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# AI in Structural Health Monitoring for Infrastructure Maintenance and Safety

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**Abstract:** This study explores the growing influence of artificial intelligence (AI) on structural health monitoring (SHM), a critical aspect of infrastructure maintenance and safety. This study begins with a bibliometric analysis to identify current research trends, key contributing countries, and emerging topics in AI-integrated SHM. We examine seven core areas where AI significantly advances SHM capabilities: (1) data acquisition and sensor networks, highlighting improvements in sensor technology and data collection; (2) data processing and signal analysis, where AI techniques enhance feature extraction and noise reduction; (3) anomaly detection and damage identification using machine learning (ML) and deep learning (DL) for precise diagnostics; (4) predictive maintenance, using AI to optimize maintenance scheduling and prevent failures; (5) reliability and risk assessment, integrating diverse datasets for real-time risk analysis; (6) visual inspection and remote monitoring, showcasing the role of AI-powered drones and imaging systems; and (7) resilient and adaptive infrastructure, where AI enables systems to respond dynamically to changing conditions. This review also addresses the ethical considerations and societal impacts of AI in SHM, such as data privacy, equity, and transparency. We conclude by discussing future research directions and challenges, emphasizing the potential of AI to enhance the efficiency, safety, and sustainability of infrastructure systems.

**Keywords:** artificial intelligence (AI); structural health monitoring (SHM); predictive maintenance; sensor networks; anomaly detection; infrastructure resilience; machine learning (ML)

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## 1. Introduction

Structural health monitoring (SHM) has become a crucial aspect of modern infrastructure management, providing vital information about the condition and safety of critical assets such as tunnels, dams, buildings, and bridges [1,2]. SHM involves the continuous or periodic assessment of a structure's health through data collected from various sensors embedded in or placed on the infrastructure. The primary goal of SHM is to detect damage or deterioration early, ensuring timely maintenance interventions and reducing the risk of catastrophic failures. By improving the ability to monitor the structural integrity of infrastructure, SHM plays a key role in extending the lifespan of assets, enhancing their safety, and optimizing their maintenance costs.

In recent years, several advanced technologies have emerged, transforming the field of SHM and enhancing its capabilities beyond traditional methods. One such innovation is the use of fiber optic sensors [3], which offer high sensitivity and the ability to monitor large structures continuously, providing real-time data on strain, temperature, and vibrations. Another significant advancement is the integration of wireless sensor networks (WSNs) [4], which reduce installation costs and complexity while enabling remote monitoring and decentralized data processing. Additionally, the rise of drone-based inspections [5] has revolutionized access to difficult-to-reach areas, allowing for detailed visual and thermal assessments. The development of digital twins (DTs)—virtual replicas of physical structures [6,7] updated with real-time data [8]—has further enabled predictive maintenance and dynamic analysis, offering a holistic view of structural behavior [9]. These emerging technologies are reshaping SHM practices, providing more comprehensive, efficient, and accurate monitoring solutions.

Beyond these technological advancements, the rise of artificial intelligence (AI) has revolutionized SHM, along with several other fields related to civil engineering [10,11] and structural engineering in particular [12], including structural modeling [13], structural optimization [14], structural reliability analysis [15], construction emission reduction [16], earthquake engineering [17–20], and many others. In SHM, AI introduces innovative approaches for data processing, damage detection, and predictive maintenance. Its ability to handle vast amounts of data, learn from patterns, and make accurate predictions has paved the way for more efficient and automated SHM systems. Machine learning (ML) [21] and deep learning (DL) [22] algorithms, artificial neural networks (ANNs) [23], and other AI-based approaches have demonstrated great potential in extracting meaningful insights from SHM data, identifying hidden damage and even predicting future structural failures. AI has improved the precision and reliability of SHM systems and has also enabled the development of smart and autonomous monitoring systems capable of functioning with minimal human intervention.

A systematic review of ML applications in SHM is presented in [24], highlighting their effectiveness in detecting damage in various civil structures like bridges, dams, and wind turbines. The review categorizes ML algorithms into two main approaches: vibration-based and image-based SHM. The study evaluates clustering, regression, and classification methods, identifies current knowledge gaps, and provides practical recommendations for enhancing ML's integration into SHM, emphasizing the growing role of IoT and big data. Vijayan et al. [25] conducted a comprehensive review of the integration of intelligent technologies, such as the Internet of Things (IoT), AI, and nondestructive testing, in SHM for civil engineering. The review highlights the significant advancements in SHM for various building types, including residential, industrial, and special structures like nuclear power plants. The use of sensors, microcontrollers, and embedded systems enhances the ability to detect structural damage, while reducing costs and reliance on manual inspections. The review emphasizes the social, economic, and environmental benefits of incorporating intelligent technologies, leading to more efficient and sustainable SHM practices.

Mondal and Chen [26] provided a comprehensive review of AI advancements in civil infrastructure SHM, highlighting significant milestones, current research trends, and future directions. The paper details applications of AI in structural inspection, emphasizing the rising integration of unmanned aerial systems and IoT technologies. It discusses key developments in image processing and predictive analytics, while also addressing contemporary issues like explainable and physics-informed AI. The review offers a roadmap for future research, guiding advancements in automated, efficient, and reliable infrastructure monitoring. Altabey and Noori [27] reviewed the application of AI-based methodologies for SHM, focusing on ML and DL approaches for system identification, feature extraction, diagnostics, and damage detection. The study highlights advancements in integrating AI with sensor networks for real-time monitoring and data analysis, predicting structural responses under complex conditions, and enhancing life cycle assessments. The authors emphasize AI's superiority in handling large datasets, enabling precise diagnostics and robust predictions, which are critical for intelligent infrastructure systems and smart city development. The work also outlines interdisciplinary applications and explores future directions in AI-enhanced SHM.

Azimi et al. [28] provide a comprehensive review of recent advancements in DL for SHM. They discuss vibration-based and vision-based monitoring techniques, highlighting challenges such as limited real-world image datasets, environmental variability, and the need for hierarchical approaches to damage assessment. The review emphasizes the importance of robust, real-time data processing and notes the limitations of current DL methods in replicating human perception. Future directions include improving data acquisition, enhancing anomaly detection, and addressing the complexities of in situ conditions.

Focusing on bridge infrastructure, Zinno et al. [29] reviewed the role of AI in enhancing data-driven SHM systems. The study highlights AI's integration with IoT and big data analytics, which is reshaping traditional SHM approaches. It discusses the application of AI techniques throughout the bridge lifecycle—from construction to maintenance—focusing on improved data analysis, predictive capabilities, and decision-making frameworks. The review outlines key advantages and challenges of AI in SHM, emphasizing its potential for real-time monitoring and intelligent transportation systems. The authors also identify future research directions for advancing AI-assisted SHM for improved bridge performance and safety. In a similar work, Zhang et al. [30] review recent advancements in applying DL to bridge SHM, utilizing big data from advanced sensing technologies. It covers DL applications in vibration-based and vision-based SHM, highlighting successful damage detection and real-world bridge implementations. The study also outlines current limitations and future prospects. Another recent review of AI applications in managing the structural health of bridges can be found in [31]. The study examines three key areas: computer vision for automated defect detection, AI-enhanced SHM using sensor data, and AI's role in predicting bridge deterioration for better risk assessment. The findings show that while computer vision and SHM integration are well covered, the main challenge lies in using AI for long-term performance prediction and risk evaluation, highlighting future research directions in this evolving field.

*Contribution and Structure of the Present Study*

This study explores the impact of AI on SHM for infrastructure maintenance and safety. It starts with a bibliometric analysis in Section 2, examining the scientific landscape of SHM research integrated with AI, ML, and DL. Using data from the Scopus database, we perform co-occurrence and co-authorship analyses to identify influential keywords, emerging research trends, and key contributing countries.

Section 3 explores seven critical areas where AI significantly impacts SHM, as illustrated in Figure 1. These areas include data acquisition and sensor networks; data processing and signal analysis; anomaly detection and damage identification; predictive maintenance, structural reliability, and risk assessment; visual inspection and remote monitoring; and SHM for resilient and adaptive infrastructure. Each section highlights AI's contributions to advancing SHM processes, improving efficiency, and enhancing infrastructure maintenance and safety.

