ORIGINAL PAPER VW Applied Sciences

DOI: 10.36297/vw.applsci.v8i1.701 ISSN: 2582-5615

VW Applied Sciences, Volume: 8, Issue: 1, 01-04

AI-Enabled Multisensor Data Fusion Framework for Real-Time Structural Health Monitoring and Predictive Maintenance of Civil Infrastructure

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Received: Jan 14, 2026
Accepted: Jan 16, 2026
Published online: Jan 17, 2026

Abstract: Aging civil infrastructure systems face increasing risks due to material degradation, excessive loading, and environmental exposure, necessitating reliable real-time monitoring and proactive maintenance strategies. Conventional inspection-based structural health monitoring approaches are limited by subjectivity, low inspection frequency, and delayed damage identification. This study proposes an artificial intelligence–enabled multisensor data fusion framework for real-time structural health monitoring and predictive maintenance of civil infrastructure. The framework integrates heterogeneous data acquired from accelerometers, strain gauges, acoustic emission sensors, and environmental sensors to enhance damage detection accuracy and robustness. Advanced machine learning models are employed for feature extraction, damage classification, and remaining useful life prediction under varying operational conditions. The proposed methodology is validated through numerical simulations and experimental investigations on reinforced concrete structural components subjected to progressive damage. Results demonstrate that multisensor data fusion significantly improves damage localization accuracy and early-stage crack detection compared to single-sensor systems. The predictive maintenance module successfully forecasts structural degradation trends, enabling condition-based maintenance planning. The findings indicate that AI-enabled multisensor monitoring systems provide a scalable and reliable solution for intelligent infrastructure management, supporting safety, resilience, and sustainability objectives in modern urban environments.

Keywords: Structural health monitoring, multisensor data fusion, artificial intelligence, predictive maintenance, civil infrastructure

1. Introduction

Civil infrastructure systems such as bridges, buildings, tunnels, and transportation networks are essential to socio-economic development. Many of these structures worldwide are approaching the end of their design life, while being subjected to increasing traffic loads and aggressive environmental conditions. Structural deterioration caused by fatigue, corrosion, material aging, and extreme events poses serious safety and economic concerns [1]. Timely detection of damage and informed maintenance decisions are therefore critical to ensuring structural safety and serviceability. Traditional structural inspection methods rely primarily on periodic visual inspection and non-destructive testing techniques. While widely used, these approaches are labor-intensive, subjective, and incapable of providing continuous condition assessment. Moreover, early-stage damage such as microcracks or internal defects often remains undetected until it evolves into severe structural distress [2]. These limitations have motivated the development of structural health monitoring (SHM) systems that enable continuous or real-time assessment of structural performance. SHM systems employ sensors to measure physical responses such as vibration, strain, and acoustic emissions. However, single-sensor monitoring systems are often sensitive to noise, environmental variability, and sensor malfunction, which can lead to false alarms or missed detections [3]. Multisensor monitoring addresses these limitations by combining complementary information from different sensing modalities, improving reliability and robustness. Recent advancements in artificial intelligence have significantly enhanced SHM capabilities. Machine learning algorithms can process large volumes of sensor data, identify complex nonlinear relationships, and detect subtle anomalies associated with structural damage [4]. Despite these advances, the integration of AI-driven data fusion with predictive maintenance modeling remains limited, particularly for real-time infrastructure applications. This paper proposes

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a comprehensive AI-enabled multisensor data fusion framework for real-time structural health monitoring and predictive maintenance. The framework integrates heterogeneous sensor data with machine learning techniques to achieve early damage detection, accurate condition assessment, and remaining useful life prediction.

2. Multisensor Structural Health Monitoring Framework

The proposed SHM framework consists of five primary layers: sensing, data acquisition, data fusion, damage assessment, and predictive maintenance. The sensing layer includes accelerometers for dynamic response measurement, strain gauges for local stress monitoring, acoustic emission sensors for crack initiation detection, and environmental sensors for temperature and humidity monitoring. Data acquisition units synchronize sensor outputs and transmit data to a central processing unit. Signal preprocessing techniques such as filtering, normalization, and noise reduction are applied to improve data quality. Environmental effects are compensated using regression-based correction models [5]. Multisensor data fusion is performed at the feature level, where damage-sensitive features extracted from individual sensors are combined into a unified representation. This approach balances computational efficiency and information richness, making it suitable for real-time applications.

