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Structural integrity assessment of concrete slabs using statistical indicators and neural networks

Evaluación de la integridad estructural de losas de concreto mediante indicadores estadísticos y redes neuronales

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Abstract

Civil structures are critical for safety and serviceability, but they are continuously exposed to deterioration mechanisms that may compromise their integrity. This study proposes a vibration-based methodology for the automatic condition assessment of concrete slabs by combining statistical indicators (SI) as to identify representative features of monitored waves, linear discriminant analysis (LDA) to reduce dimensionality and enhance class separability, and a multilayer perceptron (MLP) to automatically classify the extracted features for structural condition evaluation. The obtained results, with 97.5% validation accuracy and 99% overall accuracy, demonstrate the effectiveness of the proposed approach for the reliable identification of damage conditions in concrete slabs.

Keywords: concrete slabs, damage detection, linear discriminant analysis, mechatronics, multilayer perceptron, structural health monitoring.

Resumen

Las estructuras civiles son fundamentales para la seguridad y la funcionalidad, pero están continuamente expuestas a mecanismos de deterioro que pueden comprometer su integridad. Este estudio propone una metodología basada en vibraciones para la evaluación automática del estado de losas de concreto. Para ello, se combinan indicadores estadísticos (SI) para extraer características representativas de las señales monitoreadas, los análisis discriminantes lineales (LDA) para reducir la dimensionalidad y mejorar la separabilidad entre las clases, y un perceptrón multicapa (MLP) para clasificar automáticamente las características extraídas para evaluar las condiciones estructurales. Estos resultados, con una precisión de validación de hasta 97.5 % y una precisión global del 99 %, demuestran la efectividad del enfoque propuesto para la identificación confiable de condiciones de daño en losas de concretos.

Palabras clave: losas de hormigón, detección de daños, análisis discriminante lineal, mecatrónica, perceptrón multicapa, monitorización del estado estructural.

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Introduction

Bridges are fundamental civil structures for connectivity, transportation, and economic development [1], [2]. But, although designed for durability, their continuous exposure to dynamic loads and environmental factors progressively deteriorates critical elements such as concrete slabs and decks [2], [3]. Any undetected damage to these components compromises structural safety and service continuity [4], therefore, structural health monitoring (SHM) has become an essential discipline for assessing infrastructure condition via its dynamic properties [2], [3]. Moreover, visual inspections and local non-destructive testing techniques (*e.g.*, ultrasound or ground-penetrating radar) are common, but their intrusive nature and expertise requirement limit their effectiveness for continuous monitoring [1], [4]. In contrast, vibration-based SHM presents as a robust alternative that habilitates for global and automated structural condition assessment to overcome the limitations of traditional approaches [3].

The practical implementation of this global monitoring comprises three fundamental stages: signal acquisition, processing, and interpretation [1]. The processing stage represents the greatest technical challenge, since vibration signals in civil infrastructures, particularly in slabs, are inherently noisy and non-stationary [2]. For example, the fast Fourier transform (FFT), although reliable for quasi-stationary signals with low noise levels [5], is limited in this context because actual structural vibrations do not meet ideal conditions, as noted in [6]. In this regard, [7] combined operational modal analysis with stochastic subspace identification to estimate natural frequencies and mode shapes in pedestrian bridges; however, although crack detection was achieved, diagnostic accuracy remained susceptible to subjective interpretation.

On the other hand, [8] employed finite element models (FEM) and impact-echo test simulations to analyze concrete slabs vibration signals using the wavelet transform; the method identified cracks and notches both at the center and edges, and offered an objective signal-energy-changes-based diagnosis. Same way, [9] integrated FEM models with Shannon-entropy-optimized wavelet energy accumulation to detect and localize fatigue damage in critical structural elements of vehicular bridges. Similarly, [10] used operational modal analysis (OMA) and the frequency domain decomposition (FDD) technique to identify damage in prestressed concrete beams, commonly used in bridges, through ambient vibration. The study demonstrated that, despite natural frequencies' relative insensitivity to changes in prestressing, variations in the mode shapes obtained through FDD allow for crack (shear and flexural)-caused damage identification before the structure reaches

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its critical state. Nevertheless, implementing complex models often requires high computational load or the use of transforms that become unreliable under severe noise conditions.

In the face of these results, there is a need to develop approaches that simplify feature extraction through more direct and reliable parameters, enabling accurate, rapid, and automated structural integrity diagnoses. The present work describes a vibrational analysis methodology to automatically assess the structural condition of concrete slabs excited by an impact hammer.

Theoretical background

Statistical indicators (SI)

SI are quantitative metrics extracted from time-domain signals to identify characteristic patterns [11], which is essential for diagnosis in civil structures, electrical machines, and neurological conditions [12], [13]. They demand for fewer mathematical operations than other methods, enabling real-time implementation [14]. Such indicators can be classified into time-domain and frequency-domain categories.