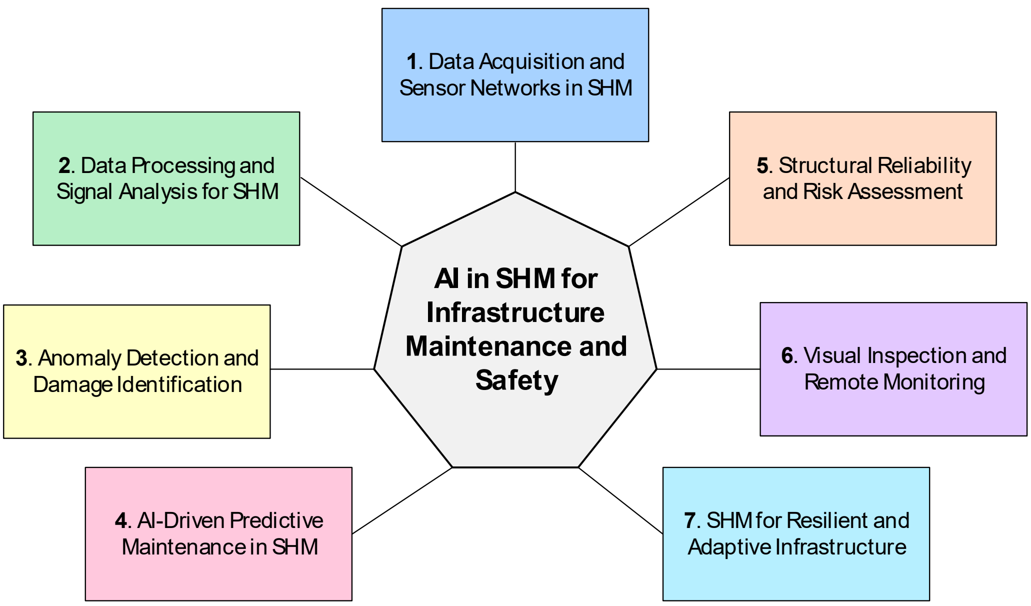



**Figure 1.** The seven areas of AI in SHM for infrastructure maintenance and safety covered in the present study.

While the present study identifies seven distinct areas where AI significantly impacts SHM, it is important to note that these categories are not entirely separate from one another. In practice, the boundaries between these areas are often blurred, as many works in the literature address multiple subjects simultaneously. There is significant overlap among these topics, with numerous studies combining elements from different areas to offer innovative solutions. Consequently, although we present specific works under distinct categories, it is equally valid to classify some of these studies in other areas due to their multidisciplinary nature and integrated approaches.

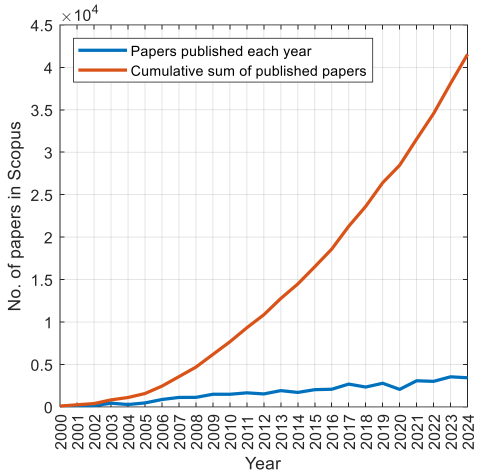
In addition to these key areas, in Section 4, this study examines the ethical and societal implications of AI in SHM, addressing critical concerns such as data privacy, equity, accountability, and transparency. The discussion highlights the risk of widening the technology gap between developed and developing regions, while also emphasizing the importance of explainability in AI models to ensure trust, fair decision-making, and clear accountability in infrastructure monitoring and maintenance.

Additionally, in Section 5, this study outlines future developments and challenges, exploring how AI is expected to further enhance SHM for infrastructure maintenance and safety. Lastly, the Conclusions Section (Section 6) synthesizes the insights gained across the different areas, emphasizing the interconnected applications of AI and their collective potential to reshape SHM, paving the way for more resilient, efficient, and safer infrastructure systems.

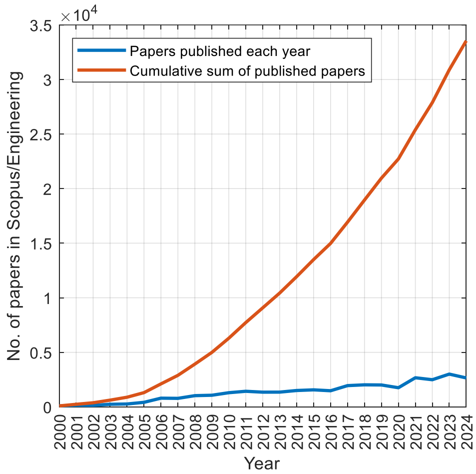
## 2. Bibliometric Analysis

### *2.1. Papers Published in the Field of Structural Health Monitoring*

The growing importance of SHM is reflected in the increasing number of scientific publications over the past two decades. A search on the Scopus database using the keyword "structural health monitoring" in the "Article title, Abstract, Keywords" fields yielded a total of **41,536** documents from 2000 to 2024 (as of 15 November 2024). When narrowed down to the "Engineering" category, the search returned **33,541** documents. The data show a significant upward trend, with yearly publications increasing steadily, particularly in the last decade. For instance, the number of publications in all fields rose from just **95** in 2000 to **3432** in 2024. Similarly, in the "Engineering" field, this number increased from **92** in 2000 to **2655** in 2024. Figure 2 illustrates this growth trend, highlighting the heightened interest and ongoing advancements in SHM research.




(**a**)




(**b**)

**Figure 2.** Scopus articles in "structural health monitoring" (query made on 15 November 2024): (**a**) all fields, (**b**) "Engineering" field only.

### *2.2. Top Keywords for SHM Combined with AI*

We conducted a co-occurrence analysis of top keywords, including both author and index keywords, using the Scopus database. The search targeted publications related to "structural health monitoring" combined with "artificial intelligence", "machine learning", or "deep learning". The search was performed using the "Article title, Abstract, Keywords" fields, covering the years from 2010 to 2025. The complete Scopus query was as follows: "TITLE-ABS-KEY (("structural health monitoring" OR "SHM") AND ("artificial intelligence" OR "machine learning" OR "deep learning")) AND PUBYEAR > 1999 AND PUBYEAR < 2026 AND PUBYEAR > 2009 AND PUBYEAR < 2026". Executed on 15 November 2024, the query returned **3390 documents**.

From these results, the top 50 keywords were identified. To ensure consistency, similar keywords were manually standardized (e.g., "SHM" was replaced with "structural health monitoring"). The full list of keyword replacements is provided in Table A1 of the Appendix A. Figure 3 shows a network visualization of the co-occurrence of these top 50 keywords, created using VOSviewer software version 1.6.20 [32]. The map features several distinct clusters, represented by different colors, with a minimum co-occurrence strength of 60.

