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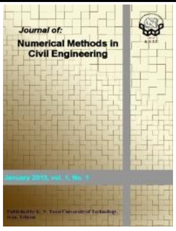

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Vibration-based damage detection of buildings using a decision-tree-based algorithm

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Abstract:

Previous studies revealed that traditional methods of damage detection (e.g., visual inspection) are time-consuming and require large monetary resources. In the last three decades, machine learning algorithms, sensor technologies, and computer science have progressively advanced, which paved the way for implementing machine learning-based damage detection frameworks. This paper presents a damage detection framework for civil structures using machine learning algorithms. The decision-tree classifier is used to classify the state of damage in the building based on the damage indicators obtained from the output acceleration signals of the building. The braced-frame structure known as the IASC-ASCE structural health monitoring benchmark building was used to verify the presented approach. The total number of 6000 Gaussian white noise signals with 10s length was applied to the case study model as ambient vibrations using the Matlab platform. Five different damage indicators, including the vibration intensity, mean period, mean, variance, and the fundamental frequency of the structure, were used to train the classifier. A Bayesian Optimization algorithm was implemented to tune the hyperparameters of the decision-tree classification learner. The results indicate that the proposed approach could estimate the state of damage in the building with promising accuracy.

1. Introduction

It is well understood that low recovery time after a damaging earthquake is one of the primary properties of a resilient system. Also, the necessary characteristic of resilient communities is the rapidity and reliability of structural safety evaluation systems after earthquakes [1, 2]. For many decades, the most popular method for Structural Health Monitoring (SHM) was the visual inspection instructions [3]. Considering the limitations of this method, its popularity has decreased in recent years [4]. One limitation is the requirement for several dedicated teams and financial resources. Thus, significant efforts have been made in this regard to automate the visual inspection process, such as proposing online image-based methods [5]. It should be noted that engineering visual inspections are limited to detecting defects that can be seen easily on the structures [6]. Thus, some significant invisible damage may remain latent during the visual inspection process.

In this regard, sensor-based SHM techniques have become more frequent in recent years. Due to the development of sensor construction technologies, the cost of sensors has decreased. Nowadays, while many researchers provide the reliable application of sensor-based SHM procedures, there is a significant amount of monetary investment required to process the data generated by a large number of sensors [7]. The achieved data may not always be capable of providing impressive information for common SHM techniques [8]. However, to evaluate the health condition of structures and infrastructures, researchers have suggested data-driven machine-learning (ML) algorithms [8-10]. In this method, statistical learning algorithms are applied to vibration data collected from structures. As a part of the data-driven method, a regression or classification learner is constructed for damage detection of structure [11, 12].

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A neural network approach was proposed by Wu et al. [13] that utilized fluctuations in the frequency response caused by damage in structural elements. Masri et al. [14] suggested a statistical approach to train an artificial neural network to identify structural variations by comparing the output vibrations with those extracted from the un-damaged structure. Worden et al. [15] proposed a framework that utilized Mahalanobis squared distances for evaluating healthy versus damaged structures. As a novelty detection problem, this method was supposed to detect damaged structures from healthy cases.

As an essential aspect of classification problems, features must be extracted to decrease the size of the input dataset for the learner. It retains the most efficient features in order to promote the classification process [16, 17].

Independent Component Analysis (ICA) [18], Principal Component Analysis (PCA) [19], and Locally Linear Embedding (LLE) [20] can be counted as the most effective tools for reducing damage indicators. Additionally, achieving a high classification rate made it essential to extract efficient indicators highly correlated with damage from the raw data [16]. Numerous studies have recently been conducted to extract effective damage indicators from vibration data to identify structural damage. Reed et al. [21] suggested an energy-based attribute named Cumulative Absolute Velocity (CAV) of the acceleration response to detect the damage in the structure. Ni et al. [22] applied the PCA-Compressed Frequency Response Functions (FRFs) to detect structural damage. Salkhordeh et al. [7] illustrated that the wavelet de-noising methods could be efficient in extracting damage indicators to diagnose the severity of damage in structures following seismic excitation. In 2019, to perform a damage detection framework for bridges, Neves et al. [23] suggested a dynamic decision-tree framework and applied the mentioned method to the numerical model in which the incident probabilities and corresponding costs are fabricated.

