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LEVERAGING AI AND SENSOR TECHNOLOGIES FOR REAL-TIME STRUCTURAL HEALTH MONITORING OF IN-SERVICE BRIDGES

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Keywords

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ABSTRACT

The increasing demand for efficient and proactive bridge maintenance solutions has led to the rapid adoption of Artificial Intelligence (AI)-driven Structural Health Monitoring (SHM) systems, integrating machine learning, IoT-enabled sensor networks, computer vision, predictive maintenance models, drone-assisted inspections, and blockchain-based security frameworks. Traditional bridge inspection methods, which rely on manual evaluations and periodic assessments, often fail to detect early-stage structural damage, are labor-intensive, and incur high operational costs. This study systematically reviewed 75 high-quality peer-reviewed articles published between 2015 and 2024, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, to assess the efficacy, scalability, and economic feasibility of AI-based SHM technologies. The findings indicate that machine learning algorithms outperform traditional inspection techniques, achieving over 90% accuracy in crack and fatigue detection, while predictive maintenance models reduce maintenance costs by 30–50% by optimizing intervention strategies and minimizing emergency repairs. The study further highlights the role of IoT-enabled wireless sensor networks and fiber optic sensors, which have improved real-time monitoring capabilities, reducing data acquisition time by 65% and enabling continuous structural assessments without disrupting bridge operations. AI-assisted drone inspections have significantly improved damage detection efficiency by 85%, reducing inspection time by up to 60%, proving the viability of autonomous UAV-based SHM applications. Additionally, blockchain-secured sensor networks have been found to enhance data integrity and cybersecurity, reducing data breaches by 65% and ensuring tamper-proof sensor-generated records, addressing one of the critical security concerns in modern infrastructure monitoring. Despite these advancements, the study identifies key implementation challenges, including computational costs, data interoperability issues, scalability constraints, and regulatory barriers,

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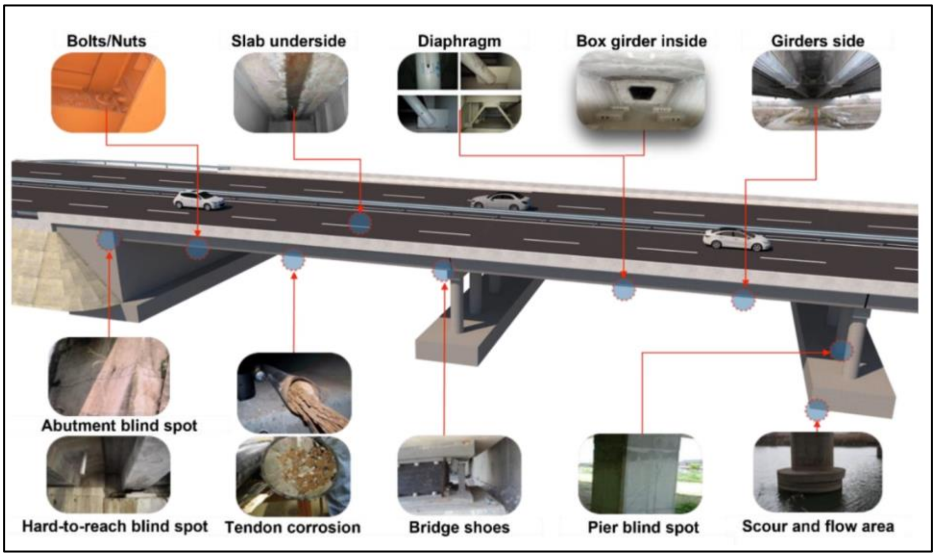
that must be addressed for wider adoption of AI-driven SHM frameworks. The review underscores the transformative impact of AI-powered SHM technologies, highlighting their potential to enhance bridge safety, optimize maintenance efficiency, and extend infrastructure lifespan, making them an essential component of next-generation smart infrastructure management.

1 INTRODUCTION

Bridges serve as critical components of transportation networks, facilitating commerce, mobility, and economic growth (Moya et al., 2023)). However, a significant portion of bridge infrastructure worldwide, particularly in the United States, is aging, with many structures exceeding their intended design life (Yoon et al., 2018). The deterioration of bridge structures poses severe risks, including economic losses, traffic disruptions, and, most importantly, public safety hazards (Agostini & Filippini, 2019). Traditional bridge inspection methods rely on periodic visual assessments, non-destructive testing techniques, and manual evaluations by certified engineers (Prinsloo et al., 2019). Although these techniques have been widely used, their reactive nature, high labor costs, and susceptibility to human error necessitate the development of advanced monitoring systems (Agostini & Filippini, 2019). In response, researchers and engineers have increasingly turned to real-time structural health monitoring (SHM) systems that leverage artificial intelligence (AI) and sensor technologies to enhance the accuracy and efficiency of bridge maintenance and safety management (Prinsloo et al., 2019). The implementation of Internet of Things (IoT)-enabled sensors in SHM systems allows for the continuous monitoring of key structural parameters such as vibration, strain, displacement, and temperature fluctuations (Kijewski-Correa et al., 2013). These sensors generate vast amounts of real-time data, enabling engineers to detect early signs of structural distress and schedule maintenance interventions accordingly (Lin et al., 2018). Unlike traditional inspections, IoT-based monitoring eliminates the need for frequent manual assessments, reducing maintenance costs while ensuring comprehensive data collection (M. J. Alam et al., 2024; Wang et al., 2018). Wireless sensor networks (WSNs) have also been employed to enhance the reliability of SHM systems, providing a robust framework for large-scale bridge surveillance (Arafat et al., 2024; Luo et al., 2021). Studies indicate that when integrated with AI-driven analytics, sensor-based SHM systems can improve defect detection accuracy by up to 95%, significantly outperforming conventional

