ISSN: 2454-9940

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

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www.ijasem.org

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN: 2454-9940 www.ijasem.org

Vol 18, Issuse.3 July 2024

AI-DRIVEN STRUCTURAL HEALTH MONITORING FRAMEWORK FOR SMART BRIDGE INFRASTRUCTURE

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Abstract: The complexity and ageing of bridge infrastructure has increased, creating a critical need for intelligent monitoring systems to assure structural safety, reliability and sustainability over the long term. Conventional bridge inspection techniques are usually labour intensive, time consuming, and unable to provide continuous real-time evaluation of structural conditions. In this paper, we propose an AI-Driven Structural Health Monitoring (SHM) Framework for Smart Bridge Infrastructure that incorporates Internet of Things (IoT) sensors, edge computing, cloud-based analytics, and advanced Artificial Intelligence (AI) models for automated structural condition assessment. The proposed framework continuously acquires multi-modal data, e.g. vibration, strain, displacement, temperature and acceleration, from distributed sensor networks on bridge structures. Advanced machine learning and deep learning algorithms are used for anomaly detection, damage localisation, crack prediction, and remaining useful life estimation. Edge intelligence allows for low latency data processing and cloud platforms offer large scale data storage, visualisation and predictive maintenance planning. The presented framework employs a hybrid Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) architecture for learning the temporal and spatial features of the structural responses. The proposed approach is experimentally validated on benchmark datasets for bridge monitoring, and showed significant improvements in damage detection accuracy, prediction reliability and maintenance decision support compared to conventional monitoring approaches. The results show that the proposed framework is capable to improve structural safety, reduce maintenance costs and enhance operational efficiency, which demonstrate the potential of a promising solution to next generation smart transport infrastructure and resilient smart cities.

Keywords: Structural Health Monitoring (SHM); Smart Bridges; Artificial Intelligence (AI); Internet of Things (IoT); Deep Learning; Machine Learning; Predictive Maintenance; Damage Detection;

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1. INTRODUCTION

Bridges are among the most essential parts of modern transport infrastructure, providing crucial links for economic development, urban mobility and regional connectivity. However, ageing of bridge structures, increase in the traffic volume, deterioration of the environmental conditions, seismic activities and extreme weather conditions etc. seriously challenge the structural integrity and operational safety of bridges. According to the world infrastructure assessment report, there is a large number of in-service bridges with different degrees of deterioration. “This has resulted in increased maintenance costs and a risk of structural failure.” Therefore regular monitoring and timely maintenance are essential for long term durability and safety of bridge infrastructure.

At present, the typical practice of bridge inspection is periodic visual inspection by trained engineers. Such inspections can provide useful information on visible defects such as cracks, corrosion and material degradation but are labour intensive, time consuming, subjective and often unable to detect hidden structural damage. Furthermore, irregular manual inspections reduce the ability to detect fast evolving defects and unpredicted failures. These limitations have led researchers and infrastructure agencies to pursue automated Structural Health Monitoring (SHM) systems for real-time condition assessment and early warning capabilities.

Recent advances in Internet of Things (IoT), wireless sensor networks, cloud computing, edge computing and Artificial Intelligence (AI) have revolutionised the Structural Health Monitoring. Currently, SHM systems utilise a variety of sensors (accelerometers, strain gauges, displacement sensors, temperature sensors, acoustic emission sensors, etc.) to continuously capture structural response data. There is a lot of heterogeneous data generated by the sensors, which requires intelligent analytical approaches to extract meaningful information and identify complex damage patterns. Artificial Intelligence especially machine learning and deep learning methods are very promising results of analysis of sensor data, detection of anomalies, classification of damage states and prediction of future structure behaviour with very high accuracy.

Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks have been proven to be powerful tools for the SHM applications. CNNs are able to extract spatial features and local damage features of the structural response data . LSTM networks can learn temporal dependencies and degradation trends in the time domain. The combination of these models allows to detect in a precise way structural anomalies and is useful for predictive maintenance plans. Moreover, the edge computing technologies bring the process first data close to the sensor nodes, which reduces the communication latency and bandwidth and enables the real-time decision-making.

