common binary classification metrics, including accuracy, precision, recall, and F1-score were performed. Additionally, the Matthews Correlation Coefficient (MCC) introduced by Matthews (1975) was used. The MCC is a valuable metric that ranges from -1 to +1.A coefficient of +1 represents a perfect prediction, 0 is an average random prediction, and -1 is an inverse prediction. It considers all aspects of the confusion matrix and excels when the model effectively predicts positive and negative classes. If there is no positive or negative measurements, MCC value will be undefined. The mathematical formulations for this metric is as follows:

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP) \cdot (TP + FN) \cdot (TN + FP) \cdot (TN + FN)}} \tag{1}$$

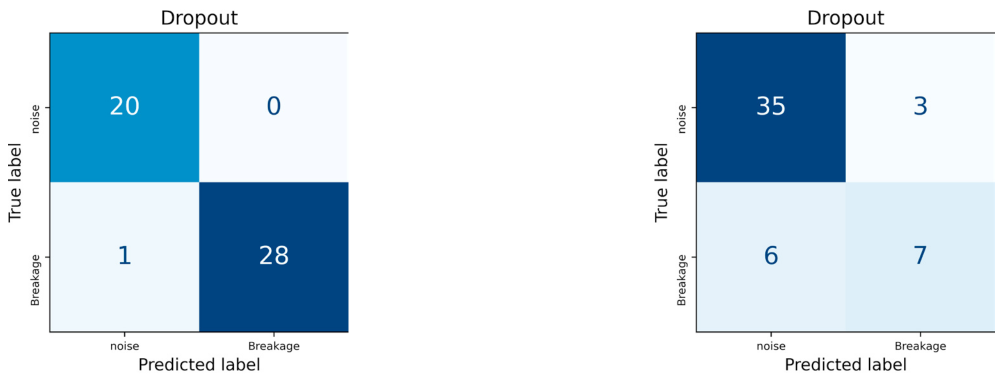
Where, TP, TN, FP, and FN stands as True Positive, True Negative, False Positive and False Negative.

4.4. *Classification Results*

The trained models were evaluated using two distinct datasets, Alveo Vecchio and Ansa del Tevere, to asses their robustness and generalization capabilities. All models experienced training for 250 epochs. This extensive training period was chosen to ensure a detailed evaluation of each model's performance and its pattern of convergence over time, as illustrated in Figure 3. An early stopping mechanism was implemented to prevent overfitting. This approach halts training if the model's improvement stops, using a patience parameter set to 5 epochs. Initially, the models were tested on the dataset derived from the Alveo Vecchio bridge. This set served as a benchmark, allowing for an initial evaluation of model performance under controlled, known conditions. The models demonstrated strong performance with the Alveo Vecchio dataset, achieving high accuracies—97.50% with STFT and 95.50% with MFCC—indicating their effectiveness in identifying wire breakage. Subsequently, the evaluation extended to a more challenging, previously unseen dataset from the Ansa del Tevere bridge. This step was crucial to examine the models' ability to generalize across new scenarios and real-world applications. The performance on the Ansa del Tevere dataset was notably different, with the highest accuracy observed being 82.50% for the MFCC-MLP model employing Dropout regularization and 73.00% using STFT (Table 3). These results underscore the importance of selecting optimal signal representation, normalization and regularization techniques. Confusion matrice on the top-performer model, which is MFCC-MLP, is provided (Fig. 4) to bring a deeper insight into model effectiveness. The considerable difference in model performance can be attributed to several factors:

- Structural Differences: The Alveo Vecchio and Ansa del Tevere bridges differ in their construction materials, age, and maintenance history. These variations can influence the acoustic properties of the structures, thus affecting the AE signal characteristics captured during the monitoring.
- Sensor Setup: Differences in the placement and sensitivity of the piezoelectric sensors used to collect the AE data may also contribute to the variance in results. Sensor placement impacts the quality and type of data captured, especially in complex structural environments where access may be restricted.
- Data Diversity: The Ansa del Tevere dataset may have included a broader range of AE not present in the Alveo Vecchio dataset, challenging the model's ability to correctly classify these new signal types. The diversity in data can significantly impact the model's learning and generalization capacity.

These factors highlight the complexity of applying machine learning models across different structural monitoring scenarios and indicate the need for tailored approaches that consider specific characteristics and conditions of each structure.



(a) (b)

Fig. 4: Confusion matrices for MFCC-MLP models with dropout regularization on Alveo Vecchio (a) and Ansa del Tevere (b) datasets.

