COBEM2023-1541 - A FRAMEWORK OF CANTILEVER BEAM FOR DAMAGE DETECTION USING ARTIFICIAL NEURAL NETWORKS

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Abstract. *Damage can be considered any change in the material, geometry, or boundary condition of a structure that creates undesirable displacements and vibrations. Information and statistical analysis of such structure allow us to determine the current structural condition for short or long periods. Damage in aerospace, civil and mechanical systems can compromise their functioning and generate future risks. In this context, early detection of damage and periodic assessment of structural integrity is necessary for the system to operate correctly and for damage to be identified, monitored, and corrected. Therefore, many Structural Health Monitoring (SHM) techniques have been used to identify and validate damage offline, near real-time, and online. These techniques use technologies that combine modern sensors and intelligent computational algorithms. Therefore, one of the techniques that are gaining great prominence in recent years is using SHM with machine learning algorithms. that provide the tools needed to enhance the capabilities of SHM systems. This study aims to identify damage in a cantilever beam using an Artificial Neural Network (ANN). The results demonstrate that the ANN algorithm effectively detected damage in noise-free data compared to traditional algorithms such as SVM and Naive Bayes.*

Keywords: *Artificial Neural Network, Structural Health Monitoring, Damage detection, Vibration signal, Machine Learning.*

1. INTRODUCTION

Structural systems are exposed to a variety of forces that can lead to damage over time, affecting system performance and posing risks to user safety. Damage can be defined as any change in the local flexibility of a structure, resulting in unwanted displacements and vibrations(Léornad *et al.*, 2001). Increasing safety is crucial to preventing accidents and extending the life of equipment and systems. Therefore, there is a general interest in efficiently identifying structural damage in a simple and timely manner to prevent accidents from occurring. Structural Health Monitoring (SHM) techniques offer essential benefits, including improved safety, reliability, high operational performance, and reduced maintenance costs.

In this context, early detection of damage requires periodic assessment of structural health to ensure the appropriate functioning of the system and to identify and correct any damage. Vibration-based methods for damage identification are widely used because changes in structural physical parameters, such as stiffness and mass, alter structural vibration characteristics. However, vibration-based damage identification methods face challenges such as modeling errors, noise in measured vibration data, and environmental effects. To address these challenges, artificial intelligence techniques based on Machine Learning (ML) have been employed. These techniques are trained to generate the most likely outcomes and validate models using unpublished datasets (Yuan *et al.*, 2020). Machine learning has demonstrated successful applications in SHM systems, integrating feature selection and statistical modeling to enable effective discrimination of relevant features (Machado *et al.*, 2017; Farrar and Worden, 2013).

Artificial neural networks (ANN) have been widely explored as an effective tool for accurate and reliable damage detection. Several studies have investigated the performance of ANNs in damage detection in different types of structures, such as aircraft, buildings, and bridges. Sousa *et al.* (2023) investigated the preference of a few supervised machine learning algorithms to identify and quantify damages. The authors show that the main data classification highly influences supervised ML algorithms but could perform the damage level accurately. Salehi *et al.* (2018) focused on evaluating the performance of supervised algorithms, such as Support vector machine (SVM), k-nearest neighbor (kNN), and ANN, in damage detection of aircraft wing stabilizers subjected to dynamic loading. They demonstrated that the SHM methodology developed using ML can efficiently detect damage in a novel self-powered sensor network, even with noise and incomplete binary data. Tsuchimoto and Kitagawa (2004) proposed a structural damage detection system that uses the natural frequencies in a five-floor structure modeled with a five-mass shear system. They used the ANN method to detect damage locations and locally identify the failure through changes in the eccentricity of the structure. ANN demonstrated good accuracy in damage detection. Nunes *et al.* (2021) implemented a methodology that combines supervised and

unsupervised ANN classification methods, such as k-means clustering, to build a hybrid classifier. This approach was evaluated through numerical simulations and experimental tests, both in the laboratory and in situ, and the hybrid classifier showed good performance in detecting known structural behaviors and identifying new structural conditions. Yuan *et al.* (2020) presented preliminary results of dynamic modeling of beam structures using physics-informed ANN. In addition, they incorporated Non-Destructive Inspection/Structural Health Monitoring (NDI/SHM) domain knowledge into the ML pipeline. This approach evaluated the damage detection paradigm through non-contact full-field measurements.

