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Small-scale damage detection of bridges using machine learning techniques and drive-by inspection methods

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ABSTRACT: The drive-by inspection approach for bridge health monitoring has received a lot of interest recently due to its advantages in mobility, economy and efficiency. The feasibility of it has been demonstrated by many studies via numerical simulations, laboratory experiments, and even field tests, when there is a noticeable damage. In terms of minor damages, however, the dynamic features (e.g., frequencies and mode shapes) of the damaged bridge are highly similar to those of the healthy one, for which traditional drive-by methods are likely to perform poorly. Machine learning techniques, which utilize the entire time-domain responses and are sensitive to tiny signal changes, have the potential to identify small-scale damages and achieve higher detection accuracy. This paper compares the performance of different machine learning methods on the indirect framework and proposes a strong classification algorithm for damage identification of bridges. Laboratory experiments were conducted to build the dataset by employing a steel beam and a scale truck model. It presents an early attempt to experimentally validate the feasibility of the drive-by inspection method to identify small structural changes in the bridge.

1 INTRODUCTION

In recent years, bridge maintenance and monitoring have become widespread concerns around the world (Malekjafarian et al. 2015). However, the direct methods for Structural Health Monitoring (SHM) have long been considered as expensive methods due to the enormous costs associated with sensor installation and maintenance (Abdulkarem et al. 2020). Moreover, because the instrumentation is permanently fixed on the bridge as a tailored SHM system, it can be challenging to transfer one monitoring framework to other bridges (Wang et al. 2022). These drawbacks restrain the broad application of direct SHM methods on bridges, and there is a need to develop an alternative strategy without instrumenting the bridge.

The drive-by bridge inspection method, an indirect SHM technique, has gained a lot of interest recently due to its benefits in mobility, economy, and efficiency (Malekjafarian et al. 2015). Studies have investigated the potential of the drive-by method in extracting bridge modal parameters, such as fundamental frequencies and mode shapes, via numerical simulations, laboratory experiments, and field tests (Yang et al. 2004; Lin & Yang 2005; Lan et al. 2022a, 2022b). Changes in modal parameters could indicate bridge deterioration, which is referred to as the modal parameter-based approach (Yang & Yang 2018).

However, most modal parameter-based methods fail to achieve satisfactory performance for small-scale damage detection due to several reasons. First, the bridge frequency, which is used in many studies as a damage indicator, lacks adequate information to indicate damage. They are easily impacted by environmental factors like temperatures (Spiridonakos et al. 2016). Second, mode shapes or their derivations are usually subject to measurement errors, disguising changes from small-scale damage (Zhang et al. 2019). Although there are some approaches based on indicators like displacement profile and moving force, similar problems have been discovered as well (OBrien et al. 2014; OBrien & Keenahan 2015; Lan 2021). Machine Learning (ML) methods can leverage the whole time-domain and frequency-domain responses rather than just peaks in the

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spectrum (Liu et al. 2020); they are sensitive to small changes in the signal (Zhang et al. 2019). The combination of ML techniques and the drive-by method has the potential to identify small-scale damage and achieve higher detection accuracy.

Currently, compared with the application of ML technology on direct SHM, there have been few studies and implementations of ML techniques on indirect SHM (Wang et al. 2022). Based on Support Vector Machines (SVM), Cerda et al. (2014) successfully identified different bridge damage states with vehicle vibration data. In 2019, Artificial Neural Network (ANN) was first applied to indirect SHM problems by Malekjafarian et al. (2019), obtaining promising results for the damage detection of bridges. These studies verified the "potential" of ML methods in indirect SHM frameworks, but the ability of ML methods for small damage detection has not been fully exploited. On the other hand, since SVM and other normal classifiers may perform poorly for small-scale damages whose dynamic responses are highly similar to those of health, it is advantageous to build a strong classification algorithm that is sensitive to minor damage features.

