

Smart Shm for Efficient Maintenance Using AI

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Abstract— This research examines the increasing role of Artificial Intelligence (AI) in Structural Health Monitoring (SHM), which is essential for ensuring the safety and durability of infra-structure systems. AI-based methods combine sensor data collection with advanced computational algorithms to perform continuous monitoring and accurate identification of structural damage. Techniques such as machine learning are applied to detect issues like cracks, deformation, and material deterioration at an early stage. The adaption of AI in SHM improves accuracy, minimizes manual inspection efforts, reduces maintenance costs and supports timely decision-making for repair and rehabilitation work. This review further examines the ethical aspects and societal implications associated with the use of AI in SHM, including concern related to data security, fairness and transparency. The study emphasizes the capability of AI to improve operational efficiency, ensure structural safety and promote sustainable management of infrastructure systems. **Keywords**—component, formatting, style, styling, insert

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I. INTRODUCTION

Structural Health Monitoring (SHM) began gaining attention in the early 2000s, particularly for monitoring long-span bridges. It offers accurate and reliable information about the condition of structures, helping to identify damage, deterioration, and crack formation. Despite its advantages, challenges such as system upkeep and efficient interpretation of large-scale sensor data have remained significant. SHM techniques range from conventional destructive methods, like core sampling, to advanced non-destructive methods, including image-based analysis.

This study proposes a data-driven approach to better assess structural health using sensors integrated within the structure. These sensors capture the impact of both environmental and human activities on structural performance. The primary focus of this work is to examine how rainfall influences crack development in buildings and how this, in turn, affects structural stability.

An Eddy current testing-based model is introduced for crack detection, as it provides more accurate results. Data collected from sensors over various time intervals is used to design an algorithm capable of predicting crack growth in three dimensions (x, y, and z axes). The developed AI model compares real-time sensor data with trained datasets to generate maintenance recommendations for users.

II. LITERATURE REVIEW

Vibration-based monitoring is one of the earliest and most significant applications of AI in SHM. Machine learning (ML) algorithms have been employed to analyze sensor data, allowing anomalies in the vibrational responses of structures to be identified and potential damage or degradation estimated (Sony et al., 2021; Wang et al., 2022).

By utilizing AI, patterns that were difficult to detect could be recognized using automated processes, making vibration-based monitoring a fundamental component of advanced SHM systems (Sun et al., 2020). As AI techniques have advanced, early ML models have evolved into more sophisticated deep learning models capable of processing larger datasets with greater accuracy, robustness, and effectiveness for vibration-based SHM.

In addition to data anomaly detection and data interpretation, AI technologies have contributed to model-based analyses in vibration-based monitoring. Typically, finite element (FE) models are developed based on engineering design documents, and the associated model parameters are then updated with sets of measured data to better represent the as-built structural behavior (Sehgal & Kumar, 2016; Ereiz et al., 2022). These procedures are intrinsically iterative and sensitive to the parameters selected for updating.

AI technologies and ML have significantly contributed to the incorporation of more complex parameterizations (Mousavi et al., 2020a; Guo et al., 2020; Lee et al., 2023). By enhancing computational efficiency and providing more accurate predictions, these techniques have enabled more effective frameworks for modal parameter identification and response prediction.

In addition to vibration-based monitoring, vision-based damage detection has undergone substantial advances owing to AI. The use of deep learning, particularly convolutional neural networks (CNNs), has enabled automated analysis of visual data captured by drones, cameras, and other imaging devices (Spencer et al., 2019; Mosalam & Gao, 2024).

Surface-level damage, such as cracks, corrosion, and spalling, can be detected with high precision, allowing large-scale infrastructure assessments to be conducted without manual inspection (Liu et al., 2014; Kim & Cho, 2018; Kim et al., 2018; Geetha & Sim, 2022, 2022, Zhang et al., 2023). These methods reduce inspection time and minimize human error, and increase safety-related, marking a significant improvement over traditional inspection methods.

