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State-of-the-art review of vibration-based bridge health monitoring using Artificial Intelligence

Zhenkun Li[1] | Kun Feng[2] | Athanasios Markou[1] | Weiwei Lin[1]

Correspondence

Dr. Zhenkun Li
Department of Civil Engineering, Aalto University, 02150 Espoo, Finland
Email: zhenkunli@aalto.fi

[1] Department of Civil Engineering, Aalto University, Espoo, Finland
[2] Faculty of Engineering, Agri-tech and the Environment, Anglia Ruskin University, Peterborough, UK

Abstract

Due to the deterioration and aging of bridge structures over the past decades, structural health monitoring (SHM) systems have garnered significant attention from researchers worldwide. SHM systems encompass multiple modules, including sensing, data collection, transmission, management, damage detection, and safety assessment. As a highly interdisciplinary field, SHM integrates various technologies such as sensor sensing, data acquisition, signal processing, and optimization. One of the promising approaches in bridge health monitoring (BHM) is vibration-based monitoring, which provides critical information for bridge condition assessment and maintenance. In recent years, advancements in computer hardware and Artificial Intelligence (AI) algorithms have significantly enhanced the capability of vibration-based BHM systems. AI, with its advanced analytical power and high sensitivity to anomalies, has been widely adopted in these applications, enabling more efficient and accurate damage detection. This paper presents a state-of-the-art review of vibration-based BHM using various AI techniques over the past two years. It explores how AI can facilitate data-driven BHM systems for bridges and discusses key aspects of the BHM process, including existing methodologies and current challenges. Additionally, the paper highlights potential research directions to guide future studies, offering insights and opportunities for researchers in the field.

Keywords

structural health monitoring, vibrations, bridge, AI

1 Introduction

Bridge structures serve as fundamental elements in worldwide transportation systems. A considerable number of bridges built in Europe last century have surpassed 50 years of service life [1]. The process of aging and deterioration has emerged as a serious problem, which presents both operational threats and structural weaknesses. For example, the collapse of the Morandi bridge in 2018 was a typical case, which underlined the importance of continuous maintenance. Bridges now face performance challenges due to escalating traffic and social changes that require updated standards. Regular health checks are essential for aging structures, as elevated loads can exceed their strength capacity.

Visual inspection, traditionally used to evaluate bridge conditions, has established itself as a main method for detecting surface failures on bridges. The established inspection technique encounters multiple major limitations because it requires engineering expertise, long periods of work, and extensive manual effort. The rising numbers of bridges being constructed faster and larger has made visual inspection inadequate for contemporary bridge monitoring needs. Damage assessment reliability suffers from subjective inspector judgments through this examination method, which leads to possible errors and inconsistent results.

The start of the 21st century has witnessed the development of structural health monitoring (SHM) systems for continuous bridge condition assessments [2]. The primary focus of SHM systems combines data acquisition with processing, followed by damage alert systems and prognostic estimates for remaining operational periods. Damage detection stands out as a crucial task in SHM systems because it allows engineers to adopt proper maintenance and repair approaches. The implementation of SHM systems includes placing different sensors across bridges to measure their health status. The detection equipment consists of fiber optic sensors [3,4], piezoelectric sensors [5], global navigation satellite system sensors [6], magnetostrictive sensors [7], and other forms of sensors. These devices detect various structural data points before further analysis proceeds. The monitoring algorithms benefit from improved robustness because of data collection on external operational factors, which include temperature and

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humidity along with traffic conditions [8]. The vibration-based SHM methods represent promising techniques because they offer effective non-destructive assessments for bridge conditions.

The traditional implementation of bridge monitoring through vibration methods mostly depends on modal parameters used to evaluate structural health by analyzing natural frequencies, mode shapes, and damping ratios. When operating under real conditions, these modal parameters demonstrate a limited ability to detect small mechanical failures or corrosion at early stages. Engineers typically encounter this damage type during practical use, but its effect on dynamic characteristics remains difficult to detect due to hardly noticeable changes [9]. No alternative dynamic fingerprinting methods proposed over the last few decades have managed to overcome operational conditions and environmental factors, which continue creating obstacles for effective damage identification in real-world applications [10].