A combined algorithm based on SVM and AdaBoost may provide a superior performance in this case. Studies show that SVM performs well on health state classification problems (Cerda et al. 2014), and combining it with a boosting algorithm may further improve its accuracy. AdaBoost can be used as a boosting strategy; it forces SVM to focus on misclassified samples from the minority class, preventing the minor damage features from being considered as noises (Kuncheva & Whitaker 2002). Linear and simple classifiers could better separate the high-dimensional spaces composed of vibration data in general, so linear-SVM is selected as the base learner in AdaBoost. However, the integration of linear SVM with AdaBoost is still difficult; it requires a suitable regularization parameter, C, to balance the "complexity" and "diversity" of SVM as the component classifier (Li et al. 2008). An optimization strategy for seeking the appropriate C value is therefore the key to building an efficient combination algorithm of AdaBoost-linear SVM.

This paper compares the performance of different ML methods on the indirect framework and proposes a strong classification algorithm, Optimized AdaBoost-linear SVM (OAB-linear SVM), for damage identification of bridges. Laboratory experiments were conducted to establish the dataset by employing a steel beam and a scale truck model. The paper presents an early attempt to experimentally validate the feasibility of the drive-by method to identify small damage in the bridge. ML models learn to identify bridge health states using raw vehicle acceleration signals as inputs. The model's performance is evaluated by its accuracy in classifying the test sets of different health statuses. The experimental results from the vehicle are also compared with those acquired directly from the bridge model to show the feasibility of the indirect SHM framework.

2 METHODOLOGY

2.1 *Background of different ML models and the proposed method*

In this study, five different ML models will be chosen as the classifiers for structural health states, in addition to the proposed algorithm. They are Linear-SVM, RBF-SVM, Gaussian Process (GP), Artificial Neural Network (ANN), and Random Forest (RF). They are algorithms commonly used in structural health state classification problems, and their summaries are as follows:

Linear-SVM: One of the most robust and accurate models of well-known ML algorithms is SVM (Evgeniou & Pontil 2001). The goal of linear-SVM is to find separating hyperplanes that can separate the dataset as reliably as possible into distinct data classes. Ideally, when the data are completely linearly separable, the hyperplanes will be as far as possible from the nearest elements of the classes.

RBF-SVM: RBF-SVM, as one of the nonlinear SVMs, replaces hyperplanes with Gaussian manifolds, but the basic principle remains the same (Evgeniou & Pontil 2001). One can adapt SVM to be a nonlinear classifier, which allows SVM to separate nonlinearly separable support vectors.

GP: GP is a generalization of the Gaussian probability distribution and can be used for classification and regression (Rasmussen & Williams 2005). It is a type of kernel model, similar to SVM, but unlike SVM, it can predict highly calibrated class membership probabilities, although the choice and configuration of the kernel used at the heart of the method can be challenging.

ANN: ANN is based on a collection of connected units or nodes called artificial neurons, which loosely resemble the neurons in a biological brain (Goodfellow et al. 2016). Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer (the input layer) to the last layer (the output layer), possibly after traversing the layers multiple times.

RF: RF is an extension of the bagging method, which uses feature randomness in addition to bagging to produce an uncorrelated forest of decision trees (Ho 1995). For classification problems, the output of RF is the class selected by most trees. RF generally outperforms decision trees, but its performance can be affected by data characteristics.

OAB-linear SVM: the proposed algorithm employs SVM with a linear kernel as component classifiers in AdaBoost and seeks its best generalization performance in damage detection. SVM is a strong classifier, and there is a need to weaken its learning abilities to benefit from AdaBoost mechanisms. It consists of a training process and an optimizing process, as shown in Tables 1 and 2, respectively. The input data is divided into a training set and a validation set with a ratio of 9:1. In the training process, AdaBoost maintains a weight distribution over training samples, which is initially configured to be uniform. Linear SVM as the component classifier is called repeatedly in a series of cycles, T. Linear SVM trains a classifier, h_t, at each iteration, t, and the distribution, w^t, is updated in each iteration based on the prediction results on the training samples. Correctly classified samples are assigned smaller weights, while misclassified samples are given larger weights. In the optimizing process, a very small C value, C_{ini}, is initially set corresponding to a linear SVM with weak learning ability. Linear SVM with this C value is then trained by AdaBoost to return an accuracy on the validation set. After that, the C value is increased slightly by C_{step}, to improve the learning ability of linear SVM. This procedure is repeated until the final cycle, S, is completed. The classifier with the highest result accuracy is chosen as optimal for the given dataset. The values of C_{ini}, C_{step}, S, and T required for the algorithm are set as 0.01, 0.1, 1000, and 50, respectively.

Table 1. Training process.