In recent years, a self-powered sensor capable of acquiring strain or acceleration output in a compressed format was developed [24-27]. These instruments store the duration of measured outputs in a set of memory cells cumulatively. In fact, the duration of each occurrence is related to the number of excessive input signals (over the predetermined thresholds). Thus, the output data is achieved as histograms of occurrences (compressed), not as time histories. To utilize this type of output for identifying structural damages, the statistical attributes of fitted steady distributions, such as mean and standard deviation (STD), prepare outputs in a very compressed form. Azimi et al. [4] deployed these features to identify the type, severity, and location of structural damage along with the Convolutional Neural Network (CNN) algorithm.

Although extensive studies have been carried out to facilitate the damage detection process in buildings, there is still a clear research gap in determining the most efficient damage indicators for machine learning-based methods. In addition, most of the previous researchers neglected the optimizing process of the ML architecture, which imposes unwanted errors on the detection accuracy of the models.

In light of previous studies, this paper developed a decision-tree-based algorithm to identify the damage scenarios of the ASCE benchmark building [28]. This case study was carried out by the Matlab platform on the numerical model of the mentioned building. To optimize the architecture of the decision-tree classification learner, the Bayesian Optimization (BO) algorithm was deployed. A total amount of 10% noise was added to the output acceleration signals to simulate the field condition.

This paper explains the utilized benchmark building first. Then the proposed classification learner is described. Next, the damage indices calculated from the structural output signal under ambient vibrations are introduced. Subsequently, the proposed framework and the optimization algorithm employed to tune the hyperparameters of the ML algorithm are described. Finally, the results of the classification learner are shown in terms of the receiver operating characteristic (ROC) curves and confusion matrices.

2. Material and Methods

2.1 Benchmark building

The under-study building is a four-story two-bay by two-bay steel braced-frame structure. This structure is a scale-model building created in the Earthquake Engineering Laboratory at the University of UBC. Also, this model is known as the IASC-ASCE SHM benchmark building [28].

As shown in Figure 1, the building has two bays with 1.25m lengths in each direction, and each story of the building has a height of 0.9m. All of the floors have two diagonal bracing members. Simulating damage to each floor is possible by removing these members. .

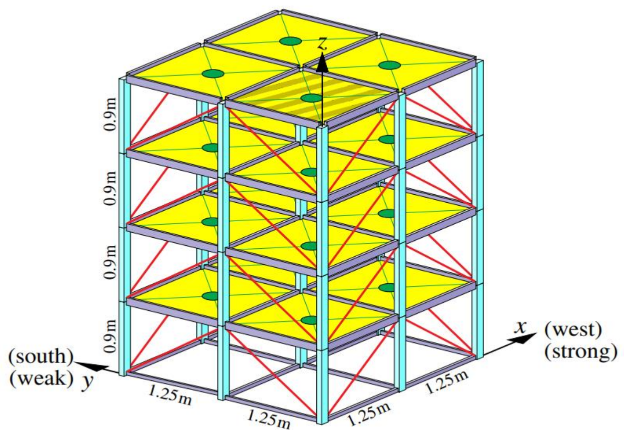


Fig. 1: A general view of the benchmark building

The finite element model of the building is a 120DOF model that is used for reducing the simulation errors by allowing out-of-plane motions and rotation of the floor slab [29]. It should be noted that the horizontal translational and vertical rotation of the nodes that belong to each floor is the same, while the out-of-plane degrees of freedom of each floor are active [4]. To record the responses in the middle column of the exterior frames, 2 accelerometers in each direction of the floors were considered.

Floor beams and columns were simulated using Euler-Bernoulli beams in the finite element model. Moreover, the braces were defined as bars without bending stiffness. The mechanical properties of the structural members are presented in Table 1.

Table 1: Cross-sectional and mechanical properties of the structure

Structural element		**Columns**	**Beams**	**Braces**
Section label		B100×9	S75×11	L25×25×3
Area of the section	(m^2)	1.33×10^{-3}	1.43×10^{-3}	0.141×10^{-3}
Moment of inertia (strong axis)	(m^4)	1.97×10^{-6}	1.22×10^{-6}	0
Moment of inertia (weak axis)	(m^4)	0.664×10^{-6}	0.249×10^{-6}	0
St. Venant torsion constant	(m^4)	8.01×10^{-9}	38.2×10^{-9}	0
Modulus of elasticity	(Pa)	2×10^{11}	2×10^{11}	2×10^{11}
Shear modulus	(Pa)	E/2.6	E/2.6	E/2.6
Mass per unit volume	(Kg/m^3)	7800	7800	7800

