Application of Artificial Intelligence and Machine Learning in Structural Health Monitoring of Civil Infrastructure

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Abstract

Background: Civil infrastructure — bridges, buildings, tunnels, dams, highways, and towers — is ageing worldwide, and deterioration from corrosion, fatigue, cracking, overloading, and environmental and seismic hazards threatens safety and serviceability. Conventional visual inspection, manual condition rating, and periodic non-destructive testing are labour-intensive, subjective, and poorly suited to continuous, large-scale monitoring.

Objective: This article reviews and critically analyses the application of artificial intelligence (AI), machine learning (ML), and deep learning (DL) to structural health monitoring (SHM) of civil infrastructure, and proposes an integrated analytical framework linking sensing, learning, and maintenance decision-making.

Methods: A critical review of peer-reviewed literature on data-driven SHM, classical ML algorithms, deep learning architectures, computer-vision-based defect detection, and intelligent infrastructure technologies (IoT, digital twins, predictive maintenance) is combined with a theoretical and comparative analysis of representative AI/ML models across vibration, strain, displacement, acoustic-emission, image, and environmental data modalities. Where actual experimental results were unavailable, hypothetical or representative comparisons are explicitly identified as such.

Results: The literature indicates that ensemble and kernel-based ML methods (random forest, support vector machine) offer interpretable, data-efficient solutions for damage classification, whereas deep learning methods (convolutional neural networks for imagery, recurrent/long short-term memory networks for time-series) provide superior automated feature extraction and predictive accuracy at the cost of larger datasets, higher computational demand, and reduced interpretability. Multimodal sensing and digital-twin integration improve robustness against environmental and operational variability, while explainable AI techniques are increasingly needed to support engineering trust and regulatory acceptance.

Conclusion: AI/ML-enabled SHM offers substantial potential to improve early damage detection, predictive maintenance, and infrastructure resilience, but practical, scalable deployment requires standardized datasets, explainable models, robust handling of environmental variability, and validated real-time edge and cloud architectures.

Keywords: Artificial Intelligence, Machine Learning, Structural Health Monitoring, Predictive Maintenance, Civil Infrastructure

1. Introduction

1.1. Aging and Deterioration of Civil Infrastructure

Bridges, buildings, tunnels, dams, and transportation networks built in the mid-twentieth century now form a large share of the operating civil infrastructure stock in many countries, and a growing proportion has exceeded, or is approaching, its design life.

Deterioration accumulates through corrosion, fatigue cracking under repeated loading, concrete carbonation and spalling, and material degradation from freeze–thaw cycles, chloride ingress, and chemical attack. Superimposed on this gradual deterioration are episodic hazards — earthquakes, floods, extreme wind, and overloading — that can precipitate sudden loss of capacity. Delayed damage detection allows minor defects to propagate into major deficiencies, increasing repair cost and, in extreme cases, leading to collapse. Infrastructure resilience and lifecycle management therefore depend on early, reliable damage detection translated into timely maintenance decisions.

1.2. Conventional Structural Health Monitoring

Conventional SHM relies on periodic visual inspection, manual condition rating, vibration-based modal testing, strain and displacement measurement at discrete locations, and non-destructive testing such as ultrasonic testing and infrared thermography. These approaches remain the historical basis for infrastructure management but carry well-documented limitations: visual inspection is subjective, dependent on inspector experience and accessibility, and limited to surface-visible defects; discrete instrumentation cannot fully characterize spatially distributed damage; and inspection intervals of one to several years are inconsistent with damage processes that progress continuously between inspections. As infrastructure networks expand and age simultaneously, the cost, labour intensity, and coverage limitations of conventional inspection increasingly constrain effective asset management at network scale.

1.3. Emergence of Intelligent SHM

Advances in low-cost sensing, wireless sensor networks, and the Internet of Things (IoT) have made dense, continuous instrumentation of civil structures increasingly feasible [16, 17, 26]. Unmanned aerial vehicles (UAVs) with high-resolution cameras now permit rapid, safer inspection of otherwise inaccessible elements, while computer vision automates interpretation of the resulting imagery. Cloud and edge computing provide the processing capacity needed for large-volume sensor data, and digital twin technology enables a continuously updated virtual representation of a structure that fuses sensor data, physics-based models, and AI-derived condition estimates [14, 15, 30]. Within this ecosystem, AI and ML have become the principal tools for transforming raw, high-dimensional, multimodal sensor data into actionable condition information, motivating this review.

