

Machine Learning On Structural Vibration Time-Series Signals For Structural Stability Prediction And Seismic Performance Evaluation

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Abstract

Machine learning-based analysis of structural vibration time-series signals has emerged as a promising approach for enhancing structural stability prediction and damage-based seismic performance evaluation. Continuous monitoring systems equipped with accelerometers and strain sensors generate large volumes of response data that can be leveraged for data-driven assessment of structural condition. This study investigates the application of supervised machine learning techniques to classify structural condition states using multi-channel vibration and strain measurements. A structured framework is developed that includes data preprocessing, feature scaling, class imbalance handling, and comparative model evaluation. Random Forest and Support Vector Machine classifiers are employed to assess their effectiveness in multi-class damage classification under imbalanced data conditions. The results demonstrate that vibration and strain features provide meaningful information for distinguishing healthy, minor damage, and severe damage states. Feature relevance analysis highlights the dominant contribution of structural strain, while class balancing improves sensitivity to less-represented damage conditions. Among the evaluated models, the Support Vector Machine exhibits the most balanced performance across structural condition states, particularly in detecting minor damage, which is critical for early-stage deterioration assessment. The findings indicate that combining interpretable vibration-based features with appropriate machine learning strategies can support reliable and practical seismic performance evaluation. The proposed framework offers a scalable foundation for sensor-based structural health monitoring and data-informed decision support in seismic risk management.

Keywords: structural vibration, seismic performance evaluation, machine learning, structural stability prediction, damage classification.

1. Introduction

The structural stability and seismic performance evaluation are the core issue in civil and structural engineering, especially in areas that are prone to seismic risks. Structure capacity to support dynamic loading and acceptable performance levels is critical in ensuring that the people are safe, there are fewer economic losses, and the infrastructure systems are resilient. Due to the aging of structures and their exposure to different environmental and operational factors, effective ways of assessing the stability continuously or close to real time becomes more crucial [1].

The traditional methods of seismic evaluation have been mostly founded on physics-driven models, empirical damage indices, and code-driven evaluation processes. Though these techniques are the foundation of structural design and assessment practice, they can be laborious in terms of structural modeling, computation, and simplifying assumptions that are not necessarily representative of real-world variability. In addition to this, these methods are usually more appropriate in design stage analysis or post event analysis as opposed to continuous monitoring with measured response data [2]. The recent developments in sensing technology have made it possible to use structural health monitoring systems which have the ability to record structural response signals continuously. Electronic accelerometers and strain sensors in particular offer high-resolution vibration time-series measurements that manifest the structural behavior variation due to stiffness degradation, damage accretion or external excitation [3].

Simultaneously, machine learning has become an effective method of complex time-series signal analysis. Machine learning methods can learn nonlinear relationships between measured responses and structural condition states without the use of explicit physical models by learning patterns directly by data. Machine learning techniques have been shown to be very promising to automated classification of structural conditions in vibration-based structural assessment, with or without noise, uncertainty, and overlap of signal properties [4]. Engineering wise, the damage-based seismic performance evaluation offers a viable and useful alternative to the all-capacity-based methods of seismic performance evaluation. The categorization of structural conditions into discrete levels of performance which include healthy, minor damage, and severe damage provides actionable information towards the inspection planning, prioritization of maintenance and post event decision-making [5]. Of these states, minor damage is especially difficult to detect, because its vibration patterns can be confused with normal structural operation, but the first signs of damage should be detected in time before the condition can deteriorate and lead to performance loss.

Although there is an increasing body of research on the use of machine learning in vibration-based structural assessment, there are still a number of limitations. The literature often focuses on severe damage or failure-related conditions, whereas relatively little focus is on the consistent detection of minor damage conditions. Moreover, most machine learning models are used as black-box predictors, which do not give much information about the contribution of each vibration and strain signal, which may be a problem in terms of interpretability and practical implementation in engineering practice [6]. Inspired by these issues, this work uses machine learning to structural vibration time-series signals to predict structural stability and evaluate seismic performance damage-based on structural stability. The objectives of this study are

- (i) To investigate the feasibility of using structural vibration and strain time-series signals for multi-class structural stability assessment,
- (ii) To examine the effectiveness of machine learning models in distinguishing different structural condition states, and
- (iii) To explore the relevance of individual vibration and strain features in supporting interpretable, signal-based seismic performance evaluation.

