A HYBRID LEARNING MODEL FOR ASSESSMENT BEAM DAMAGE DETECTION

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Abstract. Structural damage induces local flexibility into the structure generating undesirable displacements and vibrations. Such changes in the dynamic response can be used as a resource allowing us to discriminate the current structural condition and to predict its useful life for short or long periods. Early damage detection and periodic structural integrity assessment are the keys for the system to operate correctly and prolong its lifespan. Many structural health monitoring techniques have been used in technologies that combine modern sensors and intelligent computational algorithms. This study focuses on applying machine learning (ML) algorithms within a multiclass framework to monitor structural integrity, enabling the identification and quantification of damage. In this context, this paper proposes a strategy to damage detection in a beam structure based on an artificial neural network machine learning algorithm. A damage index calculated from the natural frequency builds the input dataset for the ML algorithms. The methodology combines supervised learning classification (artificial neural networks) and unsupervised (cluster k-means) methods for constructing a hybrid classifier. The results show that the hybrid classifier can correctly classify the integrity condition of the structure compared to the artificial neural network algorithm.

Keywords: Hybrid Learning, Structural Health Monitoring, Damage Detection, K-means, Neural Network Artificial.

1 INTRODUCTION

Beam-like structure elements are widely employed in various mechanical and structural systems, covering applications that encompass rotating machinery, aircraft, bridge structures, oil platforms, and wind turbines, among other instances. Such systems are subject to a multiplicity of forces, loads, and environmental influences that, throughout their operation, are susceptible to damage. Therefore, it is critical to ensure the structural integrity of the system. Early damage detection and periodic structural integrity assessment are necessary for the system to operate correctly and for damage to be identified, monitored, and corrected. Thus, many Structural Health Monitoring (SHM) techniques are being used. SHM can detect and interpret changes in the structure to obtain high performance in operation and consequently reduce maintenance costs, thus increasing the safety and reliability of the structure [1]. These techniques use technologies that combine modern sensors and intelligent computational algorithms. The extraction of damage-sensitive information and the statistical analysis of these measurements allow discriminating the current structural condition for short or long periods [2, 3]. The study by Gillich [4] investigated the ability to identify the location and intensity of cracks in a beam subjected to rocking based on natural frequency analysis. The beam was subjected to different degrees of fixity, and the results highlighted that using Artificial Neural Networks (ANN) provided more accurate estimates of crack location and severity compared to the Random Forest (RF) approach.

Sousa et al. [5] investigated the preference of a few supervised machine learning algorithms to identify and quantify damages. The authors show that the mains data classification highly influences supervised ML algorithms but could perform the damage level accurately. Salehi et al. [6] investigated three supervised algorithms (Support Vector Machine - SVM, k-Nearest Neighbors - kNN, and Artificial Neural Networks - ANN) to evaluate the damage detection performance of an aircraft wing stabilizer subjected to dynamic loading. The results revealed that the SHM approach employing ML efficiently detected damage in a novel self-powered sensor configuration, even in noise and incomplete binary data. In a similar line of research, Mansouri Nejad et al. [7] employed the combination of ANN with the Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD) to process acceleration responses measured on a structure analogous to an offshore jacket. The results revealed that DWT, compared to EMD, presented a more robust signal processing method in damage detection, notably due to a better noise reduction capability. In turn, Nunes et al. [8] proposed an approach that amalgamates ANN-based supervised and unsupervised classification techniques, such as k-means clustering, to build a hybrid classifier. The methodology's effectiveness was extensively evaluated using data from numerical simulations and experimental tests performed in laboratory and in situ environments. The performance of the hybrid classifier was highly satisfactory, evidencing its ability to identify known patterns of behavior and detect new structural conditions accurately.