This work relies on 10 time-domain, and 4 frequency-domain SI, whose mathematical expressions are displayed in Table 1. Notation works as follows:

- x_i represents the time-domain signal, with $i = 1, 2, \ldots, N$, where N is the number of data points.
- p_i denotes the FFT-computed power spectrum of x_i, likewise with $i = 1, 2, \ldots, N$, where N is the number of spectral lines
- f_i is the frequency value of the i^{th} spectral line [11].

These SI (mode, mean frequency, median, root mean square frequency, mean, frequency center, variance, root variance frequency, skewness, kurtosis, 5th moment, 6th moment and skewness factor) were selected because they provide a compact and computationally efficient representation of the vibration response, allowing the identification of changes associated with structural damage with no need of more complex signal transformations.

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Table 1. Time-domain and frequency-domain statistical indicators [14]. Source: own-elaboration.

Indicator	Mathematical definition	Indicator	Mathematical definition
	Time domain		Frecuency domain
Mode	$X_{mo} = mode(x_i)$ (1)	Mean frequency	$F_{\mu} = \frac{1}{N}\sum_{i=1}^{N} p_i$ (11)
Median	$X_{me} = magnitude(\frac{N+1}{2})$ (2)	Root mean square frequency	$F_{rms} = \frac{\sum_{i=1}^{N} f_i^2 p_i}{\sum_{i=1}^{N} p_i}$ (12)
Mean	$X_{\mu} = \frac{1}{N}\sum_{i=1}^{N} x_i$ (3)	Frequency center	$F_{fc} = \frac{\sum_{i=1}^{N} f_i p_i}{\sum_{i=1}^{N} p_i}$ (13)
Variance	$X_{\sigma^2} = \frac{1}{N-1}\sum_{i=1}^{N} x_i^2$ (4)	Root variance frequency	$F_{rvf} = (\frac{\sum_{i=1}^{N}(f_i - F_{\mu})^2 p_i}{\sum_{i=1}^{N} p_i})1/2$ (14)
Skewness	$X_{sk} = \frac{\sum_{i=1}^{N}(x_i - x_{\mu})^3}{(N-1)x_{\sigma}^3}$ (5)		
Kurtosis	$X_{ku} = \frac{\sum_{i=1}^{N}(x_i - x_{\mu})^4}{(N-1)x_{\sigma}^4}$ (6)		
5th Moment	$X_{5^{th}m} = \frac{\sum_{i=1}^{N}(x_i - x_{\mu})^5}{(N-1)x_{\sigma}^5}$ (7)		
6th Moment	$X_{6^{th}m} = \frac{\sum_{i=1}^{N}(x_i - x_{\mu})^6}{(N-1)x_{\sigma}^6}$ (8)		
Skewness factor	$X_{skf} = \frac{X_{sk}}{X_{rms}^3}$ (9)		
Kurtosis factor	$X_{kuf} = \frac{X_{ku}}{X_{rms}^4}$ (10)		

Linear discriminant analysis

Dimensionality reduction transforms high-dimensional data sets into a lower-dimensional space, by eliminating redundancies and reducing computational complexity [15]. In this respect, LDA acomplishes this objective through a linear combination of features that maximizes between-class separation and minimizes within-class variance [15], [16]. The LDA projection process from the original feature set (S_f) to a lower-dimensional subspace (V_k) requires a sequence of three steps [15]:

1) Computing the between-class scatter matrix (S_b), which measures the separability among the means of different classes.
2) Estimating the within-class scatter matrix (S_w), which quantifies the dispersion of samples relative to their class mean.
3) Constructing the transformation matrix (W) to project the data onto the subspace V_k, simultaneously maximizing S_b and minimizing S_w (15).

$$S_w W = \lambda S_b W \quad (15)$$

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Where λ represents the eigenvalues of the transformation matrix W. The solution to this problem is obtained by calculating the (scalar) eigenvalues $\lambda = \lambda_1, \lambda_2, \dots, \lambda_m$ and (non-zero) eigenvectors $V = V_1, V_2, \dots, V_m$ of $W = S_{(1/w)}S_b$, provided that S_w is non-singular and m is the number of features. These characteristics satisfy Equation (15) and provide information about the LDA space.

Multilayer perceptron neural networks (MLP)

Artificial neural networks are interconnected computational units inspired by biological neural systems [13], [17]. They are applied in data classification, process control, and systemic outcome prediction [13]. Their most common architecture is the MLP (or feed-forward network), where a basic configuration with a single hidden layer transforms an input vector $x = (x_1, \dots, x_d)^T$ into an output vector $o = (o_1, \dots, o_d)^T$.