2. Literature Review

The analysis of structural vibration has been long considered one of the effective methods to evaluate the condition and dynamic behavior of civil infrastructure. It is widely recognized that the difference in vibration properties including acceleration response, frequency content, and the pattern of strain are often correlated with the degradation of stiffness and structural damage. Conventionally used vibration-based assessment methods are based on modal analysis, signal processing, and damage indices as indicators of structural condition. Although these methods have proved to be effective in a controlled environment, they may not perform well in complex, real-life situations that include noise, environmental variability and nonlinear structural behavior.

Under the seismic performance assessment, vibration-based analysis is commonly used to assess structural response to earthquake excitation, either by means of numerical analysis or by means of post-event monitoring. Such techniques offer useful information on structural behavior and damage mechanisms but in many cases, it is necessary to have detailed physical modeling and large amounts of computational resources. Consequently, they are still not applicable to ongoing monitoring or post-event evaluation at a high rate, especially in case of large-scale or distributed infrastructure systems. The growing access to sensor-based time-series data has stimulated the use of machine learning methods in structural evaluation. Machine learning techniques are highly applicable to nonlinear time-series signals of high dimensions and have been effectively utilized in a number of damage detection and classifications using vibration in different applications [7].

The decision tree-based models and support vector machines have been popular techniques of supervised learning to classify the state of structural conditions using vibration signals. These models have demonstrated good results in the separation of healthy and damaged structures especially in the severe cases of damage where vibration signatures are very strong. Nevertheless, most of the existing literature is dedicated to binary classification or scenarios associated with collapse, whereas a relatively small number of studies are devoted to the issue of multi-class damage classification which also incorporates minor damage states. Convolutional neural networks and time-frequency representations are deep learning architectures that have additionally improved damage detection performance but tend to focus on extreme cases of damage [8-9].

Minor damage is difficult to detect because it has a subtle effect on vibration characteristics and it is confounded with normal structural behavior. Some researchers have investigated more advanced learning methods, such as hybrid physics-informed models and feature fusion techniques, to be more sensitive to early-stage damage, but most of these methods generally demand complicated architectures and large amounts of training data [10-11]. The other critical weakness of the present machine learning-based structural assessment studies is the little focus on model interpretability. Despite high classification accuracy, numerous studies consider black box models of machine learning, and they do not offer much information about the physical meaning of the input features, which may impede engineering confidence and limit its practical use [12].

The variability of the environment and operation also makes the vibration-based damage detection more difficult. Temperature effects, especially, may easily blur signal changes due to damage and cause misclassification without due consideration. The recent research has tried to solve this problem by compensation schemes and unsupervised learning schemes, but their application in seismic performance analysis is still very scarce [13]. Besides this, ensemble and benchmark-based deep learning solutions have been suggested to increase classification resilience, yet such solutions tend to focus on accuracy rather than interpretability and practical implementation factors [14-15].

Also, the imbalance of classes is a typical problem in structural monitoring data, with healthy structural conditions prevailing in the data. Unbalanced data distributions may

favor machine learning models to the majority classes and thus lead to lower sensitivity to the damage states, particularly the small damage. Even though this issue has a practical significance, it is not always considered in the current research. In general, the literature review suggests that systematic research on machine learning methods based on the integration of structural vibration and strain time-series signals to evaluate multi-class stability is required, with specific focus on minor damage detection and model interpretability.

3. Methodology

This paper takes a data-driven approach to forecast structural stability and damage-based seismic performance with structural vibration time-series signals. The suggested framework comprises the data preparation phase, feature construction phase, model training phase, and performance evaluation phase.

3.1 Dataset Description

An open-source structural health monitoring dataset based on time-series measurements of various sensors attached to a monitored structure is used to conduct the analysis. The data set consists of tri-axial acceleration data, structural strain data, and environmental temperature data measurements at a consistent time interval [16]. The data samples are coupled with structural condition label indicating one of three conditions: healthy, minor damage and severe damage. These classes are employed as supervised learning target classes.

3.2 Data Preprocessing

Preprocessing of data is done to make the input signals reliable and consistent. The timestamp is then changed into the conventional format of a datetime in order to preserve the chronological order. The records with incomplete sensor values are eliminated in order to prevent biasing in the model training. After the data cleaning stage, the rest of the samples are normalized with the help of standard feature scaling to make sure that all input variables make their contribution to the learning process. The step is very critical to distance-based classifiers and the kernel methods.