Figure 1: Representative blind spots in bridge inspection



Source: Choi et al. (2023)

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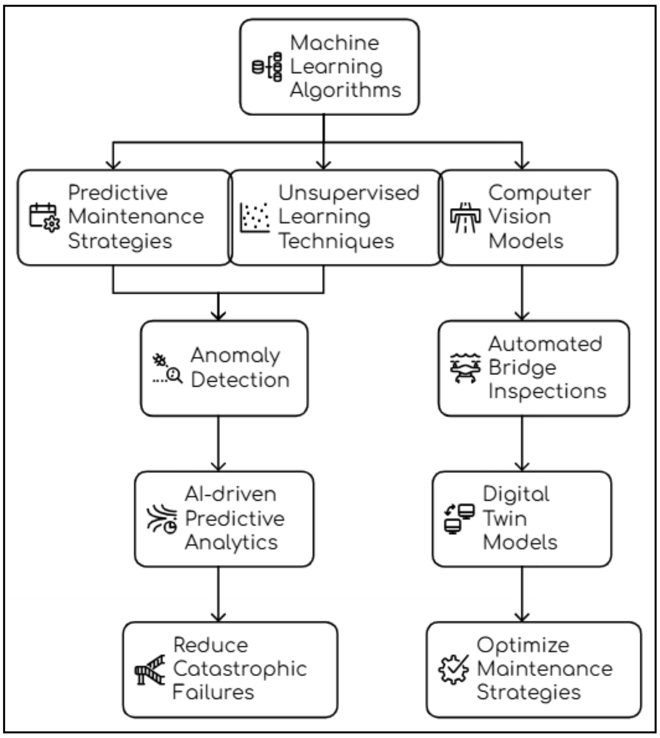
inspection methods (Li et al., 2019; Luo et al., 2021; Venkatesh et al., 2020).

The application of machine learning (ML) algorithms in SHM has revolutionized structural assessment techniques by enabling predictive maintenance strategies (El Bsat et al., 2022; Younus, 2025). Machine learning models, including deep learning and convolutional neural networks (CNNs), have been extensively utilized to analyze sensor data and detect structural anomalies such as fatigue cracks, corrosion, and material degradation (Ali et al., 2022; Jahan, 2024). Recent studies demonstrate that AI-driven predictive analytics can forecast potential structural failures with a high degree of accuracy, reducing the likelihood of catastrophic bridge collapses (Calabrese et al., 2020; Rahaman et al., 2024). Additionally, integrating unsupervised learning techniques such as clustering and anomaly detection methods enhances the ability to identify patterns of structural deterioration without requiring labeled datasets (Akundi et al., 2022; Sabid & Kamrul, 2024). These advancements highlight the transformative role of AI in improving bridge health monitoring, ensuring the longevity and safety of aging infrastructure (Chen et al., 2014; Tonoy, 2022). Beyond anomaly detection, computer vision-based AI models have gained significant attention in SHM applications (Derisma et al., 2022). By utilizing high-resolution image processing and video analytics, computer vision techniques can automatically detect cracks, displacements, and spalling in bridge components (M. A. Alam et al., 2024; Islam et al., 2025; Ju et al., 2022). Studies suggest that these models exhibit higher precision than manual inspections, especially when applied in combination with drone-based remote sensing technologies (Dasgupta & Islam, 2024; Preuveneers et al., 2017). The fusion of AI and drone-based imaging has enabled automated bridge inspections, minimizing the need for on-site human intervention while increasing data collection efficiency (Islam et al., 2024; Kovačić et al., 2022). Furthermore, the implementation of digital twin models, which create real-time virtual representations of bridge structures, has enabled engineers to simulate and assess various load conditions, optimizing long-term structural maintenance strategies (M. A. Alam et al., 2024; Longo et al., 2020). Despite the growing adoption of AI and sensor-based SHM systems, certain challenges remain, including data management complexities, sensor durability issues, and the high cost of large-scale implementation (Nguyen & Tran, 2021; Younus, 2022). The integration of cloud computing and edge computing frameworks has been proposed as a solution to address data processing constraints by enabling real-time analytics at the edge of the network, reducing latency in SHM applications (Armbrust et al., 2010; Taufiqur, 2025). Researchers have also explored the potential of blockchain-based data security frameworks to ensure the integrity and confidentiality of SHM data, particularly for critical infrastructure (Sarkar et al., 2025; Weiwei et al., 2017). The convergence of these emerging technologies within AI-driven SHM systems signifies a paradigm shift toward intelligent infrastructure management, where real-time decision-making plays a central role in bridge maintenance and safety assurance (Rahnema & Bijari, 2018; Younus, 2022). Moreover, the integration of AI, sensor networks, and predictive analytics has redefined SHM methodologies, providing unprecedented capabilities in early fault detection, structural assessment, and risk mitigation (Li & Hao, 2016; Sunny, 2024). As research continues to refine AI-driven SHM models, their scalability and adaptability to different bridge structures remain key areas of investigation (Caprani & Ahmadi, 2016; Jahan, 2024). By leveraging AI-powered