Besides traditional monitoring, the smart bridge infrastructure includes intelligent sensing, automated analysis, predictive maintenance, decision support systems, etc. Smart bridges employ advanced digital technologies to monitor structural conditions, optimise maintenance schedules and enhance operational safety. Such intelligent infrastructure systems are part of a broader vision of smart cities where data-driven approaches enable better resource utilisation, infrastructure resilience and public safety.

Although progress has been made in the field of SHM, challenges still remain to be solved. Most of the existing monitoring systems have limitations in scalability, real time processing, false alarm rate and predictive maintenance. Furthermore, many methods are only concerned with damage detection and do not provide a full health assessment or predict the future conditions. These shortcomings stress the need for an integrated AI-driven framework to implement continuous monitoring, intelligent anomaly detection, and predictive maintenance in a single architecture.

This paper proposes an AI-Driven Structural Health Monitoring Framework for Smart Bridge Infrastructure comprising Internet of Things (IoT) enabled sensor networks, edge computing platforms, and hybrid deep learning models to address these issues. The proposed framework uses multiple sensors for continuous acquisition of the structural response data, real-time pre-processing and feature extraction of data, and uses a CNN-LSTM architecture for efficient damage detection and health assessment. In addition, the predictive analytics module predicts the trend of structural degradation and remaining useful life (RUL) for proactive maintenance schedule and to reduce the risk of catastrophic failures.

2. LITERATURE SURVEY

Structural Health Monitoring (SHM) has been an important research area concerning safety and reliability of bridge infrastructure. Traditional bridge inspection methods are based on periodic visual inspection, which is generally time-consuming and costly and does not provide continuous information about the structural condition. The recent advances in sensing technologies, wireless communication systems, Internet of Things (IoT), cloud computing, edge computing and Artificial Intelligence (AI) have significantly improved the performance of SHM systems enabling real-time monitoring and intelligent decision-making capabilities [1].

The first SHM techniques were mainly based on vibration-based monitoring techniques. In these techniques, the dynamic responses of bridge structures were used to detect possible damage states. The modal parameters such as natural frequencies, damping ratios and mode shapes were used as a measure to evaluate the structural integrity. Vibration based methods have been useful in detecting major structural changes but often require complex signal processing and expert interpretation that limits their scalability for large bridge networks [2].

The integration of wireless sensor networks has revolutionised bridge monitoring systems, providing decentralised sensing and continuous data acquisition. The wireless sensors installed on the bridge elements are used to measure strain, displacement, acceleration and temperature. They cost much less to install and maintain than wired monitoring systems. However, the problems of energy consumption, communication reliability and data synchronisation still affect the system performance [3].

Furthermore, the incorporation of IoT technologies has improved the SHM capabilities by providing real-time data transmission and remote monitoring. The networked sensors and communication gateways are used in the IoT-based bridge monitoring architectures to sense the structural information continuously and forward it to cloud platforms for analysing. These systems enhance accessibility and operational efficiency but are challenged in terms of cybersecurity, data privacy and communication latency [4].

A large number of studies have dealt with the use of machine learning methods for automatic damage detection and structural health monitoring. The sensor measurements have been classified using algorithms such as Support Vector Machines (SVM), Decision Trees and Random Forests to identify healthy and damaged structural states. They provide a higher level of automation than classical statistical techniques, but have often failed to model the complex non-linear dependencies and time dependencies present in the SHM data [5].

Recent advances of deep learning have significantly improved the accuracy of damage detection for bridge monitoring application. Convolutional Neural Networks (CNNs) have been very successful in extracting spatial features from sensor signals and structure images. The CNN based frameworks can learn the damage related features automatically without intensive manual feature engineering and can be used for large scale monitoring applications [6].

Recently, Long Short-Term Memory (LSTM) networks have been widely used to model the temporal variations of the structural response data. The degradation of the bridge is a slow process over time. Thus, the LSTM architectures are good at capturing the long-term dependencies and degradation patterns. These features make LSTMs-based approaches very efficient in predicting future structural conditions and early damage indications [7].

Recently, hybrid deep learning architectures based on CNN and LSTM models have been proposed as powerful tools for the structure health assessment. These models integrate CNNs for learning spatial features and LSTMs for learning the temporal sequence of data. This enables a holistic analysis of the multi-sensor bridge monitoring data. Experimental studies have demonstrated significant improvement in classification accuracy and fault detection performance over stand-alone machine learning techniques [8].