Besides the healthy case, five different damage scenarios were considered in this study. These scenarios are presented to assess the capability of the proposed framework in identifying different damage patterns. Johnson et al. [28] proposed these damage scenarios for future researchers to validate their methods (Figure 2). In damage case *i*, all the braces in the first story are damaged by 100%. In case *ii*, all of the braces of the first and third stories are totally removed. In damage cases, *iii* and *iv*, one of the braces of the first floor is totally damaged. In addition, in case *iv*, one of the braces of the third floor is damaged too. Finally, in damage pattern *v*, one brace in each of the first and third floors has failed. Also, as shown in Figure 2, one of the beam-column connections is damaged in this case. For structural monitoring of the benchmark model, a Matlab code was developed by Dyke for simulation of the dynamic behavior of the building [30].

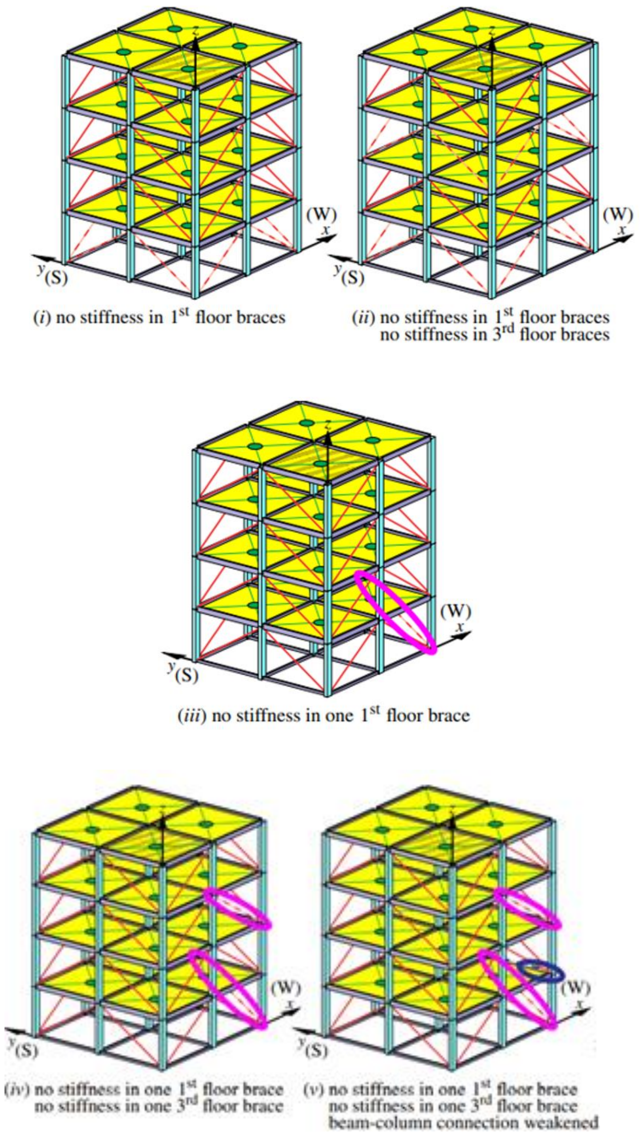


Fig. 2: Damage scenarios

2.2 Decision-tree algorithm

A Decision Tree (DT) algorithm is defined as a supervised learning method [31]. Decision trees fall into two main categories, i.e., classification and regression trees. In the first category, the algorithm predicts the outcomes as the classes in which the data will be included (classification tree). In another type of algorithm, the predicted outcomes are real numbers (regression trees). Considering the nature of the under-study problem, classification algorithms were utilized to create the prediction model.

Using the DT algorithm, the input data is divided into consecutively smaller subsets in order to construct a tree-like model of decisions and their possible outcomes [32].

The DT finds the attributes extracted from the applied training set by using processes that are likely to forecast a similar cluster. Selecting the most suitable attributes for partitioning samples at each node is the main challenge to provide a classification tree. In the process of developing decision trees, several dividing criteria were introduced. Common criteria include the Gini index, deviance, entropy, and towing rule [33].

In the DT model, each node exhibited the most likely attributes related to an event. As shown in Figure 3, the decision tree's structure is defined as root nodes, internal nodes, leaf nodes, and branches. The uppermost node of the tree, called the root node, indicates the attribute that has acquired the largest amount of information.