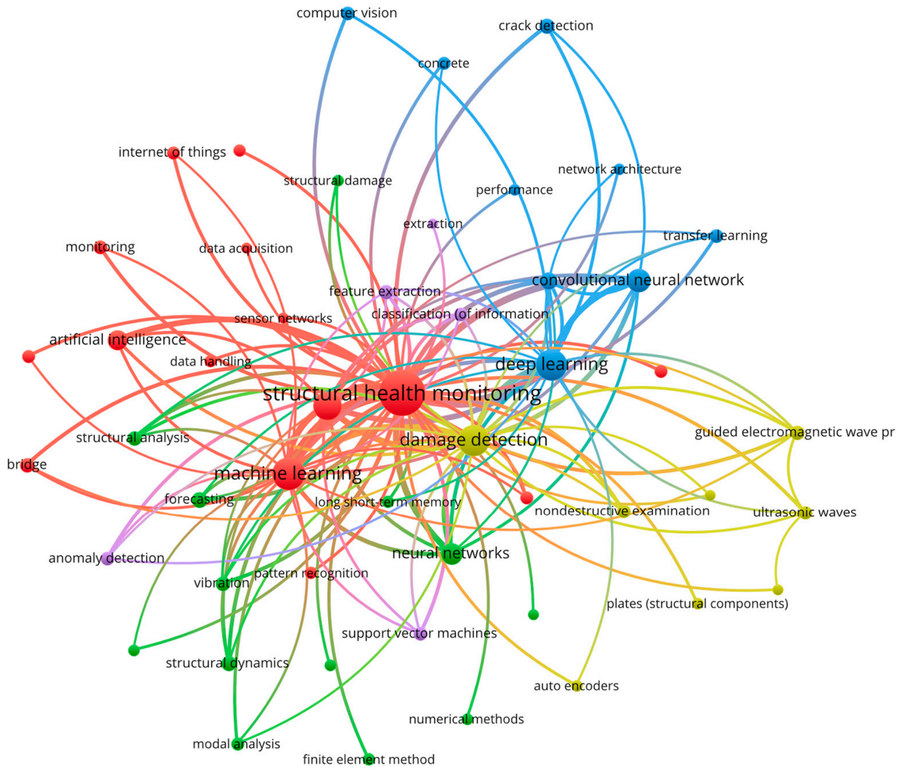



**Figure 3.** Keyword co-occurrence network map for publications on SHM and AI.

The most prominent nodes are "structural health monitoring", "learning algorithms" (red node on the left of SHM; the text is hidden in the figure), "machine learning", "deep learning", and "damage detection". These central terms are heavily interconnected, indicating that these topics form the core of the current research focus on AI-based SHM. The strong links between "machine learning" and "damage detection" highlight the extensive use of ML algorithms in identifying structural damage patterns. Similarly, the connection between "deep learning" and "convolutional neural network" reflects the popularity of convolutional neural networks (CNNs) for processing visual data in crack detection and other tasks.

The analysis identified distinct clusters, represented by different colors:

- **Red Cluster**: This cluster is focused on "machine learning", "learning algorithms", "artificial intelligence", and related terms like "sensor networks" and "data acquisition". It highlights the importance of AI techniques for data handling, monitoring, and decision-making in SHM.
- **Green Cluster**: Keywords such as "neural networks", "finite element method", and "modal analysis" dominate this cluster, reflecting research interests in integrating traditional structural analysis methods with neural-network-based approaches for enhanced predictive capabilities.
- **Blue Cluster**: The blue cluster includes terms like "deep learning", "convolutional neural network", and "crack detection", indicating a strong focus on advanced DL models for image-based inspection and damage identification.
- **Yellow Cluster**: This cluster features terms like "damage localization", "ultrasonic waves", and "nondestructive examination", showcasing the use of AI in specific testing techniques and non-invasive methods for detecting structural issues.

In the map, terms like "Internet of Things", "cloud computing", and "edge computing" are linked with sensor networks and AI, suggesting a growing trend in leveraging connected technologies for real-time SHM data analysis. The presence of terms such as "transfer learning" and "autoencoders" indicates an interest in utilizing sophisticated DL techniques for enhancing model accuracy and generalization. Despite the strong focus on AI and DL, traditional methods like "finite element analysis" still appear frequently, hinting at ongoing efforts to combine classical SHM approaches with modern AI techniques. This suggests that hybrid methodologies are a key research area.

In summary, the keyword analysis demonstrates the strong integration of AI, particularly ML and DL techniques, within SHM research, focusing on automated damage detection, data analysis, and predictive maintenance. The identified clusters indicate diverse research directions, including sensor networks, advanced imaging techniques, and DL applications, all contributing to a more efficient and intelligent approach to monitoring civil infrastructure.

### 2.3. Top Countries

Based on the same Scopus dataset as Figure 3, Figure 4 focuses on the co-authorship network among the top countries contributing to the field of SHM and AI. Setting a minimum of 5 publications per country, a connected network of 54 countries was identified, with the top 50 displayed on the map. The minimum connection strength was set to 4. In this visualization, the links (lines) between countries indicate the frequency of co-authorship, while the size of each node (bubble) represents the publication volume of each country in SHM+AI research.

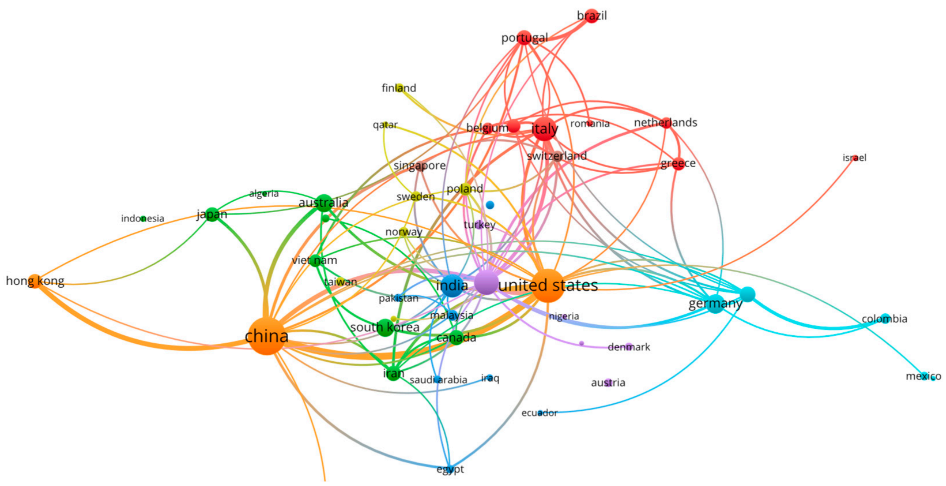



**Figure 4.** Co-authorship network map of the top 50 countries in SHM and AI research.

Figure 4 highlights strong collaboration networks between major research contributors. The US and China appear as the largest nodes, reflecting their leading roles in SHM research output. Notably, there is substantial co-authorship between the US and China, indicating frequent collaboration. European countries like the UK, Germany, and Italy also show significant interconnectedness, often collaborating with each other as well as with Asian countries like South Korea and Japan. These findings suggest a highly collaborative and international landscape in SHM+AI research, with leading countries frequently engaging in joint studies to advance the field.

## 3. Seven Areas of AI in SHM for Infrastructure Maintenance and Safety

### *3.1. AI for Data Acquisition and Sensor Networks in SHM*

Data acquisition and sensor networks are vital to any SHM system, utilizing accelerometers, strain gauges, displacement transducers, and temperature sensors strategically placed on infrastructure elements. These sensors collect data on vibrations [33], strain [34], deformation [35], and environmental conditions to assess structural health and detect damage. Wireless sensor networks (WSNs) have advanced significantly in recent years, becoming integral to SHM by enabling the efficient measurement, assessment, and maintenance of civil infrastructure [36]. However, the high data collection rates in WSNs for SHM present unique challenges in network design and optimization.

Noel et al. [37] conducted a comprehensive review of SHM utilizing WSNs, covering algorithms for damage detection and localization, as well as key network design challenges and future research directions. The review compares and discusses solutions for issues such as scalability, time synchronization, sensor placement, and data processing. Additionally, it provides an overview of testbeds and real-world implementations of WSNs for SHM. Sofi et al. [38] provide a comprehensive review of the transition from wired to wireless smart sensor networks (WSSN) in SHM, highlighting their advantages for large-scale infrastructure like bridges, multi-story buildings, and offshore platforms. The study explores advancements in wireless data acquisition and the integration of AI techniques, including ANNs, ML, and DL, to enhance data prediction and diagnosis. The review emphasizes challenges in real-world implementation and calls for standardized frameworks to bridge the gap between research and practice.

Yu et al. [36] review recent advancements in wireless smart sensor networks (WSSNs) for SHM, highlighting improvements in event-triggered sensing, multimetric sensing, and edge/cloud computing. The study examines critical developments in time synchronization, real-time data acquisition, decentralized data processing, and long-term reliability. Full-scale SHM applications are summarized, showing the effectiveness of WSSN in monitoring. The authors also discuss ongoing challenges and outline future research directions to enhance WSSN capabilities for civil infrastructure maintenance.

Sonbul and Rashid [39] conducted a systematic review of WSN platforms and energy harvesting techniques for the SHM of bridges, addressing the challenge of limited battery life in WSNs. The study analyzed 46 articles, classifying them into WSN platforms, energy harvesting methods, and combined approaches. It also examined design considerations like inspection scale (global/local), response type (static/dynamic), and sensor types, identifying 17 different sensors. The review offers a comparative analysis, aiding stakeholders in selecting optimal WSN platforms and energy harvesting techniques for effective SHM implementation.

