International Journal of Computer Science and Information Technology
ISSN: 3005-9682 (Print), ISSN: 3005-7140 (Online) | Volume 8, Number 1, Year 2026
DOI: https://doi.org/10.62051/ijcsit.v8n1.01
Journal homepage: https://wepub.org/index.php/IJCSIT/index

Research Progress on Artificial Intelligence Methods in Structural Health Monitoring

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ABSTRACT

Structural health monitoring (SHM), as a core technology for ensuring the safe operation of infrastructure and engineering equipment, has become increasingly critical amidst the accelerating urbanization and increasing number of major projects. Traditional monitoring methods, limited by manual reliance and lack of real-time performance, are unable to adapt to the full lifecycle management needs of complex structures. Artificial intelligence, with its powerful data processing and pattern recognition capabilities, offers a breakthrough solution for SHM. This article systematically reviews the research progress of AI methods in SHM. It first explains the technical foundations of monitoring data acquisition and preprocessing, then analyzes the application mechanisms of classical machine learning and deep learning in damage identification. The success of these technologies is illustrated by case studies from various engineering fields, such as bridges and aerospace. Finally, the current technical bottlenecks are analyzed and future development directions are prospected. Research indicates that AI methods have made the leap from laboratory validation to engineering applications. Classical machine learning remains practical in small and medium-scale data scenarios, while deep learning demonstrates significant advantages in complex feature extraction. However, challenges such as data quality and algorithm generalization still require improvement. In the future, through the integration of multiple technologies and the deepening of engineering practice, AI will drive SHM towards precision, intelligence, and predictiveness, providing core support for the safety assurance of major projects.

KEYWORDS

Structural health monitoring; Artificial intelligence; Machine learning; Deep learning; Damage identification; Engineering applications

1. INTRODUCTION

Structural health monitoring (SHM) aims to acquire structural status information through sensor systems and, through analysis and evaluation, diagnose damage and provide risk warnings. It is a core technology for safety management in fields such as civil engineering and aerospace. Since NASA first implemented cryogenic fuel tank monitoring in the space shuttle program in 1998, SHM technology has gradually expanded from the aerospace field to civil infrastructure such as bridges, high-rise buildings, and wind turbine towers. With the increasing complexity of structures and the deterioration of service environments, the limitations of traditional monitoring methods have become increasingly apparent. Visual inspection and ultrasonic testing, which rely on manual labor, are inefficient, have high rates of missed detection, and lack real-time monitoring capabilities. Analysis methods based on physical models are limited by structural complexity and environmental interference, making accuracy difficult to guarantee. The rise of artificial intelligence (AI) technology has provided a new path to overcome these bottlenecks. Compared with traditional methods, AI can automatically process massive amounts of sensor data, extract damage characteristics, and establish predictive models, significantly improving the accuracy and real-time nature of monitoring. In recent years, the application of AI methods in SHM has continued to expand, from damage classification using classical machine learning to image recognition using deep learning. Zhou Xingkang et al. achieved precise damage location in precast beams using convolutional neural networks, Huang et al. improved damage identification accuracy by improving the Whale Optimization algorithm, and the Liujiaxia Bridge implemented intelligent inspection of surface defects using a "drone + AI" system. These studies and applications demonstrate that AI has become a core driving force for technological innovation in SHM. This article discusses the research progress of AI in SHM, first outlining the technical foundations of data acquisition and preprocessing, which are the prerequisites for AI modeling. It then explores the application mechanisms and research results of classical machine learning and deep learning, respectively. The application effects of these technologies are then analyzed using case studies from multiple engineering fields. Finally, current challenges are analyzed and future directions are anticipated, aiming to provide reference for related research and engineering practice.

2. AI-DRIVEN STRUCTURAL HEALTH MONITORING DATA FOUNDATION AND PREPROCESSING TECHNOLOGIES

Data is the core foundation of AI applications in structural health monitoring (SHM). Its quality directly determines model performance. The complete data chain encompasses acquisition, preprocessing, and feature extraction, and continues to improve with advancements in sensing technology and algorithm optimization. Data collection relies on building a sensing network with multiple sensor types. In civil infrastructure, vibration sensors and strain gauges are primarily used to obtain structural dynamic parameters. In specialized fields like aerospace, fiber optic sensing, acoustic emission sensing, and surface acoustic wave sensing are predominant. Fiber optics can capture low-frequency strain, while acoustic emission can measure high-frequency transients. Combining these two enables multi-scale damage sensing. For example, in aerospace monitoring, piezoelectric (PZT) sensor arrays are often used to excite and receive Lamb wave signals, identifying minor damage by observing changes in propagation characteristics. The Liujiaxia Bridge monitoring system integrates multi-dimensional sensors, such as vibration and temperature, to collect data in real time and transmit it to a data center for management. Sensor deployment optimization technology uses intelligent algorithms to determine optimal placement, reducing the number of devices while ensuring monitoring coverage [1].