Artificial Intelligence (AI) techniques have experienced substantial development since software and hardware innovations have driven their progress across the previous few decades. The wide range of implementation areas for machine learning (ML) includes other domains as well as SHM [11–13]. The feature-learning capability of deep learning (DL) makes it a leading method for automatic bridge health condition assessment [14]. The high sensitivity to anomalies characteristic of DL network systems enables effective detection of small structural damage. The implementation of AI techniques for bridge health monitoring (BHM) has grown significantly over recent years to solve multiple problems within the domain. Research papers have investigated various methods of SHM that utilize AI techniques. The application of bridge monitoring through ML algorithms has been thoroughly summarized by Sonbul and Rashid [15], which included decision trees, random forests, support vector machines, k-nearest neighbors, as well as diverse neural network architecture implementations. Cha et al. [16] underwent through a detailed examination of DL-based SHM systems by explaining fundamental DL principles and mentioning recent practical applications. However, the existing reviews were published before early 2023. Multiple advanced ML and DL approaches have appeared during the last two years. For example, when two keywords "machine learning" and "bridge health monitoring" are utilized in Scopus database, 79 articles and 59 conference papers can be found from 2023 to 2025. Given the fast-growing field, a new extensive literature review is needed.

The current paper conducts an extensive review of vibration-based BHM that employs AI techniques. Section 2 demonstrates how AI techniques are implemented in BHM applications. Section 3 discusses existing approaches to BHM, including their weaknesses and potential directions for upcoming investigations. Finally, Section 4 provides concluding remarks.

2 Applications of AI in BHM

This section explores three key areas in AI-driven BHM: data anomaly detection, data recovery, and bridge damage detection. Among these, damage detection can be categorized into direct and indirect methods. The direct method involves installing sensors directly on the bridge to collect structural responses. This approach provides detailed and accurate data on bridge behavior, making it highly informative for health assessment. However, its implementation is often costly due to the need for multiple sensors to measure various system responses [17]. Also, a large amount of data will be collected and need to be addressed [18]. Conversely, the indirect method utilizes vehicle response data, where only a few sensors, typically installed on a moving vehicle, are required [19–21]. This technique is more cost-effective and convenient, as it eliminates the need for extensive sensor networks on the bridge itself. Nevertheless, extracting bridge-specific information from vehicle data presents challenges due to interference from vehicle dynamics and road roughness effects, which can obscure structural signals [22]. This section provides an in-depth discussion of these applications, highlighting recent advancements in AI techniques for each category. The outline of this section is shown in Figure 1.

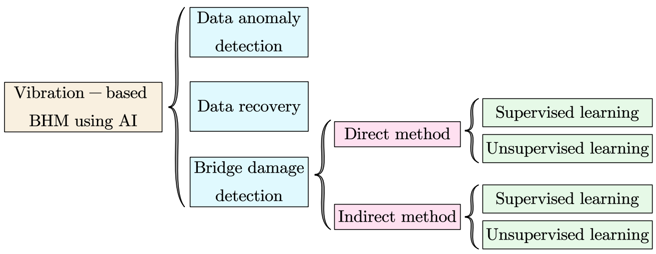

Figure 1 Outline of AI applications in BHM.

2.1 Data anomaly detection

BHM monitors bridge health from start to finish of its total service period. Extreme weather or other conditions can damage sensors, which produce either poor-quality data or data containing useless information. Duration-based quality assessment of data must take place continuously so that users can detect deviations before these deviations get included within the analysis.