The effectiveness of SHM systems depends on accurate, high-quality data, making optimal sensor placement (OSP) and network management essential yet challenging due to complex structures and vast data volumes [40]. Traditionally, sensor placement relies on manual decisions based on structural models, but this approach struggles with complex setups and large-scale monitoring needs. AI-driven approaches offer a powerful alternative, using data-driven models for OSP by analyzing structural behavior and identifying regions of high relevance for monitoring. These techniques significantly enhance the efficiency of SHM systems by focusing on critical areas, reducing redundancy, and improving data quality. One notable example is the ML-based framework proposed by Calò et al. [41], which integrates ML and explainability [42] to optimize sensor placement in prestressed concrete box-girder bridges. Using a combination of nonlinear finite element (FE) modeling and ANNs, the study predicted prestressing force reduction in unbonded tendons. The Shapley additive explanation (SHAP) approach [43] was employed to identify the most influential parameters affecting prestress losses. This information guided the OSP, enabling a cost-effective and efficient SHM strategy.

Mustapha et al. [44] highlight the importance of sensor network design, placement, and optimization, emphasizing the impact on system performance, accuracy, and costs. They also address issues like power management, data communication, and transmission challenges, while noting advancements and successful case studies on SHM applications. In another work [45], a systematic review of optimization algorithms for SHM and OSP is presented, highlighting the importance of using tailored optimization techniques to enhance system performance. The paper categorizes various algorithms, emphasizing the effectiveness of evolutionary algorithms for complex OSP problems. The study underscores the emerging role of ML in SHM, offering advantages in speed and accuracy.

In their work, Waqas et al. [45] introduce a Multi-Objective Hypergraph Particle Swarm Optimization algorithm for OSP in SHM systems. The approach integrates six established OSP methods to generate a Pareto front. The algorithm autonomously selects sensor placements, enhancing adaptability and lifecycle management. The results show superior performance in coverage and convergence, highlighting its efficiency in optimizing sensor configurations. Although the study does not use AI itself, it strongly suggests incorporating AI and big data analytics to further refine the approach for enhanced accuracy and decision-making in SHM as a future research direction.

Bhuiyan et al. [46] focus on OSP in WSNs for SHM, addressing key challenges related to communication efficiency, network connectivity, and fault tolerance. Their approach involves a multi-objective optimization strategy that balances civil engineering requirements with WSN constraints. They propose a "connectivity tree" model, enabling decentralized monitoring and maintenance while reducing communication costs and enhancing fault tolerance. The method also incorporates distance-sensitive, near-optimal sensor locations to improve network efficiency. Extensive simulations and a proof of concept on a physical structure demonstrate the effectiveness of the proposed placement strategy in extending system lifetime and maintaining robust performance.

Wang et al. [47] provide a comprehensive review of OSP strategies in SHM, covering evaluation criteria and optimization algorithms. The study categorizes evaluation metrics into six groups and optimization methods into three classes, discussing their strengths and limitations. Real-world OSP applications on bridges, high-rise buildings, and other structures are highlighted. The review identifies ongoing challenges in OSP and offers future research directions, aiming to bridge the gap between theoretical advancements and practical implementation for more effective SHM systems.

Xie et al. [48] present a neural-network-based approach for SHM using wireless sensor networks. The method utilizes distributed sensing with numerous sensor nodes that collaboratively collect and analyze vibration frequency data, which reflect the structural health status. A neural network algorithm processes these data, classifying them into healthy or unhealthy categories. The results show that this approach provides higher accuracy and robustness against environmental noise and interference, outperforming traditional SHM methods in detecting structural anomalies effectively.

Meng et al. [49] introduce a deep reinforcement learning (DRL) approach for OSP in SHM, addressing challenges such as high sensor costs and the complexity of handling large-scale structural data. Reinforcement learning (RL) is an ML paradigm where an agent learns to make decisions by interacting with an environment and receiving feedback in the form of rewards or penalties. DRL enhances traditional RL by incorporating deep ANNs, enabling it to handle high-dimensional and continuous state-action spaces effectively. In this study, the authors formulate the OSP problem as a Markov decision process (MDP), where the state represents the current sensor placement, the action involves adding or relocating sensors, and the reward reflects the quality of the sensor network based on the modal assurance criterion (MAC) [50]. The DRL framework trains an agent to optimize sensor placement iteratively by maximizing the cumulative reward, effectively balancing sensor cost and data quality. The DRL-based approach outperforms traditional optimization algorithms, particularly in complex scenarios. Case studies demonstrate the algorithm's superior performance in achieving high-quality sensor configurations with reduced costs. This highlights DRL's potential to handle the dynamic and multi-dimensional nature of SHM problems efficiently.

### *3.2. AI in Data Processing and Signal Analysis for SHM*

In SHM, data from sensor networks must be processed to assess structural health. These raw data, including vibrations, strain measurements, and acoustic emissions, require advanced techniques to identify patterns, anomalies, and signs of damage. However, sensor data are often noisy or incomplete, which can obscure critical information and complicate analysis. Traditional signal processing methods, such as Fourier transform and wavelet analysis [51], provide valuable tools for feature extraction but often struggle with the complexities of real-world SHM data, especially with noise or missing data.

AI, particularly ML and DL, has revolutionized data processing by addressing some of these challenges. AI models can filter noise, impute missing data, and extract critical features, enabling the identification of early damage indicators (e.g., cracks and corrosion) with greater precision. Nonetheless, many AI methods still face limitations when handling high noise levels or incomplete datasets, where the risk of misclassification or missed anomalies remains significant. Research into robust models and denoising techniques, such as autoencoders and generative adversarial networks (GANs) [52], offers promising directions for overcoming these issues.

Feature extraction plays a critical role in transforming raw data into actionable insights. Traditional methods such as Fourier transform and wavelet analysis remain foundational, but advanced techniques, including principal component analysis (PCA) [53], cepstral analysis [54], and empirical mode decomposition (EMD) [55], are increasingly being used to extract meaningful patterns from SHM data. These methods complement AI techniques by reducing data dimensionality and emphasizing key characteristics, improving both processing efficiency and model accuracy.

Ibrahim et al. [56] explored the use of ML approaches for SHM by focusing on low-cost, noisy accelerometer data. Their research emphasized post-disaster damage detection using inexpensive sensors to monitor building vibrations and assess damage severity. Various ML algorithms, such as support vector machines, K-nearest neighbors, and CNNs, were applied to noisy datasets to classify the structural damage. By incorporating noise-handling techniques, the study achieved high accuracy in damage detection, offering a cost-effective SHM solution. This approach significantly reduces the cost of sensor networks, making it more feasible for large-scale deployment in post-disaster scenarios.

Deep neural networks further improve accuracy by continuously learning from historical and new data, detecting complex interactions between factors like temperature and strain. This leads to earlier, more accurate failure predictions, enabling timely maintenance. AI automates much of the analysis, reducing manual interpretation, minimizing errors, and allowing SHM systems to adapt in real time. Jia and Li [57] systematically review the application of DL for SHM, focusing on data types, DL algorithms, and applications. Their analysis of 337 studies reveals that vibration signals and images are the most commonly used data types, with CNNs as the dominant DL algorithm. Challenges such as data limitations and algorithm uncertainties are highlighted, while trends like integrating SHM with DT frameworks are proposed for enhancing SHM's digitalization, visualization, and intelligent management.

Alves et al. [58] provide a critical analysis of AI techniques in SHM, focusing on ML and DL methods for detecting structural damage using vibration signals. They emphasize the potential of these tools for real-time, non-destructive safety assessments. However, concerns are raised about the interpretability of AI models and reliance on supervised learning. The study also discusses challenges in pattern recognition and decision-making, highlighting advancements and limitations within the Industry 4.0 context.

Dabbous et al. [59] explore the application of WaveNet and MiniRocket neural architectures for SHM, specifically analyzing the Z24 Bridge dataset. Their findings indicate that WaveNet effectively interprets raw vibration signals in the time domain without preprocessing, achieving state-of-the-art accuracy while reducing model size and computational complexity. MiniRocket, with its minimal configuration requirements and efficient training, serves as a practical alternative for rapid prototyping. The study also demonstrates the feasibility of deploying these models on edge computing platforms, highlighting their potential for real-time, on-site damage assessment without reliance on cloud resources.

### *3.3. AI for Anomaly Detection and Damage Identification*

Anomaly detection and damage identification are key aspects of SHM, focused on identifying deviations from normal structural behavior that may signal damage or deterioration [60]. Traditional methods rely on statistical models, signal processing, and manual analysis of sensor data like strain gauges and accelerometers. However, these methods struggle with noise from environmental factors and large data volumes, often missing early signs of damage.

