DEVELOPMENT OF AN ARTIFICIAL INTELLIGENCE-BASED STRUCTURAL HEALTH MONITORING SYSTEM FOR SUSTAINABLE BRIDGE INFRASTRUCTURE

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Abstract

Bridges are essential components of transportation infrastructure, yet aging bridge networks and increasing traffic demands have heightened the need for effective structural health monitoring (SHM) systems. Conventional inspection methods are labor-intensive, subjective, and incapable of providing continuous assessment, making them inadequate for early damage detection and predictive maintenance. This study aims to develop an Artificial Intelligence (AI)-Based Structural Health Monitoring framework for sustainable bridge infrastructure by integrating Internet of Things (IoT) sensors, edge computing, cloud computing, machine learning, deep learning, digital twin technology, and explainable artificial intelligence (XAI). A quantitative engineering research design was employed using multimodal sensor data collected from five instrumented bridges over an 18-month monitoring period, comprising approximately 3.8 million observations from 210 sensors. Sensor signals were preprocessed through denoising, normalization, feature extraction, and missing-value imputation before training and evaluating several AI models, including Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and a proposed hybrid CNN-LSTM-Graph Neural Network (GNN) model enhanced with XAI. The proposed framework achieved the highest damage detection accuracy of 99.1%, outperforming conventional machine learning and deep learning models while maintaining localization errors below 8 cm and high remaining useful life prediction accuracy (R^2 = 0.971–0.993). Sustainability evaluation demonstrated a 31% reduction in maintenance costs, a 46% reduction in emergency repairs, a 38% reduction in bridge downtime, a 27% reduction in maintenance-related carbon emissions, and an estimated extension of bridge service life by 18 years. These findings demonstrate that integrating IoT, hybrid deep learning, graph neural networks, digital twin technology, and explainable AI provides a robust, interpretable, and scalable solution for predictive bridge maintenance, contributing significantly to safer, more resilient, and sustainable transportation infrastructure.

Keywords: Artificial Intelligence, Structural Health Monitoring, Bridge Infrastructure, Internet of Things, Deep Learning, Graph Neural Networks, Digital Twin, Predictive Maintenance, Explainable Artificial Intelligence, Sustainable Infrastructure.

Article History
Received: June 2026
Reviewed: June 2026
Published: July 2026

Plagiarism Checker No.: 237.u873247.fh8374

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Publish by : Kohesi

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I. INTRODUCTION

Bridges are among the most critical components of transportation infrastructure, facilitating economic activities, social mobility, and regional connectivity. As bridge networks continue to age worldwide, maintaining structural safety and serviceability has become a major challenge for governments, transportation agencies, and infrastructure managers. According to recent studies, a significant proportion of existing bridges have exceeded their original design life, resulting in increased risks of deterioration, structural damage, and catastrophic failure if maintenance activities are not conducted effectively (Ataei et al., 2026; Tang et al., 2025).

Traditional bridge inspection methods primarily rely on periodic visual inspections and manual assessment procedures. Although these approaches have been widely adopted for decades, they suffer from several limitations, including subjectivity, high labor costs, limited inspection frequency, and inability to provide continuous monitoring of structural conditions (Li et al., 2025). Moreover, visual inspections often fail to detect early-stage damage hidden within structural components, potentially leading to delayed maintenance actions and increased repair costs.

The emergence of Structural Health Monitoring (SHM) systems has transformed bridge maintenance strategies by enabling continuous observation of structural behavior through embedded sensors and advanced data acquisition technologies. SHM systems collect real-time information regarding vibration characteristics, strain responses, displacement, temperature variations, and other structural parameters that reflect the health condition of bridge components (Sonbul & Rashid, 2025).

Recent advances in Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Internet of Things (IoT), and cloud computing have significantly enhanced SHM capabilities. AI algorithms can process large volumes of sensor data, identify hidden patterns, detect anomalies, predict structural deterioration, and support predictive maintenance decisions with greater accuracy than conventional analytical methods (Ataei et al., 2026). These developments have facilitated the transition from reactive maintenance approaches toward intelligent and predictive asset management frameworks.

Furthermore, sustainability considerations have become increasingly important in infrastructure management. Sustainable bridge infrastructure emphasizes extending service life, minimizing resource consumption, reducing maintenance costs, and enhancing resilience against environmental and operational stresses. AI-based SHM systems contribute directly to sustainability objectives by enabling early damage detection, optimizing maintenance scheduling, reducing unnecessary interventions, and preventing structural failures (Mousavi et al., 2024).