For an MLP architecture with one hidden layer, the outputs are defined by Equation (16):

$$o_{1=\beta_0} + \sum_{j=1}^{p} \beta_j \psi(\gamma_{j0} + \sum_{s=1}^{d} x_{is}\gamma_{js}), i = 1, 2, \dots, m \qquad (16)$$

Where:

γ_{js}	the weight for input x_{is}
β_j	the weight associated with hidden unit j
γ_{j0} , β_0	the biases for the hidden nodes and output units, respectively
p	the amount of hidden nodes
ψ	the activation function, which is typically non-linear [17]

Methodology

To evaluate the vibrational response of a civil structure, it is necessary to subject it to forced dynamic excitation produced by natural phenomena (*e.g.*, wind, earthquakes) or artificial tools (*e.g.*, impact hammer, mechanical shaker), that generate low-amplitude vibration responses of a noisy nature [2]. In this work, an impact hammer is used as a controlled excitation source to induce vibrational responses in concrete slabs.

First, 14 statistical indicators are extracted from the monitored signals to estimate features associated with the slab's structural condition. Then, LDA is applied to reduce the dimensionality of the feature space to 6 components. Finally, the reduced feature set is used to train and validate an MLP for automatic classification of the slab condition into *healthy* or *damaged* states. To ensure an optimal balance between the generalization capability of the network and stability throughout the training phase, the MLP architecture was defined as follows: 6 neurons in the input layer (one for each indicator), 20 neurons in the hidden layer, a number determined through iterative testing to achieve the best performance, and 2 neurons in the output layer, representing each of the structural conditions evaluated (healthy slab and damaged slab). The sigmoid activation function was selected for both the hidden and output layers. Additionally, a stratified split was implemented, allocating 60% of the data for training and 40% for validation to ensure a balanced representation of both classes.

The methodology was experimentally validated on concrete slabs, identifying alterations in the vibrational response associated with perforations (cored) and cracks in relation to an undamaged condition. Figure 1 presents a flowchart of the proposed methodology.

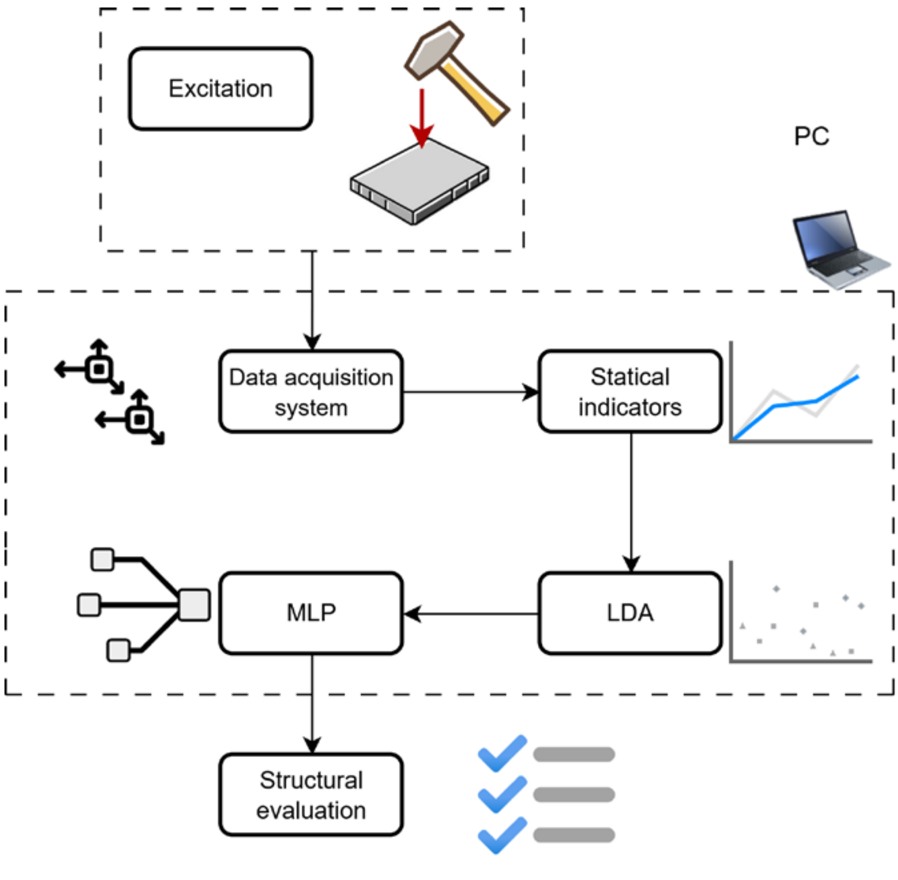

Figure 1. Flowchart of the proposed methodology. Source: own elaboration.

Experimental setup

To validate the proposed methodology, an experimental study was conducted on two 2 × 2 m, 11 cm thick concrete slabs at a height of 0.68 m above ground level. These specimens are designed to emulate slab-type structural elements commonly applied in bridge infrastructure. One slab remained in a healthy condition, while the other was subjected to controlled damage consisting of two through-thickness cores and one 0.09 m depth partial core, as shown in Figure 2. The exact location of the perforations is also indicated in Figure 3, where the green dots represent the through-thickness cores and the yellow dot represents the partial core.