Raw monitoring data is susceptible to environmental noise and equipment errors. Preprocessing is key to improving quality. Denoising, missing value imputation, and normalization techniques are commonly used. Wavelet transforms, due to their ability to effectively separate signal from noise, are widely used for denoising vibration and Lamb wave signals. To address the issue of multi-channel data synchronization, researchers have implemented a time alignment algorithm to achieve spatiotemporal alignment of heterogeneous data, laying the foundation for fusion analysis. Feature extraction bridges the gap between raw data and AI models. Time-domain, frequency-domain, and time-frequency-domain features are widely used. Han Kunlin et al. enhanced feature damage sensitivity and model recognition accuracy by using metrics and frequency band attention mechanisms.

Multi-source data fusion technology has developed rapidly in recent years. Lü Hao et al. combined sparse constraints with structural modal parameters to construct a damage identification method. Xu et al. combined modal strain energy decomposition with particle swarm optimization to form a two-stage identification strategy. Both methods demonstrate the advantages of integrating multi-dimensional information. However, data preprocessing still presents challenges: sensors in extreme environments are prone to generating abnormal data, and the multi-physics coupling of complex structures can lead to feature cross-interference. These challenges require a combination of domain knowledge and AI technology.

3. APPLICATION OF CLASSICAL MACHINE LEARNING METHODS IN STRUCTURAL DAMAGE IDENTIFICATION

Relying on a mature theoretical framework and low computational cost, classical machine learning is widely used in damage detection, classification, and localization in SHM, particularly in small- and medium-scale monitoring scenarios with limited data. These methods manually extract features and train models to establish a mapping between structural response and health status. Core algorithms include support vector machines (SVMs), random forests, and swarm intelligence optimization algorithms. SVMs have become a mainstream method for early damage identification due to their excellent small-sample classification performance. Using kernel functions, they map low-dimensional features to a high-dimensional space, enabling precise differentiation between damaged and healthy states. In bridge monitoring, SVM-based classification of vibration signal time-domain features achieves damage identification accuracy exceeding 85%. In the aerospace field, SVMs can distinguish between cracks, corrosion, and other damage types using Lamb wave signals. Random forests, leveraging the advantages of ensemble learning, are robust in scenarios with feature redundancy and noise interference. By leveraging voting across multiple decision trees, they reduce the risk of overfitting and are commonly used for quantitative damage assessment. For example, in wind turbine tower foundation monitoring, random forest models combining strain and vibration characteristics can achieve multi-level damage classification with superior accuracy compared to single decision trees.

Swarm intelligence optimization algorithms, which combine biomimetic and machine learning, offer unique advantages in damage localization. This type of algorithm simulates the behavior of biological swarms and seeks the optimal solution through iterative optimization. Commonly used algorithms include the whale optimization algorithm, particle swarm optimization algorithm, and butterfly optimization algorithm. Huang et al. studied the relationship between the substructuring method and the relative modal strain energy of elements, improving the whale optimization algorithm to enhance damage identification accuracy in numerical simulations. Li et al. incorporated sparse regularization and Bayesian reasoning into the objective function, leveraging the Jaya algorithm to enhance identification stability. Zhou Hongyuan, Khatir et al., respectively, improved the butterfly optimization algorithm and combined it with a teaching-learning optimization algorithm to overcome the localization accuracy limitations of traditional methods [2].

While classical machine learning offers advantages such as strong interpretability and high computational efficiency, it also has significant limitations: manual feature extraction relies on domain experience and lacks adaptability to complex damage patterns; the model's generalization is weak, and its transferability across structural types needs improvement. Recent research has often adopted a "feature engineering + algorithm improvement" strategy. For example, Lü Hao et al. incorporated sparse constraints into the whale-annealing hybrid algorithm, balancing positioning accuracy and computational efficiency, providing new insights for the engineering application of classic methods.

4. BREAKTHROUGHS AND INNOVATIONS IN DEEP LEARNING IN COMPLEX STRUCTURAL MONITORING

Deep learning uses multi-layer neural networks to automatically extract features and perform complex mapping, transcending the reliance of classical machine learning on artificial features. This approach offers significant advantages in processing massive amounts of SHM data and complex damage patterns. With algorithmic innovations and increased computing power, models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and autoencoders have been widely applied to core tasks such as damage identification and lifespan prediction.

