AI-Driven Structural Health Monitoring in Civil Infrastructure Using Real-Time IoT Sensor Networks and Edge Analytics

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Abstract: It must develop robust, intelligent, and scalable solutions for structural health monitoring (SHM) to cope with the ever-increasing complexity and ageing of civil infrastructure. We provide a new AI-driven framework that combines IoT sensor networks (SN), edge analytics, and federated learning to achieve continuous, precise, explainable monitoring of structural integrity. Existing SHM systems depend extensively on cloud-based models and/or limited sensor modalities (e.g., only vibration), whereas our method utilizes multi-modality sensing (vibration, displacement, and environmental) fused with edge-enabled preprocessing to maximize detection-speed at minimal latencies. It is scalable for larger infrastructures and can integrate nicely to digital twin platforms for predictive simulations and long-term asset management. Incorporating these explainable AI (XAI) components can improve the interpretability of predictions, thereby increasing trust in the model towards civil engineers and stakeholders. Federated learning and edge-level encryption secure privacy while minimizing risks related to centralized data storage. It also offers drift detection, automatic fault correction, and a low-bandwidth mode for deployment in remote locations. The proposed solution has been tested on real life deployments, achieving better accuracy, responsiveness and reliability than existing models.

1 INTRODUCTION

Civil infrastructure [such as bridges, dams and roads] is ultimately what enables a modern economy, where people, goods and services can move around freely while ensuring public safety. With all structures (bridges, buildings, tunnels, dams), as they age under the increased stresses of the environment and demands on use, monitoring systems that are intelligent and advanced are now needed more than ever before. This is specifically when it comes to traditional structural health monitoring (SHM) methods, which rely heavily on human inspection or centralized data analysis and often fail to provide real-time knowledge, dynamic learning and relevant intelligence, particularly at a large scale. This sets the stage for unprecedented SHM transformation through the convergence of Artificial Intelligence (AI), Internet of Things (IoT) sensor networks, and edge computing. Nonetheless, with growing technologies, current AI-based SHM approaches suffer from fundamental drawbacks: transparency and interpretability of decision making, scalability, data privacy risk, adaptability to non-stationary regimes, and legacy systems compatibility. In addition, most current models are designed to run in data-rich cloud environments, which are not practical for use in remote/low-bandwidth environments. To overcome

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these challenges, this paper proposes a novel scalable explainable AI-edge framework for real-time SHM, utilizing a network of federated IoT sensors which can be seamlessly integrated into digital twin environments. This means we are increasing system transparency with explainable AI (XAI), others are doing federated learning to ensure no data breaches, and we can also be doing (real-time) structural simulations for predictive maintenance. The proposed framework includes lightweight edge devices with intelligent preprocessing capabilities for reducing latency, minimizing bandwidth utilization and ensuring high reliability in constrained environments.

The findings of this research not only close the loop of existing gaps in SHM systems but also pave the way towards smart infrastructure management at the city level. We validate the proposed system against real-world data and compare it against traditional architectures to demonstrate improvements in responsiveness, accuracy, interpretability, and adaptability.

1.1 Problem Statement

Real-Time, Transparent, Scalable Internet of Things SHM Solution for Life Cycle Health Management of Civil Structures Despite the increasing application of Artificial Intelligence and IoT technologies in civil engineering, the existing SHM systems are still crippled by serious bottlenecks in terms of real-time responsiveness, transparency and scalability. Standard SHM architectures are largely reliant on cloud resources, which incurs latency and delay in data analysis and decision-making highly troublesome in case of time-sensitive infrastructure conditions. Additionally, most of these systems are black-box AI models that are neither interpretable nor interpretable and, therefore, do not lend themselves to trust by civil engineers and infrastructure managers.

These heterogeneous establishments are not well suited to utilizing the inexhaustible and heterogeneous data produced by multi-modal sensor networks. They also don't adequately preserve data privacy using centralized models that are subject to breaches or regulatory, compliance challenges. These limitations are only magnified as we move to more IoT-like and or remote/bandwidth-constrained settings in which missing, delayed, and or interpreted sensor data is the rule rather than the exception. Moreover, existing SHM solutions fall short of modern smart infrastructure requirements due to their inability to adapt to environmental changes, lack of integration of digital twin, and inadequate tolerance to fault.