III. A HISTORY OF SHM

3.1 Early Developments in AI for SHM

The application of Artificial Intelligence (AI) in Structural Health Monitoring (SHM) began in the late 20th century, primarily centered on vibration-based techniques. At that time, limitations in computer vision restricted the use of image-based

methods, leading researchers to depend mainly on signal data such as frequency response functions.

Early studies focused on Artificial Neural Networks (ANNs), especially Multi-Layer Perceptrons (MLPs), to enable automated detection of structural damage. Throughout the 1990s, researchers demonstrated the capability of neural networks to identify damage in structural components such as beams and building models, as well as to assist in updating finite element models. Dimensionality reduction methods like Principal Component Analysis (PCA) were also introduced to simplify input data and enhance model accuracy.

Despite their usefulness, these early AI approaches were limited by challenges such as high computational cost, difficulty in handling large and complex datasets, and lengthy training processes. Nevertheless, they represented a crucial shift from traditional manual assessment toward data-driven SHM methodologies, establishing a basis for future progress.

3.2 The Rise of AI in SHM

Prior to the 2000s, most AI applications in SHM were dominated by ANN-based models. While effective for relatively simple problems, these models struggled to scale when dealing with the complexity of real-world structures. This prompted researchers to explore alternative machine learning (ML) techniques.

In the early 2000s, methods such as Support Vector Machines (SVMs) gained popularity due to their improved performance in classification and damage detection tasks. Researchers further enhanced these approaches by combining them with techniques like Independent Component Analysis (ICA) and wavelet transforms, enabling better extraction of relevant features from noisy structural data.

During this phase, SHM research expanded beyond vibration analysis to incorporate additional sensing technologies, including piezoelectric sensors used in applications like railway monitoring. These advancements increased the adaptability and effectiveness of SHM systems.

By the mid-2000s, the integration of diverse ML methods addressed many of the shortcomings of earlier ANN approaches and significantly advanced the field. This evolution laid the groundwork for more sophisticated techniques, including the emergence of deep learning in SHM.

Table 1 presents a comparative overview of different AI approaches used in Structural Health Monitoring (SHM), covering both traditional machine learning methods and more recent deep learning techniques. Conventional machine learning models are generally valued for their interpretability and lower computational requirements. In contrast, deep learning methods, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs), provide superior capabilities in feature extraction and handling time-dependent data, although they typically demand large datasets and significant computational power.

Table1 : Strengths and limitations of AI methods in SHM

| Technique | Strengths | Limitations | Applications |
|-----------|-----------|-------------|--------------|
| Machine | Easy to | Performance | Vibration- |

| | | | |
|--|---|--|--|
| Learning (ML) | interpret and computationally efficient | depends heavily on manual feature extraction | based monitoring, damage identification |
| Deep Learning (CNNs) | Provides high accuracy with automatic feature learning | Requires significant computational power and large training datasets | Crack detection, image-based structural assessment |
| Deep Learning (LSTMs) | Effective for analyzing time-dependent or sequential data | Performance can degrade with poor-quality data | Vibration monitoring, damage detection in time-series data |
| Transformers (Vision/Time-Series) | Capable of learning long-range patterns and resistant to noise | Computationally demanding and data-intensive | Vision-based monitoring, tracking structural displacements |
| Graph Neural Networks (GNNs) | Captures complex relationships within structural systems | Needs graph representation of structures and high computation | Structural network analysis, damage localization |
| Physics-Informed Neural Networks (PINNs) | Combines physical laws with data for improved efficiency and accuracy | Requires strong domain knowledge and high computational effort | Hybrid physics-AI modeling, structural model updating, digital twin applications |

More recent developments, such as Transformers, Graph Neural Networks (GNNs), and Physics-Informed Neural Networks (PINNs), have further broadened the scope of AI in SHM. Transformers are particularly effective at learning long-range relationships within structural data, making them resilient to environmental and operational variability. GNNs are well-suited for representing structural connectivity, enabling improved damage detection and localization in complex systems. PINNs, on the other hand, incorporate physical laws into the learning process, enhancing model accuracy and reducing dependence on large datasets, which is especially useful in digital twin frameworks.