Branches connect internal nodes to multiple leaf nodes. Moreover, branches illustrate the probable values of connecting attributes. Leaf nodes indicate each class. In addition, a set of branches and nodes are terminated by leaf nodes.

In the DTs model, each decision node is defined as the parents of its subset nodes (children nodes). Also, the class of each point from the test subset can be located by tracing the path of the topmost node to the terminating leaf.

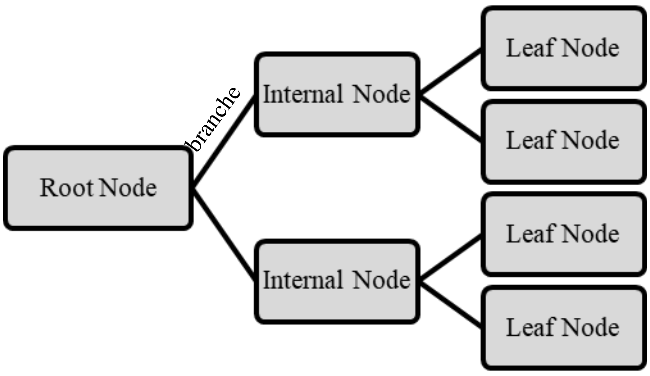


Fig. 3: Configuration of DT [34]

To overcome the overfitting problem, the *K*-fold cross-validation approach was utilized. To do so, random k-1 subsets of the training set are used to train the classifier, and the remaining subset is utilized for calculating the loss function. The cross-validation loss is determined by averaging all losses over all subsets [35].

$$CV_{loss} = \sum_{k=1}^{K} c_k \tag{1}$$

Where CV_{loss} is defined as the cross-validation loss, and c_k represents the error for each subset. In this paper, to achieve the minimum CV_{loss}, Bayesian Optimization (BO) is applied. In other words, the BO algorithm was utilized to optimize the hyperparameters of the classification learner, including the depth (maximum number of splits) and the dividing criteria of the tree. A schematic view of the presented algorithm is illustrated in Figure 4.

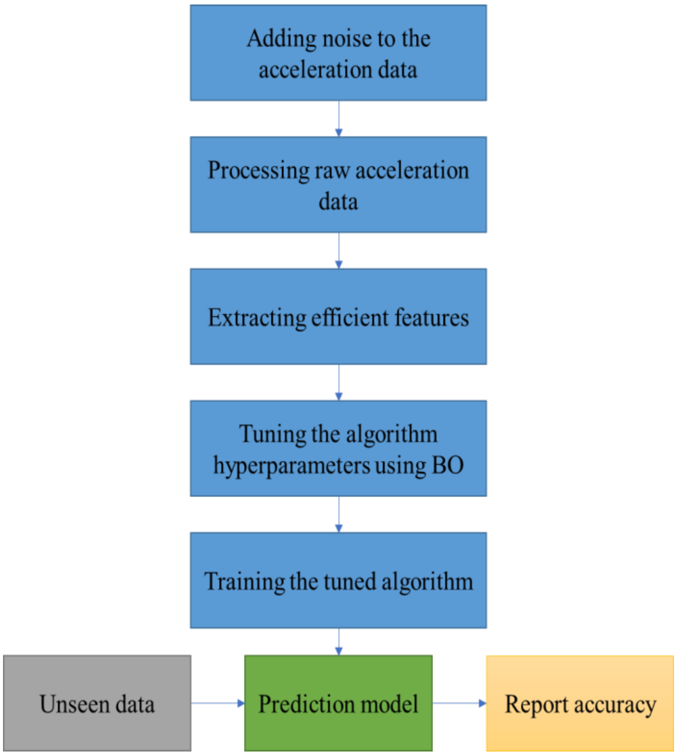


Fig. 4: A general view of the proposed algorithm

2.3 Bayesian optimization

Bayesian optimization is used by computer scientists to resolve problems related to errors caused by inappropriate settings of hyperparameters of ML algorithms. The main idea of the BO algorithm is to use a probabilistic model for the cost function rather than concentrating on the Hessian approximation and local gradient. The BO algorithm assumes that the objective function $C_V(\alpha)$ is achieved from a Gaussian Process (GP) prior as below:

$$(\alpha) \sim GP(0, K) \tag{2}$$

C_V where α is a vector of hyperparameters considered for the learner. It should be mentioned that $C_V(\alpha)$ is polluted to Gaussian noise with zero mean and σ_{noise} standard deviation. The kernel matrix, K, is then obtained using the following equation:

$$K = \Sigma + \sigma_{noise}^2 I \tag{3}$$

where Σ represents the covariance matrix, and I is an identity matrix. The covariance matrix is obtained through automatic relevance determination (Matern 5/2 kernel). The BO algorithm maximizes the expected improvement (EI) acquisition function to determine the next sampling point. Evaluating the expected improvement is more cost-effective compared to assessing only the cross-validation loss. Readers are encouraged to review Snoek et al. to obtain detailed information in this regard [36].