CNNs, with their ability to extract local features, have become the preferred choice for image-based monitoring data processing. For structural surface damage detection, CNNs can automatically identify cracks and corrosion, surpassing the accuracy limitations of the human eye. In the Liujiaxia Bridge's "drone + AI" inspection system, CNNs achieve an accuracy rate exceeding 90% for surface crack detection, capturing cracks as fine as 0.2 mm, far exceeding the human eye's 0.5 mm detection limit. One-dimensional CNNs (1D-CNNs) have significant advantages in vibration signal processing. Zhou Xingkang et al. leveraged the image optimization capabilities of 1D-CNNs to accurately identify the location and extent of damage in precast beams [3]. Researchers also constructed a multi-channel data inner product matrix and combined it with 1D-CNNs to enhance damage-sensitive features, significantly improving recognition performance in noisy environments. Furthermore, the integration of CNNs with computer vision is driving the development of non-contact monitoring. Using drone aerial imagery and CNN analysis, automated inspections of surface damage on large bridges and high-rise buildings are now possible.

RNNs and their improved long-short-term memory (LSTM) networks excel at processing time series data, making them suitable for dynamic monitoring of structural vibration and strain. LSTMs address long-sequence dependencies through a gating mechanism and can capture the evolution of structural states. In acceleration data processing, LSTM models combined with autocorrelation functions not only improve damage identification accuracy and convergence speed, but also enhance robustness to noise and missing data, maintaining stable performance even with increasing noise intensity. In aerospace structural monitoring, LSTMs analyze time-series signals such as temperature and vibration to provide early warning of fatigue damage and predict remaining life, ensuring the safety of spacecraft on-orbit.

Unsupervised learning and generative models further expand the application scenarios of deep learning. To address the scarcity of damage samples, researchers proposed an unsupervised evaluation method based on CNNs and LSTM encoders. This method trains an autoencoder model using only healthy working condition samples, discriminating damage states through reconstruction errors. The method achieves 100% recognition accuracy in scenarios with unbalanced samples. Generative adversarial networks (GANs) generate virtual damage data to alleviate the shortage of damage samples in actual engineering projects. Training with alternating real and fake data improves model generalization [4]. Despite significant progress, deep learning still faces challenges: The large number of model parameters results in insufficient real-time performance, making it difficult to meet embedded monitoring requirements; and the poor interpretability of complex networks limits trust in critical projects. These challenges need to be gradually addressed through the integration of lightweight model design and explainable AI technologies.

5. IMPLEMENTATION OF AI MONITORING TECHNOLOGY IN MULTI-DOMAIN ENGINEERING STRUCTURES

AI methods in structural health monitoring (SHM) have moved from the laboratory to engineering practice, with mature solutions developed in bridges, aerospace, and wind power. These methods improve monitoring efficiency and safety assurance capabilities, supporting the full lifecycle management of infrastructure. Bridge engineering projects are transitioning from manual inspections to intelligent monitoring. Traditional inspections of the Liujiaxia Bridge rely on high-altitude, high-risk, "Spider-Man" inspections, which are difficult to detect and conceal. The "UAV Intelligent Inspection + AI Defect Identification System," launched in early 2025, is changing this situation: drones can complete a full bridge inspection in a matter of hours, four times more efficient than traditional manual inspection [5]. The AI vision system accurately identifies minute cracks and corrosion, combines them with 3D models to create a digital twin platform for visualizing defects, and interconnects with the overload control platform to form a coordinated mechanism, resulting in a 52% year-on-year decrease in overloaded vehicles along the line. In complex bridges such as long-span cable-stayed and arch bridges, AI combined with vibration sensor data for damage location and load-bearing capacity assessment has become a routine method. In the aerospace sector, extreme environments place stringent demands on SHM, and AI demonstrates its strong adaptability. The in-orbit environment of spacecraft is difficult to monitor manually, making AI monitoring systems a necessity. NASA pioneered the use of AI-assisted monitoring in the space shuttle program, analyzing fiber optic sensor data to enable real-time management of cryogenic fuel tanks. In recent years, AI has been integrated with various sensor types: combining fiber optic sensing (low-frequency strain) with acoustic emission sensing (high-frequency events), leveraging CNNs to achieve collaborative analysis of multi-physics field signals; LSTMs process time-series data from solar wings and engines to provide fatigue damage warnings and lifespan predictions. These technologies have been validated on the space station, ensuring the safety of space missions. In wind power equipment, AI integrates vibration, strain, and environmental data to address the difficulties of traditional monitoring in providing early warnings. Han Kunlin and others used an improved convolutional neural network to simulate a pre-buried foundation model of a tunnel wind turbine, achieving high-precision damage identification. In blade monitoring, drone aerial photography combined with CNNs identifies millimeter-level cracks, and LSTMs analyze operational data to predict blade lifespan, significantly reducing operation and maintenance costs and improving the stability of renewable energy utilization. Engineering applications have demonstrated that the implementation of AI monitoring requires a balance between algorithm performance and practical application: accuracy and efficiency in bridge balance identification, reliability in aerospace, and cost and environmental adaptability in wind power. As the technology matures, AI will be applied on a large scale in even more fields.