Overall, AI in SHM has progressed from relying solely on response-based data to integrating diverse data sources such as visual inspection images, LiDAR-enabled digital models, and computer vision-based measurement systems. This integrated approach significantly improves the accuracy, scalability, and effectiveness of monitoring and maintaining critical infrastructure.

IV. AI in vibration-based SHM

4.1 Vibration-Based SHM

This section outlines the early developments in applying AI techniques to Structural Health Monitoring (SHM), particularly focusing on vibration-based methods. Broadly,

machine learning (ML) approaches in this area can be divided into two main groups:

- (1) Finite Element (FE) model-based methods, and
- (2) data-driven methods.

FE model-based approaches involve tasks such as updating model parameters, refining FE models, predicting structural responses, and identifying damage locations. In contrast, data-driven approaches rely solely on measured data to perform tasks like classification, anomaly detection, time-frequency analysis, and damage identification.

The key distinction between these two categories lies in the requirement of an FE model. Model-based techniques depend on an accurate numerical representation of the structure, which allows them to offer predictive insights, consistent with the framework of vibration-based inspection hierarchies. On the other hand, data-driven methods do not require such models and instead focus on extracting information directly from collected data. Despite these differences, both approaches share the common objective of assessing the structural condition using ML-based analysis.

V. AI in Vision-Based Damage Detection

Recent breakthroughs in deep learning have significantly advanced image recognition, classification, and applications such as autonomous driving. These developments have also been adopted in civil engineering, particularly for structural inspection tasks. When integrated with Unmanned Aerial Vehicles (UAVs), AI-driven inspection systems provide a promising alternative to conventional manual visual inspections.

However, images captured by UAVs often have limited resolution, making it necessary to capture close-range images to accurately detect and assess structural damage. As a result, large numbers of images are typically collected when inspecting full-scale infrastructure, creating a need for automated damage detection systems. Earlier approaches combined image processing techniques with machine learning models and achieved moderate success, but they often lacked strong generalization across different conditions. The introduction of deep learning has greatly improved the robustness and adaptability of image-based damage detection methods.

Research in this area has primarily focused on identifying visible surface defects in structures. Initial studies largely concentrated on detecting cracks in concrete surfaces and pavements. Over time, these approaches have expanded to include other types of damage, such as corrosion, spalling, exposed reinforcement, and efflorescence.

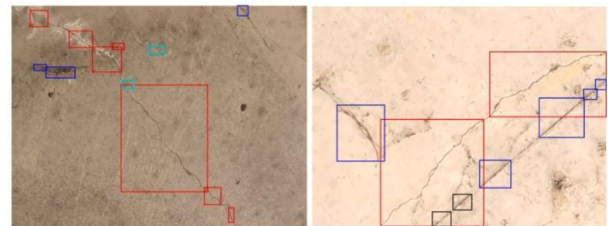
5.1 Damage Detection

Early applications of deep learning in damage detection mainly relied on classification-based Convolutional Neural Network (CNN) models. In these approaches, images were divided into smaller patches, which were then classified as either containing damage (e.g., cracks) or not. While effective for identifying the presence of damage, these methods required additional image processing steps to pinpoint the exact location of defects at the pixel level.

Similar classification-based strategies were widely used in early studies on crack detection. Since these models

operated on segmented image patches rather than full images, their outputs were limited to binary labels, necessitating further processing for detailed localization. To improve performance, some researchers introduced techniques such as collecting diverse datasets through web scraping, generating probability maps, and applying overlapping sliding windows during analysis.

There were also efforts to improve interpretability, such as incorporating explainable AI methods to better understand model predictions. Despite these advancements, early deep learning approaches often relied on clear and well-defined crack images, which restricted their ability to generalize effectively to complex, real-world scenarios.



5.2 AI for digital transformation of civil infrastructures

Digital transformation is an emerging application for utilizing AI in the construction industry. Digital models have significantly improved various aspects of the industry. Initially, digital models such as Building Information Modeling (BIM) and FE model were primarily used during the design stage. Subsequently, these models were integrated with construction sites, enabling automatic comparison of the ongoing construction stages with the planned schedule. Recently, digital models have been expanded to cover not only the design and construction stages but also to maintain post-construction structures.