In this context, a dataset is built, comprising samples of healthy and damaged cantilever beams, which serves as the basis for training the algorithms. Through exposure to this labeled and unlabeled dataset, the algorithms can differentiate between different types and severities of damage, thus facilitating accurate identification and classification. This study focuses on applying machine learning algorithms within a multi-class framework to monitor the structural integrity of a cantilever beam, enabling damage identification and quantification. The methodology combines supervised (artificial neural networks) and unsupervised (k-means clustering) learning classification methods to build a hybrid classifier. These techniques' challenges, performance characteristics, and practical considerations are discussed.

2 CLASSIFICATION METHODS

This section provides a perspective on supervised classification approaches, represented by ANN, and unsupervised, exemplified by the k-means clustering method. The fundamental distinction between these two methods is that the former relies on previously known labels (provided as input data) to define distinct classes. In contrast, the latter groups unknown objects into different clusters according to an intrinsic notion of similarity. An advantage of unsupervised methods is their ability to categorize unseen data by leveraging the inherent structures in the data to form cohesive groups [9]. In contrast, in supervised methods, the ability to classify unseen data is limited since these methods require pre-existing labels to identify the classes.

2.1 Artificial Neural Network

Artificial neural networks are data-driven supervised ML models that have attracted considerable interest across engineering domains [10]. The ANN scheme presented approach in this work comprises an input layer, three hidden layers, and an output layer, all interconnected with the previous ones. The hidden and output layers are composed of neurons that work with functions that aim to add nonlinearities to the model, known as transfer or activation functions. The adjustable weights weigh the inputs before being processed by the neurons of the layers. The ability of ANNs to combine patterns allows them to solve a wide range of problems, including damage detection and structural integrity monitoring. The total number of neurons chosen in the input layer equals the number of control variables in the input data, which should be representative enough to model the structural phenomenon. The hidden nodes in the ANN layer are processing units to obtain the weighted sum of the signals obtained from the input layers. The number of hidden layers depends on the complexity of the problem being modeled [11]. The output signal is formulated as follows:

$$O_j = f \sum (w_{ij} I_i + b) \tag{1}$$

where O_j is the output of the model, w_{ij} is the associated weight that is updated at each epoch, and I_i is the input data fed into the node with a bias term b. The final output of the sum is passed through an activation function f to obtain the final output.

2.2 k-Means Clustering

The k-means method is an unsupervised clustering technique that aims to partition a dataset into homogeneous groups or clusters, where the objects within each group are similar and different from those in the other groups. The operation of k-means involves the definition of a predetermined number of clusters, represented by ”k”, followed by the iterative allocation of the objects in the clusters to minimize the sum of the squares of the distances between the objects and the centroid of the cluster to which they are assigned. The centroid is a midpoint that represents the center of the cluster [8].

3 DAMAGE ESTIMATION IN BEAM BASED ON DAMAGE INDEX

Damage detection methods have been applied to identify and quantify structural damage through changes in the dynamic behavior signature of the system. When a crack propagates in a structure, it modifies the local stiffness, damping, and mass, changing the system’s dynamic response and modal parameters. Therefore, these changes in dynamic characteristics can be used as damage indicators compared to the original signal. Thus, the damage indices (DI) based on the natural frequency of the beams are used for damage detection in this work.

The change in natural frequency is used in damage detection methods to ascertain the structure’s integrity. In the presence of structural damage, such as a crack, the stiffness is reduced, and consequently, the natural frequency decreases. Several methods have considered natural frequency shifts to detect structural anomalies and damage. Structural damage reduces its local stiffness and induces a natural frequency shift [12]. A way to formulate the DI from the normalization of the natural frequency is described by [13], which relates the natural frequency of the undamaged system to the state under damage. Thus it is employed to create an indicator to classify the integrity of the structure, seen in equation 2, which compares the natural frequency of the damaged (ω_i^d) and undamaged (ω_i^u) beam, as

$$DI = \frac{\omega_i^u - \omega_i^d}{\omega_i^u} \tag{2}$$

3.1 Data generation

The simulated system is a cantilever beam modeled by the spectral element method (SEM) as presented in [5]. The SEM involves the exact transformation of the wave equation to the frequency domain, making it especially suitable for solving crack-related problems. The beam is excited with a unit force applied at the free end, and the response is obtained at the same point. The beam has length $L = 1m$, width 0.01m, and height 0.03m. The crack is located at $L_1 = 0.5L$, and the crack depth varies from 5 to 35% of the beam cross-section. Young’s modulus of 2.1 GPa and bulk density of 7800 kg/m^3 are the material properties. Structural cracking reduces the system’s stiffness by inducing a shift in the resonance frequencies, which can affect different modal shapes depending on the location of the crack.