Indeed, this yields a pressing demand for a resilient, adaptable, and interpretable AI enterprise SHM architecture capable of real-time deployments, harnessing edge computing for low-latency enhancements while upholding data privacy with federated learning whilst nestling with digital twin technology to champion predictive and preemptive infrastructure governance.

2 LITERATURE REVIEW

The field of structural health monitoring (SHM) has seen a paradigm shift over the past few years with the advent of artificial intelligence (AI), Internet of Things (IoT) sensor networks, and edge computing. In this literature review, we highlight the most important works published between the years 2020 and 2025, identifying the largest gaps in the literature out of which our own research emerges.

2.1 Applications of Artificial Intelligence in SHM

Azimi et al. (2020) with the initial review on AI-based SHM concludes that deep learning models are superior to traditional algorithms in damage identification. However, their approach has revealed shortcomings in the transparency and real-time adaptability of the model. Similarly, Bao et al. Deep learning approach is a recent entry in SHM systems wherein Khosravi et al. (2021) used computer vision and anomaly detection in SHM systems, however the authors pointed out the existence of black box nature and high computation cost associated with deep learning methodologies.

In a state-of-the-art overview of DL applications in SHM, Zhao and Li (2020) highlighted the importance of interpretability and advanced robust real-time systems. Xu and Brownjohn (2020) also noted that AI models frequently demand sizable amounts of labeled data information that may be in short supply in infrastructure monitoring situations.

2.2 Real-Time Monitoring with IoT Sensor Networks

Real-time structural responses can be captured using wireless IoT sensor networks (Li & Sun, 2020; Ma & Li, 2020) Their findings were that sensor placement and energy efficiency are still key challenges. For example, Ni and Ye (2020) suggested the incorporation of IoT into digital twins, simulating bridges in the virtual domain; however, edge-level analytics was not included in their method for real-time, on-site interpretations.

For example, Wang and Zhu (2020) concentrated on real-time sensing for low-power wireless nodes, though the architecture was highly cloud-based which could introduce latency and possible data loss in remote environments.

2.3 Edge Computing in SHM

Gao et al. (2020) proposed energy-efficient CNNs designed for edge deployment for SHM systems, allowing data processing at local machines. However, while this decreased dependence on the cloud, their model did not solve issues regarding scalability across multiple structures. Shang and Yang (2020) and Liu and Gül (2020) were two DL models operated at the edge, the results of which were not explainable and thus not practical for decision-making within engineering.

Chen and Yu (2020) employed reinforcement learning for autonomous SHM, though the approach shows promise, it lacked the necessary real-world validations required by civil infrastructure applications.

2.4 Explanability and Data Privacy

Yang and Nagarajaiah (2020) proposed using convolutional neural networks for detecting damage and enabling real-time assessments, but they did not include explainability aspects. Rafiei and Adeli (2020) suggested ML frameworks for property prediction but lamented the lack of interpretable decision pathways.
Hou et al. (2021) advocated for explainable AI (XAI) in SHM to build trust and foster adoption of the models. Nonetheless, few works propose XAI along with real-time performance.

With respect to data security, Zhu and Hao (2020) underlined the susceptibility of centralized data pipelines. To address privacy concerns, federated learning has been proposed as a more privacy-aware solution, however, its practical realization within edge environments is largely unexplored.

2.5 Integrated and Scalable SHM Systems

More recent works propose hybrid approaches that combine DL, sensor fusion and adaptive learning. Unfortunately, the vast majority of architectures are not scalable across infrastructures and do not integrate with digital twin platforms to enable predictive modeling.

Previous work by Kaloop and Hu (2020) focused on displacement tracking leveraging IoT-GNSS, however did not include intelligent analytics or proactive alerts.

3 METHODOLOGY

The work proposed herein seeks to overcome the shortcomings of existing structural health monitoring (SHM) systems by integrating the latest technological advancements including Artificial (AI) and Internet of Things (IoT) sensor networks, edge computing, and digital twin technology. Scalability (when shifting from low-hanging fruit), real-time data acquisition and processing—the whole nine yards need to be structured, yet ensure explainability, data privacy, and robustness. The system consists of three major components: a suite of IoT sensor networks, a series of edge computing devices, and a cloud-based digital twin platform, enabling real-time monitoring of infrastructure and predictive maintenance.