2.4 Features extraction

Feature extraction involves reducing the dimensionality of initially recorded data to obtain more feasible indicators for postprocessing purposes [37]. In the sensor-based SHM procedures, a significant amount of variables are achieved as the structural response that needs considerable computing resources for the processing stage [7]. Considering the variations in the dynamic attributes of the building following the initiation of damage in the structural elements, calculating a finite number of indexes that have a strong correlation with damage is essential. In this paper, five damage indicators, including the vibration intensity, mean period, mean, variance, and the natural frequency, were derived from the structure's acceleration responses to train the classifier.

The vibration intensity indicator was suggested by Koch [38] for evaluating the performance of structures. This index was utilized to predict structural damage for an experimental model called the Vibrar scale. The concept of using this feature was based on two facts: (1) the mean-square acceleration changes with frequency, $a^2(f)$, and (2) the damage potential is correlated to the frequency of vibrations. According to these facts, it can be concluded that the inertia forces lead to damage which is commensurate with:

$$\frac{a^2(f)}{f} = I(f) \tag{4}$$

where I is known as vibration intensity, and f represents the frequency content.

In the simple harmonic movement problem based on the maximum value of acceleration (a_0), the equation changes to $\frac{{a_0}^2}{f} = I$.

Another damage indicator utilized in this paper is the mean period. This feature suggested by Rathje et al. [39] to evaluate the seismic motions. Fourier amplitude values (FA_i) utilized along with the corresponding range of frequency to produce a weighted average period in domain of 0.05s and 4s.

The other features used to train the classification learner are the mean and variance of the signal and the fundamental frequency of the structure. The fundamental frequency of the structure was simply derived from the output acceleration signals of the structure using the Fourier transform.

2.5 Implementation

Here, a Gaussian white noise signal is applied to the benchmark building to simulate ambient vibration excitation. The spectral density of white noise which is a random signal is constant. In other words, at various frequencies, white noise has an identical intensity [40].

The duration of the input excitation was 10s, which was generated with a constant time step of 0.01s.

Generally, noise is an unavoidable portion of any measurement. Thus, the Signal-to-Noise Ratio (SNR) is a concept that is explained as the ratio of signal power to noise power and commonly measured in decibels (dB) [41]. The SNR is defined as:

$$SNR = \frac{\sigma_{signal}^2}{\sigma_{noise}^2} \tag{5}$$

where the σ is defined as the variance. To assess the capability of the presented framework in field conditions, 10% noise is added to the achieved acceleration response of the structures. Based on previous studies, this value represents the upper bound of noise level for validating any damage detection algorithm [42].

3. Results and discussion

The damage patterns considered in this study are presented in Table 2. As shown in this table, in case 1, the classifier should diagnose the intact case from the damaged case #1. In addition, to prove the efficiency of the classification procedures, four other damage patterns were utilized in this paper. Notably, the fifth damage pattern is the most complex, requiring the classifier to distinguish between the intact case and damaged cases 1, 2, 3, 4, and 5.

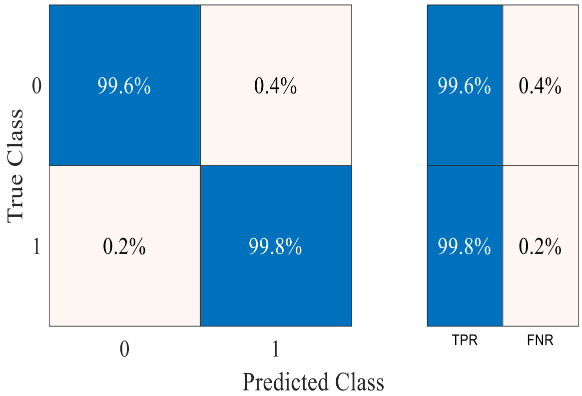
Table 2 : Damage cases

Case	Damage pattern	Mass distribution
1	Intact and 1	Symmetric
2	Intact, 1, and 2	Symmetric
3	Intact, 1, 2, and 3	Symmetric
4	Intact, 1, 2, 3, and 4	Symmetric
5	Intact, 1, 2, 3, 4, and 5	Symmetric