In 2023, Ye et al. [23] created a DL-based anomaly detection technique for SHM systems with environmental sensitivity. The method used wavelet scalograms to generate RGB images from time-series data while classification occurred through the application of a convolutional neural network (CNN) architecture based on GoogLeNet [24]. The identified method performed better than traditional approaches in detecting bridge anomalies on cable-stayed structures while dealing with restricted data availability. The assessment process experienced an increase in reliability due to reduced false alarms together with better structural evaluations. Lei et al. [25] developed a residual attention network that detected anomalies in SHM data. Mutual information-based preprocessing enabled the method to achieve good classification accuracy results. The proposed detection method exceeded established models by demonstrating exceptional capabilities in anomaly detection across all cases. Pan et al. [26] introduced a transfer learning approach for identifying anomalies in SHM. The network used data from one bridge which it had pre-trained on to process limited data from another bridge, enabling better accuracy results. The experimental validation on two bridges proved that this method provided better classification results using fewer training sets to show its potential for complex BHM analyses. Research in SHM directed its focus on developing real-time anomaly detection systems. In 2024, Kang et al. [27] developed an ML-based alert system for continuous bridge monitoring through their process of transforming one-dimensional time-series sensor data into two-dimensional tensors. The model acted as an encoder to boost structural behavior analysis; thus, it surpassed conventional threshold-based monitoring methods when detecting sensor deviations and structural anomalies.

Data anomaly detection helps engineers identify sensor-related issues early, allowing them to take timely corrective measures and ensure data quality for subsequent analysis.

2.2 Data recovery

Data loss occurs due to sensor malfunctions along with transmission errors, while the analysis suffers as well as the extraction of meaningful insights becomes limited. Different approaches have been investigated for missing data recovery through accessible available data sources. Research workers add data recovery results to current data collections to support a better evaluation of the bridge health condition status.

In 2023, the DL-based approach for missing structural response data recovery in SHM was introduced by Du et al. [28]. A multi-modal autoencoder formed the core of their method because it managed to detect temporal patterns alongside spatial structures, along with heterogeneous data correlations between sensor data. The bridge dataset demonstrated higher accuracy than standard imputation methods because it excelled at handling extensive data gaps, which positively affected the performance of SHM systems. Xin et al. [29] created a signal restoration system for BHM based on time-varying filtering-based empirical mode decomposition (TVF-EMD) associated with an encoder-decoder long short-term memory (ED-LSTM) model. The signals delivered by TVF-EMD decomposition led to intrinsic mode functions that were forecasted with ED-LSTM. Their solution, evaluated with genuine bridge measurements, performed better than standard approaches, thus creating more dependable and precise data recovery results. Lu et al. [30] presented an acceleration data restoration framework built with BiLSTM for SHM applications. The research method effectively detected spatial-temporal patterns, which led to better performance compared to traditional ML approaches. The assessment of the Z-24 bridge, coupled with the long-span bridge, demonstrated a high accuracy level, which confirmed the methodology's capability to enhance structural assessment and damage detection processes in SHM systems.

In 2024, Zhang et al. reviewed SHM data recovery methods [31]. The authors structured their analysis by dividing SHM data recovery methods into finite-element and sparse representation and statistical inference in addition to ML-based approaches while showing what made each method strong or weak. The research documented both current dilemmas and anticipated developments within SHM data recovery procedures. An et al. [32] developed a compressive sensing method for structural vibration response reconstruction by using DL principles. A dual-branch neural network from their approach processed frequency domain real and imaginary components to provide better reconstruction results than traditional methods that used sparsity assumptions. The laboratory experiment with a grandstand structure proved that this method delivered excellent results for efficient SHM data collection. Shi et al. [33] developed a reconstruction algorithm for bridge vibration responses from railway trains to boost damage evaluation in heavy-haul railway bridges. The proposed framework used an enhanced deep densely connected neural network for data reconstruction with an alternate down-sampling residual network for damage identification. The system underwent testing using genuine bridge data to prove its ability to improve anomaly detection accuracy.

Engineers can potentially achieve full bridge behavior understanding through continuous analysis which becomes possible after recovering the entire dataset. This data recovery procedure enables detection of the downstream work, such as damage detection.

2.3 Bridge damage detection

In BHM, a key task is detecting potential bridge damage, which helps engineers develop maintenance strategies and extend the bridge’s service life. Depending on the sensor installation positions, damage detection methods are categorized into two types: direct and indirect. Each method is further classified into two approaches: supervised learning and unsupervised learning.