Require: training samples with labels, $\{(\mathrm{x}_1,\ y_1), \ldots, (\mathrm{x}_i,\ y_i), \ldots, (\mathrm{x}_N,\ y_N)\}$, where x_i represents the i-th vector in the training set; y_i = {-1,1} for damaged and healthy labels.
Require: the number of iterations at which boosting is terminated, T.
Initialize the weights of sub-training samples, $w_i^1 = 1/N$ $(i = 1, 2, 3, \ldots,\ N)$.
For iteration t in T:

(1) Train a Linear SVM component classifier, h_t, on the weighted sub-training set.
(2) Compute the training error of $h_t : \varepsilon_t = \sum_{i=1}^{N} w_i^t, y_i \neq h_t(\mathrm{x_i})$.
(3) Set the weight of the component classifier $h_t : \alpha_t = \frac{1}{2}\ln\left(\frac{1-\varepsilon_t}{\varepsilon_t}\right)$.
(4) Update the weights of sub-training samples: $w_i^{t+1} = \frac{w_i^t \exp[-\alpha_t y_i h_t(\mathrm{x}_i)]}{C}$, where $\sum_{i+1}^{N} w_i^{t+1} = 1$.

Output: $f(\mathrm{x}) = \mathrm{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(\mathrm{x})\right)$.

Table 2. Optimizing process.

Require: validation samples with labels, $\{(\mathrm{x}_1,\ y_1), \ldots, (\mathrm{x}_i,\ y_i), \ldots, (\mathrm{x}_M,\ y_M)\}$.
Require: AdaBoost-linear SVM, $f(\mathrm{x})$.
Require: the number of cycles in updating the regularization parameter, S.
Require: the initial regularization parameter, C_{ini}; the step of regularization parameter, C_{step}.
For iteration s in S:

(1) Calculate the accuracy on validation sets with $f(\mathrm{x})$: accuracy[s] $= \frac{TP+TN}{TP+TN+FP+FN}$, where TP, TN, FP, FN represent true positive, true negative, false positive and false negative predictions in samples.
(2) Increase C value by C_{step}: $C = C_{step} \times s + C_{ini}$

Output: $F(\mathrm{x}) = f_{s,max}(\mathrm{x})$ corresponding to the max accuracy[s].

2.2 *Signal processing and diagnostic framework*

Raw accelerations collected from the passing vehicle will be processed to build the dataset for ML models. Figure 1 shows the processing procedure for the vehicle accelerations. For each passage, the valid acceleration segment will be cut off after the acquisition of vehicle acceleration, where peaks can be found in the acceleration records of the front axle when the vehicle enters and exits the bridge due to expansion joints at both ends; they can be regarded as indicators for selecting the effective segments. Given the passage time of T, and the sampling frequency of F, there are totally $T \times F$ discrete points in the valid segment. To reduce the influence of noise, a sliding window-based method is used to process the selected data (window length = 10, stride = 1), after which the processed time-domain signals are utilized as inputs for ML models. In the study, the experiments were conducted in a normal laboratory environment, where white noise was the main source of noise. Thus, the Gaussian function is chosen as the window function. The database obtained from vehicle responses has a total of 1600 runs, and it is split into the training set and test set with a ratio of 85%:15%. ML models learn to identify bridge health states via the training set and their performance is evaluated by the accuracy in the test set.