AI significantly improves this process by automating data analysis, efficiently handling large datasets, and detecting subtle patterns that indicate structural issues. ML and DL models can distinguish between normal environmental fluctuations and actual anomalies, providing earlier damage alerts. As AI algorithms learn from historical and real-time data, they continuously refine their understanding of structural behavior, improving detection accuracy over time.

A challenge in applying supervised learning methods is the need for labeled datasets, particularly for damaged structures. In practice, obtaining such data can be difficult and resource intensive. To address this, unsupervised learning methods have gained attention for their ability to detect anomalies and identify damage without requiring labeled data. These methods learn patterns in the normal operational behavior of structures and flag deviations as potential anomalies, making them highly suited for SHM applications. Recent advancements in unsupervised learning include the use of vibration-based data for SHM, as reviewed by Eltouny et al. [61]. Their comprehensive study categorizes state-of-the-art unsupervised learning methods for anomaly detection in SHM, with a primary focus on novelty detection. The paper emphasizes techniques such as outlier analysis, clustering, and autoencoder-based methods, showcasing their practicality in real-world scenarios where obtaining labeled data is challenging. Additionally, Xu et al. [62] introduced spatiotemporal fractal manifold learning, a novel SHM technique that reduces spatiotemporal data dimensionality for structural damage detection. It combines fractal analysis for temporal reduction with topological manifold learning for spatial reduction, effectively handling high-dimensional sensor data. By addressing the curse of dimensionality and reliance on hand-crafted features, this method enhances damage classification and visualization in vibration-based monitoring.

Wang et al. [63] developed a damage identification and localization framework using multi-level data fusion and anomaly detection techniques, demonstrated through case studies of different bridge types. By integrating accelerations, deflections, and bending moments from multiple sensor locations, their method couples principal component analysis and Mahalanobis distance for data dimensionality reduction. A deep convolutional autoencoder was employed for anomaly detection, achieving damage identification accuracy above 93% for simply supported bridges and 94.9% for continuous bridges, even for minimal damage severity. The framework is robust across varying bridge types and vehicle conditions, making it a promising tool for early infrastructure damage detection.

Kim and Mukhiddinov [64] propose a hyper-parameter-tuned CNN for detecting anomalies in SHM data, addressing issues of unbalanced datasets caused by factors like extreme weather or faulty sensors. Their method was validated using time-series data from a cable-stayed bridge, with data augmentation employed to balance the dataset. The model achieved an overall accuracy of 97.6%, demonstrating its effectiveness in identifying various types of anomalies and enhancing the reliability of SHM by ensuring cleaner, more accurate data analysis.

Bigoni and Hesthaven [65] present a simulation-based strategy for anomaly detection and damage localization in SHM. By generating synthetic datasets offline using parametric partial differential equations, they train one-class support vector machines on healthy configurations. During online monitoring, new measurements are classified as healthy or damaged, with further analysis indicating damage severity and location. A model order reduction technique minimizes computational costs, demonstrating effectiveness in 2D and 3D vibrational analyses for crack detection and localization.

Cultural heritage (CH) structures are particularly important for SHM due to their historical, architectural, and cultural significance [66]. Unlike modern infrastructure, CH structures often face unique challenges, including age-related material degradation, complex geometries, and limited access for inspection. Preserving these assets requires non-invasive SHM methods that can continuously monitor their condition without causing damage. Jiménez Rios et al. [67] conducted a systematic review of the integration of bridge information modeling, FE modeling, and bridge health monitoring to create DT for bridge management. The review highlights how DTs can generate damage scenarios to enhance anomaly detection algorithms, particularly for bridges with cultural heritage (CH) value. The review also explores the potential incorporation of Industry 5.0 concepts within DT frameworks. Carrara et al. [68] utilize DL for the SHM of heritage structures, applying time-series forecasting on seismic ambient noise data. Using a temporal fusion transformer, the study analyzes vibrations recorded during a long-term monitoring campaign on the San Frediano bell tower. The model learns the normal structural dynamics and identifies anomalies by comparing predicted and observed frequencies. This approach highlights the potential of advanced DL techniques for non-invasive monitoring and the early detection of structural issues in historic buildings.

### *3.4. AI-Driven Predictive Maintenance in SHM*

Traditional maintenance approaches—reactive (post-damage) or preventive (scheduled)—often lead to over-maintenance (increased costs) or under-maintenance (risk of failure). Predictive maintenance (PdM) [69] in SHM aims to prevent structural issues before they escalate, avoiding the pitfalls of reactive or scheduled maintenance, which can lead to increased costs or risk of failure. Unlike traditional methods, PdM uses real-time data to forecast structural health, optimizing resource use.

AI can enhance PdM by continuously analyzing historical and real-time sensor data, identifying subtle signs of damage. ML models adapt predictions based on changing conditions like traffic, weather, and material wear, enabling precise maintenance scheduling. AI's strength lies in learning and analyzing complex interactions among factors, offering accurate forecasts and reducing manual inspections. This proactive approach improves safety, minimizes downtime, and extends asset lifespan, advancing smarter infrastructure management.

De Simone et al. [70] present an IoT-based approach for monitoring reinforced concrete structures, focusing on preventive maintenance. The system utilizes a Raspberry Pi microprocessor and low-cost MEMS accelerometers to monitor vibrations continuously, offering a cost-effective alternative to traditional methods. The data collected by the sensors are processed with DL techniques to predict potential structural issues and forecast maintenance needs. The study highlights the system's effectiveness in improving safety and extending the lifespan of aging buildings.

A study from Ucar et al. [71] explores the integration of AI into predictive maintenance (PdM) systems, highlighting advancements in data analytics and AI technologies that enhance system performance and adaptability in complex environments. It reviews state-of-the-art techniques, discusses challenges and opportunities, and examines the role of AI in real-world PdM applications, including human–robot interactions, ethical considerations, and testing and validation processes.

Zonzini et al. [72] present an IoT-based SHM architecture aimed at predictive maintenance for industrial sites and civil structures. The system features a multi-layer design, integrating micro-electro-mechanical system accelerometers for operational modal analysis, a World Wide Web Consortium (W3C) Web of Things-based data acquisition layer, and a distributed data storage and analytics layer utilizing ML. This approach emphasizes scalability, versatility, and interoperability. Validation on a metallic frame structure demonstrated effective monitoring capabilities, highlighting the potential for enhanced damage detection and predictive analysis in real-world applications.

### *3.5. AI in Structural Reliability and Risk Assessment*

Structural reliability and risk assessment are crucial for ensuring the safety and functionality of infrastructure [73]. Reliability focuses on evaluating a structure's performance over its lifespan, while risk assessment examines the likelihood and impact of potential failures due to events like extreme weather or earthquakes. Risk assessment plays a vital role in informed decision-making, helping determine when maintenance or intervention is necessary in the face of uncertainty, thereby optimizing resource allocation and minimizing the potential for catastrophic failures [74]. Traditional approaches use probabilistic models and simulations (e.g., Monte Carlo) but often struggle with real-world complexity, dynamic conditions, and the growing influx of monitoring data.

AI enhances SHM by providing advanced tools to model complex behaviors and uncertainties. Unlike traditional methods, AI analyzes large, multidimensional datasets from sensors and historical records in real time, identifying trends and correlations while adapting predictions based on new data for more accurate assessments.

AI's holistic analysis integrates material properties, environmental conditions, and degradation, enabling early issue detection. For instance, AI can forecast how temperature and traffic affect a bridge's lifespan, guiding proactive maintenance. Real-time updates in risk assessments enable data-driven decisions, optimizing resources, improving resilience, and ensuring safer, longer-lasting structures.

Tygesen et al. [75] examine advanced SHM methods for the predictive maintenance of offshore structures. The approach includes system identification (linear and nonlinear), Bayesian FEM updating, wave load calibration, and the quantification of uncertainties from data. It integrates damage detection and reassessment analysis to enhance structural reliability. A key aspect is the risk- and reliability-based inspection planning (RBI), which tailors maintenance schedules to the actual structural condition, offering a data-driven, adaptive strategy for offshore asset management. This work sets the foundation for further exploration of predictive techniques in offshore dynamics.