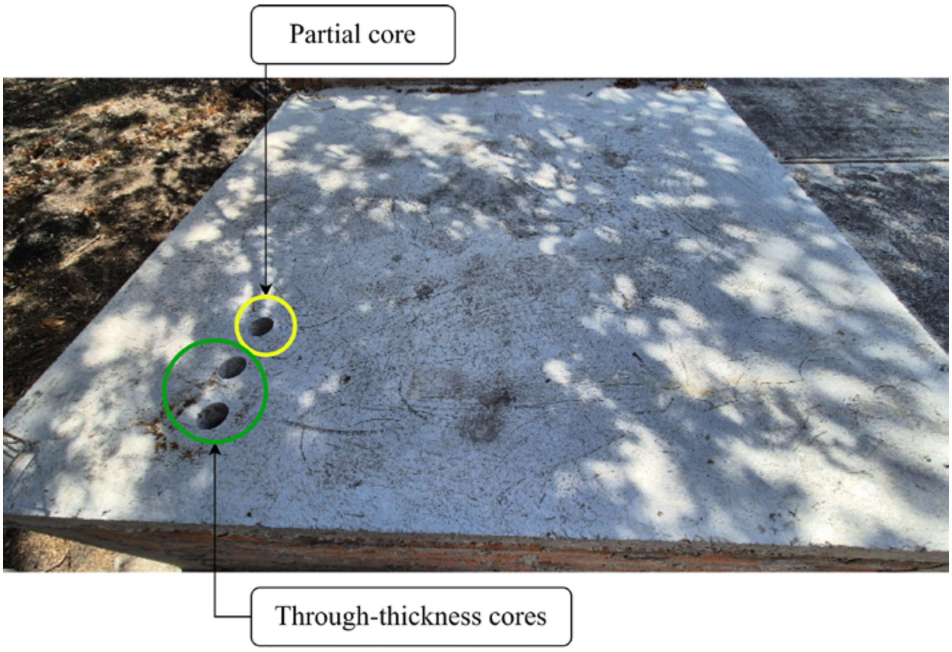

FIGURE 2. Induced cored perforations in the concrete slab: through-thickness (circled green) and partial (circled yellow). Source: own photograph.

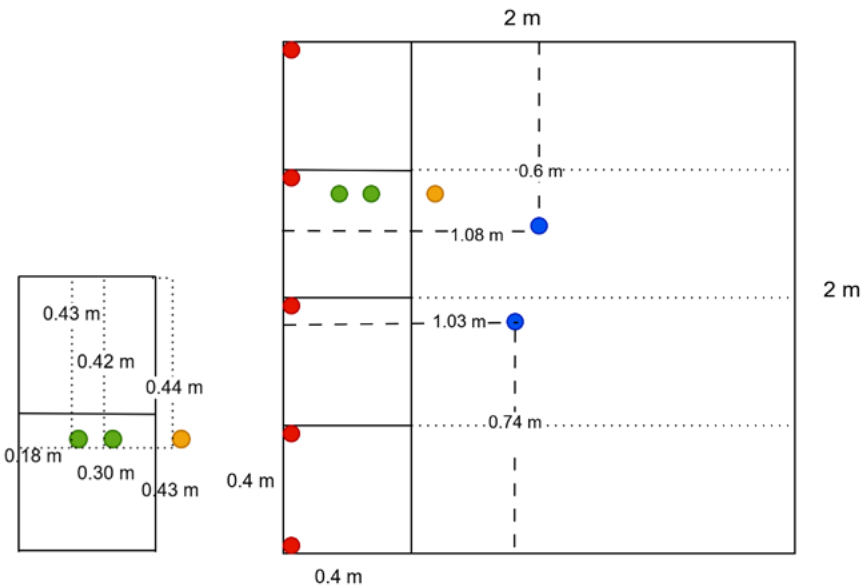

FIGURE 3. Perforation distribution and sensor locations. Source: own elaboration.

A Kistler 9728A20000 impact hammer was used as the excitation source to induce the vibrational response of the slabs. To measure this response, a vibration monitoring system consisting of two Kistler 8395A triaxial analog accelerometers was implemented (Figure 4). The first sensor recorded the structural response along the A_x, A_y, and A_z axes through channels 1, 2, and 3, respectively. Similarly, the second accelerometer captured vibrations for the same axes across channels 4, 5, and 6. Each accelerometer has a 0-1000 Hz frequency response and a sensitivity of 400 mV/g ±10 g measurement range. The locations of the sensors are represented in Figure 3 by blue dots. The sampling frequency was fixed at 2000 Hz in accordance with the accelerometers operating bandwidth. This value satisfies the Nyquist-Shannon criterion of at least twice the maximum frequency component of interest (1000 Hz), thereby preventing aliasing and ensuring proper digitization of the acquired vibration signals [18].