This study aims to investigate the application of ANN for damage detection in cantilever beams in the context of SHM. The proposed algorithm uses as the input layer the damage index obtained from the Frequency Response Function (FRF) of the system in healthy and damaged conditions, considering the presence of presumed white noise. To evaluate the performance of the proposed algorithm, comparisons were made with traditional supervised classification methods of ML.

2. DAMAGE DETECTION METHODOLOGY

Damage detection methods have been applied to identify 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, which changes the dynamic response and modal properties of the system. These changes in dynamic characteristics can be used as damage indicators compared to the original signal. Therefore, damage indices based on FRF are employed for damage identification.

In this work, SHM techniques based on vibration signals are used. Figure 1 presents an overview of the adopted methodology. The process starts with the acquisition of the dynamic response of the structure through a numerical simulation interface of a cantilevered beam. Then, estimation and verification occur, with normalization using the damage index (DI) and the generation of the database that will serve as input to the Artificial Neural Network (ANN). The last step consists of training and testing the model, with 80% of the data used for training and 20% for testing. The test data is implemented in the multiclass ANN algorithm, using the *Tensor Flow* package. This approach aims to improve the monitoring and analysis of structural health, enabling the early identification of damage and helping to make decisions related to the maintenance and safety of structures.
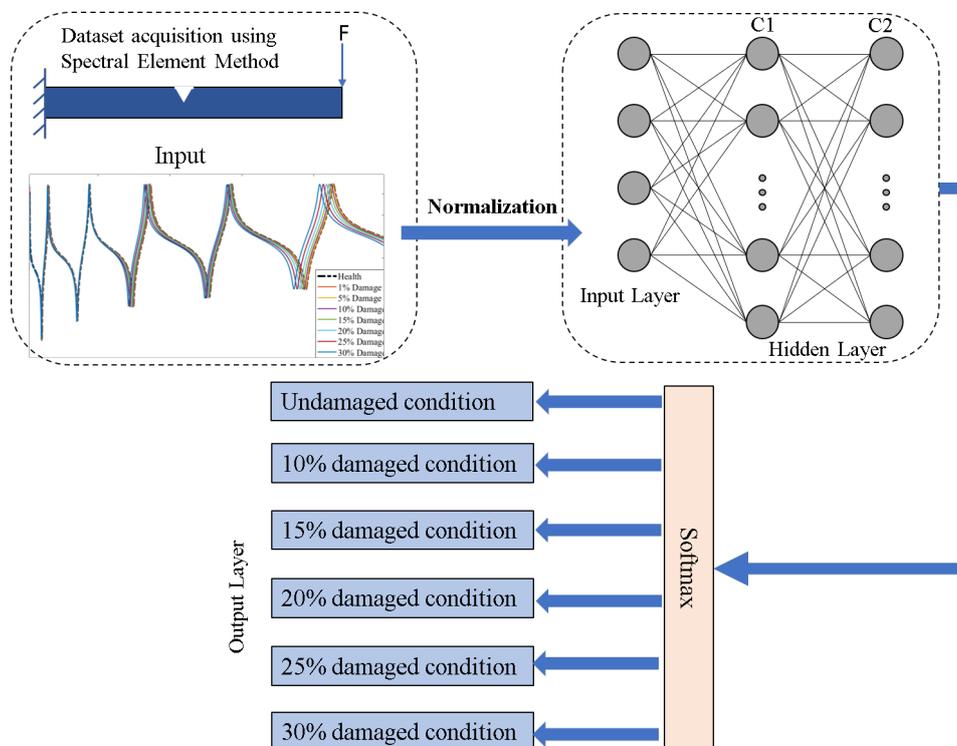

Figure 1: Flowchart of the damage assessment process.