2. Related Work

2.1. Conventional Data-Driven SHM

Early data-driven SHM relied on statistical pattern recognition applied to modal parameters — natural frequencies, mode shapes, and modal curvature — under the premise that damage alters stiffness and therefore measurable dynamic properties [28, 29]. Frequency- and time-domain damage indices were developed to flag deviations from a baseline healthy condition, but proved sensitive to environmental and operational variability such as temperature and traffic loading, which can produce apparent frequency shifts comparable to those caused by damage.

2.2. Machine Learning Algorithms

Classical ML algorithms — support vector machines, random forests, decision trees, k-nearest neighbours, and artificial neural networks — have been widely applied to map extracted vibration or strain features onto damage-state labels [1, 2]. These methods generally require manual or semi-automated feature engineering but offer interpretable decision rules and can perform well with moderate dataset sizes, making them attractive for damage classification and condition-index estimation [1].

2.3. Deep Learning

Deep learning removes much of the manual feature-engineering burden by learning hierarchical representations directly from raw or lightly processed data. Convolutional neural networks (CNNs) dominate image-based defect recognition [3, 4, 5, 6], while recurrent neural networks and long short-term memory (LSTM) networks model the temporal dependencies in acceleration, strain, and displacement time-series for structural response prediction [8, 9, 10, 11, 12, 13]. Autoencoders support unsupervised anomaly detection by learning a compressed representation of baseline behaviour and flagging reconstruction errors as candidate anomalies [2]. Transfer learning is frequently used to adapt models pretrained on large image datasets to the smaller, structure-specific datasets typical of SHM [6].

2.4. Computer Vision

Vision-based deep learning has been applied extensively to automated identification of cracks [3, 4, 5, 6, 21, 22], corrosion [23], spalling, delamination, and other surface deterioration. Semantic segmentation networks provide pixel-level defect localization rather than simple image-level classification, enabling quantitative assessment of crack width, length, and density, and supporting more objective condition rating than manual inspection [21, 22].

2.5. Intelligent Infrastructure

IoT-enabled sensor networks, digital twins, and cloud analytics increasingly integrate AI/ML models into continuous infrastructure management workflows [14, 15, 16, 17, 30], supporting predictive maintenance that moves beyond fixed inspection schedules toward condition- and risk-based intervention. Despite this progress, the literature identifies persistent gaps: limited large, standardized, publicly shared damage datasets; sensitivity to sensor noise and missing data; poor generalization across structures of different geometry and material (domain shift); limited interpretability of deep models, constraining engineering trust [18, 19]; elevated false-alarm rates under environmental variability; substantial computational requirements; and a shortage of long-term, field-scale validation beyond short pilot deployments.

3. AI and Machine Learning for Structural Health Monitoring

3.1. Data Acquisition

SHM data are acquired through accelerometers, strain gauges, displacement transducers, fibre-optic sensors, acoustic-emission sensors, temperature and humidity sensors, fixed cameras, and UAV-mounted imaging systems, increasingly networked through IoT infrastructure. Multimodal sensing — combining dynamic response with strain, environmental, and image data — improves robustness because different damage mechanisms manifest more clearly in different modalities; surface cracking is most directly observed through imagery, whereas stiffness reduction is more readily inferred from vibration data.

3.2. Data Preprocessing

Raw sensor data typically require noise filtering, treatment of missing or corrupted samples, normalization, and, for vibration and acoustic data, signal-processing techniques such as Fourier or wavelet transforms. Feature extraction, dimensionality reduction, and feature selection reduce redundancy and computational burden while preserving damage-sensitive information, and are especially important for classical ML models that do not learn features automatically.

3.3. Machine Learning Approaches

Supervised learning suits damage classification and condition-rating tasks where labelled data are available, while unsupervised learning — particularly autoencoder- and clustering-based novelty detection — is preferred where only baseline, undamaged data can be reliably obtained, the common situation for in-service structures [2]. Semi-supervised learning offers a compromise, supplementing limited labelled data with larger volumes of unlabelled baseline data. Reinforcement-learning concepts have been explored for adaptive sensor placement and inspection scheduling, though their SHM application remains comparatively immature.