5. Conclusion

This study introduces a novel approach employing MLP models to classify wire breakage and environmental noise within the context of prestressed concrete bridges. Central to this approach is the application of dynamic signal representations, specifically STFT and MFCC, for the extraction of appropriate features. This study underscores the importance of signal representation in enhancing the efficacy of feature extraction processes. Notably, the successful application of MFCC efficiently captures spectral features, reducing data dimensionality and facilitating model training. To face the prevalent challenge of limited data availability, the MixUp technique was implemented as an augmentation strategy. Among the various models assessed, the implementation of Dropout regularization emerged as particularly effective, showcasing notable proficiency in detecting wire breakages under real-world conditions. These

Table 3: Perfromance metrics of MLP models across STFT and MFCC

Representations	Dataset	Models	**Accuracy**	**Precision**	**Recall**	**F1-score**	**MCC**
STFT	Alveo Vecchio	Baseline	97.50	97.00	100.00	98.50	85.00
		Batch	96.50	97.00	95.50	96.50	93.00
		Dropout	92.00	91.50	100.00	95.50	48.00
	Ansa del Tevere	Baseline	26.50	54.00	24.00	33.00	3.00
		Batch	68.00	54.00	**84.00**	47.00	22.00
		Dropout	73.00	**80.00**	78.00	**74.00**	56.00
MFCC	Alveo Vecchio	Baseline	95.50	100.00	91.20	95.50	91.00
		Batch	98.00	100.00	96.50	98.50	96.00
		Dropout	98.00	100.00	96.50	98.50	96.00
	Ansa del Tevere	Baseline	67.00	33.30	30.80	32.00	9.00
		Batch	78.50	75.00	23.00	35.30	35.00
		Dropout	**82.50**	70.00	54.00	61.00	**58.00**

findings indicate the significant potential of deep learning algorithms in the domain of structural health monitoring, while highlighting the necessity for continued refinement and enhancement of these models to enhance their performance and generalization capabilities across diverse real-world applications. Exploration of advanced machine leanring techiques, including but not limited to Neural Dynamic Classification, Ensemble Learning, and Self-supervised learning can be used with the aim of further advancing the model's performance. Tailoring these models to the unique characteristics of different bridge structures is identified as a crucial next step.

The contribution of this research to the field is multifaceted, offering a methodology that is not only accurate but also cost-effective and non-invasive. This represents an improvement in ongoing efforts to ensure the structural integrity and longevity of bridges and similar infrastructures. Moreover, the utility of the proposed approach extends beyond the detection of wire breakages, containing a wider spectrum of structural damage mechanisms, becoming an effective tool for continuous safety monitoring.

References

Balsamo, L., Betti, R., Beigi, H., 2014. A structural health monitoring strategy using cepstral features. Journal of Sound and Vibration 333, 4526–4542.

Beigi, H., 2011. Fundamentals of Speaker Recognition. Springer US, Boston, MA.

Chun, P., Yamane, T., Maemura, Y., 2022. A deep learning-based image captioning method to automatically generate comprehensive explanations of bridge damage. Computer-Aided Civil and Infrastructure Engineering 37, 1387–1401.

Farhadi, S., Corrado, M., Borla, O., Ventura, G., 2024. Prestressing wire breakage monitoring using sound event detection. Computer-Aided Civil and Infrastructure Engineering 39, 186–202.

Gao, Y., Kong, B., Mosalam, K.M., 2019. Deep leaf-bootstrapping generative adversarial network for structural image data augmentation. Computer-Aided Civil and Infrastructure Engineering 34, 755–773.

Hampshire, T.A., Adeli, H., 2000. Monitoring the behavior of steel structures using distributed optical fiber sensors. Journal of Constructional Steel Research 53, 267–281.

Khedmatgozar Dolati, S.S., Malla, P., Ortiz, J.D., Mehrabi, A., Nanni, A., 2023. Identifying NDT methods for damage detection in concrete elements reinforced or strengthened with FRP. Engineering Structures 287, 116–155.

Logan, B., 2000. Mel Frequency Cepstral Coefficients for Music Modeling. In Proceedings of the 1st International Symposium on Music Information Retrieval 270, 11.

MacKay, D.J.C., 2019. Information theory, inference, and learning algorithms. 22nd printing ed., Cambridge University Press, Cambridge.

Matthews, B., 1975. Comparison of the predicted and observed secondary structure of T4 phage lysozyme. Biochimica et Biophysica Acta (BBA) - Protein Structure 405, 442–451.

Mesaros, A., Heittola, T., Virtanen, T., Plumbley, M.D., 2021. Sound Event Detection: A tutorial. IEEE Signal Processing Magazine 38, 67–83.

RILEM Technical Committee (Masayasu Ohtsu)**, 2010. Recommendation of RILEM TC 212-ACD: acoustic emission and related NDE techniques for crack detection and damage evaluation in concrete*: Test method for classification of active cracks in concrete structures by acoustic emission. Materials and Structures 43, 1187–1189.

Sigtia, S., Stark, A.M., Krstulovic, S., Plumbley, M.D., 2016. Automatic Environmental Sound Recognition: Performance Versus Computational Cost. IEEE/ACM Transactions on Audio, Speech, and Language Processing 24, 2096–2107.

Zhang, C., Bengio, S., Hardt, M., Recht, B., Vinyals, O., 2021. Understanding deep learning (still) requires rethinking generalization. Communications of the ACM 64, 107–115.

Zhang, H., Cisse, M., Dauphin, Y.N., Lopez-Paz, D., 2017. mixup: Beyond Empirical Risk Minimization. arXiv preprint arXiv:1710.09412 .