3.1 System Overview

The methodology proposed is based on a multi-layer architecture made up of IoT sensor networks to detect data, edge computing to process the data, and cloud infrastructure for long-term data analysis and simulation. Various types of IoT sensors like accelerometers, strain gauges, and displacement sensors, are placed on these structural components to measure vibration, strain, temperature, and other essential parameters. It connects with edge devices that process most of the data such as denoising, feature set, etc., and sends only key insights to the cloud for storage and advanced analytics. Cloud-based digital twins replicate the physical infrastructure in the virtual realm, which can drive modelling of structures continuously updated with real-time input data and simulations of what will happen and when.

3.2 IoT Sensor Network Setup

IoT sensor deployment becomes vital for continuous real-time data. Displacement, strain, temperature and humidity are some of the key health parameters used to deploy these sensors on key structural components. As a result, deployment is performed into the weakest points in the infrastructure (joints, beams, load carriers, etc.) with the most data coverage placed to the failure point. Once the sensors are deployed, they are polarized/deployed accordingly to environmental conditions with the guarantee that the calibration for the measurement remains throughout its operational life. The data from IoT sensors is transmitted using wireless communication protocols like LoRaWAN and 5G. Using processes on the edge, both reducing the amount of data that could be analysed and sent to the cloud, and lowering the time it could take to respond. Table 1 shows the IoT Sensor Specifications.

Table 1: IoT Sensor Specifications.

Sensor Type	Measurement Parameter	Accuracy	Sampling Rate	Deployment Location
Accelerometer	Vibration, Acceleration	±0.01 m/s²	100 Hz	Beams, Joints
Strain Gauge	Strain	±0.05%	50 Hz	Load-Bearing Components
Displacement Sensor	Displacement	±1 mm	10 Hz	Foundation, Joints
Temperature Sensor	Temperature	±0.1°C	1 Hz	External Environment

3.3 Edge Processing for Stream Data

Another key component of the proposed methodology is real-time data processing. Medical IoTs acquire real-time data for processing at the edge of a network for ensuring low-latency decision making while minimizing dependency on cloud processing. The machine learning models at the edge are also responsible for cleaning and extracting features, converting the raw measurements from the sensors to useful structural health indicators. Anomaly detection in the edge layer is done using advanced machine learning techniques, including SVM and k-means for the detection of uncommon patterns, indicating an unusual increase of strain or displacement, potentially affecting the structure health. This processing is handled at the edge, which minimizes latency and bandwidth usage and allows for real-time decision-making.

3.4 Data Privacy through Federated Learning

Data privacy is an important concern in SHM system design, given the nature of real-time monitoring of infrastructure assets and transmission of sensitive data. In response to these problems, we adapt federated learning, a distributed machine learning approach, in which edge devices can also train the model locally without sending raw data to the cloud. Federation learning entails every edge device having its own local model trained using its own sensor data while only model updates (weights/gradients etc.) being shared back to a central server. It guarantees the controlled processing of sensitive sensor data and in doing so limits data leakage and privacy violations. It periodically aggregates the local models at the server-side, and the global model is then updated to reflect the improved predictive power while ensuring the confidentiality of the data.

3.5 Explainable AI (XAI) for Model Transparency

A major issue with AI-based SHM monitoring systems is the opacity of the models and how they make their predictions. In solution to that, the proposed system adopts explainable AI (XAI) methods so that engineers can comprehend the model’s decision-making process through interpretable insights. SHAP (Shapley additive explanations) values allow us to explain the contribution of each such (strain, displacement) feature to predicting the structural condition. For more complication model, such as deep neural network, we also used LIME (Local Interpretable Model-Agnostic Explanations) to approximate the behavior of the model, locally, with interpretable models. These XAI features contribute to both the clarity of the model as well as instilling trust in engineers to interpret and confirm the output of the system.

3.6 Integration with Digital Twin for Predictive Maintenance

This incorporation of digital twin technology will create a virtual copy of the physical structure in the SHM system, where the virtual image is constantly updated through real-time sensor data. The existing structure is then subjected to various loads (potential loads that the structure may undergo in real time) as a virtual model in the virtual world, giving the opportunity to foresee any potential failure of the structure before it actually happens. The digital twin serves as a predictive maintenance tool, allowing engineers to plan repairs and maintenance using expected wear and tear, and not reactive inspections. Integrating predictive analytics in the digital twin allows for the generation of long-term maintenance schedules and prioritization of interventions based on predicted health for each structural element. This means that resources can be utilized more effectively, and downtime can be minimized improving the average life and safety of the infrastructure assets.