3.4. Deep Learning and Computer Vision

CNN-based image classification, object detection, and semantic segmentation automate identification and localization of structural defects from photographic or UAV imagery [3, 4, 5, 6, 21, 22]. RNN and LSTM architectures process sequential accelerometer, strain, or displacement data to predict structural response under operational or seismic loading and support time-series anomaly detection [8, 9, 10, 11, 12, 13]. Hybrid architectures combining convolutional feature extraction with recurrent temporal modelling are increasingly used where spatial and temporal information must be jointly represented.

3.5. Explainable AI

The opacity of deep learning models constrains adoption in safety-critical decisions, where practitioners need some understanding of why a model flagged, or failed to flag, potential damage [18, 19]. Explainable AI techniques — feature-importance ranking, SHAP values, and class-activation mapping for vision models — provide post-hoc interpretability reconcilable with engineering judgment, supporting trust, auditability, and eventual regulatory acceptance of AI-assisted SHM decisions.

3.6. Predictive Maintenance

AI-based SHM supports predictive maintenance by enabling earlier damage detection than fixed-interval inspection, estimating remaining useful life from degradation trends, prioritizing maintenance by risk, and informing risk-based inspection scheduling. This shift from reactive or time-based to condition-based maintenance can reduce lifecycle maintenance expenditure while improving safety margins, provided predictions are reliable and well-calibrated.

4. Materials and Methods

This article is a theoretical and comparative analysis based on critical review of the peer-reviewed literature; no new laboratory or field experiments were conducted. Numerical comparisons in Section 5 and Tables 1 and 2 not directly attributed to a cited study are explicitly identified as hypothetical, representative, or conceptual, and should not be interpreted as measured experimental results.

4.1. Analytical Framework

A conceptual framework for AI-based SHM was developed to structure the comparative analysis: data acquisition, preprocessing, feature extraction, AI/ML model application, damage detection, condition assessment, prediction, and maintenance decision (Figure 1). This framework organizes the discussion of specific AI/ML techniques and their role within the overall SHM workflow.

4.2. Representative Data Modalities and Damage Conditions

Representative data considered include structural acceleration and other vibration characteristics, strain, displacement, temperature and broader environmental conditions, and structural images. Corresponding damage conditions include cracking, corrosion, stiffness reduction, abnormal vibration signatures, excessive deformation, and surface deterioration, consistent with damage types reported across the literature.

4.3. AI/ML Models Compared

Five representative model families are compared: random forest and support vector machine as classical ensemble/kernel methods suited to feature-based classification with moderate data requirements; artificial neural networks bridging classical ML and deep learning; convolutional neural networks for image-based defect detection; and long short-term memory networks for time-series response prediction, discussed in relation to the classification, regression, or anomaly-detection tasks each best suits.

4.4. Data Processing and Model Development Considerations

Consistent with standard ML practice, model development typically partitions data into training, validation, and testing sets, employs cross-validation to assess generalization, and applies hyperparameter optimization and regularization to reduce overfitting. Feature engineering remains important for classical ML, while deep learning relies more heavily on large, diverse training data for comparable generalization.

4.5. Performance Metrics

Classification tasks are commonly evaluated using accuracy, precision, recall, and F1-score; regression and prediction tasks use RMSE, MAE, and R^2. Computational time is reported where real-time deployment is a design objective.

4.6. Environmental and Operational Effects

Temperature, humidity, traffic loading, wind, and operational variability influence measured structural response independently of any actual damage, and, if unrepresented in training data, can cause models to misattribute environmentally driven changes to deterioration, elevating false-alarm rates and undermining field reliability.

5. Results and Performance Evaluation

5.1. Machine Learning Performance

Random forest and SVM classifiers achieve competitive classification performance on feature-engineered vibration and strain data at comparatively low computational cost, retaining relatively high interpretability that supports their use where transparency is prioritized or labelled data are limited [1]. ANN-based models generally improve accuracy on nonlinear structure–response relationships relative to RF/SVM but require larger training sets and closer control of overfitting.

5.2. Deep Learning Performance

CNN-based approaches have repeatedly demonstrated high accuracy for image-based crack and corrosion detection, in several cases exceeding 95% classification or segmentation accuracy on benchmark datasets [3, 5, 6], reflecting the benefit of automated hierarchical feature extraction over hand-crafted features. LSTM-based models similarly outperform classical time-series methods for structural and seismic response prediction [8, 9, 10, 11, 12, 13], but both CNN and LSTM approaches depend on larger, more diverse training datasets than classical ML and impose greater computational demand, particularly during training.