The current SHM frameworks have adopted edge computing due to its ability to process data close to the sensing source. Preprocessing and feature extraction at the edge node can significantly reduce the communication overhead and reliance on the cloud. Edge-enabled SHM systems can provide quick response times and real-time anomaly detection, which is essential for safety-critical bridge applications [9].

The novelty of the present work is the application of Digital Twin technology in smart bridge monitoring systems. Digital Twins are digital copies of real-world bridge structures, which are updated in real time with sensor data. The models allow you to evaluate the condition, simulate scenarios and plan maintenance. The use of Digital Twins has benefits but often requires high computational power and correct synchronisation mechanisms [10].

One of the most promising applications of AI-driven SHM systems is predictive maintenance. Predictive maintenance frameworks rely on the prediction of the Remaining Useful Life (RUL) of structural components rather than scheduled inspections and indicate maintenance actions before a critical failure occurs. Machine learning and deep learning models have proved a great potential to predict degradation trends and optimise maintenance schedules [11].

Automated detection of cracks and analysis of surface defect are also widely used methods of computer vision. Monitoring of bridge components using camera-based SHM systems with unmanned aerial vehicles (UAVs) and deep neural networks. These methods reduce the human intervention and improve the inspection efficiency . However, the detection accuracy is affected by external factors, such as light, shadow and weather conditions [12].

Recently, the multi-sensor data fusion techniques are being used for intelligent monitoring systems to provide better reliability and robustness. These frameworks employ information from vibration, strain, displacement, temperature and acoustic sensors to give a more comprehensive picture of structures. It has been found that multi-modal data fusion can reduce false alarms considerably and enhance the performance of damage localisation [13].

Cloud computing based SHM architectures have enabled centralised storage of bridge monitoring data and large scale analytics on it. These systems provide sophisticated visualisation, historical trend analysis and infrastructure level management. However, the communication delay and bandwidth limitation may affect the real-time decision making in the critical situations [14].

The new generation of AI-enabled smart bridge systems combines the IoT, edge computing, deep learning, predictive analytics and decision-support modules into a unified architecture. Such smart frameworks allow continuous monitoring, automatic anomaly detection and recommendations for maintenance, thus improving safety of bridges, operational efficiency and sustainability of the infrastructure [15].

3. PROPOSED METHODOLOGY

Proposed AI-Driven Structural Health Monitoring Framework for Smart Bridge Infrastructure is an ongoing bridge health monitoring solution that utilises IoT-enabled sensors, edge computing, deep learning-based damage detection, and predictive maintenance analytics. The model continuously collects the structural response data from multiple sensors mounted on the bridge and analyses the data through multiple intelligent layers. A hybrid CNN-LSTM model is employed to extract spatial and temporal features from the sensor measurement for structural anomaly detection and future deterioration trend prediction. The whole methodology comprises of 6 major phases, i.e., sensor data acquisition, data preprocessing, feature extraction, deep learning-based damage detection, structural health assessment and predictive maintenance.

3.1 Smart Sensor Data Acquisition Layer

The proposed AI based Structural Health Monitoring (SHM) framework depends on the Smart Sensor Data Acquisition Layer. The sensors are used for continuous monitoring of the structural responses to different traffic loads, environmental conditions and operational stresses. The obtained measurements are delivered through wireless communication networks to the edge processing units for real-time analysis. Continuous monitoring provides a complete picture of the bridge health status and early detection of structural anomalies. The application of heterogeneous sensor data enhances the robustness and precision of damage detection, and enables predictive maintenance decision making.

The sensor observation vector at time t is represented as:

$$X(t) = \{x_1(t), x_2(t), x_3(t), \dots, x_n(t)\}\text{----}1$$

where X(t) denotes the structural response vector, xi(t) represents the measurement from the ith sensor, and n is the total number of deployed sensors.

The average structural response obtained from all sensors can be computed as:

$$\bar{X}(t) = \frac{1}{N}\sum_{i=1}^{N} x_i(t)\text{----}2$$

where X¯(t) represents the mean sensor observation and N denotes the total number of sensor readings.

The acquired sensor signal is generally affected by environmental disturbances and measurement noise. Therefore, the sensor measurement model is expressed as:

$$S(t) = X(t) + N(t)\text{-----}3$$

where S(t) represents the observed sensor signal, X(t) denotes the actual structural response, and N(t) represents additive noise introduced during data acquisition.