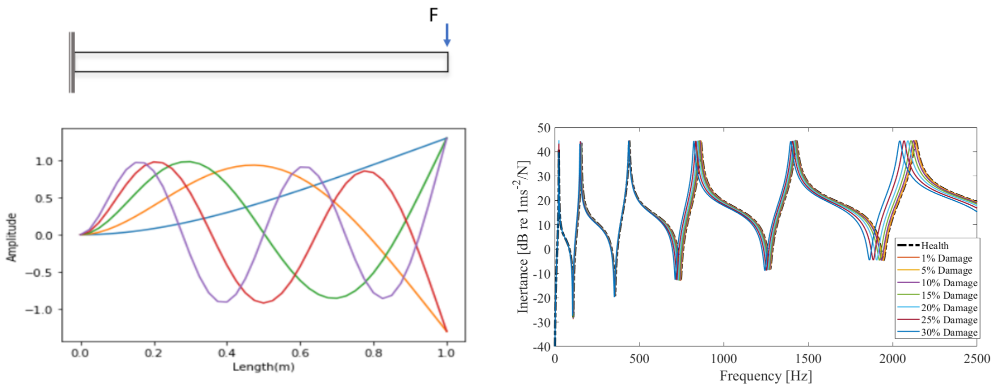
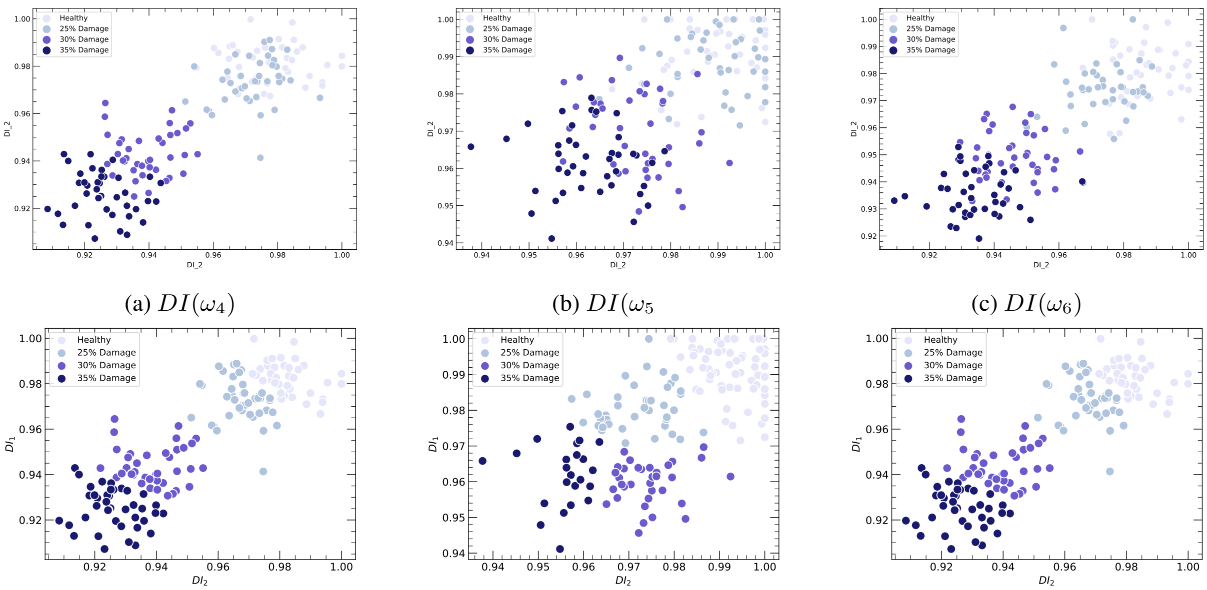


Figure 1. Schematic design of the cantilever beam, modal shape, and inertance FRFs for different crack depth levels.