Hosser et al. [76] present a framework for reliability-based assessment of transport infrastructures using data from SHM. The methodology integrates probabilistic safety analysis with SHM data, aiming to enhance the reliability of deteriorated structures while addressing the high costs associated with SHM. The framework is demonstrated through a substitute structure, showcasing its potential for optimizing inspection and monitoring strategies in infrastructure management.

Wang et al. [77] provide a comprehensive review of ML applications in risk and resilience assessment for structural engineering, focusing on buildings, bridges, pipelines, and electric power systems. The study analyzes the existing literature across six ML attributes: method, task type, data source, analysis scale, event type, and topic area. The key findings highlight ML's potential to advance risk assessment frameworks but also identify challenges, such as data limitations and integration issues. The authors suggest future research directions to enhance ML's role in improving structural resilience.

### 3.6. AI in Visual Inspection and Remote Monitoring

Visual inspection is crucial for SHM, especially for large, complex structures like bridges, skyscrapers, and dams. Traditional visual inspections involve manual checks for damage (e.g., cracks and corrosion), often requiring difficult and time-consuming access. AI revolutionizes this process by automating damage detection using advanced image recognition and computer vision algorithms, analyzing visual data faster and more accurately than human inspectors [78]. Computer vision algorithms can now autonomously detect cracks and other defects across a wide range of civil infrastructure materials, including asphalt, concrete, and metal [79]. This automated approach enables faster, more accurate assessments, reducing labor costs and enhancing the overall efficiency of SHM processes.

Nowadays, remote monitoring uses drones, cameras, and sensors to continuously gather data, enabling non-invasive condition assessments. Computer vision systems coupled with AI offer continuous, real-time monitoring, allowing for proactive maintenance and reducing repair costs. They can detect early-stage defects like cracks and spalling by comparing current images with historical data, enabling earlier interventions. Drones equipped with AI enhance their capabilities further, conducting autonomous inspections, capturing high-resolution images, and analyzing damage in real time without human involvement.

CNNs have proven highly effective in addressing various computer vision challenges. They are particularly effective for processing spatial data, such as image-based or grid-structured sensor data, and excel in damage localization tasks. However, they require large, labeled datasets for training and are computationally intensive. In structural engineering, CNNs are extensively applied for crack detection in infrastructure. Ali et al. [80] provide a comprehensive review of the significant research conducted in this area, emphasizing the use of CNNs for classifying and segmenting crack images, demonstrating their effectiveness in accurately identifying structural defects. Similar works have been conducted for pavement crack detection [81,82], concrete crack detection [83–86], wooden structure defects [87–89], and others [90].

Sabato et al. [91] review recent advancements in AI-enhanced noncontact sensing methods for SHM. They highlight the integration of optical sensors and image-processing algorithms, such as photogrammetry, infrared thermography, and laser imaging, which provide accurate, continuous spatial data on structural conditions. The incorporation of AI algorithms has further streamlined and improved the efficiency of these assessments. The authors also discuss future directions for advancing AI-aided, image-based sensing techniques in SHM applications.

Mishra and Lourenço [92] reviewed the application of AI, DL, and computer vision techniques for the visual inspection of CH sites, focusing on the detection of defects such as weathering, joint damage, surface cracks, and erosion. The study highlights the use of AI to assist traditional visual inspections, enhancing the accuracy and confidence in damage assessments. The review also emphasizes the potential of integrating AI with drones and IoT technologies for more comprehensive and efficient CH conservation efforts, suggesting a promising direction for future research.

Mishra et al. [93] developed a DL-based visual inspection model for CH structures using the YOLOv5 object detection algorithm. The study focused on detecting defects such as discoloration, exposed bricks, cracks, and spalling. The model was trained on a large dataset and validated using a case study of the Dadi–Poti tombs in New Delhi. YOLOv5 achieved a high mean average precision (mAP) of 93.7%, outperforming traditional manual inspection and the faster R-CNN model, highlighting its effectiveness in CH defect detection.

Teng et al. [94] evaluate concrete crack detection using the YOLO_v2 network with 11 feature extractors, finding that 'resnet18' offers the best precision (AP = 0.89) and computational efficiency. Models like 'alexnet' prioritize speed, while 'googlenet' and 'mobilenetv2' show strong performance. The study highlights the importance of feature selection, training epochs, extraction layers, and image size on detection accuracy, confirming YOLO_v2's effectiveness for real-time crack detection in concrete structures.

Rajadurai and Kang [95] utilized a fine-tuned AlexNet CNN for automated crack detection in concrete, achieving a high prediction accuracy of 99.9% on validation and test datasets. The model applied transfer learning and image augmentation for classification into crack and no-crack categories. Performance metrics, including precision, recall, accuracy, and F1 score, were all 0.99. Despite challenges like shadows and surface roughness in cross-dataset images, the model maintained robust performance, with accuracy slightly reduced to 0.81–0.89%, confirming its reliability for real-world applications.

Recent advances in UAV-based SHM highlight the significant potential of integrating drones with AI, advanced sensors, and computer vision for infrastructure assessment. Fayyad et al. [5] provide a comprehensive overview of drone-based SHM, emphasizing the potential of drones as a transformative fly-by technique for infrastructure assessment. The study identifies four key research clusters: UAV-enabled vision-based monitoring, the integration of drones with advanced sensors and AI, applications involving modal analysis and energy harvesting, and automation in SHM. The paper highlights rapid advancements in integrating AI, DL, and computer vision, while also identifying existing research gaps and suggesting new directions for future work. Similar innovations are evident in the works of Kang and Cha [96], who use ultrasonic beacons for precise navigation in complex areas like under bridges, paired with DL crack detection, and Zhao et al. [97], who employ UAV photogrammetry and 3D reconstruction techniques for accurate dam inspections. The approach demonstrates improved efficiency in damage detection and inspection, highlighting its potential for emergency monitoring of dam infrastructure.

Additionally, Ngeljaratan et al. [98] study the use of computer vision for seismic safety monitoring of pipelines, showcasing advanced feature extraction and matching techniques validated through shake-table tests. Sankarasrinivasan et al. [99] further extend these capabilities with a real-time UAV-based framework integrating image processing for crack detection and surface degradation assessment, demonstrating a cost-effective, scalable approach for large-scale infrastructure monitoring. Collectively, these works emphasize the growing role of UAVs combined with AI and image processing in enhancing SHM's accuracy, efficiency, and real-time capabilities.

### *3.7. AI in SHM for Resilient and Adaptive Infrastructure*

Resilient and adaptive infrastructure is vital in addressing challenges from climate change, natural disasters, and aging systems. Resilience refers to a structure's capacity to endure and recover from adverse conditions, while adaptability involves the ability to modify behavior or configuration in response to environmental changes. Traditional methods rely on robust design and retrofitting but can lead to overdesign and increased costs. For example, Bhuiyan et al. [100] explore the deployment of WSNs for SHM with a focus on fault tolerance and resilience. The proposed approach enhances the adaptive capabilities of WSNs by strategically placing backup sensors, ensuring reliable operation even in the event of faults. The results from simulations and experiments demonstrate improved resilience, enabling long-term, reliable SHM for critical infrastructure systems.

Javadinasab Hormozabad et al. [101] review recent advances in integrating structural control, SHM, and energy harvesting for smart city infrastructure. The study highlights the importance of developing adaptive, resilient systems capable of self-diagnosis, self-powering, and self-healing. Integrated structural control and health monitoring (ISCHM) systems are emphasized as key innovations for enhancing resilience by reducing dynamic responses and enabling rapid damage detection. The paper discusses significant developments and identifies future research areas for designing autonomous ISCHM systems, paving the way for resilient, adaptive infrastructure in smart cities.

AI offers advanced capabilities in SHM to enhance resilience and adaptability, using real-time data analysis to detect stress, material fatigue, and environmental impacts early on. AI-driven SHM systems process vast sensor data, identifying potential issues before they escalate. Predictive models simulate future scenarios, enabling engineers to proactively address vulnerabilities. AI also supports adaptive infrastructure by adjusting structural properties like stiffness or damping in response to environmental stimuli, optimizing performance and safety. This real-time control reduces maintenance needs and extends service life through condition-based strategies.

The integration of AI into SHM facilitates smarter, adaptive infrastructure capable of handling both immediate and long-term challenges. By enhancing monitoring, predictive analysis, and control, AI helps maintain safer, more durable structures. As infrastructure demands grow and environmental risks intensify, AI-driven SHM will play a critical role in creating resilient, efficient, and future-proof systems.