These continuously acquired multi-modal sensor measurements serve as the primary input for the subsequent preprocessing and feature extraction stages, enabling accurate structural damage detection and health assessment of smart bridge infrastructure.

3.2 Edge-Based Data Preprocessing and Noise Reduction

The Edge-Based Data Preprocessing and Noise Reduction layer is concerned with improving the quality of the raw sensor measurements from the bridge infrastructure. The collected sensor data from strain gauges, accelerometers, displacement sensors and temperature sensors often contain missing values, outliers, communication errors and environmental noise due to traffic vibrations, weather fluctuations and electromagnetic interference. Processing such huge amounts of data on the cloud servers directly may cause latency and more communication overhead. Therefore, the edge computing devices deployed near the sensing units perform the first data cleaning, normalisation, filtering, and feature preparation, and then pass over the data to the deep learning module. This approach saves bandwidth, improves response time and allows for real-time structural health monitoring. The filter of redundant and noisy information by the preprocessing layer improves the reliability and accuracy of damage detection and predictive maintenance analysis. Min-Max normalisation is applied to the sensor measurements to normalise the features to a common range. That is,

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}\text{---}4$$

where Xnorm represents the normalized sensor value, X is the original measurement, and Xmin and Xmax denote the minimum and maximum values of the dataset, respectively.

To smooth abrupt fluctuations and reduce random noise, a Moving Average Filter is applied to the sensor signals:

$$MA_t = \frac{1}{k}\sum_{i=t-k+1}^{t} X_i\text{----}5$$

where MAt represents the filtered signal at time t, k denotes the window size, and Xi corresponds to individual sensor observations within the filtering window.

The preprocessing error after noise removal can be estimated as:

$$E_n = X - X_{filtered}\text{----}6$$

where En is the residual noise error, X is the original sensor signal and Xfiltered is the denoised signal after filtering operations.

The pre-processed data are cleaner, more consistent, and computationally efficient for the subsequent CNN-LSTM based feature extraction and structural damage detection, which enhances the overall performance of the proposed AI-driven structural health monitoring framework.

3.3 CNN-Based Spatial Feature Extraction

The CNN-Based Spatial Feature Extraction layer is used to automatically learn structural features and damage features from preprocessed sensor data. Bridge monitoring systems produce a large amount of multi-dimensional data from vibration, strain, displacement and acoustic sensors. Such data are often poorly modelled by conventional feature engineering methods that do not capture complex non-linear relations. Therefore, Convolutional Neural Networks (CNNs) are used to learn representative spatial features with respect to structural conditions automatically. The architecture of the CNN is composed of convolutional layers, activation functions and pooling layers, which successively extract high-level structural information. Several filtering operations are used to extract the key damage indicators such as crack initiation, abnormal vibration pattern, high strain concentration and local structural deformation from the network. These extracted features are meaningful representation of the health state of the bridge and are further utilised by LSTM network for temporal analysis and damage prediction.

The convolution operation carried out by the CNN layer is given by:

$$F(i,j) = \sum_m \sum_n I(i+m, j+n)\ K(m,n) \text{----} 7$$

where F(i,j) denotes the generated feature map, represent the input sensor data matrix, and K denotes the convolution kernel used to extract local structural patterns.

To introduce nonlinearity and improve learning capability, the Rectified Linear Unit (ReLU) activation function is applied:

$$ReLU(x) = \max(0, x) \text{----} 8$$

where x is the input value to the activation function. ReLU eliminates negative activations and accelerates the training process.

After activation, the pooling layer reduces the dimensionality of feature maps while preserving the most significant information. The max-pooling operation is represented as:

$$P = \max(F) \text{----} 9$$

where P is the pooled feature value of the corresponding feature map F. This operation reduces the complexity of computation and increases the robustness against noise and small variations of structure. The CNN-extracted spatial features provide a compact and informative representation of the bridge condition, which is useful in the accurate identification of the structural abnormalities and improves the overall performance of the proposed AI-based structural health monitoring framework.