Figure 1 demonstrates the effect of a crack with different degrees of severity on the dynamic response of the beam, and in this case, the fourth, fifth, and sixth mode shapes were the most affected by the damage. In addition, the natural frequencies, estimated from the dynamic response, are employed to calculate the DIs. The dataset was constructed using three natural frequencies of the braced beam, which for the undamaged state are $\omega_4 = 865$ Hz, $\omega_5 = 1430$ Hz, and $\omega_6 = 2136$ Hz, relating the fourth, fifth and sixth mode shapes. In preparing the dataset, random values of DIs were generated for training and testing ML algorithms with 160 samples. The crack flexibility used to model the crack was considered a random variable modeled with normal distribution and a coefficient of variation of 10%.

Figure 2 shows a scatter plot of the correlated dataset obtained for the damaged beam with 25, 30, and 35% crack depths. Figures 2a, 2b, and 2c display the correlation DI_1 and DI_2 calculated with the fourth, fifth, and sixth natural frequency, respectively, are manually classified. Figures 2d, 2e, and 2f show the DI_1 and DI_2 correlation calculated with the fourth, fifth, and sixth natural frequency, respectively, classified through the non-supervised algorithm, K-means, using k=4. A false positive estimate was observed in the prognostic process with the manually classified data due to the high correlation of points for all natural frequencies, which can directly influence the algorithm's performance. Unlike the data classified through K-means, at crack depths of 25, 30, and 35%, the DIs tend to gather around 0.97, 0.95, and 0.92, respectively. After that, following the DI values, the dataset was labeled into four integrity classes, 25-Damage, 30-Damage, and 35-Damage. DI higher than 0.98, comprising the crack severity between 1 to 20%, was assumed to be a healthy condition of the structure.



(a) $DI(\omega_4)$ (b) $DI(\omega_5)$ (c) $DI(\omega_6)$

(d) $DI(\omega_4)$ with k-means (e) $DI(\omega_5)$ with k-means (f) $DI(\omega_6)$ with k-means

Figure 2. Scatter plot correlating the data set of samples of groups of DIs obtained for the damaged beam with a crack depth of 25, 30, and 35 %. (a-c) DI correlations are sorted manually, and (d-f) DI correlations are sorted with k-means.

3.2 Cross-validation of dataset

The architecture of the ANN designed in this paper is of sequential type, using the Keras library, which means that the layers are stacked sequentially. The network has three layers with ReLU activation, the output layer with a number of units equal to the number of classes in the problem, and softmax activation for multiclass classification. The optimizer used is *adam*, the loss function is *categorical crossentropy*, suitable for multiclass classification problems, and the evaluation metric is *categorical accuracy*. The classifier is configured with the parameters epochs = 400 (number of training epochs) and batch size = 10 (batch size for training).

The determination of suitable hyperparameters was performed through a strategic cross-validation process. This process involved varying the units present in the hidden layers of the neural model, with the discrete values of 10, 50, 100, and 150 neurons selected as exploration points. The adoption of the cross-validation method is justified by its ability to mitigate any systematic biases that may manifest during the testing phase. In particular, the technique segregates the datasets into distinct training and test plots, in proportions of 75% and 25%, respectively. The cross-validation process adopted was based on dividing the dataset into ten discernible partitions (cv = 10), in which the properly trained neural network was evaluated in each partition iteratively. The selective metric for evaluating this performance was accuracy, an evaluation measure that quantifies the model's ability to make accurate predictions of sample classes.