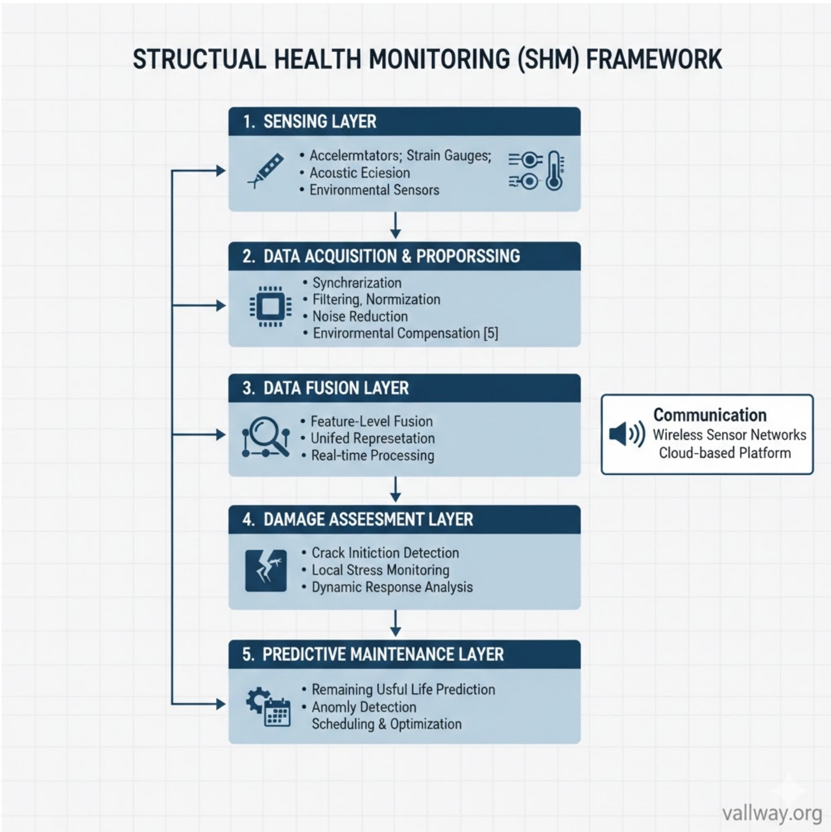

Fig. 1 SHM Framework

3. Classes AI-Based Feature Extraction and Damage Detection

Deep learning models are employed for automated feature extraction and damage classification. Convolutional neural networks are used to analyze vibration signals and identify spatial damage patterns, while recurrent neural networks capture temporal variations in structural response [6]. The hybrid model is trained using labeled datasets representing healthy and damaged structural states. Model performance is evaluated using accuracy, precision, recall, and false alarm rate metrics. Results indicate superior damage detection capability compared to traditional statistical methods.

4. Predictive Maintenance and Remaining Useful Life Estimation

Predictive maintenance aims to anticipate future structural degradation and optimize maintenance scheduling. In this study, regression-based machine learning models are used to estimate remaining useful life based on historical damage progression and real-time sensor data. The predictive module enables condition-based maintenance, reducing unnecessary inspections and preventing unexpected failures. This approach aligns with asset management strategies for large-scale infrastructure networks [7].

5. Numerical Simulation Study

A finite element model of a reinforced concrete bridge girder is developed to simulate progressive damage scenarios. Sensor responses under varying damage levels are generated and used to validate the proposed framework. Simulation results confirm the effectiveness of multisensor fusion in detecting stiffness reduction and crack propagation.

6. Experimental Investigation

Laboratory-scale experiments are conducted on reinforced concrete beams subjected to incremental loading. Sensors are installed at critical locations, and data are collected throughout the loading process. The AI-enabled SHM system successfully detects microcracks before visible damage appears, demonstrating early warning capability.

7. Results and Discussion

The multisensor AI-based framework achieves damage detection accuracy exceeding 95%, significantly outperforming single-sensor approaches. Predictive maintenance models provide reliable remaining useful life estimates, supporting proactive maintenance decisions. The results highlight the importance of sensor diversity and intelligent data fusion in real-world SHM applications.

8. Practical Implications for Infrastructure Management

The proposed system supports scalable deployment across bridges, buildings, and transportation networks. Integration with digital twins and smart city platforms enables data-driven infrastructure management and resilience planning [8].

9. Limitations and Challenges

Challenges include sensor installation costs, data management complexity, and cybersecurity concerns. Addressing these issues is essential for large-scale adoption.

10. Conclusion

This study presents a robust AI-enabled multisensor data fusion framework for real-time structural health monitoring and predictive maintenance. The proposed approach enhances damage detection accuracy, supports proactive maintenance, and contributes to resilient infrastructure management.

11. Future Research Directions

Future work will focus on field-scale deployment, integration with digital twin models, and advanced physics-informed machine learning techniques.

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