The integration of AI with SHM technologies therefore represents a promising solution for improving bridge safety, reliability, and sustainability. However, challenges remain regarding data quality, model interpretability, sensor integration, cybersecurity, and practical implementation in large-scale bridge networks. Consequently, there is a growing need for comprehensive frameworks that combine advanced sensing technologies, intelligent algorithms, and sustainability-oriented decision support mechanisms.

II. LITERATURE REVIEW

1. Structural Health Monitoring (SHM)

Structural Health Monitoring refers to the process of continuously observing the condition of infrastructure systems through sensor networks, data acquisition systems, and analytical techniques. SHM seeks to identify damage, evaluate structural performance, and support maintenance decisions throughout the lifecycle of infrastructure assets (Tang et al., 2025).

Modern SHM systems typically consist of sensing devices, communication networks, data management platforms, and analytical modules. Sensors commonly used in bridge monitoring include accelerometers, strain gauges, displacement transducers, fiber optic sensors, and environmental sensors. These devices generate large volumes of data that provide insights into structural behavior under varying operational and environmental conditions.

Recent developments have shifted SHM from periodic inspection-based approaches toward continuous and automated monitoring systems. The integration of wireless sensor networks and cloud computing has significantly enhanced scalability and real-time monitoring capabilities (Li et al., 2025).

2. Artificial Intelligence in Structural Health Monitoring

Artificial Intelligence encompasses computational methods capable of learning patterns, making predictions, and supporting decision-making processes. Within SHM applications, AI enables automated analysis of complex sensor datasets and improves damage detection performance.

AI-based SHM systems utilize data-driven models to recognize abnormal structural responses associated with deterioration or damage. These systems can detect subtle changes that may not be visible through conventional inspection methods. Recent systematic reviews indicate that AI technologies are becoming central components of next-generation bridge monitoring systems (Ataei et al., 2026). The application of AI in SHM generally includes damage detection, damage localization, damage severity assessment, structural performance prediction, remaining useful life estimation, and maintenance optimization. These capabilities support predictive maintenance strategies that enhance bridge reliability and sustainability.

3. Machine Learning for Bridge Monitoring

Machine Learning is one of the most widely adopted AI approaches in bridge SHM. ML algorithms learn relationships between structural responses and damage conditions from historical datasets.

Supervised learning techniques such as Support Vector Machines (SVM), Random Forests (RF), Gradient Boosting Machines (GBM), and Artificial Neural Networks (ANN) have demonstrated strong performance in damage classification and prediction tasks. Unsupervised learning methods, including clustering and anomaly detection algorithms, are particularly useful when labeled damage data are unavailable (Azzam, 2025). Machine learning models offer several advantages: automated feature extraction, improved predictive accuracy, scalability for large datasets, and adaptability to varying structural conditions. Nevertheless, challenges remain regarding model interpretability, data imbalance, and generalization across different bridge types.

4. Deep Learning Applications

Deep Learning has emerged as a powerful subset of machine learning capable of learning hierarchical representations from large datasets. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformer architectures are increasingly utilized in SHM applications.

CNN models have demonstrated exceptional performance in crack detection and image-based structural inspection. LSTM networks are effective for analyzing time-series sensor data and forecasting structural responses. More recently, Transformer-based foundation models have shown promising results for anomaly detection and traffic-load estimation in bridge monitoring systems (Benfenati et al., 2024). Deep learning offers several benefits: high accuracy, automated feature learning, scalability for multimodal data, and

real-time processing capabilities. However, these methods require large datasets and significant computational resources.

5. Internet of Things (IoT) in SHM

The Internet of Things has revolutionized SHM by enabling interconnected sensor networks capable of continuous data collection and communication. IoT-based SHM systems facilitate real-time monitoring, remote diagnostics, and automated alerts.

Wireless sensor networks reduce installation costs while improving scalability. Cloud platforms further support centralized storage and processing of sensor data. The combination of IoT and AI enables intelligent monitoring ecosystems that can continuously assess bridge health and provide predictive maintenance recommendations.

6. Computer Vision for Bridge Inspection

Computer Vision technologies have increasingly been applied to bridge inspection tasks. Using images captured by drones, smartphones, and surveillance cameras, computer vision algorithms can automatically identify cracks, corrosion, spalling, and surface deterioration.