6. CURRENT CHALLENGES AND FUTURE DIRECTIONS FOR AI IN STRUCTURAL HEALTH MONITORING

AI methods have achieved significant results in the field of structural health monitoring (SHM), but challenges remain in terms of technical maturity, engineering adaptability, and industry standards. The integration of multidisciplinary technologies offers new solutions to these challenges and promotes the upgrading of AI monitoring technology.

Currently, AI applications in SHM face three core challenges. First, data constraints. In real-world engineering, health status data is abundant, but damage samples are scarce. Damage data under extreme operating conditions is even more difficult to obtain, resulting in insufficient model generalization. Furthermore, sensor data is susceptible to environmental interference such as temperature and humidity, and noise and missing values severely impact model performance. For example, in aerospace structural monitoring, sensor signal interference under extreme conditions remains a bottleneck affecting AI diagnostic accuracy. Second, insufficient algorithm engineering adaptation exists. Deep learning models have large parameter counts and complex computations, making real-time analysis difficult on embedded devices and edge nodes. While computationally efficient, classic algorithms lack adaptability to complex damage patterns. Furthermore, most algorithms exhibit "black box" characteristics and lack interpretability, which reduces engineer confidence and limits their application in critical structures. Third, there is a lack of system integration and industry standards. Existing monitoring systems are mostly simple combinations of "sensors + algorithms," lacking integrated designs that collaborate across multiple technologies. Furthermore, there are no standardized criteria for evaluating AI monitoring results and data sharing specifications, making it difficult to compare monitoring results from different systems, hindering the large-scale deployment of the technology.

Future research could address four key areas: First, integrating data-driven approaches with physical models. Physical models can be used to generate virtual damage data to address sample gaps, and data-driven adjustments to physical model parameters can be used to improve adaptability. For example, combining finite element models with CNNs has demonstrated superior performance in precast beam damage identification. Second, developing lightweight and interpretable algorithms can reduce the complexity of deep learning through model compression and parameter optimization to adapt to real-time monitoring. Attention mechanisms and causal reasoning can be introduced to clarify the relationship between damage characteristics and identification results. Third, building a multi-technology collaborative intelligent monitoring system, integrating digital twins, edge computing, and AI to form an integrated "perception-analysis-decision-making" system [6]. The integration of the Liujiaxia Bridge's digital twin and AI inspections has already demonstrated synergistic advantages. Fourth, improving industry standards and establishing standards for AI monitoring data collection, annotation, and sharing. Accurately develop model performance evaluation metrics and result verification processes.

In addition, emerging technologies such as federated learning, blockchain, and small-sample learning present new opportunities, potentially overcoming challenges such as data privacy, data authenticity, and sample scarcity, bringing revolutionary breakthroughs to the SHM field.

7. CONCLUSION

This paper systematically reviews the research progress of artificial intelligence methods in the field of structural health monitoring (SHM), analyzing them from the perspectives of data foundations, algorithm applications, engineering practices, and future directions. It reveals the core logic behind AI's transformation of SHM from traditional empirical reliance to data-driven intelligence.

Data preprocessing technologies lay the foundation for AI applications. Optimizing sensor network deployment, combined with wavelet transforms and feature fusion, improves the quality and availability of monitoring data and addresses issues such as noise interference and ambiguous features in raw data. Classical machine learning and deep learning form a complementary landscape: Support vector machines and swarm intelligence optimization algorithms remain practical in small-sample, low-complexity scenarios, and algorithmic improvements have enhanced damage localization accuracy. Convolutional neural networks and long-short-term memory networks, by transcending reliance on artificial features, have demonstrated significant advantages in image recognition and time-series signal analysis, achieving technological breakthroughs in bridge surface damage detection and aerospace structural fatigue warning. Engineering practices across multiple fields have validated the practical value of AI: the Liujiaxia Bridge's "drone + AI" system increased inspection efficiency by fourfold, achieving damage identification accuracy exceeding 90%. AI monitoring in aerospace ensures the safety of spacecraft on-orbit; and intelligent monitoring of wind power equipment significantly reduces operation and maintenance costs, demonstrating that AI has moved from the laboratory to the construction site, becoming a core technology for structural safety.

Challenges facing AI in SHM include insufficient data quality, difficulty in engineering algorithm adaptation, and a lack of industry standards. Future breakthroughs are expected through the integration of data-driven and physical models, the development of lightweight and interpretable algorithms, the construction of a multi-technology collaborative system, and the improvement of industry standards. As the technology matures, AI will drive the transformation of SHM from "post-event maintenance" to "pre-event prevention" and from "manual inspection" to "intelligent diagnosis." This will support the full lifecycle safety management of major projects and play a vital role in urbanization and infrastructure upgrades.

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