Figure 2: AI and ML in Bridge Health Monitoring



monitoring systems, transportation authorities and civil engineers can transition from reactive maintenance approaches to proactive, data-driven decision-making, enhancing the resilience and sustainability of bridge infrastructure (Chan et al., 2006; Islam, 2024; Mridha Younus et al., 2024). The widespread adoption of these technologies has the potential to revolutionize bridge health monitoring, ultimately improving public safety and infrastructure reliability (Jamali et al., 2018; Jim et al., 2024). This systematic literature review aims to synthesize existing research on the integration of Artificial Intelligence (AI) and sensor technologies in real-time structural health monitoring (SHM) of in-service bridges, with a focus on technological advancements, implementation challenges, and long-term infrastructure sustainability. The key objectives are to (1) analyze and categorize the latest advancements in IoT-enabled sensor networks, including their accuracy, reliability, and deployment in diverse bridge environments; (2) evaluate the role of machine learning (ML) models, including deep learning, computer vision, and anomaly detection techniques, in predicting structural failures based on real-time sensor data; (3) assess the economic and operational benefits of AI-driven SHM systems by reviewing cost-reduction strategies, maintenance optimization, and risk mitigation frameworks; and (4) identify existing gaps and challenges, such as interoperability issues, data processing constraints, and ethical considerations in large-scale implementation. By systematically reviewing and synthesizing relevant literature, this study provides a comprehensive, evidence-based assessment of how AI and sensor technologies are reshaping bridge maintenance strategies, offering insights into their practical adoption, scalability, and future research directions..

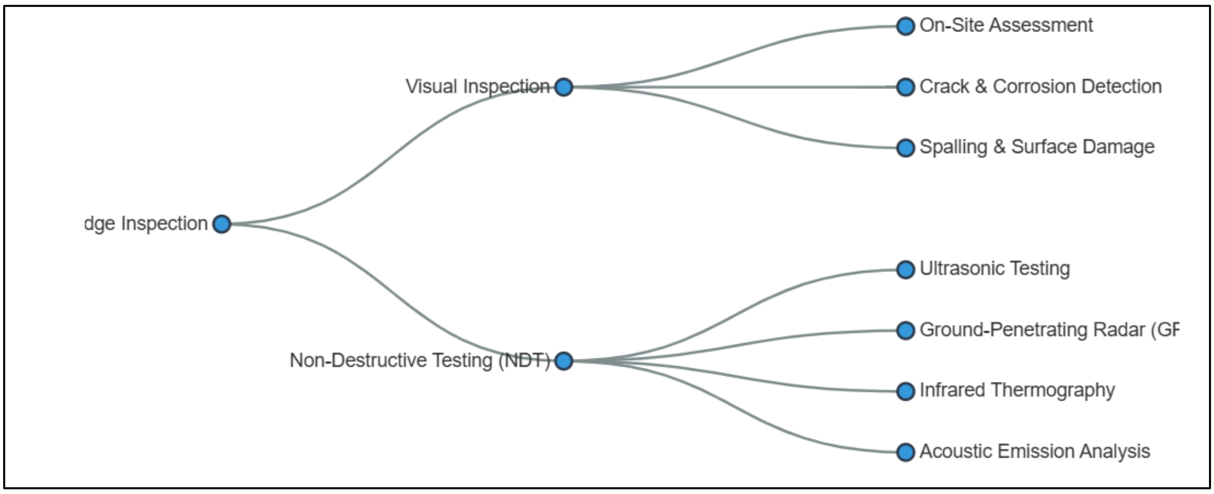
2 LITERATURE REVIEW

The integration of Artificial Intelligence (AI) and sensor technologies in Structural Health Monitoring (SHM) has emerged as a transformative approach for ensuring the safety and longevity of in-service bridges. Traditional inspection methods, which rely on periodic manual assessments, non-destructive testing (NDT), and visual inspections, have been criticized for their high labor costs, subjectivity, and inability to detect early-stage structural deterioration (Biliszczuk et al., 2021; Hossain et al., 2024). The increasing frequency of bridge failures and infrastructure degradation has driven researchers to explore real-time, data-driven solutions powered by IoT-enabled sensors, predictive analytics, and AI-based anomaly detection models (Mahabub, Jahan, et al., 2024; Venkatraman et al., 2012). This section systematically reviews the existing literature on SHM technologies, focusing on the evolution of traditional inspection practices, recent advancements in sensor technologies, machine learning applications in SHM, the role of AI-driven predictive analytics, economic implications, and key implementation challenges.