Table 1. Cross-validation of algorithms.

Algoritms	**Cross- validation**	**Units - Mean Accuracy**				**Units - Standard Deviation**			
		10	**50**	**100**	**150**	**10**	**50**	**100**	**150**
Hybrid algorithm	$DI(\omega_4)$	32,20	84,37	91,25	90,00	26,90	8,94	8,00	11,59
	$DI(\omega_5)$	40,00	75,62	88,75	90,62	39,05	16,16	8,29	10,55
	$DI(\omega_6)$	27,50	84,37	95,00	87,5	26,98	13,47	4,68	13,69
ANN	$DI(\omega_4)$	16,25	57,50	65,62	58,12	26,98	28,61	26,55	26,38
	$DI(\omega_5)$	3,75	27,50	25,00	23,12	11,25	33,56	23,88	23,72
	$DI(\omega_6)$	18,75	58,12	66,25	69,37	29,18	19,57	8,00	14,64

Table 1 shows the results obtained by performing cross-validation in the context of the structural damage indices $DI(\omega_4)$, $DI(\omega_5)$ and $DI(\omega_6)$, applied to a cantilever beam. This analysis encompasses both the supervised approach and the hybrid algorithm. Those referring to 100 neurons stand out among the neuronal unit values explored, revealing a superior performance compared to the other configurations. In this scenario, the average accuracy reaches remarkable levels, ranging from 88.75% to 95%, accompanied by a standard deviation between 4.68% and 8.29% for the hybrid algorithm. As for the supervised ANN algorithm, the results are average accuracy between 25.00% and 66.25%, with a standard deviation between 8.00% and 26.55%. These results show that the hybrid algorithm, employing an arrangement of 100 neurons for each of the three hidden layers, is a suitable option for effectively identifying the degree of structural deterioration. In this context, the selection of performance metrics for evaluating the algorithms will be based on using these sets of 100 neurons.

4 NUMERICAL RESULT

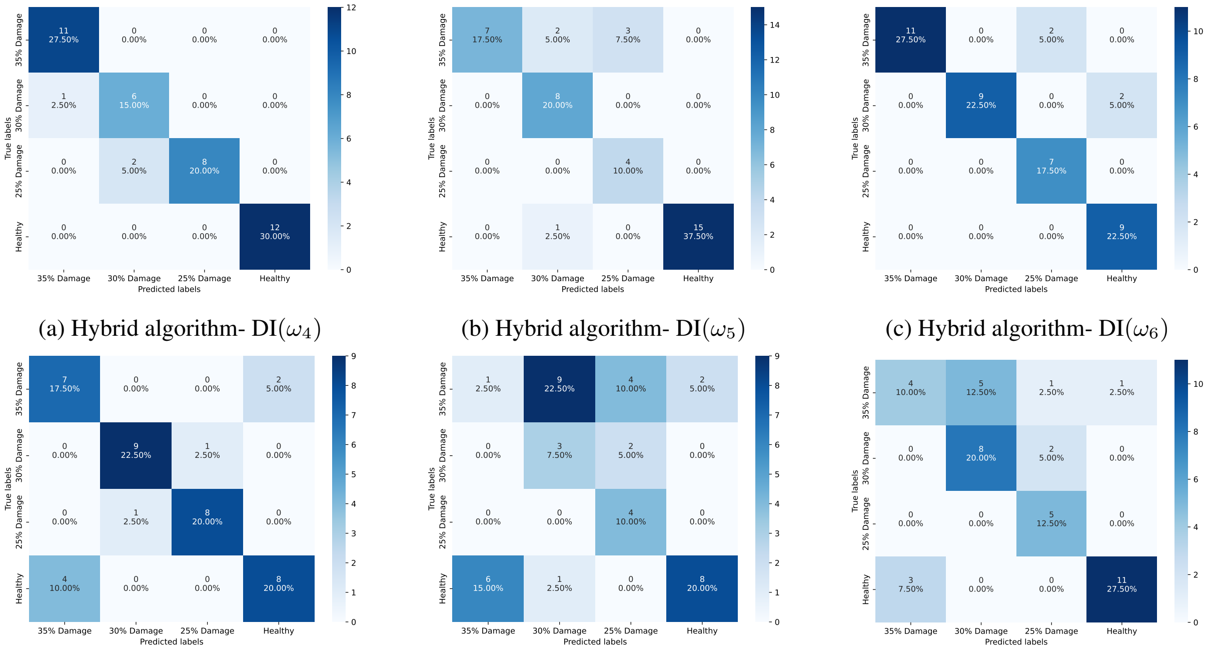
The damage quantification using natural frequency-DI considered the beam in intact and damaged condition with crack severity of 25, 30, and 35%, thus including four classes in the damage identification. Accuracy, Precision, Recall, and F1 score metrics evaluate the result of the algorithm-defined classification for test data. The values of the performance metrics are shown in Table 2. The accuracy metric represents how well the model correctly guessed all positive class classifications. The precision metric represents how well the model correctly guessed all classifications of positive classes. The recall represents the number of positive class predictions made from all positive examples in the dataset, and the F1-score is the average between precision and recall. The comparison of the accuracy of damage detection estimation ranges from 40% to 93% between the algorithms for the natural frequencies of the three DIs, ω_4, ω_5, and ω_6. In the case of the hybrid algorithm, it achieved higher accuracy with 93%, 85%, and 90% for DI(ω_4), DI(ω_5), and DI(ω_6), respectively. Precision, recall, and F1-score metrics followed the accuracy results, validating the algorithm's damage estimation.