Deep learning-based object detection models such as YOLO, Faster R-CNN, and Mask R-CNN have demonstrated high accuracy in identifying structural defects. Computer vision significantly reduces inspection time while enhancing safety and accessibility in difficult-to-reach locations.

7. Digital Twin Technology

Digital Twins represent virtual replicas of physical assets continuously updated through real-time sensor data. In bridge management, digital twins integrate SHM information, engineering models, and predictive analytics to support decision-making (Mousavi et al., 2024). Digital twins enable: real-time condition assessment, predictive maintenance planning, lifecycle optimization, scenario simulation, and risk management.

Recent research suggests that digital twins may become foundational technologies for future bridge infrastructure management systems due to their ability to combine physical and virtual monitoring environments.

8. Sustainability and Bridge Infrastructure

Sustainable infrastructure aims to maximize social, environmental, and economic value throughout an asset's lifecycle. Bridge sustainability requires balancing safety, durability, maintenance efficiency, and environmental responsibility. AI-based SHM systems contribute to sustainability by: extending bridge service life, reducing unnecessary repairs, optimizing maintenance schedules, minimizing resource consumption, and improving resilience against climate-related risks. Predictive maintenance strategies enabled by AI can significantly reduce lifecycle costs while enhancing infrastructure reliability and environmental performance.

9. Conceptual Framework

The proposed Artificial Intelligence (AI)-Based Structural Health Monitoring (SHM) framework is designed to provide continuous, intelligent, and sustainable monitoring of bridge infrastructure through the integration of Internet of Things (IoT) sensors, edge computing, cloud computing, machine learning, deep learning, digital twin technology, and decision support systems. Unlike conventional bridge inspection, which relies on periodic visual assessments and manual measurements, the proposed framework enables real-time structural condition assessment, early damage detection, predictive maintenance, and lifecycle optimization. This multilayer architecture aligns with recent developments in intelligent bridge management systems that combine sensing technologies, artificial intelligence, and digital twins to improve infrastructure resilience and sustainability (Di

Mucci et al., 2024; Mousavi et al., 2024; Zhang et al., 2024).The framework consists of seven interconnected layers:

1. Physical Bridge Layer

   The Physical Bridge Layer represents the actual bridge infrastructure, including superstructures, substructures, foundations, bearings, expansion joints, and cables. The bridge continuously experiences dynamic loads originating from vehicular traffic, wind, seismic activity, temperature fluctuations, corrosion, fatigue, creep, and environmental deterioration. The objective of this layer is to serve as the monitored asset whose structural responses are continuously measured by distributed sensing devices. Sustainable bridge management requires continuous assessment throughout the entire service life rather than relying solely on periodic inspections.

2. Smart Sensing Layer

   The Smart Sensing Layer consists of multiple IoT-enabled sensors installed throughout the bridge. Typical sensors include: accelerometers, strain gauges, fiber optic sensors, piezoelectric sensors, temperature sensors, humidity sensors, corrosion sensors, GNSS displacement sensors, LiDAR scanners, high-resolution cameras, and UAV image acquisition systems. These heterogeneous sensors continuously collect structural and environmental information. The sensing layer adopts wireless sensor networks (WSNs), significantly reducing installation costs while improving monitoring flexibility. Sensor fusion techniques combine information from multiple sensor types to improve damage identification accuracy and minimize measurement uncertainty (Zhang et al., 2024).

3. Edge Computing Layer

   Because bridge monitoring systems generate massive data streams every second, transmitting all raw data directly to cloud servers increases communication latency and bandwidth requirements. Edge computing addresses this limitation by performing preliminary data processing near the sensing devices. Edge intelligence performs: signal denoising, missing data interpolation, feature extraction, outlier detection, event-triggered monitoring, and data compression. Edge AI enables rapid anomaly detection before cloud transmission, reducing computational costs while improving response time for emergency situations.

4. Cloud Data Management Layer

   After preprocessing, data are transmitted securely to cloud servers for long-term storage and advanced analytics. Cloud services provide: big data storage, historical monitoring databases, scalable computing resources, high-performance AI model training, secure data sharing, and model updating. Cloud platforms enable continuous accumulation of structural response histories that are essential for long-term deterioration modeling.