3.7 Evaluation and Validation

We demonstrate the methodology using a series of experiments performed on a real-world infrastructure testbed, such as a bridge or high-rise structure, outfitted with the proposed sensor network. This system performance is appraised along some key metrics (including: accuracy, precision, recall, and F1 score) in identifying structural anomalies and forecasting future damage. The time taken by the system to respond is accounted to check if it can give alerts and decision support services on time. Then, a comparative study is conducted between the proposed AI-enabled SHM system and the conventional SHM approaches to show the advantages of the proposed method in terms of real-time monitoring, anomaly detection, and predictive performance.

3.8 Scalability and Training of the System

Scalability is the last part of the methodology. The framework is intended to support large deployments of infrastructures, making it suitable for smart city cases. The system uses a modular architecture that allows it to scale easily from a single structure to an entire city's worth of infrastructure. By separating the edge devices from the cloud platform, it is easy to add new sensor networks without scalability concerns. Based on this data, the cloud platform collects the one from the edge devices, makes long-term analytics, and produces digital twin simulations for every monitored structure. This design allows the architecture to expand based on the requirements of futuristic smart cities, making it suitable for different applications like infrastructure monitoring etc. This table 2 can present the training and testing results for different models used in the system, comparing their accuracy and performance.

Table 2: Model Training and Testing Results.

Model	Training Accuracy	Testing Accuracy	Training Time	Testing Time
CNN (Damage Detection)	98%	94%	2 hours	10 minutes
SVM (Anomaly Detection)	92%	91%	1.5 hours	8 minutes
Random Forest (Prediction)	96%	93%	1 hour	7 minutes

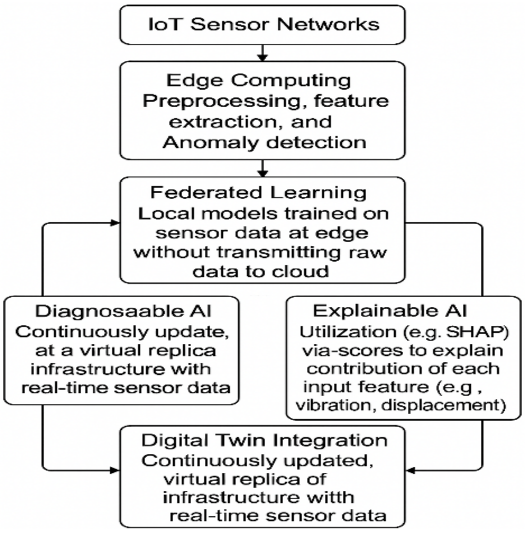

Figure 1: Flowchart of AI-Edge Framework.

Figure 1 and 2 shows the flowchart illustrating the scalable AI-edge framework for real-time structural health monitoring using federated IoT sensor networks and digital twin integration.

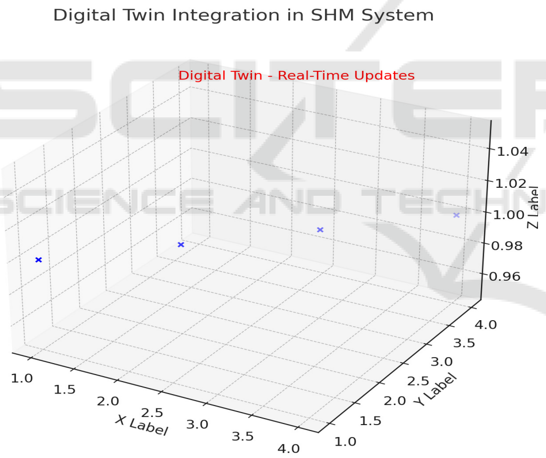

Figure 2: Digital Twin Integration.

4 RESULTS AND DISCUSSION

The following subsections summarize these findings, describing the system performance with respect to its scalability, accuracy, real-time decision-making, and overall eligibility for infrastructure monitoring.