2.3.1 Direct method

Supervised learning. Over the past two years, researchers have been exploring supervised learning techniques. This approach requires labelled data to train the model, enabling it to identify features in unseen data.

In 2023, Svendsen et al. [34] presented a hybrid SHM framework connecting experimental data to numerical modeling for steel bridge damage identification. The authors created synthetic data through finite element model calibration under different conditions, which allowed them to develop a ML model for detecting structural anomalies across environmental change. The damage identification technique showed improved outcomes through this method, compared to the approach without hybrid SHM processes. Sarwar and Cantero [35] built a probabilistic deep neural network system that used vehicle-based data for bridge damage evaluation. The method integrated observation data from bridges and vehicles and used probabilistic DL to measure prediction uncertainty. Various numerical analyses under diverse operating and environmental environments showed how this detection system achieved precise results by reducing both measurement noise and temperature fluctuations along with random traffic disturbances. Modal analysis of bridge structures implemented ML algorithms as part of its operational framework. Mao et al. [36] developed a computerized operational modal analysis system, which specialized in analyzing long-span bridges. A combination of convolutional autoencoder technology refined modal frequency identification, while the self-organizing map

(Kohonen network) performed mode classification within this approach. Real bridge data analysis, along with simulations, demonstrated that this system operated proficiently for structural parameter observation while decreasing human involvement in the process. The topic of explainable ML models became important within the field of SHM. Cardellicchio et al. [37] established an AI framework that automatically detected defects in reinforced concrete bridges using methods with explainable AI features. A set of CNNs trained on genuine defect photos achieved model interpretation through Class Activation Maps. Tests of historical bridges demonstrated that this approach strengthened damage evaluation and maintained degraded facilities throughout their lifespan. Prediction models were used for detecting changes in the dynamic characteristics of bridge behavior. The research team of Ye et al. [38] designed an ML-based system that detected wind-induced vibrations in cable-stayed bridges at an early stage. The authors established a predictive system for girder and tower vibrations through the use of random forest modeling on real bridge data acquired from typhoon conditions. Structural safety increased through predictive forecasting because this technology enabled precautionary decision-making when wind conditions deteriorated. Noori Hoshyar et al. [39] examined ways to enhance the classification methods in SHM through their study. The authors created four support vector machine (SVM)-based methods to enhance classification results by implementing integrated solutions for data misclassification and combined kernel approaches. New laboratory-established models demonstrated superior results against standard SVM in crack identification tasks, thus providing better automated bridge infrastructure damage assessment methods. Xu et al. [40] delivered a comprehensive overview of ML applications to concrete and steel bridge damage detection and assessment through their review of numerous ML techniques. The authors analyzed current methods by categorization and described preprocessing difficulties before assessing method performance. Standardized image-based damage detection approaches, together with transformer models and physics-informed approaches, provided opportunities to enhance SHM reliability according to the review.

In 2024, the field of damage detection also employed hybrid ML approaches using minimal actual data. The supervised learning system developed by Bud et al. [41] unified real bridge monitoring information with simulated finite element model outputs. This methodology assisted classifiers in carrying out damage detection together with localization and classification functions even when real damage data was scarce. The framework, assessed using Z-24 Bridge benchmark data, demonstrated environmental resistance, which improved the dependability of SHM applications. The identification of damage in cable-stayed bridges through their monitoring operations became possible using the hybrid ML framework that Pham et al. [42] developed. The authors combined particle swarm optimization for finite element model updating with categorical gradient boosting (CatBoost) for damage detection in their method. Tests of a bridge case demonstrated how the detection method excelled at complex cable damage identification during benchmark evaluation, thus proving better capabilities for structural health assessments. The real-time assessment of prestressed concrete railway bridges received contributions through an ML framework developed by Marasco et al. [43]. Analysis of extended monitoring records enabled researchers to deploy Extreme Gradient Boosting and Multi-Layer Perceptron models that generated anomaly detection thresholds to support more efficient damage discovery during the initial phase and predictive maintenance activities. Researchers implemented DL optimization methods for detecting widespread bridge degradation in addition to real-time monitoring programs. The team of Doroudi [44] developed a DL framework that combined signal processing techniques like multivariate empirical mode decomposition and wavelet transforms to produce better features. Tests on Tianjin Yonghe Bridge utilized hyperparameter tuning through a meta-heuristic optimization algorithm, which applied to LSTM, CNN, and MLP models to achieve strong damage identification accuracy.