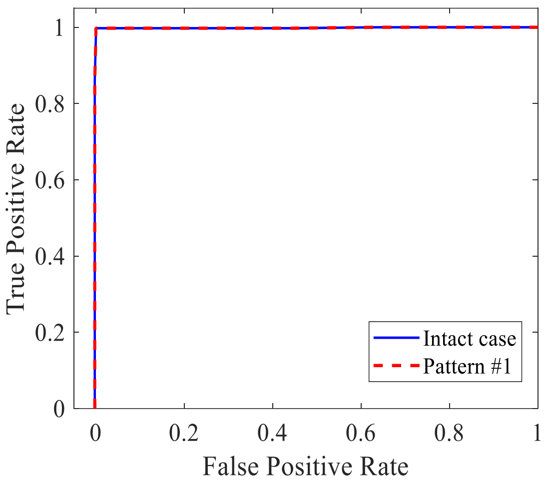
The results of the classification procedure are discussed in this section. To present the result clearly, ROC curves and confusion matrices were obtained. Furthermore, the cross-validation accuracy is presented for each classification case. The rows of the confusion matrix represent the real class of samples, while the columns indicate the predicted class. It should be noted that the term TPR is defined as the true positive rate, and the FNR is the false negative rate. The ROC curve is a plot showing the TPR versus the FPR. Readers can refer to Fan et al. [43] for more details about ROC curves. Higher classification accuracy is observed in the ROC curve near the upper-left corner of the diagram. In addition, the AUC term (area under the ROC curve) is a measure of classification accuracy. As the AUC approaches 1, the prediction is more accurate. In the following, the results of the recommended approach are presented.

The average accuracy of the prediction model in determining the damaged cases was 96.02%, with mean accuracies of 99.70%, 99.40%, 96.50%, 94.76%, and 89.78% attained for damage cases 1 to 5, respectively.

The confusion matrix and ROC curve for damage pattern 1 are illustrated in Figure 5.



(a) Confusion matrix

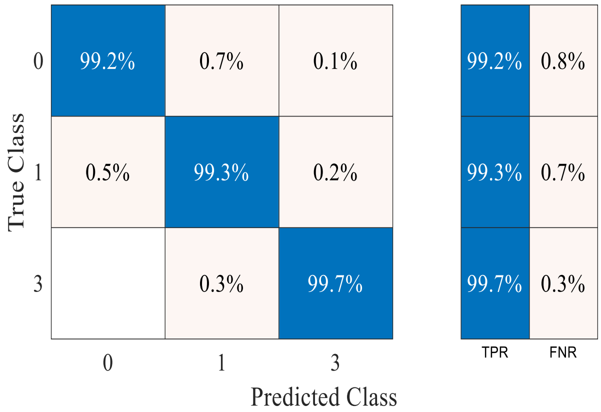


(b) ROC curve

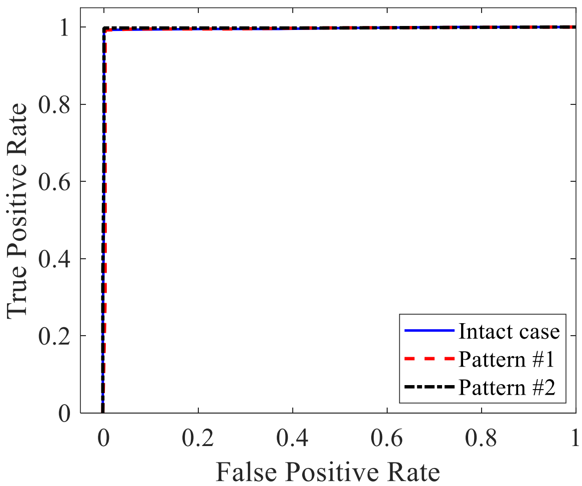
Fig. 5: confusion matrix and ROC curves for case #1

As shown in this figure, the minimum TPR is 99.6% which is related to predicting the intact building from a damaged case. In addition, 0.4% of false predicted samples indicate the promising accuracy of the classifier in this scenario.

The confusion matrix and ROC curves for scenario #2 are shown in Figure 6. A close look at this figure reveals that the developed framework provides promising accuracy in predicting desired damaged cases. The maximum FNR is 0.8% which belongs to predicting the intact model. According to this figure, the ROC curves extend to the top left corner of the diagram, indicating the flexibility of the trained classifier for unseen data.