3.3 Feature Set Construction

The feature set of inputs has five variables, which include acceleration-responses along directions X, Y and Z, structural strain and temperature. The dynamic response of the vibration of the structure is measured using acceleration signals and structural deformation and damage development is measured using strain measurements. Temperature is also added to explain the possible environmental influences on sensor values and structural reaction. They are represented in their numerical form with these features directly used to maintain physical interpretability and to eliminate manual feature engineering.

3.4 Problem Formulation

Prediction of structural stability is defined as a multi-class classification problem, and each sample falls into one of three conditions of structural conditions, including healthy, minor damage, and severe damage. The aim is to be able to learn a mapping between the multi-channel vibration and strain signals and the structural condition labels associated with these labels.

3.5 Machine Learning Models

This study explores three machine learning models. A random forest classifier is used as a baseline model because it is very strong and it features nonlinear interaction of features. In order to eliminate the issue of class imbalance, Synthetic Minority Over-Sampling Technique (SMOTE) is used on the train data along with the Random Forest model. The effectiveness of a Support Vector machine classifier against overlapping classes of damage in the feature space is then evaluated with a Support Vector machine classifier having balanced class weights.

3.6 Model Training and Validation

A stratified split is used to split the dataset into training and testing subsets so as to maintain the proportions of the classes. The training data only are used to train the models, and they are tested on unseen test data to determine their generalization performance. Parameters of feature scaling are also obtained using the training set and used consistently to the test set to avoid data leakage.

3.7 Evaluation Metrics

The evaluation metrics applied in model performance are the overall classification accuracy, precision, recall and F1-score of each class. The patterns of misclassification are analyzed using confusion matrices, whereas the discriminative capability is measured using receiver operating characteristic (ROC) curves and area under the curve (AUC) values. The methods of dimensionality reduction and feature importance analysis are also used to justify interpretability of the learned models.

4. Results

The section includes a thorough assessment of the suggested machine learning framework used on structural vibration time-series signals to predict structural stability and damage-based seismic performance evaluation. All the results are achieved with the help of an independent test data to guarantee the objective evaluation of the generalization ability of the model.

4.1 Dataset Characteristics and Class Distribution

A total of 904 samples were retained in the analysis after data cleaning and elimination of records where there were missing values. The data are composed of five input variables three orthogonal acceleration components, structural strain, and temperature and a target variable that is the state of structural condition. Table 1 indicates the distribution of structural condition states after preprocessing. As demonstrated, there is a clear imbalance in the dataset, with the Healthy condition being the most prevalent with Minor Damage and Severe Damage states in the second and third place respectively. This imbalance is representative of realistic structural monitoring situations where the damage situations are less common than the normal operating situations. Figure 1 represents the visual representation of this distribution.

Table 1. Distribution of structural condition classes after preprocessing

Structural Condition	Label	Number of Samples
Healthy	0	637
Minor Damage	1	165
Severe Damage	2	102
Total		904

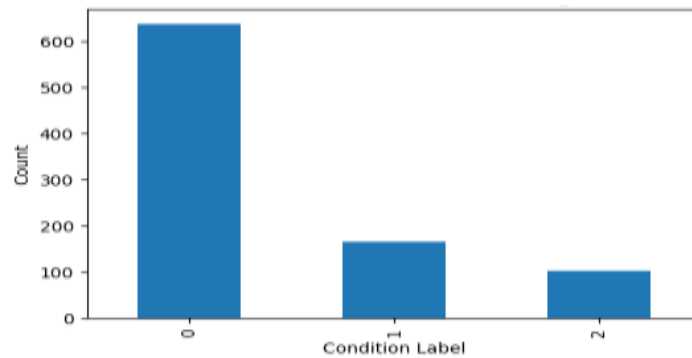


Figure 1. Distribution of structural condition labels after data cleaning.

4.2 Baseline Random Forest Classification Results

A Random Forest (RF) classifier was utilized as a control model to test the possibility of multi-class structural condition classification with the help of vibration and strain signals. The RF model had a total accuracy of 78.45 per cent on the test data, which suggests that the features of vibration can be used to capture the information of the structural condition. The model has high predictive power of healthy structural states but misclassification is mostly noted between minor damage and healthy states. This action shows how hard it is to identify early-stage damages, in which alterations in vibration nature are commonly faint and are frequently mixed with normal structural behavior.