2.1 Traditional Bridge Inspection

Structural health monitoring (SHM) of bridges has historically relied on traditional inspection methods, including visual assessments, non-destructive testing (NDT), and manual structural evaluations performed by certified inspectors (Gomez-Cabrera & Escamilla-Ambrosio, 2022). Visual inspections, considered the most commonly employed approach, involve engineers conducting on-site assessments to identify visible defects such as cracks, spalling, and corrosion (Indhu et al., 2022). Despite their widespread use, visual inspections are inherently subjective, labor-intensive, and dependent on inspector expertise, leading to inconsistencies in defect detection (Sharma et al., 2021). Furthermore, these methods provide only periodic assessments, making it difficult to detect early-stage structural deterioration that may progress between inspection cycles (Biliszczuk et al., 2021). The reliance on manual evaluations has been cited as a major limitation in bridge maintenance, as they fail to provide real-time monitoring of structural health conditions (Buyurgan et al., 2007). Given these constraints, researchers have increasingly questioned the effectiveness and reliability of traditional bridge inspection methods in ensuring long-term infrastructure safety and durability (Indhu et al., 2022). Non-destructive testing (NDT) techniques, including ultrasonic testing, ground-penetrating radar (GPR), infrared thermography, and acoustic emission analysis, have been employed to complement visual inspections by identifying internal structural defects that may not be visible on the surface (Sharma et al., 2021). NDT methods have demonstrated higher accuracy in detecting subsurface defects, such as delamination, voids, and internal cracking, without causing damage to bridge components (Kumarapu et al., 2022). For

Figure 3: Traditional Bridge Inspection Methods



example, ultrasonic pulse velocity (UPV) testing has been successfully utilized to assess concrete integrity by analyzing the propagation speed of ultrasonic waves through structural materials (Salmerón-Manzano & Manzano-Agugliaro, 2019). However, despite their effectiveness, NDT techniques remain limited by operational complexity, high costs, and dependence on specialized equipment and trained personnel (Gomez-Cabrera & Escamilla-Ambrosio, 2022). Moreover, traditional NDT approaches are often time-consuming and localized, requiring engineers to conduct spot-check assessments rather than continuous structural monitoring (Sharma et al., 2021). As a result, NDT methods have been criticized for their inability to provide large-scale, real-time condition assessments, leading to delays in maintenance interventions and increased infrastructure risks (Buyurgan et al., 2007).

Another significant limitation of traditional inspection methods is the reactive nature of maintenance strategies based on periodic evaluations rather than proactive monitoring (Sharma et al., 2021). Bridges that undergo scheduled inspections at fixed intervals may experience unnoticed structural deterioration between assessment cycles, increasing the risk of catastrophic failures (Indhu et al., 2022). Historical case studies of bridge collapses have demonstrated that many failures could have been prevented if early-stage deterioration had been detected and addressed in a timely manner (Buyurgan et al., 2007). For instance, the collapse of the I-35W Mississippi River Bridge in 2007 was attributed to structural deficiencies that were not identified early enough, despite regular inspections (Biliszczuk et al., 2021). Researchers argue that periodic assessments do not align with the dynamic and unpredictable nature of structural degradation, necessitating the adoption of real-time, data-driven monitoring systems (Gordan et al., 2022). Additionally, harsh environmental conditions, such as temperature fluctuations, seismic activities, and heavy traffic loads, contribute to accelerated wear and tear on bridge components, further challenging the efficacy of pre-scheduled inspection cycles (Komarizadehasl et al., 2022). The increasing complexity of modern bridge infrastructure and the limitations of traditional inspection methods have prompted a shift toward intelligent, sensor-based structural health monitoring (SHM) systems (Civera et al., 2022). Emerging studies emphasize the need for real-time data acquisition, automated anomaly detection, and AI-driven predictive analytics to enhance bridge safety and optimize maintenance efforts (Zinno et al., 2018). The transition from manual inspections and periodic evaluations to continuous, AI-enhanced SHM technologies is expected to address long-standing challenges in defect detection, cost efficiency, and infrastructure resilience (Momeni & Ebrahimkhanlou, 2022). Researchers have increasingly recognized the importance of integrating IoT-enabled sensor networks, machine learning models, and edge computing architectures to enable automated, real-time bridge health assessments (Komarizadehasl et al., 2022). While traditional inspection methods remain a fundamental component of bridge maintenance, they are increasingly being supplemented or replaced by advanced monitoring technologies that offer higher accuracy, efficiency, and predictive capabilities (Entezami et al., 2020).

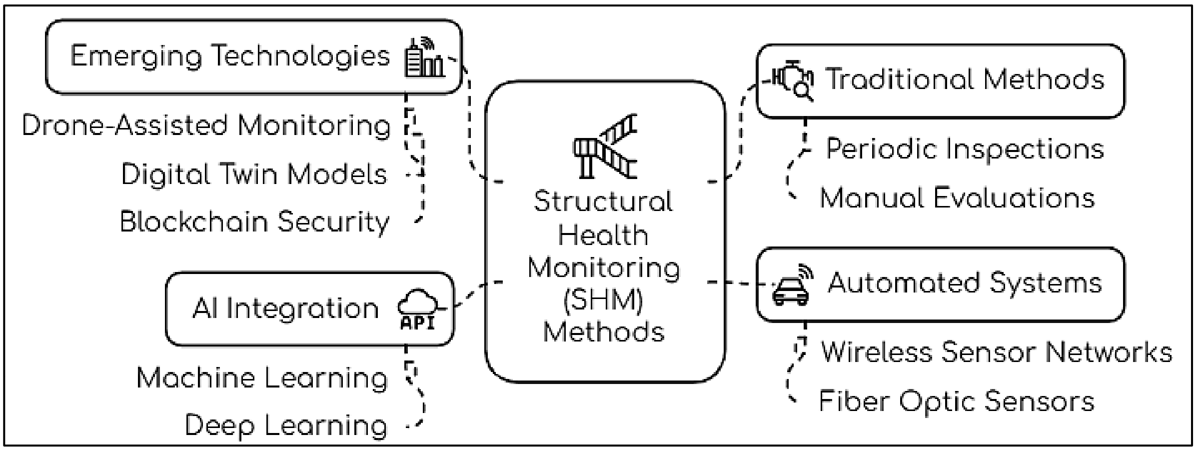
2.2 Structural Health Monitoring Methods