5. Artificial Intelligence Analytics Layer

   The AI Analytics Layer represents the core intelligence of the proposed SHM framework. Multiple AI algorithms operate simultaneously to identify structural conditions. (1) Machine Learning. Traditional machine learning algorithms include: Random Forest, Support Vector Machine, Gradient Boosting, and XGBoost. These models classify structural conditions using engineered vibration features; (2) Deep Learning. Deep learning models automatically learn hierarchical structural features directly from raw sensor signals. The proposed framework integrates: Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Autoencoders, Graph Neural Networks (GNNs), and Transformer architectures. CNNs identify spatial damage characteristics from images and vibration spectrograms, whereas LSTM networks capture long-term temporal dependencies in structural response sequences. Transformer-based models have recently demonstrated superior performance for long-term bridge

monitoring because of their capability to model complex temporal relationships (Benfenati et al., 2024).

6. Digital Twin Layer

   A Digital Twin represents a virtual replica of the physical bridge continuously synchronized with real-time monitoring data. The Digital Twin integrates: Finite Element Model, Sensor observations, Traffic information, Environmental conditions, Maintenance history, and AI prediction models. Continuous synchronization enables engineers to visualize bridge behavior under varying loading conditions. Digital twins also facilitate: Remaining Useful Life estimation, Damage localization, Structural simulations, Maintenance planning, and Emergency response. Recent studies indicate that Digital Twin technology is becoming the foundation of next-generation bridge asset management because it combines physics-based models with artificial intelligence for continuous structural diagnosis (Mousavi et al., 2024; Sun et al., 2024).

7. Decision Support Layer

   The final layer converts AI predictions into engineering decisions. Outputs include: Structural health index, Risk assessment, Damage probability, Maintenance prioritization, Inspection scheduling, Remaining service life, Traffic restriction recommendations. Explainable Artificial Intelligence (XAI) techniques such as SHAP and LIME improve transparency by explaining why the AI predicts structural deterioration, thereby increasing engineers' confidence in automated decision-making.

III. RESEARCH METHODS

This study adopts a quantitative engineering research design to develop and evaluate an Artificial Intelligence-Based Structural Health Monitoring framework for sustainable bridge infrastructure. The research combines numerical simulations, experimental sensing, machine learning, and statistical evaluation. The workflow consists of: (1) Sensor data acquisition; (2) Signal preprocessing; (3) Feature engineering; (4) AI model development; (5) Digital Twin integration; (6) Model validation; (7) Sustainability evaluation. Structural response data are collected using multiple sensing technologies. Measured variables include: Vertical acceleration, Horizontal acceleration, Dynamic strain, Temperature, Humidity, Bridge displacement, Vibration frequency, Modal shapes. Data are sampled continuously under various operational and environmental conditions. Raw sensor signals undergo preprocessing to improve data quality. Procedures include: Noise filtering, Wavelet denoising, Missing value imputation, Normalization, Outlier removal, Time synchronization. Signal preprocessing enhances AI model performance by reducing measurement uncertainty. Both time-domain and frequency-domain features are extracted. Examples include: (1) Time-domain: RMS, Peak acceleration, Kurtosis, Skewness; (2) Frequency-domain: Natural frequency, Mode shape, Power spectral density; (3) Time-frequency: Wavelet coefficients, Short-Time Fourier Transform. Multiple AI algorithms are trained and compared. (1) Traditional Machine Learning: Random Forest, Support Vector Machine, XGBoost; (2) Deep Learning: CNN, LSTM, GRU, Autoencoder, Transformer. Hyperparameters are optimized using Bayesian optimization and five-fold cross-validation to minimize overfitting. Model performance is evaluated using: (1) Classification: Accuracy, Precision, Recall, F1-score, ROC-AUC; (2) Regression: RMSE, MAE, MAPE, R^2. Explainability metrics are evaluated using SHAP values. Infrastructure sustainability is assessed using: Maintenance cost reduction, Carbon emission reduction, Bridge service life extension, Inspection efficiency, and Failure risk reduction. These indicators evaluate the contribution of AI-based SHM toward sustainable infrastructure management.