In 2025, lightweight bridge structures received ML application treatment. Numerous studies, such as Dadoulis et al. [45] demonstrated CNN-based technology as a method for detecting lightweight bridge damage under moving load conditions. The research design utilized simulated acceleration response data to train their model into developing a system that classified different damage conditions. A steel beam laboratory test confirmed how the proposed model enhanced vibration-based bridge monitoring by improving its reliability. Ghiasi et al. [46] developed a steel bridge anomaly detection framework through the utilization of Siamese CNNs. Their method applied generally to multiple structures by effectively detecting section loss caused by corrosion. The Siamese CNN framework operated with both finite element and experimental data to deliver high accuracy as it provided an extendable data-driven SHM solution for large-scale bridge network monitoring.

Transfer learning (TL) stands as a strong addition to SHM to create an advanced method that promoted damage detection while extending to various conditions. The work by Teng et al. [47] integrated TL into vibration-based structural damage detection by applying one-dimensional CNNs with domain adaptation mechanisms. A CNN initially received numerical bridge model data containing singular damage conditions to perform training; afterward, it underwent improved training through adaptation to multi-damage situations accompanied by various structural sizes and experimental datasets. Such a methodology enhanced both identification accuracy while reducing overfitting effects and speeding up convergence, which enabled vibration-based SHM systems to work with different bridge structures. The concept of TL received further development by Giglioni et al. [48] for improving population-based structural health monitoring (PBSHM) capabilities across multi-span girder bridges. Feature transformation in their approach allowed an ML model trained on one bridge to identify damage patterns in different bridges. A laboratory-scale experimental benchmark enabled testing of this framework, which achieved superior damage detection performance in various bridge scenarios under different environmental conditions, thus proving PBSHM effective for broad-scale infrastructure applications. The research by Xin et al. [49] adapted MobileViT, a hybrid Transformer-CNN model, and

TL approaches for identifying damage in arch bridges. The method converted acceleration response data into cross-correlation matrices, which enhanced structural assessments during condition evaluation procedures. The framework's accuracy, as well as its low data requirements and sensor reliability, was proved through experimental and numerical evaluation. With TL integrated into the framework, researchers improved both operational reliability and operational speed regarding structural anomaly detection in arch bridges compared to pure DL-based techniques. Research results highlighted how TL surged in importance for SHM because it improved detection methods along with their adaptive capability while enhancing their reliability. By bridging the gap between numerical simulations and real-world scenarios, TL-driven methods provided more scalable and efficient solutions for monitoring diverse bridge structures under varying environmental and operational conditions.

Supervised learning methods make it possible for researchers to locate essential damage indicators within bridge vibrations. The need for labeled data remains a challenge when using these methods since collecting data for damaged bridge conditions can be very difficult.

Unsupervised learning. Unsupervised learning methods have become popular in SHM because of data acquisition challenges hence providing efficient solutions to detect damage and adapt domains in BHM applications. Such techniques remove the necessity of labelled data, which proves essential for practical field implementations.