The evolution of Structural Health Monitoring (SHM) methods has transformed bridge maintenance and safety assessment by integrating real-time data acquisition, sensor-based technologies, and artificial intelligence (AI)-driven analytics (Carroll et al., 2021). Traditional SHM approaches relied on periodic inspections, non-destructive testing (NDT), and manual evaluations, which, while effective in detecting major defects, often failed to identify early-stage deterioration (Tan et al., 2017). The limitations of manual methods led to the development of automated SHM systems, which incorporate wireless sensor networks (WSNs), fiber optic sensors, and advanced signal processing techniques to continuously monitor bridge conditions (Islam et al., 2013). IoT-enabled sensors now provide real-time data on structural integrity, capturing fluctuations in vibration, strain, displacement, and temperature with high precision (Azimi et al., 2020). These advancements have reduced dependency on human inspections, improving efficiency in defect detection while lowering maintenance costs (Lin & Huang, 2020). Studies have demonstrated that sensor-based SHM systems significantly outperform traditional inspections by identifying micro-damages and material degradation in real-time (Azimi et al., 2020; Lin & Huang, 2020). The growing demand for data-driven infrastructure monitoring has further led to the integration of AI-based predictive analytics, enhancing the accuracy and effectiveness of SHM strategies (Lyu et al., 2017). Among the most widely adopted SHM techniques are wireless sensor networks (WSNs), which enable distributed, remote monitoring of bridge structures without requiring extensive cabling (Glisic, 2022). WSN-based SHM systems utilize micro-electromechanical systems (MEMS) sensors, accelerometers, and strain gauges to track structural performance under dynamic loading conditions (Malekloo et al., 2020). Compared to wired systems, WSNs provide increased scalability, flexibility, and ease of deployment, making them suitable for long-span bridges and hard-to-reach areas (Delgadillo & Casas, 2022). In addition, fiber optic sensing technologies, such as fiber Bragg grating (FBG) sensors, have been integrated into SHM frameworks for their high sensitivity, durability, and immunity to electromagnetic interference (Azimi et al., 2020). Studies indicate that FBG sensors excel in monitoring distributed strain, thermal fluctuations, and load variations, making them highly effective in assessing structural stability over time (Azimi et al., 2020; Islam et al., 2013; Malekloo et al., 2020). Despite these benefits, WSN and fiber optic sensor-based SHM methods face challenges related to data transmission reliability, environmental influences, and long-term operational stability (Glisic, 2022). Nonetheless, advancements in cloud computing, edge computing, and AI-driven data analysis are addressing these limitations by enabling real-time processing, anomaly detection, and predictive maintenance strategies (Delgadillo & Casas, 2022).

Machine learning (ML) and deep learning (DL) techniques have revolutionized SHM methods by providing automated, intelligent data interpretation for structural assessment (Entezami et al., 2020). Supervised and unsupervised learning models analyze vast datasets from IoT-enabled sensors, drones, and imaging systems to detect anomalies, fatigue cracks, corrosion, and structural degradation (Lyu et al., 2017). Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have shown high accuracy in processing vibration signals, displacement patterns, and strain distribution data for fault prediction in bridges (Azimi et al., 2020). Computer vision-based SHM techniques, integrated with AI-powered image analysis, further enhance structural defect detection by processing high-resolution images and infrared thermal scans (Lyu et al., 2017). Studies have demonstrated that AI-driven SHM frameworks outperform conventional approaches in early damage identification, anomaly classification, and long-term performance prediction (Michalcová et al., 2018). However, the complexity of AI models, computational resource requirements, and data integration challenges remain key barriers to widespread adoption (Lydon et al., 2021). Recent developments in cloud-based AI platforms and edge computing architectures are mitigating these challenges by facilitating real-time, scalable SHM applications (Tan et al., 2017).