2.1 Data-drive and damage index

The simulated system is a cantilever beam modeled using the spectral element method (SEM). SEM involves the exact transformation of the wave equation to the frequency domain, making it especially suitable for solving crack-related problems. One of the advantages of SEM is that it requires a reduced number of elements to model the system compared

to other computational methods, and it offers an exact solution for the beam behavior at a high frequency with a low computational cost. SEM has been widely used in several structural dynamics applications, such as airborne transmission (Soares, 2022), smart materials (Moura, 2022; Machado, 2022), and structural monitoring.

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 0.01 m, and height 0.03 m. The crack is located at $L_1 = 0.5L$, and the crack depth varies from 10 to 30% of the beam cross-section. The material properties are Young's modulus of 2.1 GPa and bulk density of 7800 kg/m^3. The structural crack reduces the system's stiffness, inducing a shift in the resonance frequencies, affecting different modal shapes depending on the crack location. The normalization is estimated from the dynamic response generated by the FRF, which is employed to calculate the DI.

The DI is formulated by comparing a reference signal, usually derived from the system considered damaged or with a healthy signature, to the one provided by the system in the presence of discontinuity or damage (Machado and Dos Santos, 2015; Barreto *et al.*, 2021). DIs are associated with estimation techniques for damage quantification and reveal important information about structural health. The Frequency Response Assurance Criterion (FRAC) Heylen and Lammens (1996) is used in this work. FRAC is a damage index that correlates FRF signals, where a strong correlation is indicated by one unit, which represents the undamaged state. In contrast, the lower correlation, tending to zero, means damage condition and its severity. Equation (1) formulates the FRAC, which compares the FRF signal of the cracked beam (H_{ij}^d) and the healthy beam indicated by (H_{ij}^u). As a crack directly influences the system's vibration, the DI can detect and quantify the damage. The index compares the FRFs of the beam in cracked and intact conditions. Therefore, all the energy response information of the spectrum is incorporated into the FRAC.

$$FRAC_{ij}(\omega) = \frac{\|H_{ij}^d(\omega)(H_{ij}^u(\omega))^*\|^2}{[H_{ij}^u(\omega)(H_{ij}^u(\omega))^*][H_{ij}^d(\omega)(H_{ij}^d(\omega))^*]} \tag{1}$$

where $*$ defines the complex conjugate operator. The excitation is applied at the jth coordinate and the response function at the ith coordinate. The index compares the FRFs of cracked and pristine beams, thus the entire spectrum energy response information.

2.1.1 Artificial Neural Network

ANN are data-driven supervised ML models that have attracted considerable interest in all engineering domains (Mishra, 2021). An ANN comprises an input layer, two hidden layers, and an output layer, all interconnected with the previous ones. They are composed of weights and biases that are adjusted based on a dataset provided to them to train the model. The ability of ANNs to combine patterns allows them to solve a wide range of problems. 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 (Vakhshouri and Nejadi, 2018). The output signal is formulated as follows:

$$O_j = f \sum (w_{ij} I_i + b) \tag{2}$$

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.

3. NUMERICAL RESULT

The FRAC DIs were calculated using the FRF of the beam in intact and damaged conditions for beam crack sizing 10, 15, 20, 25, and 30% of the beam cross-section. In this simulation, 3% white noise was incorporated into the FRFs to investigate the robustness of the ML algorithm in damage detection. The dataset contains the DIs estimated from 240 FRFs samples counting different levels of crack severity. Therefore, following the DI values, the multiclass dataset was labeled as healthy, 10-Damage, 15-Damage, 20-Damage, 25-Damage, and 30-Damage, which were used as output values of the ANN.