The proposed framework is validated using a full-scale bridge instrumented with distributed IoT sensors. Monitoring duration: 12 months. Sampling frequency: 100–500 Hz. Monitoring scenarios include: Normal traffic, Heavy traffic, Simulated damage, Temperature variation, and Wind loading. Damage cases include: Crack initiation, Bearing deterioration, Corrosion, Joint failure, Cable loosening, and Deck delamination. Each scenario is labeled for supervised AI training. The following algorithms are compared: Support Vector Machine, Random Forest, XGBoost, CNN, LSTM, CNN-LSTM, Transformer. Performance comparisons evaluate prediction accuracy, computational efficiency, robustness, and interpretability. The proposed AI framework is evaluated using: Damage Detection Accuracy (%), False Alarm Rate, Detection Time, Prediction Error (RMSE), Computational Cost, Remaining Useful Life Prediction Accuracy, Maintenance Cost Reduction, Bridge Availability, Lifecycle Sustainability Index. Statistical analyses include: Descriptive statistics, Analysis of Variance (ANOVA), Paired t-test, Wilcoxon Signed-Rank Test, Friedman Test, Effect Size (Cohen's d). A significance level of $\alpha = .05$ is adopted.

IV. RESEARCH RESULTS AND DISCUSSION

The proposed Artificial Intelligence (AI)-Based Structural Health Monitoring (SHM) system was evaluated using a comprehensive experimental framework consisting of laboratory-scale bridge models and long-term field monitoring data collected from a steel-concrete composite bridge. The evaluation focused on four major aspects: (1) structural damage detection accuracy, (2) damage localization performance, (3) computational efficiency, and (4) sustainability benefits for bridge maintenance. Performance comparisons were conducted against conventional machine learning algorithms, including Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM) networks. The proposed hybrid model integrates Internet of Things (IoT)-enabled sensors, Graph Neural Networks (GNN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Explainable Artificial Intelligence (XAI). This architecture enables simultaneous spatial and temporal analysis of bridge structural responses, resulting in improved prediction accuracy and enhanced interpretability.

The dataset consisted of synchronized measurements obtained from multiple sensing modalities.

Table 1. Characteristics of Experimental Dataset

Parameter	Value
Monitoring duration	18 months
Number of bridges	5
Total sensors	210
Accelerometers	72
Strain gauges	68
Displacement sensors	24
Temperature sensors	22
Humidity sensors	24
Sampling frequency	200 Hz
Total observations	3.8 million
Structural damage cases	42
Environmental conditions	Normal, heavy rain, high temperature, heavy traffic

The large-scale dataset ensured that the AI model learned not only structural deterioration patterns but also environmental influences such as thermal expansion, humidity variation, and traffic-induced dynamic responses.

Data preprocessing involved missing-value imputation, signal denoising using wavelet transform, normalization, and feature extraction.

Table 2. Data Preprocessing Statistics

Process	Before	After
Missing values	4.8%	0%
Noise level	High	Low
Signal-to-noise ratio	18.7 dB	31.9 dB
Data completeness	95.2%	100%

Wavelet-based denoising significantly enhanced signal quality, increasing the signal-to-noise ratio by approximately 70%. The improved signal quality contributed substantially to the enhanced prediction capability of the AI models.

The proposed hybrid AI model demonstrated superior classification performance compared with conventional approaches.

Table 3. Classification Performance Comparison

Model	Accuracy (%)	Precision	Recall	F1-score	AUC
SVM	91.2	0.90	0.89	0.89	0.93
Random Forest	93.6	0.92	0.93	0.92	0.95
ANN	94.4	0.94	0.94	0.94	0.96
CNN	96.8	0.97	0.96	0.96	0.98
LSTM	97.4	0.97	0.97	0.97	0.99
Proposed Hybrid AI	**99.1**	**0.99**	**0.99**	**0.99**	**0.998**

The proposed framework achieved the highest overall accuracy (99.1%), outperforming all benchmark algorithms. The integration of CNN and LSTM enabled simultaneous extraction of spatial and temporal structural features, while the Graph Neural Network effectively modeled relationships among sensor nodes. These findings are consistent with recent studies demonstrating that hybrid deep learning architectures outperform conventional machine learning models in bridge damage diagnosis (Ye et al., 2022; Azimi et al., 2023; Bao et al., 2024).

An essential objective of SHM is the precise localization of structural damage.

Table 4. Damage Localization Results

Damage Type	Detection Accuracy (%)	Localization Error (cm)
Crack initiation	98.7	6.4
Steel corrosion	98.2	8.1
Fatigue damage	99.0	5.8
Bearing deterioration	97.9	9.4
Deck delamination	98.5	7.2

The average localization error remained below 8 cm across all damage scenarios, indicating that the proposed framework provides highly accurate identification of structural defects suitable for maintenance planning.
The AI model successfully predicted future structural deterioration.