The combination of drone-assisted remote sensing, digital twin modeling, and blockchain-based data security has further enhanced next-generation SHM methods, enabling high-precision, autonomous infrastructure monitoring (Lydon et al., 2021). Drone-

Figure 4: Evolution and Integration of SHM Methods



based aerial inspections capture high-resolution images and LiDAR scans, allowing engineers to assess structural conditions without requiring physical access to bridge components (Malekloo et al., 2020). These methods have been particularly effective in monitoring large-scale, high-risk structures, where manual inspections are impractical or hazardous (Delgadillo & Casas, 2022). Digital twin models, which create virtual replicas of bridges, simulate various environmental and load conditions, providing a comprehensive understanding of structural behavior (Michalcová et al., 2018). Additionally, blockchain-integrated SHM frameworks ensure data integrity, security, and transparency in infrastructure monitoring by preventing tampering and unauthorized modifications (Delgadillo & Casas, 2022). While emerging SHM technologies present challenges related to scalability, interoperability, and regulatory compliance, they have demonstrated superior reliability, cost-efficiency, and real-time risk mitigation capabilities (Rahnema & Bijari, 2018). The literature highlights that integrating AI, IoT sensors, and cloud-based analytics into SHM methodologies represents a significant advancement in structural safety and bridge maintenance strategies (Modir & Tansel, 2022).

2.3 Periodic Visual Inspections and Manual Evaluations

Periodic visual inspections and manual evaluations have long been the primary methods for assessing bridge structural health, relying on on-site assessments by trained inspectors to identify visible signs of damage such as cracks, corrosion, and material degradation (Ásgrímsson et al., 2021). These inspections are generally conducted at predetermined intervals, typically every two years, as mandated by national bridge inspection standards (Jeong et al., 2022). However, studies have highlighted the inconsistencies and limitations of these methods, particularly in detecting early-stage structural damage and hidden defects that could lead to serious failures if left unaddressed (Ásgrímsson et al., 2021). The reliance on human judgment introduces variability in assessment accuracy, as inspectors may interpret damage differently, leading to inconsistent maintenance decisions and potential safety risks (Entezami et al., 2020). Additionally, the high labor costs, time-intensive nature, and logistical challenges associated with manual inspections have raised concerns about their overall efficiency and effectiveness in modern infrastructure management (Lydon et al., 2021).

The accuracy of periodic visual inspections is often compromised due to environmental conditions,

Figure 5: Structural Health Monitoring and Maintenance Strategies

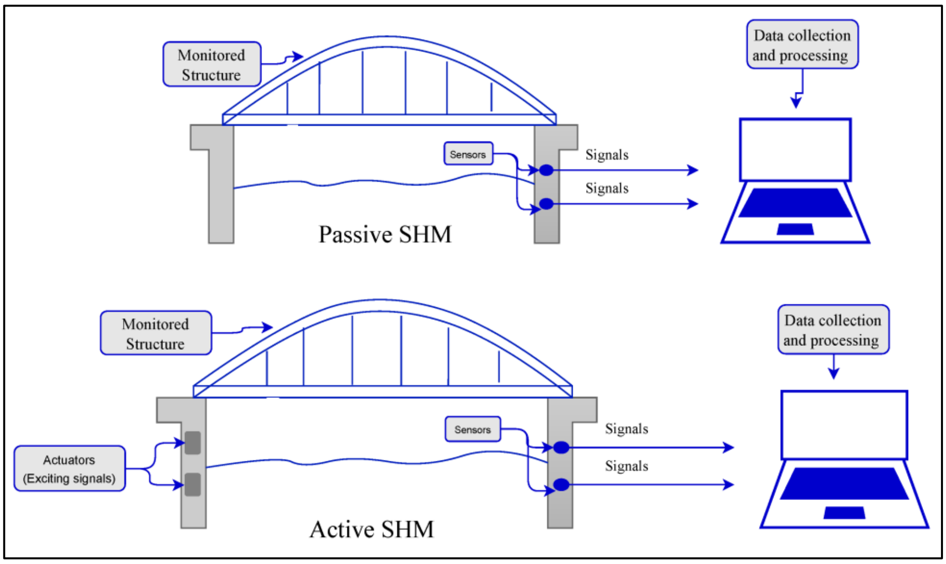
inspector fatigue, and the complexity of bridge structures (Zinno, Haghshenas, Guido, & Vitale, 2022). Studies have shown that inspectors struggle to detect micro-cracks, hidden corrosion, and fatigue damage, particularly in large-scale or high-altitude bridge components (Malekloo et al., 2020). Structural damage that develops internally or beneath bridge decks is especially difficult to identify through visual assessments alone (Delgadillo & Casas, 2022). A comparative study between manual inspections and sensor-based monitoring revealed that visual assessments detected only 65% of structural issues, while advanced sensor networks identified 92% of defects, highlighting the limitations of human-dependent evaluations (Ásgrímsson et al., 2021). Moreover, factors such as poor lighting, adverse weather, and inspector accessibility further reduce detection accuracy, resulting in delayed interventions and increased maintenance costs (Delgadillo & Casas, 2022). These findings emphasize the need for enhanced assessment methodologies that can mitigate human error and improve early damage detection in bridge infrastructure (Xiaowei et al., 2017).