The architecture of the ANN designed in this work is sequential, meaning the layers are stacked sequentially. Table 1 shows the configuration of the proposed method. The first layer is flattened, which converts the input data into a one-dimensional array. The next two layers are Dense layers with 100 neuron units each and ReLU activation. These layers are called dense layers because each neuron in a layer is connected to all neurons in the previous layer. The last layer is also a Dense layer with several unique unit classes and a *softmax* activation function. The softmax function generates a probability distribution over the classes. The optimizer model was defined as *adam*, the loss function as *"sparse categorical cross-entropy"* (suitable for multiclass classification problems), and the metric as accuracy to evaluate the model performance. The parameter *validation split* is set to 0.1, which means that 10% of the training data will be used for

validation. The parameter epochs are set to 400, indicating the number of times the model will iterate over the entire training dataset.

Table 1: Parameters configuration of ANN.

| Number Layer	Layer Name	Output Shape
First Layer	Flatten	3
Second Layer	Dense 1	100
Third Layer	Dense 2	100
Fourth Layer	Dense 3	6

Figure 2a and 2c show the accuracy curve for the proposed methods on datasets. The accuracy of training and validation reaches 1.0 after reaching 400 epochs. The results show that the ANN has an excellent feature extraction capability on the braced beam. In Figure 2b and 2d, the loss curve of the ANN model is smooth, which shows an excellent adaptation ability and training process, both for data without noise and for data with 3% white noise.
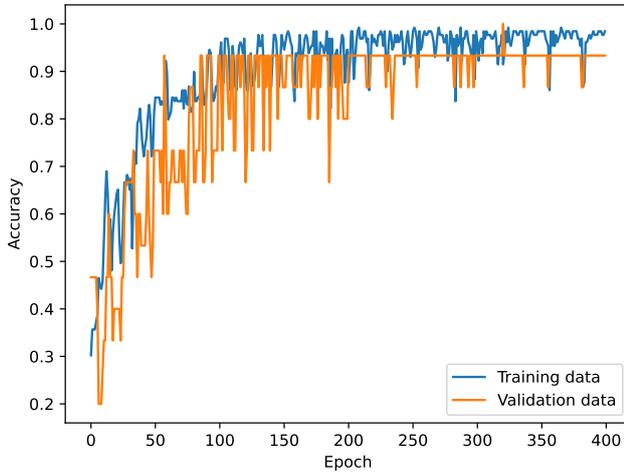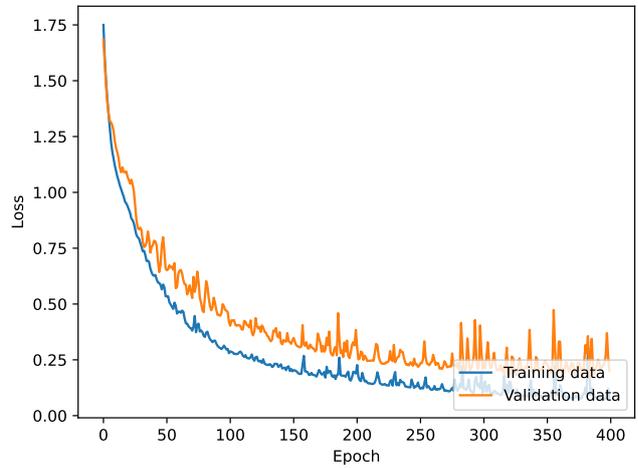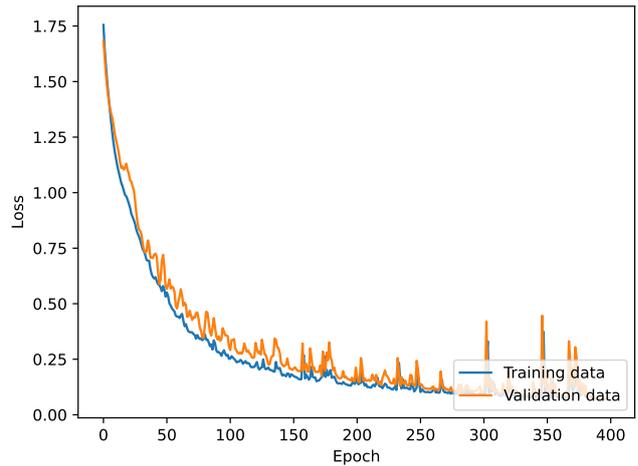