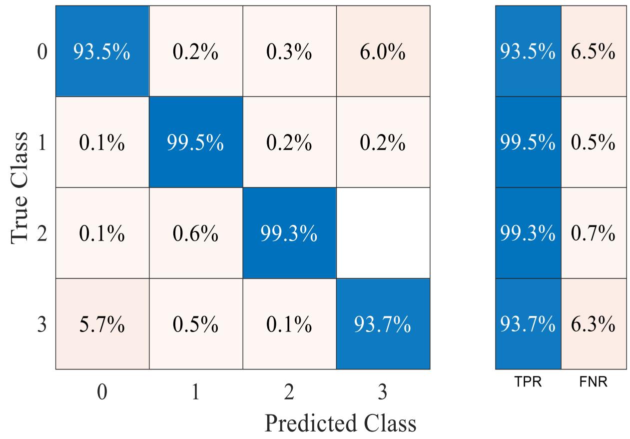
(a) Confusion matrix



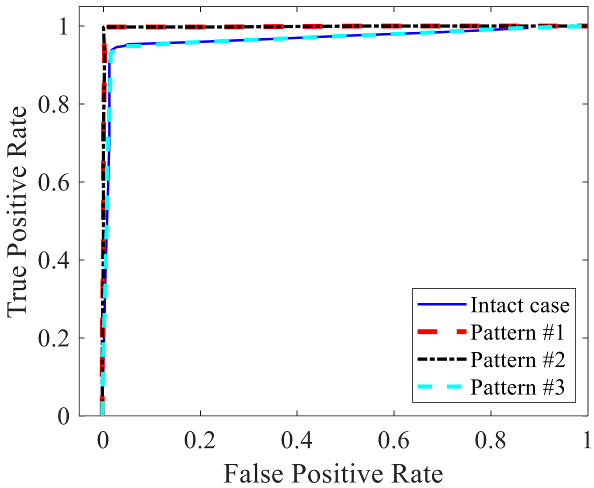
(b) ROC curve

Fig. 6: confusion matrix and ROC curves for scenario #2

According to the confusion matrix and ROC curves presented for damage scenario #3 (Figure 7), the minimum true positive rate for this scenario was 93.5%. In this case, the FNR was 6.5%. As shown in this figure, all the ROC curves extended to the top left corner of the diagram, consequently having an area under the curve. Therefore, the damage indicators presented in this study are highly correlated with the structural damage of the steel-braced frame structure.



(a) Confusion matrix

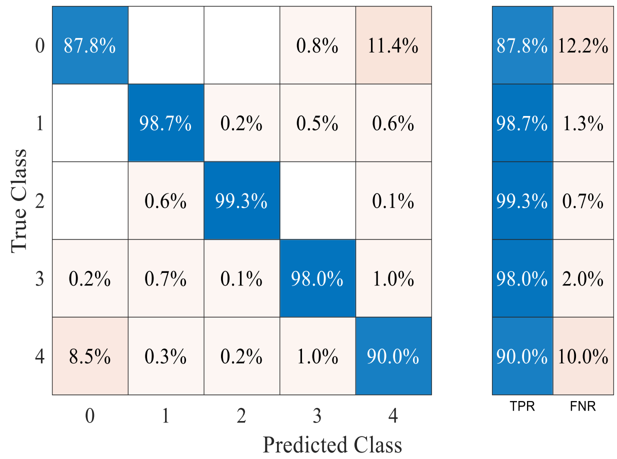


(b) ROC curve

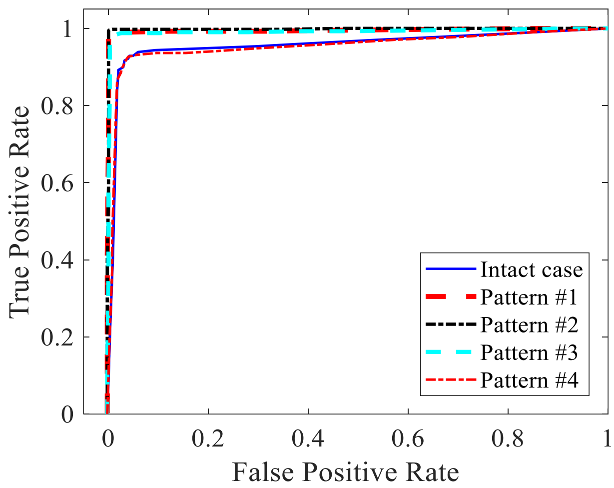
Fig. 7: confusion matrix and ROC curves for case #3