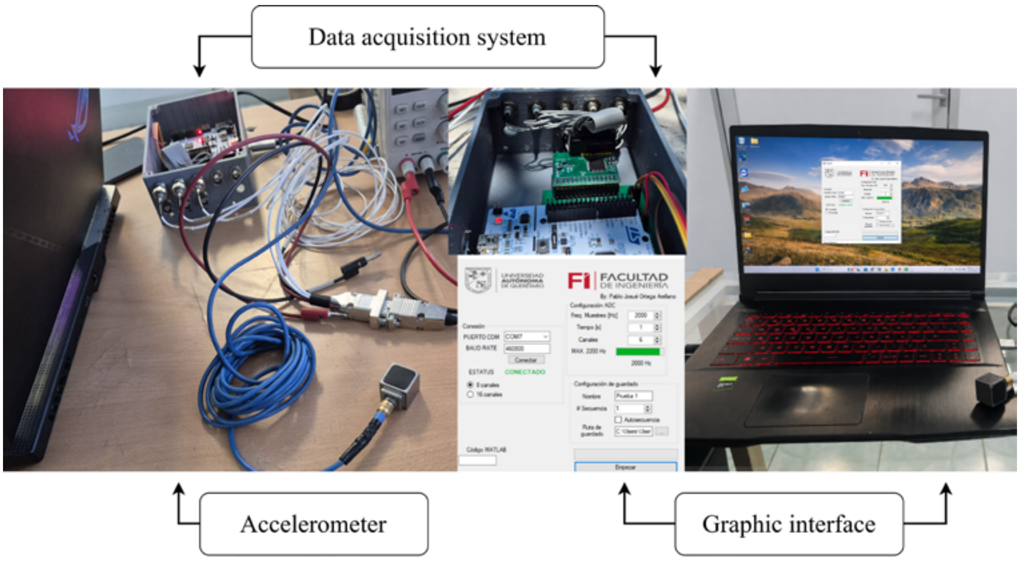

FIGURE 4. Vibration monitoring system. Source: own elaboration.

The responses are measured using a custom-designed data acquisition system based on an STM32 Nucleo board (model MB1136), which integrates an STM-32F401R microcontroller with an ARM Cortex-M4 core featuring a floating-point unit (FPU) and support for DSP instructions. The integrated analog-to-digital converter offers a 16-bit resolution with a sampling capability of up to 2.4 MHz.

For the tests, a 0.4 × 0.4 m grid was imposed on the edge of the damaged slab, coinciding with the proximity of the cored holes. Five impact points were established as observed in Figure 3 (red dots), and each was excited 10 times with the hammer, totaling 50 tests per specimen. The same conditions were replicated on the healthy slab, ultimately obtaining 100 experimental tests (50 per condition). The response capture time was set to 5 seconds; however, the vibrational responses were subsequently trimmed to a 2 second window, consisting of 0.5 seconds prior to impact detection and 1.5 seconds following it in order to focus the analysis on the transient region of greatest dynamic interest, as the impact of energy dissipates rapidly due to the slab volume being significantly larger than the areas of interest.

Results and discussion

Figure 5 presents the vibrational responses obtained for both conditions. For illustrative purposes, only the results corresponding to the first sensor (channels 1 to 3) per condition are shown. As it can be observed, differences are not apparent between the slabs; for this reason, it is necessary to apply processing methods to adequately differentiate the structural conditions of the specimens. Subsequently, the trimmed vibration signals produced a total of 84 statistical indicators. This process enabled the extraction of quantitative features that describe the distribution and temporal evolution of the responses. These features serve as the fundamental input for the next stage of the methodology.

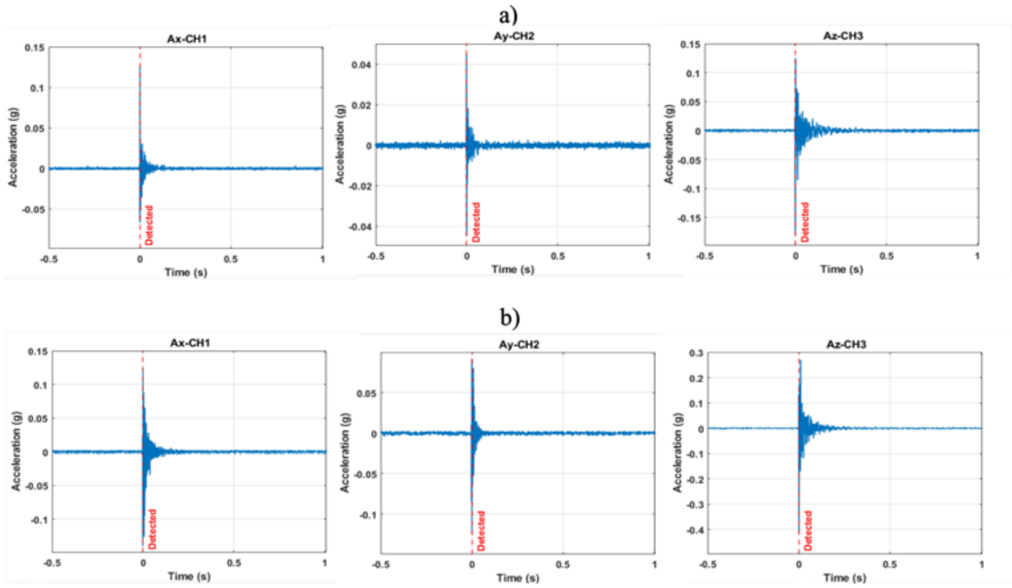

FIGURE 5. Raw time-domain signals for a) healthy and b) damaged concrete slabs. Source: own elaboration.