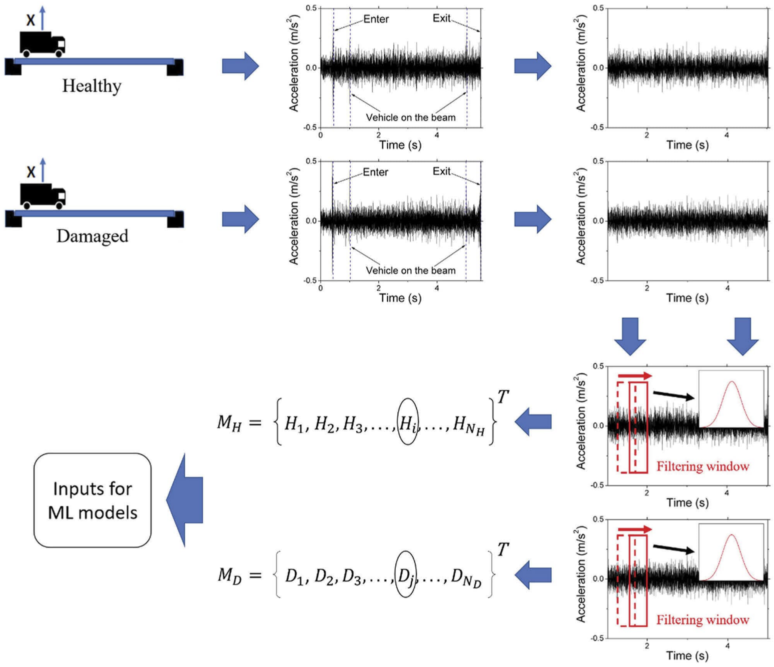


Figure 1. Signal processing procedure.

3 EXPERIMENTAL PROGRAM

Laboratory experiments were performed to validate the methodology using a steel beam and a scale truck model with an engine. Instead of inducing real structural damage, damaged states were simulated by adding masses to the beam to avoid permanent or irreversible destruction. It is a common practice in the laboratory that has been proven feasible by many studies, such as those conducted by Zhang et al. (2019), Liu et al. (2020), and Lan et al. (2023). The data acquisition system, which is PC-driven and has a sampling rate of 2 kHz, is the same for both the beam and the truck model; it is connected with sensors via wires. The sensors used in the study are made by Bruel & Kjær (TYPE 4371), and relevant specifications are provided as follows: frequency range (0.1 – 12600 Hz), weight (11 gram), and sensitivity (1.0 pC/ms^{-2}).

3.1 *Bridge and vehicle models*

Bridge model: Physical properties of the beam model (HEA400) are listed as follows: elastic modulus E = 199 GPa; density $\rho = 7.85 \times 10^3$ kg/m^3; length L = 4.4 m; section area

A = 15898 mm^2, and moment of inertia $I = 8.564 \times 10^7$ mm^4. The setup and dimension details can be referred to in Figure 2. The setup includes an acceleration ramp, a deceleration ramp, and a guide rail (see Figure 3a) that is used to adjust the path of the vehicle so that it can pass straight through the beam. As artificial damage, masses were added to different locations of the beam (see Figure 3b); the details will be discussed later. For comparison purposes, three accelerometers were also instrumented at $0.1L$, $0.5L$, and $0.9L$ of the steel beam (see Figure 3c), respectively, to obtain the bridge vibrations during the vehicle's passage.

Vehicle model: Tamiya's Mercedes-Benz 1850L was employed as the vehicle model (see Figure 4a). Except for the weight, this engine-driven 1/14 scale model (568 mm × 202 mm) realistically captures the configuration of a full-sized truck. The self-weight of the vehicle model is 4.05 kg, and a 6-kg mass is added inside the vehicle body; thus, the overall vehicle weight is 10.05 kg. Four accelerometers were mounted on the front of the car, the vehicle body, the rear axle, and the front axle, respectively, as described in Figure 4b, c. The maximum speed of the vehicle model is 0.9 m/s, and this speed is used in the test. Additionally, an acceleration ramp is employed to guarantee the maximum speed can be reached before the vehicle enters the bridge. The velocities maintain similar in each run.