In 2023, Entezami et al. [50] created an unsupervised meta-learning system that focused on extended bridge monitoring of concrete and steel infrastructure by managing large datasets and partial data gaps. The method implemented spectral clustering with nearest cluster selection and locally robust Mahalanobis-squared distance detection to decrease environmental fluctuations successfully. This monitoring method delivered increased accuracy for spot detection of long-term structural damage, producing dependable results even under varying conditions. Xu et al. [51] proposed an unsupervised DL method for bridge condition assessment that relied on probability-based relationships between structural quasi-static responses. Their algorithm merged variational autoencoders with generative adversarial networks to accomplish deflection-tension relationship reconstruction and translation. The SHM application benefited from this method because it used the Wasserstein distance indicator to detect cable damage in real-world bridges while reducing dependency on synchronized loading and improving overall robustness. The study introduced by Entezami et al. [52] delivered a fully non-parametric ML solution that focused on short-term SHM using restricted vibration information. The method incorporated hierarchical clustering of features alongside density-based damage alarm detection, which successfully reduced the impact of environmental fluctuations. The approach delivered accurate initial detection results through analysis of authentic bridge data while requiring minimal labeled training datasets. The research by Lüleci et al. [53] introduced CycleWDCGAN-GP to produce synthetic vibration response data from limited datasets for SHM. Their approach allowed them to predict structural damage in advance by reproducing the natural transition between different structural states. The proposed method improved the efficacy of DL-based SHM by generating valuable training data that addressed the restricted availability of real damage datasets. The unsupervised learning process in vibration-based SHM received a detailed evaluation by Eltouny et al. [54], who analyzed diverse ML approaches while reviewing benchmark datasets and identifying barriers to research translation into operational applications. Their findings emphasized the potential of novelty detection and clustering approaches while also highlighting critical gaps in environmental variability modeling and automated decision-making processes.

In 2024, Ge and Sadhu [55] extended data transformation approaches by creating a domain adaptation framework that combined physical constraint models and self-attention architecture into the CycleGAN architecture. Their method combined simulated with real structural information to enhance both data feature adjustment and accuracy prediction of models. This framework built SHM model stability levels for more dependable real-world implementations. The research community behind vibration-based SHM introduced a multi-head self-attention LSTM autoencoder for structural damage diagnosis through the work of Ghazimoghadam and Hosseinzadeh [56]. The model used ambient vibration signal reconstruction error analysis to find damage, determine its spatial position, and measure structural health deficiencies. Laboratory testing, together with Z24 bridge evaluations, showed that this approach performed better than standard autoencoders because it detected subtle faults in various locations. A frequency-enhanced vector-quantized variational autoencoder for efficient structural vibration response compression was developed by Xue et al. [57]. A combination of dual-branch feature extraction techniques with sensor position encoding enabled their approach to achieve both high compression rates and accurate modal results. The newly developed method enhanced the storage efficiency of collected data and data transfer reliability.

The aforementioned research demonstrate how unsupervised learning transforms SHM operations by solving problems with issues such as scarce data, environmental changes, and feature transformation. The combination of DL approaches with generation models and domain adaptation expertise enables robust and scalable data-efficient bridge monitoring solutions.

2.3.2 Indirect method

The field of indirect SHM has started gaining increased interest because it offers a low-cost solution for bridge assessment. It gets enhanced through vehicle-bridge interaction fused with ML along with DL approaches to establish better drive-by monitoring procedures that circumvent direct structural instrument requirements.

Supervised learning. Supervised learning techniques represent the standard approach for vehicle response-based methods, just like direct methods.

In 2023, Hajializadeh [58] created a DL-based system to detect railway bridge damage using train-borne acceleration data. The CNN model used TL to process spectrogram images of vibration signals, which resulted in effective damage state classification under different speed and rail conditions. The results confirmed the strong potential of using indirect SHM for railway monitoring through this method. The research of Lan et al. [59] developed an optimized AdaBoost-Linear SVM framework for performing indirect bridge monitoring through analysis of vehicle acceleration data. A modification of SVM hyperparameters produced better classification precision according to laboratory testing outcomes. The method proved that vehicle-based monitoring provided an efficient solution for replacing traditional direct SHM systems. Lan et al. [60] developed a framework for damage diagnosis that used unprocessed vehicle acceleration data instead of ML-based features. A new damage index combined with a location index enabled the method to effectively measure damage extent while precisely identifying affected areas, thus improving drive-by monitoring systems. The research of Li et al. [61] added value to bridge damage detection through their development of an SVM model using Mel-frequency cepstral coefficients (MFCCs). The conversion of vehicle vibration signals into MFCCs allowed the method to extract features from both low and high frequencies, which boosted efficiency and classification performance. Li et al. [62] developed the assumption accuracy method through the combination of frequency-domain characteristics with principal component analysis and MFCCs. The assumption accuracy method proved beneficial because it did not require damage labels for data analysis, which made it suitable for practical applications. Li et al. [63,64] conducted research about smartphone-based footbridge monitoring through the analysis of scooter vibrations. The researchers developed a two-dimensional CNN model that processed time-frequency representations to achieve better results than a one-dimensional CNN using frequency spectra. Field tests and simulations demonstrated the validity of this approach, enhancing damage sensitivity while reducing environmental noise disturbances and extending indirect SHM capabilities beyond traditional vehicle-based methods.