The confusion matrix and ROC curves for damage scenario #4 are depicted in Figure 8. According to this figure, the minimum TPR is 87.8% which is related to a healthy structure. As can be seen, the ROC curves extended to the top left corner of the diagram, and the minimum AUC value was 0.94 for the healthy structure. Therefore, the proposed algorithm was capable of identifying the damage scenario among multiple cases of damage patterns with acceptable accuracy and generalization.

According to Figure 9, the maximum false negative rate of the prediction model for scenario #5 is 25.8%, which corresponds to the estimation of case #5. This false prediction resulted from the similarity of damage patterns #4 and #5. In both of these patterns, one brace on the first and third floors was removed, and the difference is about one connection that was weakened in pattern #5 and healthy in pattern #4. According to the ROC curves obtained for the classifier, all the curves were close to the top left corner of the diagram, and the minimum AUC was 0.93 for pattern #5. This minimum value of AUC proves the reliability of the proposed method in predicting the damage condition of braced-frame structures, even if multiple damage scenarios with similar damage mechanisms are the case.

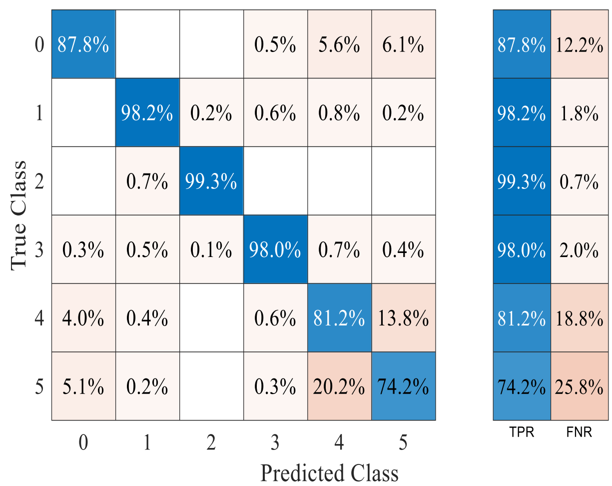


(a) Confusion matrix

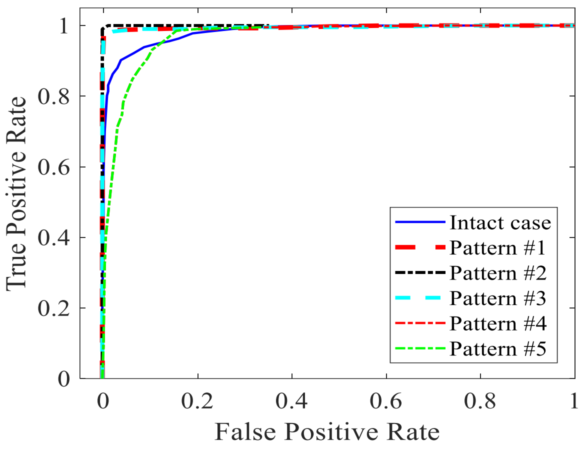


(b) ROC curve

Fig. 8: confusion matrix and ROC curves for case #4



(a) Confusion matrix



(b) ROC curve

Fig. 9: confusion matrix and ROC curves for case #5

4. Conclusions

This paper proposed a decision tree-based damage detection approach for detecting the damage scenarios in braced-frame structures under ambient vibrations. A maximum intensity of 10% noise was added to the acceleration responses to simulate the field condition. Then, five different damage indicators were obtained from the acceleration signals recorded from the structure. Bayesian Optimization (BO) was employed to tune the hyperparameters of the classification learners. The following major conclusions have resulted herein:

- The proposed algorithm was able to identify multiple damages with promising accuracy.
- The proposed features had a good correlation with the damage scenarios considered for the building.
- Bayesian Optimization (BO) minimized the errors related to the improper architecture of the classification learner.
- The field condition was simulated by adding 10% noise to the recorded acceleration signals.
- The ROC curves obtained for the classifiers indicate that the proposed algorithm is flexible and reliable for unseen input data.
- It should be declared that the uncertainties related to the material properties, geometrical details, etc. were not considered in this study. Further studies are required to explore such effects on damage detection of buildings.

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