Next, LDA application revealed six influential indicators (k = 6), of which five correspond to root variance frequency and one to root-mean-square frequency. The resulting 3D subspace, which serves as the basis for class separability, is shown in Figure 6.

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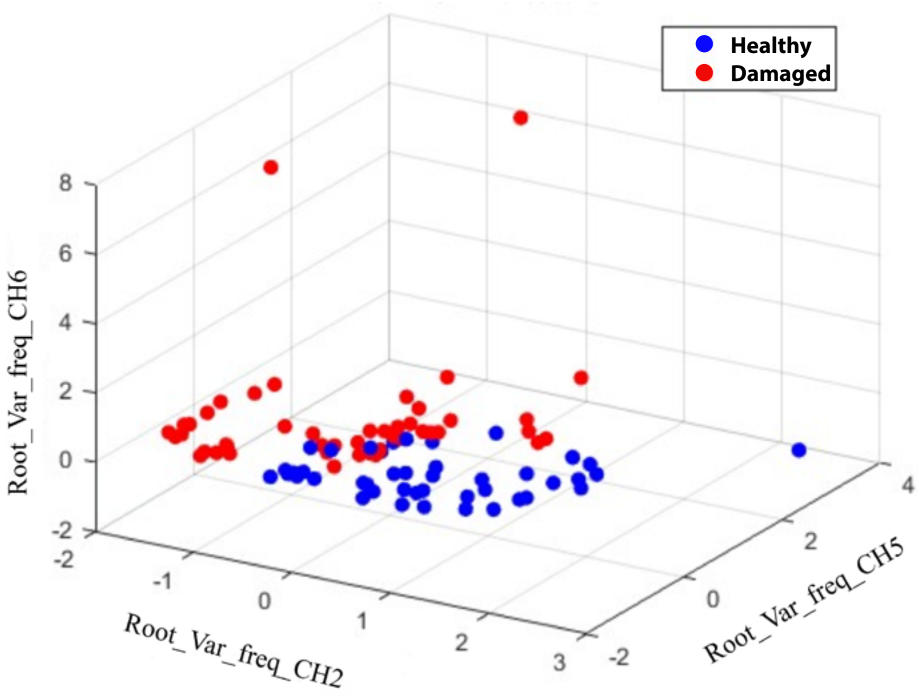

Figure 6. Three-dimensional subspace obtained via LDA. Source: own elaboration.

Finally, regarding the training process, Figure 7 shows the network performance. The best validation performance was achieved at epoch 20, reaching a cross-entropy value of 0.04915. The convergence of the training and validation curves indicates a stable learning process without signs of overfitting, as the validation error remains close to the training error before stabilizing.

The confusion matrix for the validation stage (Figure 8) shows a high degree of reliability, achieving 97.5% accuracy. The network correctly identified all 20 healthy samples and 19 out of 20 damaged samples.

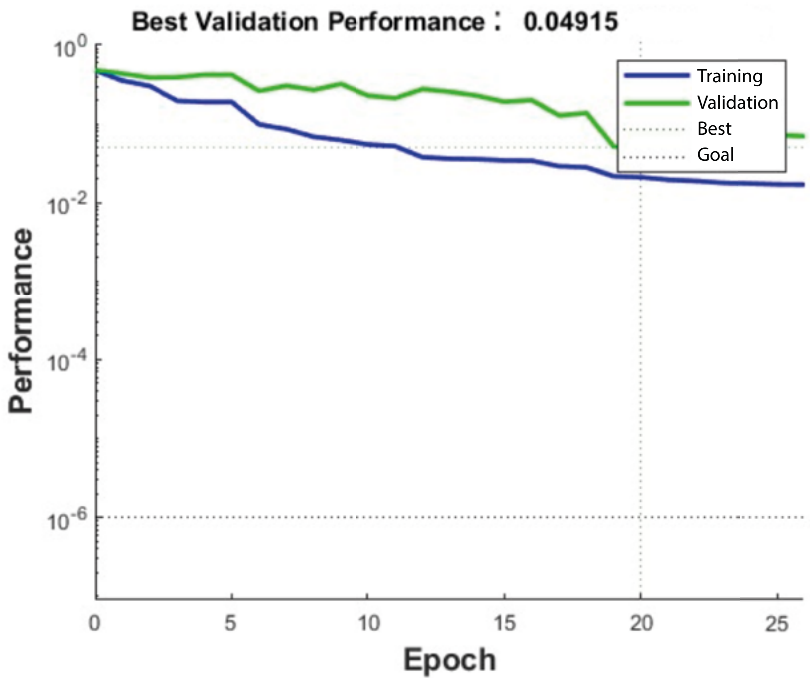

Figure 7. Training and validation performance curves for the MLP. Source: own elaboration.