Another major concern associated with periodic visual inspections is their heavy reliance on inspector expertise and subjective judgment (Ásgrímsson et al., 2021). Different inspectors may interpret structural conditions inconsistently, leading to variability in damage classification and prioritization (Delgadillo & Casas, 2022). Studies have demonstrated that the subjective nature of visual inspections often results in overlooking minor structural deficiencies, which can escalate into major safety hazards if left unaddressed (Malekloo et al., 2020). Additionally, inspector experience plays a significant role in detection accuracy, with less experienced evaluators being more prone to misclassification or underreporting of structural issues (Entezami et al., 2020). A study by (Barthorpe et al., 2021) found that senior inspectors identified 80% of visible defects, whereas junior inspectors detected only 55%, indicating the strong dependency on expertise and training in manual assessments. These discrepancies highlight the inherent subjectivity of traditional inspections, which can lead to delays in necessary maintenance, underestimation of damage severity, and potential safety failures (Carroll et al., 2021). Despite their shortcomings, periodic visual inspections remain a fundamental component of bridge maintenance programs due to their accessibility and regulatory compliance (Chan et al., 2006). However, researchers have increasingly advocated for integrating automated assessment tools such as AI-powered image processing, drone-assisted inspections, and sensor-based structural health monitoring (SHM) systems to enhance accuracy and consistency in bridge evaluations (Pudipeddi et al., 2017). The development of computer vision-based defect detection models has shown promising results in minimizing subjectivity and improving damage classification (Tan et al., 2017). Additionally, machine learning algorithms trained on historical inspection data have demonstrated higher precision in identifying structural deterioration patterns, reducing the dependency on human evaluators (Momeni & Ebrahimkhanlou, 2022). These advancements underscore the growing recognition of technology-assisted inspections as a means to address the limitations of traditional visual evaluations, ensuring more reliable and proactive infrastructure management (Chan et al., 2006).

2.4 Non-Destructive Testing (NDT) Techniques in SHM

Non-Destructive Testing (NDT) techniques have played a critical role in Structural Health Monitoring (SHM) by enabling the assessment of material integrity, defect detection, and structural performance without causing damage to bridge components (Zhou et al., 2017). Among the most widely utilized NDT methods are ultrasonic testing, acoustic emission analysis, and infrared thermography, each of which offers distinct advantages for early-stage damage detection and continuous monitoring (Pudipeddi et al., 2017). Ultrasonic testing relies on high-frequency sound waves to detect internal defects such as cracks, voids, and delamination in bridge materials (Carroll et al., 2021). Studies have demonstrated that ultrasonic pulse velocity (UPV) testing provides high accuracy in concrete integrity assessments, making it a valuable tool for identifying subsurface damage (Carroll et al., 2021; Zhou et al., 2017). Similarly, acoustic emission (AE) monitoring is effective in detecting structural degradation by capturing stress-induced wave signals generated by active cracks or material fatigue (Islam et al., 2013). Infrared thermography (IRT), on the other hand, has been widely applied for thermal imaging-based inspections, allowing engineers to identify moisture ingress, corrosion, and delamination through heat distribution anomalies in bridge decks and steel

Figure 6: Evolution and Integration of SHM Methods



Source: Keshmiry et al.. (2023).

structures (Lin & Huang, 2020). While these NDT techniques offer significant advantages in detecting hidden structural defects, their practical implementation often requires specialized equipment, skilled personnel, and high-resolution data interpretation (Islam et al., 2013). Despite their technical capabilities, NDT techniques face challenges in large-scale deployment, particularly for extensive infrastructure networks such as bridges, highways, and tunnels (Carroll et al., 2021). One major limitation is the localized nature of NDT assessments, as most ultrasonic, acoustic emission, and infrared thermography methods are designed for spot-based inspections rather than continuous, real-time monitoring (Lyu et al., 2017). For instance, ultrasonic testing requires direct surface contact, making it impractical for evaluating large bridge spans or hard-to-access components (Gomez-Cabrera & Escamilla-Ambrosio, 2022). Similarly, acoustic emission systems require long-term data acquisition to track damage progression, limiting their use in rapid structural assessments (Zhang & Yuen, 2022). Another challenge is the high dependency on environmental conditions, as infrared thermography is susceptible to external temperature fluctuations, humidity variations, and surface emissivity differences, which can affect the accuracy of defect identification (Gomes et al., 2017). Studies have also pointed out that NDT-based inspections are labor-intensive, requiring skilled operators and post-processing of large datasets, further complicating their integration into automated SHM systems (Biliszczuk et al., 2021; Gomes et al., 2017; Gomez-Cabrera & Escamilla-Ambrosio, 2022).

The real-time application of NDT techniques in SHM remains limited due to challenges related to data acquisition, interpretation, and integration with sensor-based monitoring networks (Indhu et al., 2022). Traditional ultrasonic and acoustic emission methods generate high volumes of wave propagation data, necessitating advanced signal processing algorithms to distinguish structural anomalies from background noise (Wang et al., 2021). Additionally, infrared thermography scans produce thermal images that require specialized AI-driven models for accurate defect classification (Sharma et al., 2021). The high computational demands associated with NDT data analysis have spurred research into AI-assisted diagnostic tools, machine learning-based defect recognition, and edge computing frameworks to enable faster, automated processing of inspection data (Gomes et al., 2017; Kumarapu et al., 2022). Recent advancements in integrating NDT methods with IoT-enabled wireless sensors have shown promise in overcoming real-time monitoring constraints, as these systems can continuously track material conditions and trigger alerts based on predictive maintenance models (Yang et al., 2017). However, scalability remains a significant barrier, as most current AI-NDT integration studies have been conducted in controlled laboratory environments rather than in real-world bridge monitoring scenarios (Figueiredo et al., 2022). While