5.3. Sensor and Data Quality

Higher sensor density improves spatial resolution of damage localization, while data quality — completeness, synchronization, and signal-to-noise ratio — directly influences model accuracy; missing data and sensor noise both degrade prediction reliability and increase false-alarm risk, motivating the preprocessing steps in Section 3.2.

5.4. Environmental Variability

Environmental and operational variability remains among the most consistently identified challenges: temperature-induced frequency shifts and traffic-induced strain variation can be comparable in magnitude to damage-induced changes, so models trained without adequate environmental representation are prone to false positives under changing seasonal or loading conditions.

5.5. Predictive Maintenance

Where implemented, AI-based SHM supports earlier warning of developing damage, more targeted inspection prioritization, condition-based maintenance scheduling, and improved allocation of limited maintenance resources across an asset portfolio, consistent with the risk-informed asset management described in Section 3.6.

5.6. Scalability

Deploying AI-based SHM at increasing scale — from a single structure to a bridge network, urban system, or regional transportation network — introduces challenges of data volume, heterogeneous sensor and structure types, communication bandwidth, and the need for models that generalize across structures rather than being retrained per asset; this remains one of the least mature aspects of AI-enabled SHM.

Tables 1 and 2 synthesize these qualitative findings into a structured, representative comparison of algorithm characteristics, reflecting general patterns reported across the cited literature rather than a single controlled experiment.

Table 1: Artificial Intelligence and Machine Learning Techniques for Structural Health Monitoring

Algorithm	Input Data	SHM Application	Major Advantage	Major Limitation
Random Forest (RF)	Vibration features, strain, environmental data	Damage classification, condition rating	Robust to noise; low overfitting; interpretable feature ranking	Limited automatic feature learning; performance saturates on raw signals
Support Vector Machine (SVM)	Modal features, statistical damage indices	Binary/multiclass damage classification	Effective with small, high-dimensional datasets	Kernel and hyperparameter selection sensitive; weak on very large datasets
Artificial Neural Network (ANN)	Sensor time-series, extracted features	Response prediction, anomaly scoring	Captures nonlinear structure–response relationships	Requires careful architecture tuning; risk of overfitting
Convolutional Neural Network (CNN)	Images, spectrograms, UAV imagery	Crack, corrosion and spalling detection/segmentation	Automatic hierarchical feature extraction from images	Large labelled datasets and high computational demand
Long Short-Term Memory (LSTM)	Acceleration, strain, displacement time-series	Structural response and remaining-life prediction	Captures long-range temporal dependencies in dynamic data	Sequential training is computationally intensive; limited interpretability
Autoencoder-based approaches	Baseline (undamaged) vibration/strain data	Unsupervised anomaly and novelty detection	Does not require labelled damage data	Sensitive to environmental/operational variability; threshold selection is subjective

Table 1 summarizes representative AI/ML techniques discussed in Sections 2 and 3 alongside their typical input data, principal SHM application, and major advantages and limitations reported in the literature. It illustrates the general trade-off between automated feature learning (favouring deep learning) and interpretability and data efficiency (favouring classical ML).

Table 2: Comparative Evaluation of AI-Based Structural Health Monitoring Approaches

Method	Damage Detection	Computational Demand	Interpretability	Real-Time Suitability	Data Requirement
Random Forest / SVM	Moderate–High (feature-based)	Low	High	High	Low–Moderate
Shallow ANN	Moderate–High	Moderate	Moderate	Moderate–High	Moderate
CNN (image-based)	High (visual defects)	High	Low–Moderate	Moderate (edge-dependent)	High
LSTM (time-series)	High (dynamic response)	High	Low	Moderate	High
Autoencoder (unsupervised)	Moderate (novelty detection)	Moderate–High	Low	Moderate–High	Moderate (baseline data only)

Table 2 presents a representative, conceptual comparison — not derived from a single controlled experiment — of damage-detection capability, computational demand, interpretability, real-time suitability, and data requirement across the five model families, consistent with the qualitative patterns reported across the cited studies.