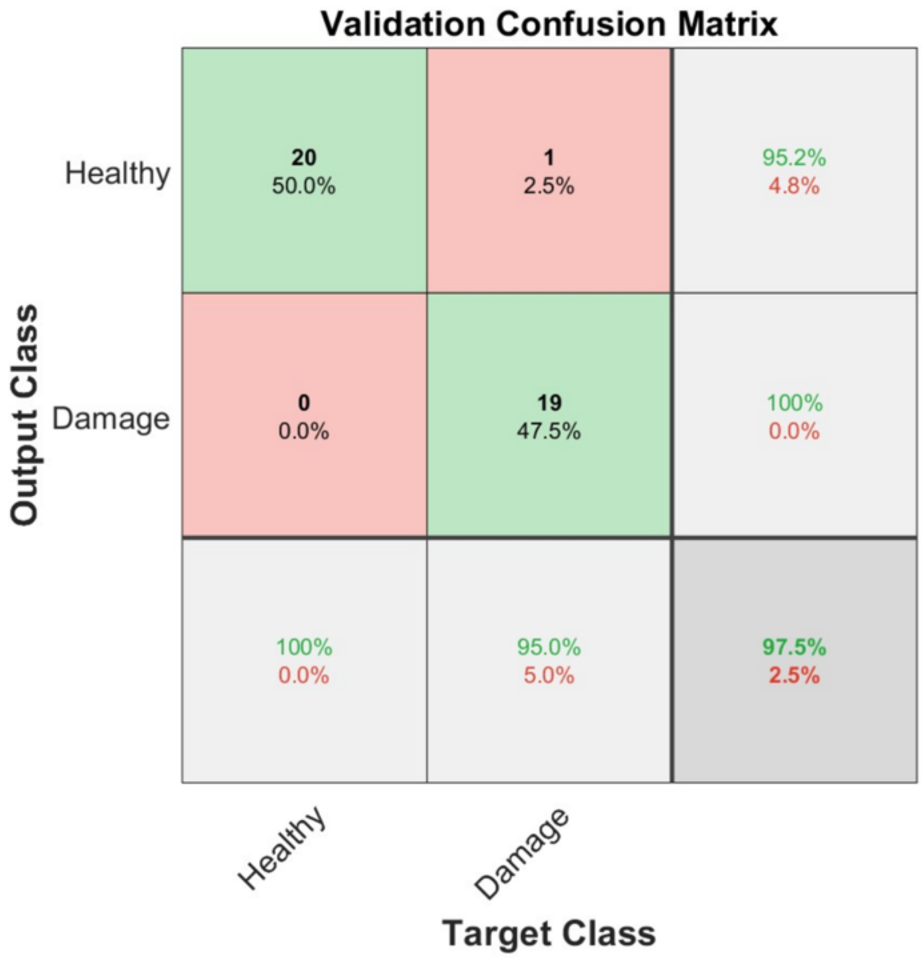

Figure 8. Matrix resulting from the MLP application. Source: own elaboration.

When considering the entire dataset, the system reached a global accuracy of 99%, with only one misclassification in the total universe of 100 samples. The concentration of results along the main diagonal confirms that the MLP, fed with the selected indicators, can establish robust decision boundaries capable of distinguishing subtle structural changes in the concrete slabs.

Conclusions

This study demonstrates the effectiveness of the proposed methodology, which integrates SI, LDA, and MLP to automatically assess the condition of concrete slabs. In particular, the integration of these techniques allowed for a significant dimensionality reduction, transitioning from 84 initial features to the 6 most discriminant indicators, primarily associated with root variance frequency, thereby optimizing computational efficiency. The proposed model achieved a reliable classification accuracy of 97.5%, successfully distinguishing between healthy and damaged states. This high level of accuracy validates the synergy between energy-based statistical features and non-linear classifiers for reliable structural diagnosis.

However, while the binary classification proved robust, the current scope is limited to the detection of damage as a single class. Future research should focus on the implementation of multi-class algorithms to achieve precise localization and quantification of damage severity. Furthermore, evaluating the system under varying environmental conditions and across diverse damage typologies will be essential to enhance the generalizability and readiness of the model for real-time, large-scale infrastructure monitoring.

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Referencias

[1] C. J. Hernández-Maqueda *et al.*, "Incipient Damage Detection in a Truss-Type Bridge using vibration responses and MUSIC technique," presented at the 2022 IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC), Ixtapa, Mexico, 2022, Nov. 9-11, 2022.