4.3 Feature Importance Analysis

The feature importance analysis was performed with the help of the Random Forest model in order to understand the contribution of individual input signals. The values of the importance of the features ranked are summarized in Table 2. Figure 2 displays that structural strain is the most influential feature, which implies that it is highly sensitive to the damage severity and structural deformation. The components of horizontal acceleration also play a significant role, which indicates their contribution to the dynamic response characteristics capture. The impact of temperature and vertical acceleration is relatively lower and implies that the two factors play a secondary role in the classification process.

Table 2. Feature importance ranking obtained from the Random Forest model

Feature	Importance Score
Strain ($\mu\epsilon$)	0.445
Accel_X (m/s^2)	0.194
Temp ($^{\circ}C$)	0.137
Accel_Z (m/s^2)	0.112
Accel_Y (m/s^2)	0.111

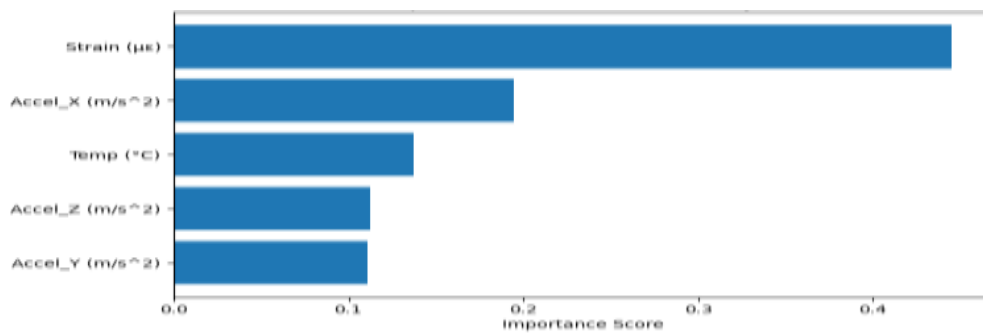


Figure 2. Feature importance ranking

4.4 Effect of Class Imbalance Handling Using SMOTE

The Synthetic Minority Over-sampling Technique (SMOTE) was used before training the model to handle the effects of the imbalance of the training data. Before and after SMOTE, the class distribution in the training set is summarized in Table 3, and it was possible to see that all structural condition classes were balanced to an equal number of samples. The model of the Random Forest trained on the SMOTE-balanced data had an overall classification accuracy of 75.14%. Even though this is a minor decrease in the global accuracy relative to the baseline RF model, the balanced training process has better sensitivity to the minority damage states, which is indicative of the trade-off between overall accuracy and fair performance by class.

Table 3. Training class distribution before and after SMOTE

Structural Condition	Label	Before SMOTE	After SMOTE
Healthy	0	509	509
Minor Damage	1	132	509
Severe Damage	2	82	509

4.5 Support Vector Machine Classification Results

A Support Vector Machine (SVM) classifier was then tested with equal class weights to enhance further classification robustness when there is an imbalance in the classes. The SVM model was the best at generalization as it was found to have the highest overall classification accuracy of 79.01, as compared to all other tested models. Figure 3 presents the confusion matrix of the SVM classifier. The SVM shows better balance between the structural condition states than the baseline RF model, having less misclassification of the damage classes and more reliable identification of minor and severe damage conditions.

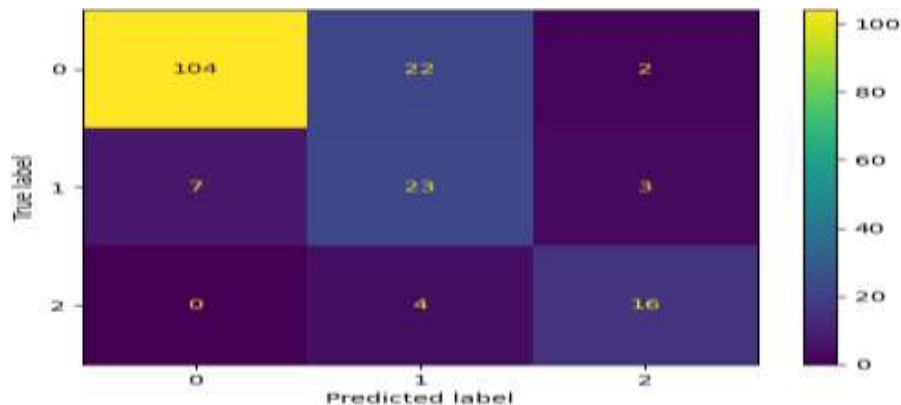


Figure 3. Confusion matrix of the SVM classifier on the test dataset.