In 2024, recurrent neural networks improved ML models for drive-by monitoring. The authors of [65] developed a damage detection method based on Long Short-Term Memory networks that utilized vehicle-bridge interaction models for contact point response data. The damage index based on Euclidean Distance allowed their method to detect structural anomalies with high precision. The numerical simulations showed that road roughness reduced effectiveness, but further improvements were required for real-world applications. Researchers conducted experimental testing of drive-by monitoring systems. The authors Corbally and Malekjafarian [66] implemented their data-driven algorithm through experiments on laboratory-scale vehicle-bridge interaction models. The proposed method established the Operating Deflection Shape Ratio as an indicator to detect both midspan cracking and seized bearings. The researchers Corbally and Malekjafarian [67] created a DL-based framework that performed damage type, location, and severity classification. A vehicle–bridge interaction model provided training data labels to develop a detection system that reached high accuracy levels independently of pre-established damage scenarios and established itself as an efficient alternative to traditional SHM. Indirect SHM benefited from improved performance through the implementation of DL-based image processing techniques. A 2D CNN for indirect bridge damage identification was introduced by Chen et al. in [68], which converted vehicle acceleration signals into time-frequency images through continuous wavelet transform. The method showed excellent localization abilities together with effective suppression of road surface irregularities. Wang et al. [69] created a data-derived method to detect breathing cracks in plate-like bridges. The damage indicator of contact point displacement variation led to the training of a CatBoost model on data from finite element simulations. Numerical simulations, together with laboratory experiments, validated the framework, which exhibited resistance to road roughness along with varying vehicle speeds.

Unsupervised learning. The development of drive-by SHM now uses unsupervised learning methods, domain adaptation techniques, and autoencoder-based approaches to enhance bridge damage assessment capabilities. These methods make it possible to eliminate extensive datasets while improving the scalability together with the practicality of indirect monitoring across diverse structures throughout various operational conditions.

In 2023, Liu et al. [70] established HierMUD as a hierarchical multi-task unsupervised domain adaptation framework that transferred knowledge from labeled bridges to unlabeled ones. With its use of adversarial learning, HierMUD extracted domain-invariant task-informative features that led to accurate damage detection and localization alongside quantification needs without any target domain labelling requirements. This diagnostic system used several bridge and vehicle platforms, which led to substantial improvements in real-world diagnostic outcomes. The exploration of real-time damage detection in structures became possible through DL-based approaches. Li et al. [71] established a bridge monitoring system that operated in real time through the implementation of deep auto-encoders. The analysis of short-time vehicle vibration frequency responses rather than extended signals proved effective for reducing noise disturbances. The continuous beam laboratory model demonstrated 86.2% accuracy when testing the system, which indicated its viability for quick SHM implementation. Drive-by SHM frameworks benefited from the improved effectiveness that unsupervised learning techniques provided. The researchers Calderon Hurtado et al. [72] created an adversarial autoencoder system for performing indirect bridge surveillance. The model generated accurate reconstructions of vehicle acceleration signals under healthy conditions, so damage detection became possible by analyzing deviations from these expected responses. Testing through simulations and laboratory experiments confirmed the system's resistance to environmental fluctuations while achieving better results than standard unsupervised methods.