(a) $DI(noisefree)$ (b) $DI(noisefree)$
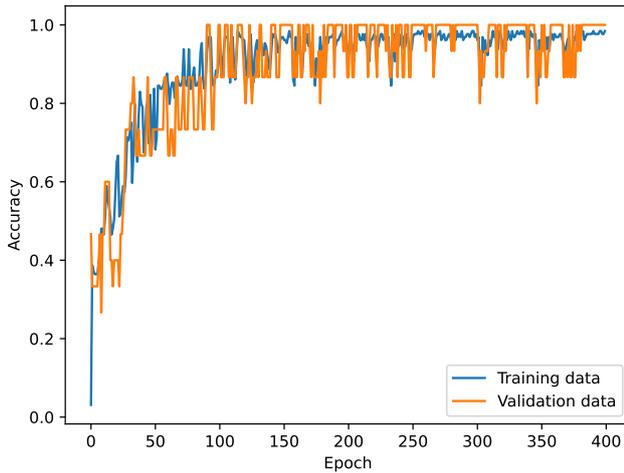
(c) $DI(3\%noise)$ (d) $DI(3\%noise)$

Figure 2: Training and validation of accuracy and loss history of the ANN algorithm.

3.1 Comparative Analysis for Different Methods

To verify the advantages of the proposed method, classical ML algorithms, including support vector machine and Naive Bayes, are selected to evaluate the cantilever beam for the degree of damage, using the performance metric accuracy in detecting structural damage. Support vector machines are supervised ML techniques developed from statistical learning theory that can be used for the classification and regression of clustered data. The purpose of an SVM is to construct

a hyperplane using a margin, defined as the distance between the hyperplane and the closest points that lie along the marginal line called support vectors. Naive Bayes methods are a set of ML algorithms, being a probabilistic classification method based on Bayes' theorem with the assumption of independence between attributes, considered a simple technique for building classifiers with models that assign class labels to instances of the problem, represented as vectors of attribute values, where class labels are drawn from some finite set (Zhang, 2004).

Each algorithm has hyperparameters that must be set and tested for optimal performance in the application cases. In the SVM case, the radial basis function (RBF) kernel function was used, and a grid search was used to determine the penalty parameters as C=10. The multiclass strategy used was one-on-one. The tolerance for the stopping criterion is set to $1e^{-3}$, sufficient to satisfy the error criterion. In the Naive Bayes class, the Gaussian-NB case was defined.

Table 2: Comparison result between the proposed method and ML algorithms.

ML algorithms	Accuracy(%)	
	Noise Free	3% Noise
Artificial Neural Network	100	93,75
Support Vector Machines	97,92	93,75
Naive Bayes	93,75	93,75

All ML techniques achieved good damage detection with high accuracy when the data is affected by noise and when it is not affected. However, the results show the ANN can detect 100% accuracy on the data without noise, and can effectively detect the damage, shown in table 2.

4. CONCLUSION

This paper investigated the ANN-supervised ML technique to detect damage in a numerically simulated cantilever beam for different crack levels using a vibration-based signature, the FRF. The vibration methods were calculated using spectral elements, and the damage index FRAC was used to normalize FRF. ML algorithms were trained and evaluated using the dataset to determine the structural condition of the beam. The ANN analysis includes the accuracy and error in damage detection evaluation. The results show that the ANN algorithm effectively detected the damage for noise-free data compared to traditional SVM and Naive Bayes algorithms.

5. ACKNOWLEDGEMENTS

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