4.6 ROC Curve Analysis

One-vs-rest Receiver Operating Characteristic (ROC) curves were also used to assess the discriminative ability of the SVM classifier as shown in Figure 4. The values of the Area Under the Curve (AUC) were 0.90 of healthy, 0.82 of minor damage, and 0.98 of severe damage. Such findings suggest that separability between structural condition states is very strong especially the severe damage safety critical class, and this shows the SVM model to be reliable in the process of identifying critical structural conditions.

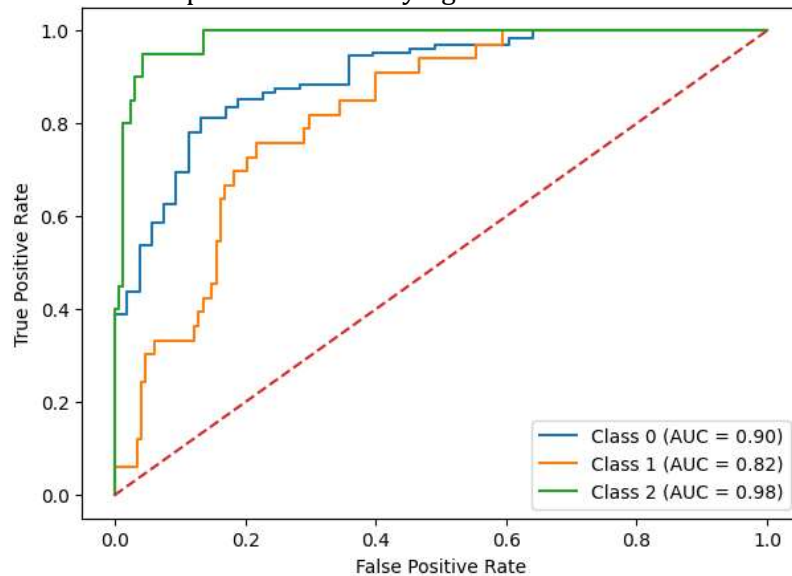


Figure 4. One-vs-rest ROC curves for the SVM classifier.

4.7 Feature Space Visualization

Principal Component Analysis (PCA) was used to reduce the dimensionality of the training data and then visualize the class separability in the reduced-dimensional feature space. The obtained two-dimensional PCA projection is presented in Figure 5. The projection shows some overlap of the healthy and minor damage samples whereas the severe damage samples are more separated. The results of this observation are in line with the classification results and reflect the innate difficulty of identifying early-stage damage using vibration signals alone.

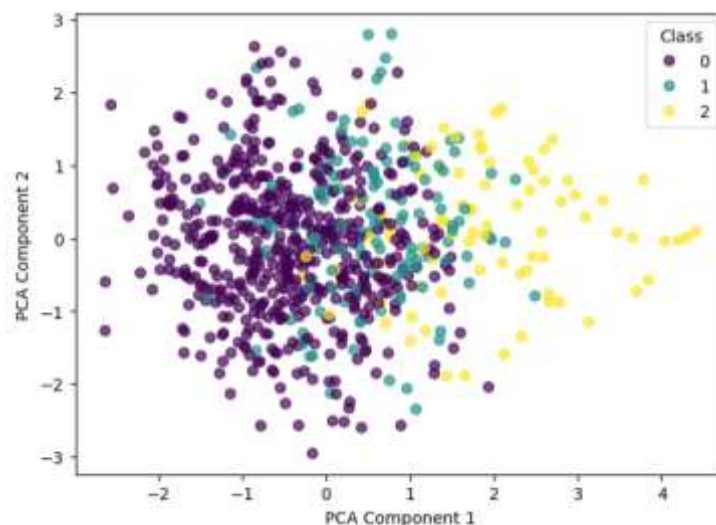


Figure 5. PCA projection of training samples colored by structural condition labels.

4.8 Comparative Model Performance

A comparative summary of the performance of the Random Forest, Random Forest with SMOTE, and Support Vector Machine models is presented in Table 4. This comparison highlights the trade-offs between global accuracy and damage-state sensitivity across models. While SMOTE improves minority-class recall, the SVM model provides the most balanced performance across all structural condition states.