However, generating digital models, particularly for maintenance purposes, is difficult. Although most digital models are generated based on design-stage drawings, some structures may have lost or are poorly preserved drawings. Even if the drawings are well-preserved, the actual structure may differ owing to manufacturing errors or deterioration. Therefore, obtaining accurate as-is information about a structure is essential for creating digital models for maintenance purposes.

5.3 AI for measurement of civil infrastructures

Measuring structural displacement is an important task in SHM because many applications, such as system identification, damage detection, and FE model updating, rely on the accurate measurement of structural vibrations. In addition, displacement can provide information regarding structural conditions. Traditionally, structural accelerations were used for various SHM approaches, not because they were the most important measurements, but because they were easier to measure. Installing linear variable differential transformers to measure displacement often required additional installations, such as scaffolds. In contrast, accelerometers could simply be installed on structural components to measure acceleration.

However, advances in computer vision have changed the trends in these measurements. Currently, a single commercial camera is used to measure multiple points of structural displacement. Vision-based measurements do not require any additional installation of scaffolds or sensors. The camera can be placed outside the structure, eliminating the need for traffic control during the installation procedures. Although there were initial issues with vision-based measurements such as finding appropriate locations for camera installation, temporal aliasing, and rolling shutter effects, researchers have been developing novel methods to overcome these challenges.

Recently, video-based measurement techniques have made substantial progress owing to significant advances in artificial intelligence (AI) technology. CNNs are used to aid traditional vision-based measurement systems, enhance accuracy, and automate measurement processes. Furthermore, some newly introduced vision-based displacement measurement methods have been developed based on deep learning methods, such as hybrid methods that combine traditional trackers with deep learning networks.

In addition to measuring the displacement of structures, deep learning methods are utilized to estimate the traffic load applied to civil infrastructure. CNNs and other deep learning methods have been applied to identify the weights of vehicles, pedestrians, and other types of loads.

VI. Summary And Conclusion

The incorporation of Artificial Intelligence (AI) into Structural Health Monitoring (SHM) has fundamentally transformed the way infrastructure is monitored and maintained. As highlighted in this review, AI has considerably enhanced SHM by enabling more sophisticated data analysis, anomaly detection, and predictive maintenance capabilities. Applications ranging from vibration-based monitoring to vision-based damage detection, 3D digital modeling, and visual measurement techniques illustrate how AI addresses the increasing complexity of modern infrastructure systems.

Vibration-based SHM has leveraged machine learning (ML) algorithms to automatically detect damage patterns from structural vibration data, improving both efficiency and accuracy. Similarly, vision-based damage detection has benefitted from deep learning models, such as Convolutional Neural Networks (CNNs), which enable faster and more reliable identification of surface defects, providing a strong alternative to traditional manual inspections. The digitalization of SHM, through AI integration with LiDAR and photogrammetry, has produced detailed three-dimensional representations of structures, supporting better-informed maintenance and safety decisions. Moreover, vision-based measurement approaches allow for non-contact monitoring of structural displacements, facilitating real-time tracking of structural behavior.

Looking forward, research should prioritize adaptive AI models capable of self-learning, decentralized data processing through federated learning, and the use of Physics-Informed Neural Networks (PINNs) to enhance model transparency and reliability. The combination of AI-driven SHM with natural language processing (NLP) and generative AI could automate maintenance workflows and provide interactive decision support. Furthermore, integrating digital twin frameworks with mixed reality (MR) technologies can deliver immersive visualization and enable real-time interaction with structural data, fundamentally changing how engineers perform inspections and predictive maintenance.

In summary, AI has become an essential component in improving the effectiveness and scalability of SHM systems. Its capacity to deliver timely, accurate, and extensive monitoring solutions addresses the growing challenges posed by aging infrastructure. The developments discussed in this review demonstrate AI's potential to ensure the safety, reliability, and longevity of critical infrastructure. Continued research and integration of AI technologies will be crucial to meeting the future demands of infrastructure monitoring and management.

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