Table 2. Comparison of performance metrics between supervised algorithm and hybrid algorithm.

Metrics	**ANN**			**Hybrid algorithm**		
	DI(ω_4)	**DI(ω_5)**	**DI(ω_6)**	**DI(ω_4)**	**DI(ω_5)**	**DI(ω_6)**
Accuracy	80	40	70	93	85	90
Precision	81	39	68	92	82	90
Recall	81	55	74	91	88	92
F1-Score	80	41	69	91	82	90

Therefore, these metrics alone do not provide sufficient information to diagnose possible errors associated with the estimation made by the algorithms. Thus, the confusion matrix is also used to track the classification of the dataset. Figures 3 show the confusion matrices containing values and percentages predicted by the algorithms.

Where, Figures 3(a, b, c) are estimated by ANN algorithm, Figures 3(d, e, f) by hybrid algorithm. The accuracy of the hybrid algorithm for DI(ω_4) reached 93% due to two misclassifications in the sample for the 30 damage condition, with one sample assumed to be 35 damage and two samples 25 damage classified as 30 damage. The hybrid algorithm was found to be more robust compared to the ANN algorithm.



(a) Hybrid algorithm- DI(ω_4) (b) Hybrid algorithm- DI(ω_5) (c) Hybrid algorithm- DI(ω_6)

(d) ANN- DI(ω_4) (e) ANN- DI(ω_5) (f) ANN- DI(ω_6)

Figure 3. Confusion matrix of multi-class classification of DI natural frequency damage using a, b, c) ANN, d, e, f) Hybrid Algorithm