Table 4. Comparative performance of evaluated machine learning models

Model	Overall Accuracy	Minor Damage Recall	Severe Damage Recall
Random Forest	0.7845	0.18	0.70
Random Forest + SMOTE	0.7514	0.33	0.85
Support Vector Machine (Balanced)	0.7901	0.70	0.80

5. Discussion

Machine learning on structural vibration time-series data offers a promising direction of further development of structural stability prediction and damage-based seismic performance assessment. The results of the research provide an idea of the reaction of various learning strategies on the nature of vibration and strain signals and the difficulties of the process of identifying different degrees of structural damage. The presence of the imbalance between healthy and damaged structural conditions is in line with realistic monitoring conditions and is essential in the development of model behavior. States of minor damage are especially problematic because they cause a modest effect on vibration and are mixed with normal structural behaviour. This property is the reason behind the lower sensitivity of baseline learning methods and the necessity to employ specific strategies in case of the need to detect damage at the initial stages [17].

The results of the Random Forest classifier prove that ensemble-based models can be useful to describe nonlinear relationships between multi-channel vibration features and the state of structural conditions. Good results in healthy and severe damage classification show that the significant structural alterations can be easily identified by the vibration signal. Nevertheless, small sensitivity to small damage indicates that more mechanisms are required to improve discrimination in less clear damage signatures. The dominance of structural strain in damage classification as highlighted by the feature relevance analysis supports the physical association of structural strain to deformation and stiffness degradation. The components of acceleration help in capturing the dynamic response properties whereas the environmental temperature has a secondary role. The correspondence of the relevance of features and familiar structural behavior enhances the interpretability and engineering plausibility of the presented framework [18].

Oversampling of training data enhances the learning capacity of the model to acquire decision boundaries that are linked to minority damage states. Even though this method presents a trade-off in the overall classification accuracy, it increases the detection of damage conditions that are important to seismic performance assessment. This type of trade-off is especially applicable to safety-related applications, in which the cost of not detecting damage may be more important than the cost of more false alarms. The Support Vector Machine is the most balanced in terms of the structural condition states among the evaluated classifiers. Its capacity to deal with overlapping distributions of features and build strong decision boundaries allows it to be more sensitive to minor damage and still be able to detect severe damage reliably. This observation means that the use of kernel-based learning approaches would be appropriate in the vibration-based structural assessment problems that have complex and overlapping signal patterns [19].

The above-mentioned behavior of feature space also demonstrates that it is intrinsically difficult to distinguish early-stage damage based on the vibration data alone, and also proves that serious damage presents more distinguishable response patterns [20]. These results highlight the significance of using a combination of informative characteristics, balanced learning, and appropriate classifiers in order to achieve successful structural stability evaluation [21].

In general, the findings can be used to emphasize the prospects of machine learning-based solutions in aiding credible and interpretable seismic performance assessment with the help of structural vibration time-series signals [22]. The proposed framework provides a practical basis of data-driven structural health monitoring and decision support by tackling the issue of class imbalance and exploiting physically meaningful response characteristics.

6. Conclusion

Machine learning on structural vibration time-series data provides a highly versatile and effective method of developing structural stability forecasting and damage-based seismic performance assessment. With the help of sensor-based acceleration and strain data, data-driven models can successfully reproduce multifaceted links between structural response attributes and hidden damage conditions. The results of this paper show that the features of vibration-based and strain-based can be used as adequate sources of discriminative information to aid in multi-class structural condition evaluation with the help of the corresponding learning strategies. Ensemble and kernel-based machine learning models can be used to model nonlinear response patterns related to various damage severities, whereas balanced training methods are also important in increasing sensitivity to those damage conditions that are less represented. Specifically, the detection of minor damage should be improved to enable early intervention and structural performance management over time. The relevance of features analysis shows the prevailing role of structural strain in damage classification as it is directly related to deformation and stiffness degradation. The significance of the acceleration components is further highlighted by the fact that dynamic response information is critical in the vibration-based assessment. The combination of features that can be interpreted physically and robust machine learning models increases the transparency and engineering credibility of the proposed framework. In a practical sense, the results highlight the need to align the model selection and evaluation criteria with safety-focused goals, instead of focusing on the overall accuracy. This is because the capability to consistently identify damage conditions, particularly those relating to premature degradation or structural hazard is the key to successful seismic performance appraisal and decision support. The given framework, in general, offers an interpretable and scalable basis of data-driven structural health monitoring based on vibration time-series signals. Future studies can be oriented towards adding the data of long-term monitoring, explicit seismic excitation data, and sophisticated learning systems to enhance the robustness and application in real-world infrastructure systems.

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