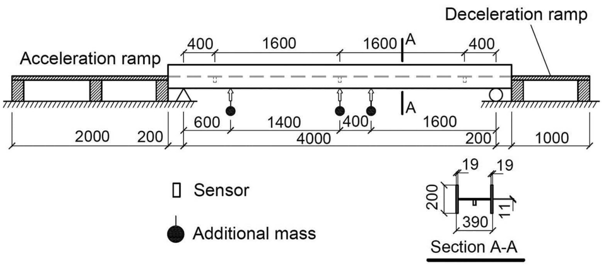
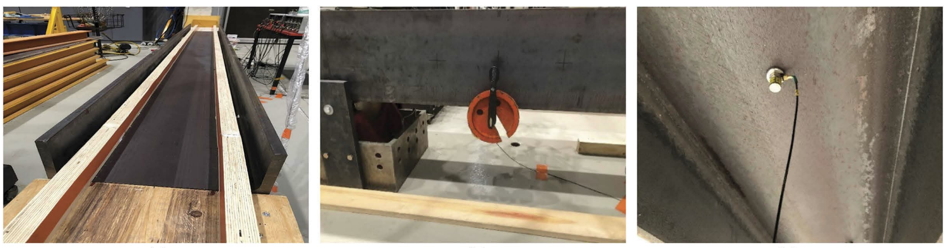
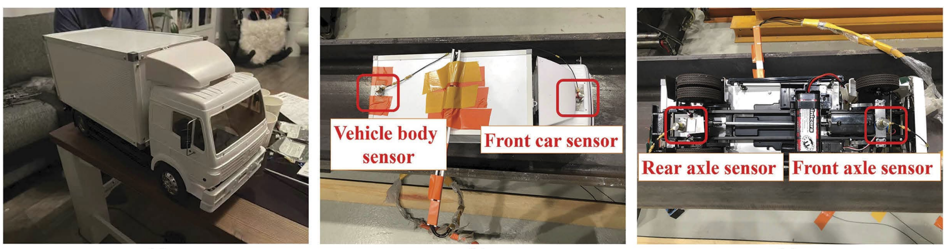


Figure 2. Details of the beam model (unit: mm).



(a) (b) (c)

Figure 3. Setup for the beam model: (a) guide rail; (b) added mass; (c) accelerometer.



(a) (b) (c)

Figure 4. Setup for the vehicle model: (a) scale vehicle model; (b) sensor installation (top); (c) sensor installation (bottom).

3.2 *Experimental dataset*

For the diagnostic framework, data from both intact and damaged states of bridges are required. The vehicle was driven across the bridge repeatedly to acquire the dataset for training and testing the ML models. There are totally 8 cases of health states including the healthy case used as baseline; these cases were collected from 3 damage locations and 5 damage severities, as described in Table 3. The placement of mass at different locations is used to validate the viability of the method; $0.5L$ (2 m) and $0.6L$ (2.4 m) stand for the damage locations at and near the mid-span of the bridge, and $0.15L$ (0.6 m) represents the damage location near the bridge support. Due to the larger vibration responses in the mid-span bridge, the detection performance of the mid-span is usually better than that near the support. $0.15L$, as one of the most unfavorite location cases, is chosen to investigate the sensitivity of the method to the bridge damage by using various mass sizes. Each state contains 200 vehicle passages to establish the experimental dataset. Thus, there are 200 (runs) × 8 (cases) × 7 (sensors) = 11200 (signals), and each signal has 8000 discrete points corresponding to 4s of "valid segments".

Table 3. Health state description.

Case No.	Location	Weight	Runs	Case No.	Location	Weight	Runs
0	0	0 (Healthy)	200	4	0.6 m	2 kg (0.4%)	200
1	0.6 m	20 kg (4%)	200	5	0.6 m	1 kg (0.2%)	200
2	0.6 m	10 kg (2%)	200	6	2 m	20 kg (4%)	200
3	0.6 m	5 kg (1%)	200	7	2.4 m	20 kg (4%)	200

4 RESULTS AND ANALYSIS

4.1 *Damage indication performance*

The main parameters of Linear-SVM, RBF-SVM, GP, ANN, and RF are determined by Grid Search (LaValle & Branicky 2004), as shown in Table 4. While the hyper-parameters of AB-linear SVM are tuned by the proposed optimizing method. The performance of each ML model is assessed via 5-fold cross-validation. The results from the rear axle sensor are illustrated herein, while results from sensors on other positions will be discussed later. Table 5 shows that the accuracy of ML algorithms decreases as the damage becomes less severe. The smallest damage of 1 kg (0.2%) used in the experiment can be successfully detected by ML models with accuracy ranging from 63.3% to 76.7%. The closer the accuracy is to 50% (random guess), the poorer the detection performance is, or the ML model is just not suitable for the SHM framework. Among these models, OAB-linear SVM outperforms other models by better classifying the damage states, which provides higher accuracy. It improves the accuracy by 6.2% on average when compared to the linear SVM, and by 5% to 16.6% compared to other algorithms. This is due to AdaBoost forces the linear SVM as a component classifier to concentrate on misclassified samples from the minority class, avoiding the minor damage features from being considered as noise. It is found that ML methods, especially the proposed algorithm, are of great significance for the identification of minor damages, which can expand the lower limit of detectable damage range.