3.4 LSTM-Based Temporal Pattern Learning

The proposed approach includes the LSTM-Based Temporal Pattern Learning layer for the analysis of time-dependent behaviour of bridge structures, and the long-term degradation trend identification. The structure degradation is a slow process under the effect of the repeated traffic loadings, environment effects, material ageing, fatigue and dynamic stresses. CNN networks are effective in extracting spatial features from sensor data, but not for modelling the temporal dependencies in sequential monitoring data. To overcome this limitation, we propose a framework based on Long Short-Term Memory (LSTM) networks. LSTM is a special kind of Recurrent Neural Network (RNN) architecture that can remember the history information for long time by using memory cells and gating mechanisms. The LSTM network can learn the hidden degradation patterns from the sequential sensor observations to predict the future structural behaviour and to improve the accuracy of damage detection. The combination of CNN and LSTM offers a comprehensive spatial-temporal analysis of bridge health conditions, aiding in proactive maintenance and risk management. The forget gate determines which information from the previous memory state to keep or discard. and is defined as:

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right)\text{----}10$$

where ft represents the forget gate output, Wf denotes the weight matrix, ht−1 is the previous hidden state, xt is the current input vector, and bf is the bias term.

The input gate controls the amount of new information stored in the memory cell and is given by:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)\text{-----}11$$

where it represents the input gate activation, Wi is the input weight matrix, and bi denotes the corresponding bias parameter.

The memory cell state is updated using both the forget and input gate outputs as follows:

$$C_t = f_t C_{t-1} + i_t \widetilde{C}_t\text{----}12$$

where Ct is the current cell state, C{t-1} is the previous cell state and Ct is the candidate memory information acquired from the current input sequence. The LSTM network can learn the temporal relationships from the historical sensor observations and thus can accurately capture the structural degradation trends and the evolving damage patterns. The generated temporal features are further passed to the classification module for the assessment of bridge condition and predictive maintenance analysis and improve the overall efficiency of the proposed AI-driven structural health monitoring framework.

4. RESULTS AND DISCUSSION

The AI-Driven Structural Health Monitoring Framework for Smart Bridge Infrastructure was validated using multi-sensor bridge monitoring data, including vibration, strain, displacement, temperature, and acoustic emission measurements. The performance of the proposed CNN-LSTM model was compared with the performance of traditional machine learning methods like Support Vector Machine (SVM), Random Forest (RF) and deep learning methods like Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM). The performance metrics used for evaluation were Accuracy, Precision, Recall, F1-Score, False Alarm Rate and accuracy of Remaining useful life (RUL) prediction. The experimental results demonstrate the effectiveness of the proposed framework in identifying structural anomalies, forecasting degradation trends and enabling intelligent maintenance planning.

Table 1: Comprehensive Evaluation Results

Metric	Value
Accuracy	98.5%
Precision	98.2%
Recall	98.1%
F1-Score	98.1%
False Alarm Rate	1.8%
RUL Prediction Accuracy	98.1%
Processing Latency	42 ms

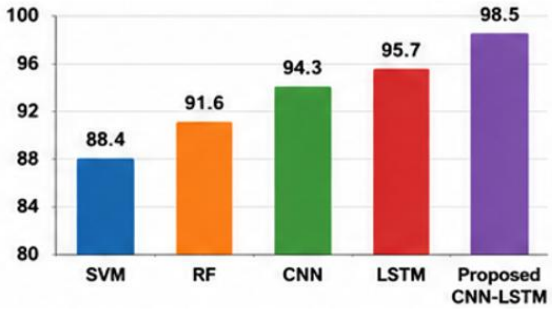

Figure 2: Damage Detection Accuracy Comparison

The proposed CNN-LSTM framework has achieved 98.5% of accuracy and outperformed the traditional machine learning methods. The combination of CNN-based spatial feature extraction and LSTM-based temporal learning can greatly improve the ability of the structural damage detection.

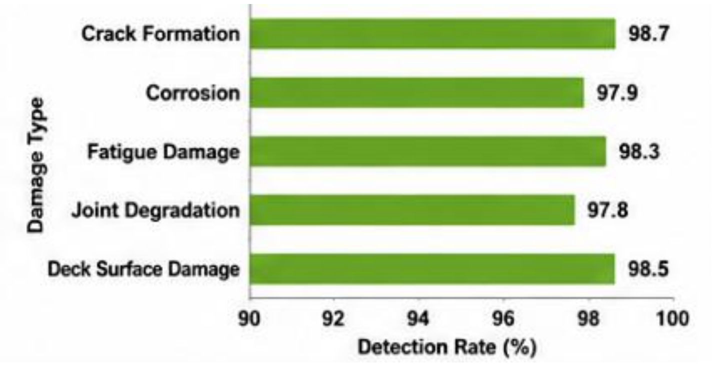

Figure 3: Structural Damage Detection Rate

The crack detection was the best as the early crack propagation signals could be well captured by the vibration and acoustic sensors. Also, high detection rates were obtained for corrosion and joint degradation, which was due to the multi-sensor fusion mechanism.