Fan et al. [102] examine the use of ML in reinforced concrete bridge engineering, focusing on how ML enhances resilience through improved design, construction quality management, and inspection. The study highlights ML techniques applied to the form-finding of long-span structures, structural reinforcement, and optimization, illustrating ML's capacity to manage complex engineering data. This review shows that ML is driving new research directions in resilient bridge engineering, promoting adaptive and durable infrastructure solutions.

Martakis et al. [103] explore the fusion of damage-sensitive features using ML techniques to enhance the resilience and adaptability of SHM systems. By combining gradient-boosted decision trees and CNNs, the study improves damage classification accuracy. The domain-adversarial neural network (DANN) framework enables effective knowledge transfer from simulations to real-world data, even with limited healthy-state data. The approach demonstrates robust predictive performance, highlighting its potential for adaptive, resilient SHM applications in varying structural configurations.

## 4. Ethical and Societal Implications of AI in SHM

As AI continues to advance and integrate into various sectors, its application in SHM brings both remarkable opportunities and complex ethical and societal challenges [104]. SHM plays an essential role in ensuring the safety, reliability, and longevity of infrastructure, directly affecting public safety, economic stability, and environmental sustainability. Traditionally, the responsibility for monitoring and maintaining infrastructure has been entrusted to engineers and technical professionals, who apply their expertise to analyze data, make informed decisions, and execute maintenance strategies. These processes have historically relied on human judgment and ethical responsibility, grounded in public trust, as infrastructure is vital to the well-being of millions of people.

However, as AI-driven SHM systems become more widespread, ethical concerns emerge, particularly regarding the balance of automation, human oversight, and societal impact [105]. One of the primary ethical questions is related to data privacy [106]. AI-powered SHM systems collect massive amounts of data, not only about structural conditions but also environmental, operational, and, in some cases, personal data, especially in the context of smart city infrastructures [107]. This raises important questions about how these data are collected, stored, used, and protected. The sheer volume of data being processed by AI systems increases the risk of misuse or unauthorized access, posing a significant challenge to privacy and security. Policymakers and industry leaders must address how to safeguard sensitive information while maintaining the efficiency and effectiveness of AI-based SHM systems.

Another major ethical consideration involves transparency [108] and accountability [109]. AI algorithms, while highly efficient, often function as "black boxes", making decisions based on complex patterns and models that may not be easily explainable. In the context of SHM, this can lead to questions about responsibility. For instance, if an AI system fails to detect a critical structural defect or issues an incorrect maintenance recommendation, it may not be clear whether the fault lies with the technology, the engineers overseeing it, or the organizations deploying it. This ambiguity could create challenges in assigning accountability, especially when human lives and public safety are at stake. Ensuring transparency in how AI systems make decisions and providing explainable AI (XAI) models [110,111] are critical steps toward addressing this issue. The topic of explainable AI has recently gained attention in the fields of construction [112] and SHM [113] as well.

The societal implications of AI integration in SHM also extend to the potential displacement of skilled labor [114]. Traditionally, infrastructure monitoring and maintenance have required the expertise of engineers and technicians who physically inspect structures, interpret data, and make decisions. As AI automates more of these processes, the demand for manual inspections and human decision-making could decrease, leading to concerns about job displacement. While AI promises to enhance efficiency and reduce human error, it also risks marginalizing the role of skilled workers in infrastructure management, potentially leading to a shift in the workforce. Policymakers and industry stakeholders must consider strategies for retraining and reskilling workers to ensure that technological advancements benefit society as a whole rather than leading to widespread unemployment in technical fields.

The increasing reliance on AI-driven SHM systems raises concerns about overdependence on technology. While AI significantly improves accuracy and speed in detecting structural anomalies and predicting maintenance needs, it can also diminish the role of human intuition and expertise in decision-making. Research has shown that excessive trust in automated systems may lead to automation bias, where users are more likely to overlook their own assessments or fail to challenge AI-generated decisions [115,116]. Striking a balance between AI-driven automation and human oversight is essential to ensure responsible and safe infrastructure management [117].

As AI technology advances globally, there is a growing concern that wealthier, technologically advanced countries may harness its benefits more effectively, widening the gap between developed and underdeveloped nations [118]. This disparity can lead to increased inequalities in economic growth, access to AI-driven solutions, and technological progress. Similarly, in the context of AI applied to SHM, there is a risk that wealthier regions may benefit disproportionately from enhanced infrastructure monitoring, while underdeveloped or resource-constrained areas are left behind. This could exacerbate existing inequalities in infrastructure safety and quality, further deepening the divide between well-resourced urban centers and vulnerable, underfunded regions. Addressing this concern requires a concerted effort to make AI-driven SHM solutions accessible and affordable for all, ensuring that the benefits of these technologies are distributed equitably.

The integration of AI into SHM introduces a range of ethical and societal challenges that must be carefully managed. While AI offers significant advantages in terms of efficiency, accuracy, and predictive capabilities, it also raises important questions about data privacy, accountability, labor displacement, and equity. Addressing these concerns is essential for the responsible and ethical deployment of AI in any context [119], and infrastructure management is not an exception. To ensure public trust and maximize the societal benefits of AI, policymakers, engineers, and industry leaders must work together to develop clear guidelines, transparency mechanisms, and strategies for addressing the ethical implications of AI-driven SHM systems. By doing so, AI can be harnessed to create safer, more resilient infrastructure while upholding ethical standards and fostering social equity.

## 5. The Future of AI in SHM for Infrastructure Maintenance and Safety

The future of AI in SHM for infrastructure maintenance and safety looks promising, fueled by advances in technologies like IoT, modern sensor systems, real-time data analytics, and 5G connectivity. These innovations are set to boost the efficiency, accuracy, and flexibility of SHM systems, paving the way for smarter infrastructure management. In the following sections, we highlight eight emerging trends in AI-integrated SHM that show great potential for shaping the next generation of monitoring solutions.

### *5.1. Integration with IoT and IoT-Enabled Sensors*

One of the most significant advancements on the horizon is the deeper integration of AI with IoT-enabled sensors. IoT refers to the network of interconnected devices that can communicate and exchange data in real-time. By embedding IoT-enabled sensors across infrastructure assets, SHM systems will be able to collect an unprecedented volume of real-time data related to stress, strain, vibrations, temperature, humidity, and other environmental factors. These sensors can be deployed in remote or hard-to-reach areas, continuously transmitting data to central AI systems for analysis. AI will process this real-time data, enabling near-instant decision-making, detecting anomalies as they happen, and providing immediate alerts for maintenance or repairs. The combination of AI and IoT will allow for the creation of fully autonomous SHM systems that can operate without human intervention, enhancing both the scope and reliability of infrastructure monitoring.

### *5.2. Drones and Autonomous Inspection Technologies*

Drones and autonomous vehicles will play an even greater role in the future of SHM. Currently, drones are already being used for visual inspections and collecting data from hard-to-reach areas [5,96]. In the future, these drones will be equipped with more advanced AI-powered systems that allow them to autonomously conduct detailed structural assessments, using advanced imaging technologies like LiDAR, thermal sensors, and high-resolution cameras. AI algorithms will analyze the collected data in real-time, identifying defects such as cracks, corrosion, or material fatigue. This capability will further reduce the need for manual inspections, enhance the frequency of inspections, and improve safety for human workers, especially in hazardous environments like high bridges, skyscrapers, and offshore structures.

Today's systems typically rely on cloud-based solutions for data processing and analysis. However, future advancements will see drones equipped with more sophisticated AI capabilities, enabling fully autonomous operations with onboard data analysis. Such self-contained drones would eliminate the need for server connections, making them ideal for inspecting remote or isolated infrastructure, reducing manual labor, and increasing inspection frequency and safety in hazardous environments.

### *5.3. Advanced Sensor Technologies and Fiber Optic Sensors*

The next generation of SHM will make use of cutting-edge sensor technologies, including fiber optic sensors [120]. These sensors are capable of providing continuous real-time data on strain, temperature, and other structural parameters with exceptional sensitivity [121]. Fiber optic sensors are ideal for monitoring large-scale infrastructure such as bridges, dams, and tunnels because of their durability, precision, and ability to cover long distances. In the future, AI systems will process data from these sensors in real time, allowing for early detection of anomalies and providing insights into long-term structural behavior. As sensor technologies become more sophisticated, AI-powered SHM systems will be able to monitor infrastructure health with greater accuracy, providing more nuanced and actionable insights.