Table 4. Major parameters of classification algorithms.

Algorithm	Configuration	Algorithm	Configuration
Linear-SVM	C=5	ANN	hidden_layer_sizes=(10, 4), alpha=1, max_iter=1000
RBF-SVM	gamma=0.01, C=5	RF	n_estimators=1000, max_features=20
GP	Kernel=10 * RBF(10)		

4.2 *Performance comparison for sensor locations*

The above results are acquired from the rear axle sensor, and the results from different sensor locations are presented in Table 6, where the results of the bridge sensor are used here to compare the direct and indirect methods. These results are based on OAB-linear SVM, as it has the highest accuracy, and similar results can be seen in other models. The data for the front-car

Table 5. Classification performance for ML models.

Cases	Details	OAB-linear SVM	Linear-SVM	RBF-SVM	GP	ANN	RF
Case1	0,15L, 20kg	88.3 %	83.3 %	73.3 %	75.0 %	81.7 %	78.3 %
Case2	0,15L, 10kg	85.0 %	78.3 %	70.0 %	71.7 %	78.3 %	75.0 %
Case3	0,15L, 5kg	81.7 %	75.0 %	68.3 %	70.0 %	75.0 %	71.7 %
Case4	0,15L, 2kg	78.3 %	73.3 %	65.0 %	66.7 %	73.3 %	68.3 %
Case5	0,15L, 1kg	76.7 %	70.0 %	63.3 %	65.0 %	71.7 %	66.7 %
Case6	0,5L, 20kg	93.3 %	86.7 %	76.7 %	81.7 %	85.0 %	83.3 %
Case7	0,6L, 20kg	91.7 %	85.0 %	76.7 %	78.3 %	85.0 %	85.0 %

sensor are not included in the table because the contact between the front car and the rail limits its free vibration. It can be observed that there is no significant difference in the accuracy of varied sensor locations, The similarity of results from the vehicle and bridge sensors implies that the indirect SHM framework is equally effective as the direct SHM system. Furthermore, the effectiveness of ML methods is not limited to a specific SHM framework or sensor location.

Table 6. Comparison performance for sensor locations.

Cases	Details	Car body	Rear axle	Front axle	Beam1	Beam2	Beam3
Case1	0,15L, 20kg	88.3 %	88.3 %	86.7 %	88.3 %	88.3 %	88.3 %
Case2	0,15L, 10kg	83.3 %	85.0 %	85.0 %	85.0 %	85.0 %	85.0 %
Case3	0,15L, 5kg	81.7 %	81.7 %	81.7 %	81.7 %	81.7 %	81.7 %
Case4	0,5L, 20kg	78.3 %	78.3 %	76.7 %	78.3 %	78.3 %	78.3 %
Case5	0,15L, 1kg	73.3 %	76.7 %	75.0 %	76.7 %	76.7 %	76.7 %
Case6	0,5L, 20kg	93.3 %	93.3 %	91.7 %	95.0 %	95.0 %	95.0 %
Case7	0,6L, 20kg	90.0 %	91.7 %	90.0 %	91.7 %	91.7 %	91.7 %

5 CONCLUSION

In this paper, the performance of different ML methods is compared, and a strong classification algorithm is proposed for the indirect SHM framework. Laboratory experiments using a steel beam and a scale truck model were performed to obtain the dataset. Additional weights on the beams as "artificial damage" are used to validate the effectiveness of different ML methods and the proposed algorithm in damage detection, especially small damages. Based on the experimental results, the following conclusions can be drawn:

(1) ML methods are sensitive to damage. The ML methods used in this paper have accuracy ranging from 63.3% to 76.7% for small damage (0.2% severity), among which the proposed algorithm, OAB-linear SVM, shows the highest accuracy of 76.7%. They could expand the lower limit of the detectable damage range, which is of great benefit to the detection of minor damage.
(2) OAB-linear SVM is demonstrated to outperform other ML models in the study, with improvements ranging from 5% to 16.6%. This could allow it to become a preferable option for damage detection problems.
(3) The indirect SHM framework can be equally effective as the direct SHM system, and the effectiveness of ML methods is not limited to a specific SHM framework or sensor location.

A frontier of research is the integration of ML models with semi-supervised or unsupervised learning frameworks to build a new generation of smart bridges.

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