Fig 1: AI-Enabled Structural Health Monitoring Framework

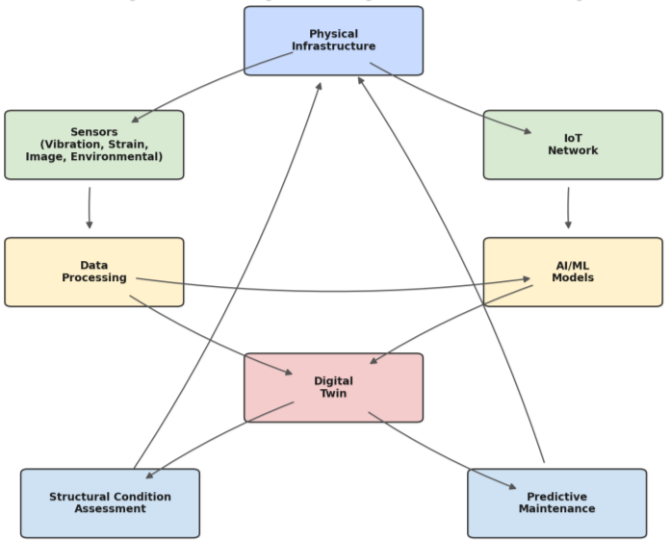

Fig 2: Integrating of Multimodal Sensing, Machine Learning, and Digital Twin Technologies for Intelligent Infrastructure Monitoring

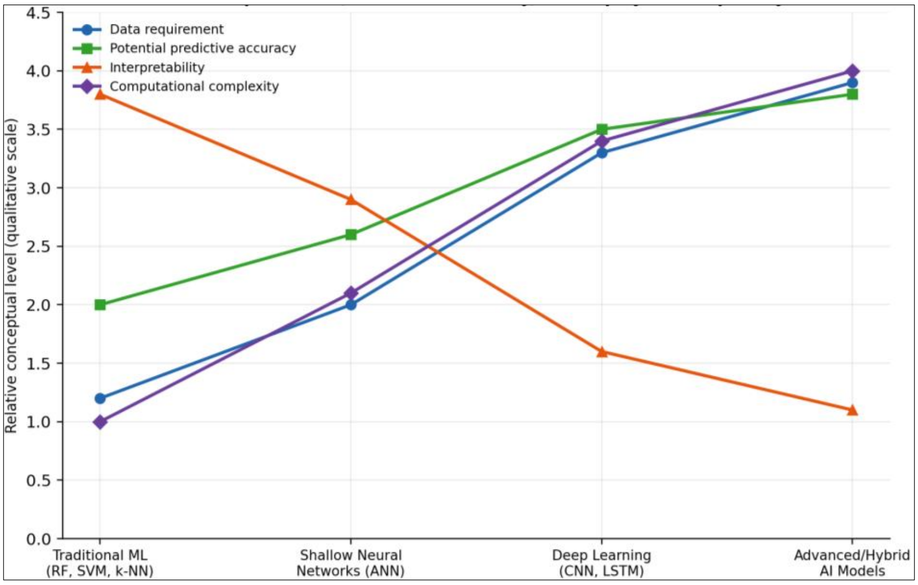

Figure 3: Conceptual Relationship Between AI Model Complexity, Data Reqirement, Prediction Accuracy, and Deployment Capability

6. Discussion

6.1. Accuracy Versus Interpretability

The literature indicates an inverse relationship between model complexity and interpretability: deep learning generally achieves higher accuracy on complex, high-dimensional data such as images and raw time-series, but its internal decision processes are substantially harder to interpret than classical ML models such as random forest or SVM, complicating engineering verification of individual predictions [18, 19].

6.2. Data Requirements

Model generalization depends jointly on dataset size and diversity relative to model complexity: deep architectures with large parameter counts require correspondingly large, diverse training data to avoid overfitting to structure-specific artefacts, whereas classical ML can often achieve acceptable generalization with smaller, well-engineered feature sets.

6.3. Environmental Robustness

Distinguishing genuine structural damage from environmentally or operationally driven changes in measured response remains a central challenge; robust AI-based SHM must explicitly represent temperature, humidity, traffic, and wind effects in training data or model architecture to avoid systematically elevated false-alarm rates in field deployment.