### *5.4. Real-Time Monitoring and Early Warning Systems*

Future SHM systems will not only focus on continuous monitoring but also on the integration of real-time early warning systems. By utilizing AI, real-time data from sensors, and predictive analytics, these systems will be capable of forecasting potential failures with even greater accuracy. For instance, in seismic-prone areas, AI models could predict the impact of earthquakes on buildings and bridges, triggering early warnings for evacuation or emergency response [122]. This real-time analysis will allow for dynamic risk mitigation strategies, helping to prevent infrastructure disasters before they occur.

### *5.5. The Role of Digital Twins in SHM*

Digital twins—virtual replicas of physical assets—are expected to play a significant role in the future of SHM [123]. These digital models will be continuously updated with real-time data from sensors embedded in physical structures, allowing AI to simulate different scenarios, analyze the structure's response to various stressors, and predict future performance. By integrating AI and DTs, SHM systems will be able to simulate the long-term effects of environmental factors, loading conditions, and maintenance activities, providing highly accurate predictions of when and where damage is likely to occur. This will revolutionize the planning and execution of infrastructure maintenance, ensuring that repairs are made proactively rather than reactively. Efforts to integrate DTs with SHM and AI are ongoing [124], although challenges in merging traditional SHM systems with DT platforms remain a focus of research [125].

### 5.6. Advanced Data Analytics and Blockchain for Data Integrity

SHM systems generate vast amounts of data, requiring advanced analytics to uncover patterns and correlations essential for identifying structural risks and failures. Techniques such as DL and advanced ANNs enhance the accuracy and efficiency of SHM by enabling precise analysis of complex datasets. However, managing and storing the terabytes of data produced daily by IoT-enabled devices and real-time monitoring systems presents significant challenges. Traditional storage infrastructures often struggle with scalability, cost, and retrieval speed. Emerging solutions, including cloud-based systems, distributed architectures, and advanced compression techniques, show promise but raise concerns about data accessibility, latency, and security. Future research must address these trade-offs to ensure that storage systems can meet the increasing demands of SHM applications.

Blockchain technology offers a complementary solution by ensuring data integrity and security [126]. It provides an immutable, tamper-proof record of sensor data, safeguarding maintenance logs and enhancing transparency in large-scale projects [127]. When integrated with AI, blockchain can validate data integrity in real time during large-scale processing, preventing data tampering or loss. This combination can strengthen SHM systems, making them more reliable and resilient as they evolve to manage growing data volumes from sensors, drones, and IoT devices.

### 5.7. Fifth-Generation Cellular Network Technology and Enhanced Connectivity for SHM

The rollout of 5G networks [128] will greatly enhance the capabilities of AI-powered SHM systems. Fifth-generation networks' ultra-low latency and high-speed connectivity will allow for real-time data transmission from IoT-enabled sensors, drones, and other devices, even in remote locations [129]. This enhanced connectivity will facilitate the seamless integration of vast sensor networks and enable AI to process data in real time, significantly improving the speed and responsiveness of SHM systems. With 5G networks, AI-driven SHM systems will be able to monitor large-scale infrastructure with unprecedented efficiency, providing instant feedback on structural health and facilitating immediate intervention when needed.

### 5.8. Large-Scale SHM and AI-Driven Maintenance Systems

As AI and related technologies advance, the scope of SHM systems will expand to cover entire cities or regions through centralized AI platforms. Large-scale SHM systems [130] will continuously monitor multiple infrastructure assets—such as bridges, roads, tunnels, and buildings—simultaneously, analyzing data from thousands of sensors in real time. AI-powered platforms will provide infrastructure managers with a comprehensive overview of the health and condition of all critical assets, allowing for coordinated, city-wide maintenance strategies. This will transform urban planning and infrastructure management, creating smarter, safer, and more resilient cities in the future.

## 6. Conclusions

AI is reshaping SHM, driving advancements in the maintenance, safety, and resilience of infrastructure systems. By processing large volumes of real-time data, identifying patterns, and predicting structural behavior, AI enables more efficient and proactive management compared to traditional methods. This review underscores AI's significant contributions across key SHM areas, such as optimizing sensor networks, automating data processing, and enabling precise anomaly detection and damage identification.

AI's role in predictive maintenance is particularly transformative, allowing infrastructure managers to transition from reactive or time-based strategies to efficient, condition-based approaches. By accurately forecasting failures, AI-driven systems optimize resource allocation, reduce unnecessary repairs, and extend asset lifespans. Additionally, AI enhances structural reliability and risk assessment by modeling complex behaviors and integrating diverse datasets, enabling engineers to better anticipate and mitigate risks.

As infrastructure systems face challenges such as climate change, aging materials, and extreme events, AI's predictive and adaptive capabilities will become increasingly critical. These technologies offer opportunities to ensure resilience and sustainability, enabling infrastructure to withstand dynamic environmental conditions and perform efficiently over time.

Ethical and societal considerations, however, must accompany these advancements. Issues surrounding data privacy, transparency, accountability, and equitable access to AI-driven SHM solutions must be addressed to prevent regional disparities and ensure responsible integration. Balancing automation with human oversight remains vital to maintain trust and effectiveness.

Looking ahead, integrating emerging technologies such as IoT, 5G networks, blockchain, and advanced sensors with AI will shape the next generation of SHM systems. These innovations will provide real-time insights into infrastructure health, enhancing failure prevention, optimizing maintenance, and ensuring longer service lives.

AI offers unprecedented opportunities to revolutionize SHM, improving the safety, efficiency, and longevity of infrastructure. By addressing its ethical implications and embracing its transformative potential, AI can help build smarter, more resilient systems capable of meeting society's future needs.

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## Abbreviations

| | |
|---|---|
| AI | Artificial intelligence |
| ANN | Artificial neural network |
| CH | Cultural heritage |
| CNN | Convolutional neural network |
| DANN | Domain-adversarial neural network |
| DL | Deep learning |
| DRL | Deep reinforcement learning |
| DT | Digital twin |
| EMD | Empirical mode decomposition |
| FE | Finite element |
| GAN | Generative adversarial network |
| IoT | Internet of Things |
| ISCHM | Integrated structural control and health monitoring |
| MAC | Modal assurance criterion |
| MDP | Markov decision process |
| ML | Machine learning |
| OSP | Optimal sensor placement |

| | |
|---|---|
| PCA | Principal component analysis |
| PdM | Predictive maintenance |
| RL | Reinforcement learning |
| SHAP | Shapley additive explanations |
| SHM | Structural health monitoring |
| W3C | World Wide Web Consortium |
| WSN | Wireless sensor network |
| WSSN | Wireless smart sensor networks |

## Appendix A

In this appendix, we present the thesaurus file used for data cleaning in the VOSviewer [32] analysis of keywords related to SHM and AI. The thesaurus file plays a crucial role in standardizing the terminology used across the dataset, allowing for more accurate co-occurrence analysis and network mapping. By replacing variations and synonyms of keywords with a single, consistent label, the thesaurus file helps to eliminate redundancy and enhance the clarity of the resulting keyword network.

The table below lists the original keyword labels (in the "label" column) and their standardized replacements (in the "replace by" column), as used in the VOSviewer software for the analysis. This approach ensures that closely related terms were grouped together, providing a more cohesive view of the research landscape. The complete thesaurus file is presented in Table A1.

**Table A1.** Thesaurus file for standardizing keyword labels in VOSviewer analysis.

| Label | Replace by |
|---|---|
| acoustic-emissions | acoustic emission |
| artificial neural networks | neural networks |
| bridges | bridge |
| concretes | concrete |
| convolution | convolutional neural network |
| convolutional neural networks | convolutional neural network |
| damage identification | damage detection |
| features extraction | feature extraction |
| health monitoring | structural health monitoring |
| label | replace by |
| learning systems | learning algorithms |
| machine learning algorithms | machine learning |
| machine learning techniques | machine learning |
| machine-learning | machine learning |
| neural-networks | neural networks |
| shm | structural health monitoring |
| structural damage detection | damage detection |
| structural damages | structural damage |
| structural health | structural health monitoring |
| structural health monitoring (shm) | structural health monitoring |
| structural health monitoring s | structural health monitoring |
| structural health monitoring systems | structural health monitoring |
| ultrasonic guided wave | ultrasonic waves |
| vibration analysis | vibration |

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