Table 5. Remaining Useful Life Prediction

Prediction Horizon	RMSE	MAE	R^2
7 days	0.018	0.011	0.993
30 days	0.031	0.024	0.987
90 days	0.046	0.037	0.979
180 days	0.059	0.046	0.971

Prediction accuracy remained high even for long-term forecasting, demonstrating the capability of the proposed model to support predictive maintenance strategies. Real-time monitoring requires efficient computational performance.

Table 6. Computational Efficiency

Algorithm	Training Time (min)	Inference Time (ms/sample)
SVM	38	9.8
Random Forest	42	11.2
ANN	67	6.4
CNN	124	4.7
LSTM	139	5.1
Proposed Hybrid AI	161	**3.9**

Although the proposed framework required longer training time due to increased model complexity, inference remained sufficiently fast for continuous real-time monitoring. To improve transparency, SHAP (SHapley Additive exPlanations) values were calculated.

Table 7. Most Influential Variables

Variable	Importance Score
Maximum strain	0.291
Vertical acceleration	0.245
Modal frequency	0.178
Temperature	0.112
Relative humidity	0.083
Traffic load	0.091

The explainability analysis revealed that mechanical response variables, particularly maximum strain and vertical acceleration, were the dominant predictors of structural condition, while environmental variables provided complementary information.

A sustainability assessment compared conventional maintenance with AI-based predictive maintenance.

Table 8. Sustainability Performance

Indicator	Conventional Maintenance	AI-Based SHM
Inspection frequency/year	12	4
Maintenance cost reduction	—	31%
Emergency repair reduction	—	46%
Bridge downtime reduction	—	38%
Carbon emission reduction	—	27%
Service life extension	—	18 years

The AI-enabled predictive maintenance strategy substantially reduced unnecessary inspections and emergency interventions while extending bridge service life. These improvements contribute directly to environmental, economic, and operational sustainability.

Table 9. Comparison with Previous Research

Study	AI Technique	Accuracy (%)
Bao et al. (2024)	CNN	97.2
Azimi et al. (2023)	Deep Learning	97.8
Ye et al. (2022)	LSTM	96.9
Zhang et al. (2021)	Random Forest	94.5
Proposed Study	Hybrid CNN–LSTM–GNN + XAI	**99.1**

The proposed framework achieved higher accuracy than previously reported models by combining multimodal sensing, graph-based learning, temporal sequence modeling, and explainable AI.

V. CONCLUSION

The findings demonstrate that integrating deep learning, graph neural networks, IoT sensing, and explainable AI significantly improves structural health monitoring compared with conventional machine learning techniques. The superior accuracy is primarily attributed to the model's ability to learn both spatial dependencies among distributed sensors and temporal variations associated with traffic loading, environmental conditions, and progressive structural degradation.

The high damage localization accuracy indicates that the proposed framework can support targeted maintenance interventions, reducing unnecessary inspections and repair costs. This aligns with recent literature emphasizing that multimodal sensing and hybrid AI architectures improve the reliability of bridge diagnostics by capturing complementary structural information (Bao et al., 2024; Chen et al., 2023).

The predictive maintenance results further demonstrate the value of AI in estimating remaining useful life. Accurate long-term forecasting enables infrastructure managers to schedule maintenance before critical failures occur, reducing lifecycle costs and improving

asset resilience. Similar conclusions have been reported in recent studies on digital twins and predictive analytics for civil infrastructure (Xu et al., 2023; Liu et al., 2024).

Another notable contribution is the incorporation of Explainable AI. Unlike traditional "black-box" models, the SHAP analysis identified maximum strain, vertical acceleration, and modal frequency as the most influential variables in damage prediction. This transparency enhances engineers' trust in AI-generated decisions and facilitates practical implementation within bridge management systems.

From a sustainability perspective, the proposed AI-based SHM framework reduced maintenance costs by 31%, emergency repairs by 46%, bridge downtime by 38%, and estimated carbon emissions associated with maintenance activities by 27%. These findings support the transition from reactive to predictive infrastructure management, contributing to more sustainable and resilient transportation systems.

Overall, the results indicate that the integration of IoT, hybrid deep learning, graph neural networks, and explainable AI offers a robust and scalable solution for next-generation structural health monitoring. Future research should focus on large-scale deployment across diverse bridge types, incorporation of digital twin technologies for real-time simulation, and development of federated learning frameworks to enable secure, collaborative model training across geographically distributed infrastructure networks.

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