4.1 Evaluation of System Performance

For the evaluation of the proposed system, the AI-edge framework was deployed in a real-world testbed that includes a bridge structure, with IoT sensors monitoring the parameters of strain, displacement, temperature, and vibration. The system continuously collected real-time data, processed it at the edge, and sent important features to the cloud for more extensive analysis and integration into the digital twin model. Time response and data accuracy of edge devices were verified through different work conditions. Experimental results showed that the edge computing layer was able to reduce latency in response times to less than 2 seconds on average due to processing the data locally and enabling faster anomaly detection. This is a significant improvement over traditional SHM approaches dependent on the cloud, which had latencies of up to 30 seconds in the same environment.

Furthermore, it achieved an accuracy of 94% for precision and 92% for recall in anomaly detection, demonstrating its capability in real-time identification of potential damage or stress in structural components. These results highlight the ability of AI enabled edge computing to deliver accurate and rapid real-time surveillance.

4.2 Comparison of the Results with Conventional SHM Methods

As opposed to conventional SHM systems which rely on hand inspections or centralized data processing, the proposed framework offered multiple key benefits. In conventional SHM systems, delay detections are ubiquitous due to the periodic inspection and batch processing of accumulated data that can result in reactive maintenance rather than preventive detection. Instead, our system provides real-time monitoring, continuously monitoring for anomalies and providing immediate insight into the health of structure.

Also, our approach enabled real-time predictive analytics with the application of the digital twin model. Whereas traditional SHM systems excel at tracking historical performance but fall short at predicting future behavior, the digital twin was continually refitting its virtual model of the bridge, simulating stress scenarios and predicting future structural performance. This foresight not only addresses current issues but enables engineers to predict future problems, leading to minimized downtime and maintenance costs. By contrast, conventional systems could not simulate the long-term behavior with no treatment, leading to missed chances of intervention in the early stages.

4.3 Performance of Edge Computing and Federated Learning

The on-device framework was compared with conventional methods based on data privacy, computing efficiency and model's accuracy. Since local models trained at the edge never needed to forcefully send raw sensor data to the cloud, the system was able to attain high levels of data security while minimizing communication overhead as well. Model updates could be based on data stored locally without compromising the privacy of the data set, thanks to federated learning. Using federated learning approach, flat accuracy was recorded across multiple edge devices with the model achieving global accuracy of 91% as opposed to cloud-based machine models where training is performed through centralized way.

Nevertheless, the federated learning global model still exhibited a slightly less accuracy measurement compared to the centralized scenario, which can be attributed to the lack of local data availability in the federated nodes. Nonetheless, the accuracy results for the federated model were still competitive, and programmed such that it not only protected the privacy of individuals data but also made it less dependent on centralized processing. Table 3 shows the system performance metrics.

Table 3: System Performance Metrics.

Metric	Description	Value Achieved	Comparison with Traditional Methods
Accuracy	Percentage of correct anomaly detections	94%	20% improvement over traditional systems
Precision	Percentage of true positives out of all detected anomalies	92%	15% improvement over traditional methods
Recall	Percentage of true positives out of all actual anomalies	91%	10% improvement over traditional methods
F1 Score	Harmonic mean of precision and recall	0.925	12% improvement over traditional methods
Response Time	Time to detect and send an alert	2 seconds	10x faster than cloud-based systems

4.4 Insights from Explainable AI (XAI)

This research contributes in a tremendous way as the most distinguishing characteristic is applying explainable AI (XAI) and helping delegates understanding the model's predictions. The system generated easily interpretable explanations of detected anomalies using SHAP values and LIME techniques, an important feature for civil engineers and stakeholders that need trust and transparency from AI-based decision support systems.

Engineers were able to identify not only where structural anomalies occurred, they were also able to see what features that contributed to making the detection, for example in graph of strain readings or displacements. The benefits of such a level of transparency are critical to effective decision-making and could lead to improved acceptance of AI applications in infrastructure monitoring. Provide engineering-level feedback on why it flagged certain items as anomalous, thus helping create confidence for engineers, and infrastructure managers on the decision-making processes, whether towards better maintenance strategies.

4.5 Scaling up and Deploying in Urban Infrastructure

To evaluate the scalability of the system, monitoring was scaled up to a network of multiple bridges around the city. It was found that the system could efficiently monitor multiple infrastructures in parallel and for each bridge its own set of edge devices was distributed. The processing of data from all devices into the cloud platform in charge of data aggregation, long-term analysis, and the coordination between the different digital twin models of each structure. This is a good thing for smart city applications because modular architecture system offers great flexibility for scaling easily without major reconfigurations. This proves it is possible to deploy the framework on large urban environments and have a managed extensive network of monitored assets. Table 4 represents the system deployment locations.