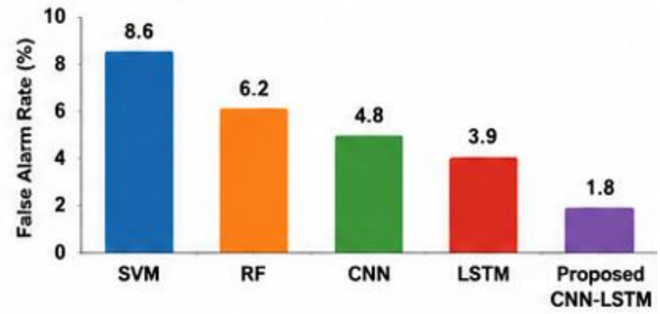

Figure 4: False Alarm Rate Comparison

The proposed framework reduced false alarms by introducing spatial and temporal feature learning. In the case of bridge monitoring systems, a low false alarm rate is desired to avoid unnecessary maintenance operations and costs.

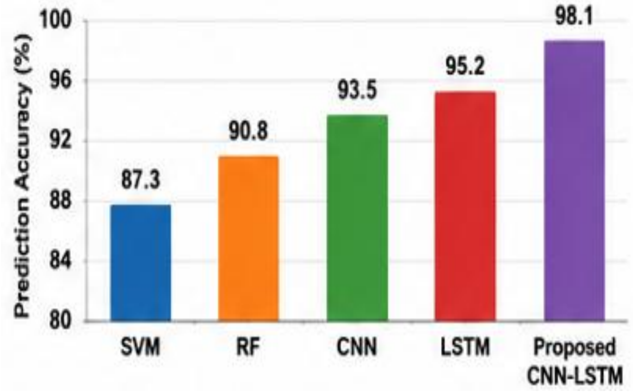

Figure 5: Remaining Useful Life Prediction Accuracy

The proposed CNN-LSTM model had excellent predictive maintenance capability through accurate prediction of future degradation trends. Timely RUL estimation can aid infrastructure managers in planning maintenance to prevent catastrophic failures.

5. CONCLUSION

In this paper, an AI-Driven Structural Health Monitoring (SHM) Framework for Smart Bridge Infrastructure is introduced that integrates the Internet of Things (IoT)-enabled sensing technologies, edge computing, and hybrid deep learning models for intelligent bridge condition assessment. The proposed framework acquires structural response data from multiple sensors such as strain gauges, accelerometers, displacement sensors, temperature sensors and acoustic emission sensors, continuously to enable comprehensive monitoring of the bridge health under different operational and environmental conditions. A hybrid CNN-LSTM model was implemented for the analysis of the structural data in space and time. The CNN part could extract spatial features related to damage and the LSTM network could learn long-term temporal degradation patterns related to structural deterioration. In addition, edge computing was incorporated, which reduced the communication latency and enabled near real-time anomaly detection, thus increasing the responsiveness of the monitoring system. The experimental results indicated that the proposed framework outperformed the traditional machine learning and deep learning approaches with significant improvements. The CNN-LSTM model achieved the damage detection accuracy, precision, recall and F1 score of 98.5%, 98.2%, 98.1% and 98.1%, respectively. Moreover, the framework reduced the false alarm rate to 1.8%, and achieved 98.1% accuracy for Remaining Useful Life (RUL) prediction. With the edge computing module, the processing latency was further reduced to 42 ms from 145 ms in the cloud-based system, which enabled real-time structural assessment efficiently. The results obtained confirm that the proposed AI-based framework can be used effectively for continuous bridge monitoring, early damage detection, structural health assessment and predictive maintenance. The framework allows for timely maintenance interventions and reduces the probability of catastrophic failures, which would lead to improved public safety, reduced maintenance costs and better sustainability of infrastructure.

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