6.4. Multimodal AI

Combining vibration, strain, image, and environmental data within a single framework can compensate for the limitations of any single modality — for example, cross-validating vibration-based anomaly flags against visual evidence of surface damage — and is an increasingly active direction, though standardized multimodal fusion methods for SHM remain comparatively immature.

6.5. Real-Time SHM

Edge deployment offers low-latency, bandwidth-efficient inference for continuous monitoring but is constrained by limited computational and power resources on field hardware, particularly for larger deep models; cloud architectures offer greater capacity at the cost of latency and connectivity dependence, motivating hybrid edge–cloud architectures in recent IoT-enabled SHM systems [16, 17].

6.6. Practical Implementation

Beyond model performance, practical implementation must address sensor installation and maintenance cost, long-term data storage, cybersecurity of networked sensing infrastructure, periodic model updating as structures age or are retrofitted, interoperability between heterogeneous platforms, and alignment with engineering standards and regulatory expectations, all of which vary widely in maturity across jurisdictions.

6.7. Research Gaps

Priority future-research areas include large-scale, standardized, openly shared SHM datasets; broader adoption of explainable AI tailored to engineering decision-making [18, 19]; transfer learning across structurally dissimilar assets; federated learning for collaborative model development without centralizing sensitive data; deeper digital-twin integration with real-time AI inference [14, 15, 30]; multimodal learning frameworks; edge AI optimized for field hardware constraints; and long-term field validation beyond short pilot deployments.

7. Conclusion

This review has examined AI, ML, and deep learning applications in structural health monitoring of civil infrastructure, synthesizing evidence on damage detection, classification, anomaly detection, structural response prediction, and predictive maintenance across vibration, strain, displacement, acoustic-emission, image, and environmental data. Classical ML methods such as random forest and SVM offer interpretable, data-efficient solutions well suited to feature-based damage classification, while convolutional and recurrent deep learning architectures provide superior automated feature extraction and predictive performance for image- and time-series-based tasks, at the cost of larger datasets, greater computational demand, and reduced interpretability. Multimodal data integration, combined with digital-twin architectures, offers a path toward more robust, continuously updated condition assessment than any single data modality alone. Realizing the full benefit of AI-enabled SHM for infrastructure safety, resilience, and lifecycle management will require sustained attention to data quality and availability, model generalization across dissimilar assets, interpretability for engineering decision-making, real-time deployment constraints, cybersecurity, and the standardization and validation needed for regulatory acceptance. Continued development along these directions offers substantial potential for increasingly intelligent, autonomous, and resilient civil infrastructure monitoring.

References

1. Malekloo A, Ozer E, AlHamaydeh M, Girolami M. Machine learning and structural health monitoring overview with emerging technology and high-dimensional data source highlights. Struct Health Monit. 2022;21(4):1906-1955.
2. Eltouny K, Gomaa M, Liang X. Unsupervised learning methods for data-driven vibration-based structural health monitoring: a review. Sensors. 2023;23(6):3290.
3. Cha YJ, Choi W, Büyüköztürk O. Deep learning-based crack damage detection using convolutional neural networks. Comput Aided Civ Infrastruct Eng. 2017;32(5):361-378.
4. Cha YJ, Choi W, Suh G, Mahmoudkhani S, Büyüköztürk O. Autonomous structural visual inspection using region-based deep learning for detecting multiple damage types. Comput Aided Civ Infrastruct Eng. 2018;33(9):731-747.
5. Dung CV, Anh LD. Autonomous concrete crack detection using deep fully convolutional neural network. Autom Constr. 2019;99:52-58.
6. Ali L, Alnajjar F, Al Jassmi H, Gocho M, Khan W, Serhani MA. Performance evaluation of deep CNN-based crack detection and localization techniques for concrete structures. Sensors. 2021;21(5):1688.
7. Scarselli G, Nicassio F. Machine learning for structural health monitoring of aerospace structures: a review. Sensors. 2025;25(19):6136.
8. Qin Y, Song D, Chen H, Cheng W, Jiang G, Cottrell GW. A dual-stage attention-based recurrent neural network for time series prediction. In: Proceedings of the 26th International Joint Conference on Artificial Intelligence