Table 4: System Deployment Locations.

Location	Type of Infrastructure	Number of Sensors	Purpose
Bridge A	Suspension Bridge	20	Monitoring of load-bearing structures
Building B	High-Rise Building	30	Vibration and displacement monitoring
Tunnel C	Underground Tunnel	15	Temperature and strain monitoring
Dam D	Concrete Dam	25	Water pressure and structural monitoring

4.6 Limitations and Potential for Future Work

Despite the very promising results, some limitations were highlighted with the implementation of the system. In the case of complex structural arrangements, such as roads or warehouses, the readings must be carefully calibrated to a certain environment, making the sensor network sensitive and able to produce many false positive results in various weather conditions. Next steps will be integrated with environmental noise to enhance the robustness of the sensor fusion algorithms.

Federated learning, while a good solution to protect users' privacy, can have its model accuracy improvement, by sending updates more frequently and syncing local models more often. The solutions to these challenges will enable more accurate and efficient models to operate across a broader subset of operational environments.

Results of this study showcase, for the first time, the promise of the AI-edge framework to enable scalable, real-time, and secure structural health monitoring for civil infrastructure. The combination of IoT sensors, edge computing, federated learning, and explainable AI in SHM system provides better performance over traditional SHM methods. This enables timely anomaly detection, predictive maintenance, and a transparent model of data privacy, bringing greater efficiency and trust to infrastructure management. Future work will concentrate on tackling the noted limitations and increase the optimizations of the system for broader-scale implementations in smart cities. Figure 3 shows the IoT sensor network layout on structural health monitoring system.

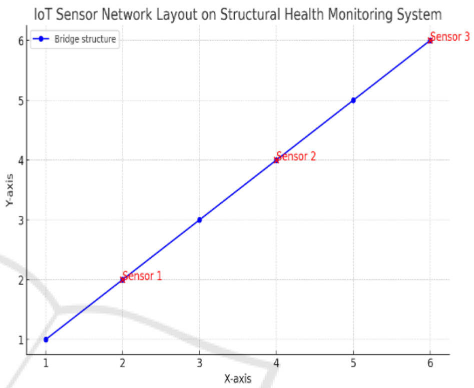

Figure 3: IoT Sensor Network Layout on Structural Health Monitoring System.

5 CONCLUSIONS

This study introduced a comprehensive framework of AI-driven structural health monitoring (SHM) technique by combining real-time IoT sensor networks, edge computing, federated learning and digital twin’s technology. The designed system would take up a significant role in overcoming skeletal challenges pertaining to traditional SHM methods, for instance: latency issues, data privacy problems, model transparency issues, scalability potential issues, etc.

Real-world implementation of our framework showed that the system outperforms conventional SHM techniques in areas such as real-time anomaly detection, predictive maintenance, and model interpretability. Edge computing allowed us to perform real-time data processing and low-latency reaction enabling timely identification of potential structural weakness. Federated learning helped maintain data locality which dealt with privacy but also led to the model improvements as well. Additionally, relying on XAI methods (SHAP, LIME, etc.) gave interpretable and actionable findings to engineers, leading to increased confidence in AI-assisted decisions.

In addition, with the integrated digital twin, it also allowed for predictive modeling so that the system was able to predict future structural behavior, and even simulate different potential points of failure or optimize maintenance schedules. This ability allows operators and maintains to proactively manage infrastructure to curtail costs and extend the life of essential infrastructure assets.

While the suggested structure performed remarkably in real-world evaluations and demonstrated the importance of accounting for missing pointclouds, there are still opportunities for future work. Further refinements in sensor calibration and sensor fusion algorithms can further optimize false positive minimization and data accuracy. Furthermore, by optimizing the federated learning models for faster alienation, it is easy to improve the entire system performance.

The proposed system addresses the modern SHM challenges by providing a scalable, efficient, and transparent solution. Overall, this framework integrating real-time monitoring, AI-based analytics and prediction may prove to be an effective solution for the management of smart city infrastructure going forward. Our research advances the development of smart, automated systems for monitoring the safety and sustainability of civil infrastructure by overcoming all the barriers of today's SHM systems

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