[2] J. P. Amezquita-Sánchez and H. Adeli, "Signal Processing Techniques For Vibration-Based Health Monitoring Of Smart Structures," *Archives of Computational Methods in Engineering*, vol. 23, no. 1, pp. 1-15, 2014, DOI: 10.1007/s11831-014-9135-7

[3] C. Zhang *et al.*, "Vibration feature extraction using signal processing techniques for structural health monitoring: A review," *Mechanical Systems and Signal Processing*, vol. 177, art. 109175, 2022, DOI: 10.1016/j.ymssp.2022.109175

[4] A. Moreno Gómez, "Detección, localización y cuantificación de daños en estructuras civiles metálicas midiendo vibraciones," Ph.D. dissertation, Facultad de Ingeniería, Universidad Autónoma de Querétaro, México, 2019. [Online]. Available: https://ri-ng.uaq.mx/handle/123456789/1693

[5] Y. Yang, Y. Zhang, and X. Tan, "Review on Vibration-Based Structural Health Monitoring Techniques And Technical Codes," *Symmetry*, vol. 13, no. 11, p. 1998, 2021, DOI: 10.3390/sym13111998

[6] T. Q. Nguyen, D. P. Nguyen, P. T. Nguyen, and T. T. Nguyen, "Enhanced structural damage detection through combined MODWT and FFT for power spectral density separation in beam vibration analysis," *Journal of Low Frequency Noise, Vibration and Active Control*, vol. 44, no. 3, pp. 1746-1773, 2025, DOI: 10.1177/14613484251320234

[7] Á. E. Rodríguez Suesca, “Evaluación de vibraciones en el diagnóstico de estructuras: Estudio de comportamiento de estructuras en deterioro,” Ph.D. dissertation, Departamento de Ingeniería, Universidad de Granada, España, 2021. [Online]. Available: https://babel.banrepcultural.org/digital/collection/p17054coll23/id/1833

[8] H. Jahangir, M. Khatibinia, and M. Mokhtari Masinaei, “Damage Detection in Prestressed Concrete Slabs Using Wavelet Analysis of Vibration Responses in the Time Domain,” *Journal of Rehabilitation in Civil Engineering*, vol. 10, no. 3, pp. 37-63, 2022, DOI: 10.22075/jrce.2021.23385.1510

[9] J. M. Machorro López *et al.* “Método basado en entropía-WAVELET para eficientar la identificación de daño en puentes,” Instituto Mexicano de Transporte, Querétaro, México, Publicación Técnica No. 778, 2023.

[10] E. Gandelli, G. Rossini, S. G. Mantelli, and F. Minelli, “Damage detection of prestressed concrete beams affected by shear and flexure cracks through vibration monitoring,” *Engineering Structures*, vol. 304, art 117572, 2024, DOI: 10.1016/j.engstruct.2024.117572

[11] Y. Lei and Z. Wu, “Time series classification based on statistical features,” EURASIP *Journal on Wireless Communications and Networking*, vol. 2020, art. 46, 2020, DOI: 10.1186/s13638-020-1661-4

[12] C. A. Perez-Ramirez *et al.*, “Time-frequency techniques for modal parameters identification of civil structures from acquired dynamic signals,” *Journal of Vibroengineering*, vol. 18, no. 5, pp. 3164-3185, 2016, DOI: 10.21595/jve.2016.17220

[13] J. J. Yanez-Borjas *et al.*, “A new damage index based on statistical features, PCA, and Mahalanobis distance for detecting and locating cables loss in a cable-stayed bridge,” *International Journal of Structural Stability and Dynamics*, vol. 21, no. 9, art. 2150127, 2021, DOI: 10.1142/S0219455421501279

[14] R. de Almeida Cardoso, A. Cury, and F. Barbosa, “Automated real-time damage detection strategy using raw dynamic measurements,” *Engineering Structures*, vol. 196, art. 109364, 2019, DOI: 10.1016/j.engstruct.2019.109364

[15] S. Balakrishnama and A. Ganapathiraju, *Linear discriminant analysis: A brief tutorial*, USA: *Institute for Signal and Information Processing*, 1998.

[16] A. Tharwat, T. Gaber, A. Ibrahim, and A. E. Hassanien, “Linear discriminant analysis: A detailed tutorial,” *The European Journal on Artificial Intelligence*, vol. 30, no. 2, pp. 169-190, 2017, DOI: 10.3233/AIC-170729

[17] S. Chakraborty and M. Ghosh, “Applications of Bayesian Neural Networks in Prostate Cancer Study,” in *Handbook of Statistics*, vol. 28, R. Chakraborty, C. R. Rao, and P. Sen, Eds. The Netherlands: Elsevier, 2012, pp. 241-262, DOI: 10.1016/B978-0-44-451875-0.00009-9.

[18] C.E. Shannon, “Communication in the Presence of Noise,” *Proceedings of the IRE*, vol. 37, no. 1, pp. 10-21, 1949, DOI: 10.1109/JRPROC.1949.232969

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