In 2024, Hurtado et al. [73] created an entirely automated drive-by BHM system using computer vision with unsupervised techniques. The method examined frequency-domain vehicle reactions through a combination of empirical Fourier decomposition with convolutional autoencoders. Numerical testing and experiments validated this method to be robust against road roughness effects as it maintained high performance levels for automated bridge condition assessment. A specialized drive-by monitoring system targeting railway infrastructure was created by de Souza et al. [74]. They used Log-Mel spectrograms from train acceleration data to establish their sparse autoencoder system. The model utilized damage indices based on statistical distribution computations, which showed both strong sensitivity for detecting initial damage and operational and environmental robustness, thus making them ideal for high-speed railway conditions. The authors Fernandes et al. [75] designed a scour damage detection system for railway bridges, which combined deep autoencoders with optimally positioned sensors for selected applications. Their model used vehicle acceleration data to detect stiffness reductions at bridge piers, which was a signature sign of scour-related deterioration. Numerical simulations verified that the method had excellent precision for identifying minimal scour damage while managing operational ranges and enhancing proactive maintenance of railway bridges.

3 Discussions and suggestions

The recent developments in vibration-based BHM through artificial intelligence techniques have been the focus of this last section. Applications of AI have enhanced the accuracy and efficiency while introducing automation to SHM systems while handling three fundamental issues related to abnormality detection, data restoration, and bridge inspection. The review reveals multiple significant trends together with difficulties that have appeared.

At present, AI-based SHM employs supervised learning approaches because supervised learning techniques achieve superior accuracy during training with labelled datasets. The acquisition of damage-labelled data preserves significant challenges, thus driving deep interest toward unsupervised and semi-supervised learning methods. Unsupervised learning technology like autoencoders and clustering algorithms demonstrate their usefulness for uncovering anomalies automatically, which makes them suitable for practical applications that do not use labelled damage information.

AI-driven SHM faces considerable obstacles from environmental factors along with operational conditions that can affect its performance. The monitoring system produces incorrect outcomes because temperature shifts together with humidity and heavy traffic patterns make it difficult to detect damage. Domain adaptation techniques alongside TL and physics-informed AI modelling enable researchers to overcome this issue by separating structural variations resulting from damage from those caused by environmental factors.

When performing SHM, practitioners must select between direct and indirect monitoring methods as essential monitoring elements. Direct monitoring uses sensors attached to bridges to deliver precise structural data, but it demands substantial effort as well as high financial costs. Vehicle response monitoring provides a less expensive method for conducting indirect SHM in comparison to direct sensor installations. Representing the natural vibrations of bridges from additional sources like road conditions and vehicles poses a detection difficulty. ML techniques support the development of physics-based methods to improve indirect monitoring methods while making them suitable for practical applications.

Real-time SHM systems and predictive maintenance utilizing AI continue to develop at a rapid pace, which allows engineers to develop warning systems for early structural deterioration identification. Essential structural safety improvements together with operational efficiency increase due to the combination of ML with edge computing and cloud-based platforms [76,77]. Research needs to enhance computing efficiency for the implementation of real-time AI-based SHM systems, which allows deployment at scale and produces effective infrastructure monitoring solutions.

4 Conclusions

Using AI techniques for vibration-based BHM has shown great potential in bridge engineering. These approaches have shown significant detection capabilities and improved efficiency and automation degree for bridge condition assessment. This review has highlighted key methodologies, advancements, and existing challenges in current studies. Some concluding remarks can be drawn:

1) DL models have significantly improved the sensitivity of SHM systems to minor bridge damage and shown great potential to surpass traditional modal-based approaches.
2) Due to the limited data for damaged cases, the transition from supervised to unsupervised learning is critical for achieving scalable and generalized damage detection models.
3) Environmental and operational variability remains a challenge for practical engineering applications, which necessitates the development of robust AI models.
4) The indirect method offers a cost-effective alternative to traditional sensor-based systems, but challenges in extracting bridge information from vehicle dynamics need further investigations.

Based on the authors' best understanding, future research in this field needs to focus on AI applications together with emerging techniques, e.g., digital twins, edge computing, and Internet of Things, to create more adaptive and intelligent bridge monitoring frameworks. In addition, as this field is highly interdisciplinary, it requires collaboration among civil engineers, AI researchers, and policymakers. Such cooperation is essential for developing standardized AI-driven SHM solutions that enhance the safety of bridges worldwide.

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