5 CONCLUSION

This study delved into exploring the hybrid algorithm technique, which incorporates supervisory elements from ANN and unsupervised components from k-means clustering, to address the task of structural damage detection in a numerically simulated cantilever beam. This beam was subjected to different levels of cracks, and its condition was evaluated using a signature based on vibration information. Specifically, the natural frequency of the beam, normalized by the damage index, served as the basis for this evaluation. The vibration analysis methods were obtained employing spectral element-based calculations, allowing the detailed characterization of the beam behavior. Subsequently, algorithms were developed and trained based on the available dataset, aiming to discern the structural condition of the beam accurately. In this context, cross-validation was employed to carefully select the optimal hyperparameters, maximizing the effectiveness of the algorithms. Comprehensive metrics were employed to evaluate the algorithms' performance, including cross-validation and measures such as accuracy, precision, recall, F1-score, and the confusion matrix. These indicators were applied to the analysis of the damage detection capacity of the studied algorithms. Comprehensive metrics were employed to evaluate the algorithms' performance, including cross-validation and measures such as accuracy, precision, recall, F1-score, and the confusion matrix. These indicators were applied to analyze the studied algorithms' damage detection capability. The results showed that the hybrid algorithm excelled in effective damage detection compared to the supervised ANN algorithm. These findings support the proposed hybrid model's effectiveness in identifying compromised structural conditions.

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References

[1] A. Rytter. *Vibrational Based Inspection of Civil Engineering Structures*. PhD thesis, Denmark. Ph.D.-Thesis defended publicly at the University of Aalborg, April 20, 1993 PDF for print: 206 pp., 1993.

[2] C. R. Farrar and K. Worden. SHM- ML Persoective - Operational Evaluation. *Structural health monitoring: a machine learning perspective*, pp. 55–63, 2013.

[3] M. F. M. d. Silva. *MACHINE LEARNING ALGORITHMS FOR DAMAGE DETECTION IN STRUCTURES UNDER CHANGING NORMAL CONDITIONS*. Dissertação de mestrado, Graduate Program in Electrical Engineering of the UFPA, 2017.

[4] C. S. C. R. C. G. G.-R. P. Z.-I. A. M. N.; Tufisi. Gillich. Beam Damage Assessment Using Natural Frequency Shift and Machine Learning. *Sensors*, vol. 22, n. 22, 2022.

[5] A. A. S. R. d. Sousa, J. d. S. Coelho, M. R. Machado, and M. Dutkiewicz. Multiclass supervised machine learning algorithms applied to damage and assessment using beam dynamic response. *Journal of Vibration Engineering Technologies*, 2023.

[6] H. Salehi, S. Das, S. Chakrabartty, S. Biswas, and R. Burgueno. A methodology for structural health diagnosis and assessment using machine learning with noisy and incomplete data from self-powered wireless sensors. , n. March 2018, pp. 31, 2018.

[7] N. Mansouri Nejad, S. B. Beheshti Aval, M. Maldar, and B. Asgarian. A damage detection procedure using two major signal processing techniques with the artificial neural network on a scaled jacket offshore platform. *Advances in Structural Engineering*, vol. 24, n. 8, pp. 1655–1667, 2021.

[8] L. A. Nunes, R. P. F. Amaral, F. S. Barbosa, and A. A. Cury. A hybrid learning strategy for structural damage detection. *Structural Health Monitoring*, vol. 20, n. 4, pp. 2143–2160, 2021.

[9] A. Behnia, C. H. Kian, M. GhasemiGol, A. Sepehrinezhad, and A. M. Ahmad. Advanced damage detection technique by integration of unsupervised clustering into acoustic emission. *Engineering Fracture Mechanics*, vol. 210, pp. 212–227, 2019.

[10] M. Mishra. Machine learning techniques for structural health monitoring of heritage buildings: A state-of-the-art review and case studies. *Journal of Cultural Heritage*, vol. 47, pp. 227–245, 2021.

[11] B. Vakhshouri and S. Nejadi. Prediction of compressive strength of self-compacting concrete by anfis models. *Neurocomputing*, vol. 280, pp. 13–22. Applications of Neural Modeling in the new era for data and IT, 2018.

[12] A. S. M. R.. Machado and J. M. C. Dos Santos. Spectral element-based method for a one-dimensional damaged structure with distributed random properties. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, vol. 1, pp. 1–16, 2018.

[13] J. J. Sinou. A review of damage detection and health monitoring of mechanical systems from changes in the measurement of linear and non-linear vibrations. *Mechanical Vibrations: Measurement, Effects and Control*, , n. June, pp. 643–702, 2009.