(IJCAI). 2017. p. 2627-2633.
9. Li T, Pan Y, Tong K, Ventura CE, de Silva CW. A multi-scale attention neural network for sensor location selection and nonlinear structural seismic response prediction. Comput Struct. 2021;248:106507.
10. Perez-Ramirez CA, Amezquita-Sanchez JP, Valtierra-Rodriguez M, Adeli H, Dominguez-Gonzalez A, Romero-Troncoso RJ. Recurrent neural network model with Bayesian training and mutual information for response prediction of large buildings. Eng Struct. 2019;178:603-615.
11. Kavianpour P, Kavianpour M, Jahani E, Ramezani A. A CNN-BiLSTM model with attention mechanism for earthquake prediction. J Supercomput. 2023;79(17):19194-19226.
12. Elsaid A, El Jamiy F, Higgins J, Ostrowski J, Desell T. Optimizing long short-term memory recurrent neural networks using ant colony optimization to predict turbine engine vibration. Appl Soft Comput. 2018;73:969-991.
13. Yu J, Zhou W, Jiang L. Response spectra of fitted post-seismic residual track irregularity for high-speed railway. Earthq Eng Struct Dyn. 2023;52(2):350-369.
14. Sun Z, Jayasinghe S, Sidiq A, Shahrivar F, Mahmoodian M, Setunge S. Approach towards the development of digital twin for structural health monitoring of civil infrastructure: a comprehensive review. Sensors. 2025;25(1):59.
15. Sakr M, Sadhu A. Recent progress and future outlook of digital twins in structural health monitoring of civil infrastructure. Smart Mater Struct. 2024;33(4):043001.
16. Sonbul OS, Rashid M. Towards the structural health monitoring of bridges using wireless sensor networks: a systematic study. Sensors. 2023;23(20):8468.
17. Chakali D, Pollayi H, Rao P. IoT based structural health monitoring of bridges using wireless sensor networks. Asian J Civ Eng. 2024;25:5889-5898.
18. Luckey D, Fritz H, Legatiuk D, Peralta Abadia JJ, Walther C, Smarsly K. Explainable artificial intelligence to advance structural health monitoring. In: Cury A, Ribeiro D, Ubertini F, Todd MD, editors. Structural Health Monitoring Based on Data Science Techniques. Cham: Springer; 2022. p. 331-346.
19. Rudin C. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nat Mach Intell. 2019;1(5):206-215.
20. Mangalathu S, Jang H, Hwang SH, Jeon JS. Data-driven machine-learning-based seismic failure mode identification of reinforced concrete shear walls. Eng Struct. 2020;208:110331.
21. Zhou S, Song W. Deep learning-based crack segmentation for civil infrastructure: data types, architectures, and benchmarked performance. Autom Constr. 2022;146:104678.
22. Di Benedetto A, Fiani M, Gujski LM. U-Net-based CNN architecture for road crack segmentation. Infrastructures. 2023;8(5):90.
23. Ta QB, Huynh TC, Pham QQ, Kim JT. Monitoring of corroded and loosened bolts in steel structures via deep learning and Hough transforms. Sensors. 2020;20(23):6888.
24. Bao Y, Guo Y, Li H. A machine learning-based approach for adaptive sparse time-frequency analysis used in structural health monitoring. Struct Health Monit. 2020;19(6):1963-1975.
25. Bao Y, Xiang Z, Li H. Adaptive subset searching-based deep neural network method for structural reliability analysis. Reliab Eng Syst Saf. 2021;213:107778.
26. Lynch JP, Loh KJ. A summary review of wireless sensors and sensor networks for structural health monitoring. Shock Vib Dig. 2006;38(2):91-128.
27. Abdulkarem M, Samsudin K, Rasid MFA, F-Ismail F. Wireless sensor network for structural health monitoring: a contemporary review of technologies, challenges, and future direction. Struct Health Monit. 2020;19(3):693-735.
28. Farrar CR, Worden K. An introduction to structural health monitoring. Philos Trans R Soc A. 2007;365(1851):303-315.
29. Avci O, Abdeljaber O, Kiranyaz S, Hussein M, Gabbouj M, Inman DJ. A review of vibration-based damage detection in civil structures: from traditional methods to machine learning and deep learning applications. Mech Syst Signal Process. 2021;147:107077.
30. Spencer BF, Hoskere V, Narazaki Y. Advances in computer vision-based civil infrastructure inspection and monitoring. Engineering. 2019;5(2):199-222.

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