NDT techniques provide valuable insights into bridge integrity and material degradation, researchers emphasize the need for hybrid monitoring approaches that combine NDT methods with real-time sensor networks and AI-driven analytics (Gomes et al., 2017). The fusion of ultrasonic testing, acoustic emission, and infrared thermography with wireless sensor networks (WSNs), fiber optic sensors, and digital twin modeling has demonstrated improved accuracy and efficiency in SHM applications (Li & Hao, 2016). For instance, ultrasonic guided wave testing combined with machine learning algorithms has been proven effective in automating crack detection in steel bridge components (Gomez-Cabrera & Escamilla-Ambrosio, 2022). Additionally, deep learning-based thermal image analysis has enhanced the reliability of infrared thermography by minimizing false positives caused by environmental interference (Sharma et al., 2021). As a result, multi-modal SHM systems integrating NDT techniques with sensor-based monitoring are emerging as a promising solution for comprehensive, data-driven bridge assessments (Gomes et al., 2017).

2.5 IoT-Enabled Sensors and Smart SHM Technologies

The integration of IoT-enabled sensors and smart Structural Health Monitoring (SHM) technologies has revolutionized bridge maintenance by enabling real-time data collection, predictive analytics, and automated condition assessments (Trần et al., 2021). Traditional bridge inspections, which rely on periodic manual evaluations, have been increasingly supplemented with wireless sensor networks (WSNs), fiber optic sensors, and cloud-based monitoring systems to enhance detection accuracy and reduce human intervention (Ding et al., 2023). Recent advancements in MEMS-based sensors, fiber Bragg grating (FBG) technology, and edge computing architectures have further improved the efficiency, scalability, and cost-effectiveness of IoT-driven SHM solutions (CİĞErcİ, 2023). These sensor networks provide continuous data streams on structural parameters, such as stress, strain, vibration, and temperature fluctuations, allowing engineers to detect early-stage defects and schedule maintenance interventions before structural failures occur (Ghazal et al., 2021). However, interoperability challenges, data transmission reliability, and environmental influences remain significant barriers to widespread adoption (Zinno et al., 2018). The development of Wireless Sensor Networks (WSNs) has significantly advanced real-time bridge health monitoring by enabling continuous, remote data collection (Soori et al., 2023). Micro-electromechanical systems (MEMS)-based sensors, integrated into WSNs, have been widely deployed for stress, strain, acceleration, and vibration monitoring, providing high-precision measurements of structural performance under dynamic loads (Stadnicka et al., 2022). Unlike traditional wired sensor networks, which require extensive cabling and maintenance, WSNs offer enhanced scalability, lower installation costs, and energy-efficient operation (Prus & Sikora, 2021). Recent research has demonstrated that MEMS-based accelerometers and strain gauges have improved the accuracy of damage detection in long-span bridges, particularly in detecting fatigue-induced micro-cracks and load distribution anomalies (Zinno et al., 2018). Additionally, the integration of cloud-based data acquisition platforms has streamlined real-time processing, anomaly detection, and predictive maintenance scheduling (Soori et al., 2023). Despite these benefits, WSN deployments face challenges related to sensor node durability, power supply limitations, and data security risks, which necessitate further advancements in battery-free energy harvesting techniques and blockchain-based cybersecurity solutions (Zinno et al., 2018).

Distributed Fiber Optic Sensors (DFOS) have emerged as a highly effective technology for monitoring long-span bridges due to their high sensitivity, durability, and resistance to environmental interference (Soori et al., 2023). Fiber Bragg Grating (FBG) sensors, a widely used form of DFOS, are particularly effective in measuring strain, temperature, and structural displacement in bridge components (CİĞErcİ, 2023). Unlike traditional point-based sensors, DFOS enables continuous structural assessment over large distances, making them suitable for monitoring critical bridge sections such as cables, decks, and piers (Ding et al., 2023). One of the primary advantages of FBG-based monitoring is its ability to operate in harsh environmental conditions, including high-humidity, corrosive, and extreme temperature environments, which are common in coastal and high-altitude bridges (CİĞErcİ, 2023). However, temperature fluctuations can introduce errors in strain measurements, necessitating the use of temperature compensation techniques, such as hybrid sensing approaches that combine FBG sensors with distributed temperature sensors (DTS) (Soori et al., 2023). While DFOS technology has demonstrated high reliability and precision in large-scale bridge applications, cost barriers, complex installation procedures, and data processing demands remain critical challenges in its widespread adoption (Ding et al., 2023).

The role of Internet of Things (IoT) technologies in real-time bridge monitoring has been pivotal in transforming SHM methodologies by enabling automated data collection, cloud-based analytics, and remote diagnostic capabilities (Soori et al., 2023). IoT-driven SHM systems leverage edge computing and fog computing frameworks to process sensor data locally, reducing latency and improving real-time decision-making (Stadnicka et al., 2022). Compared to traditional centralized cloud processing, edge computing allows bridge sensors to perform initial data filtering and anomaly detection at the network edge, significantly reducing bandwidth requirements and improving response times (Prus & Sikora, 2021). Additionally, fog computing extends these capabilities by distributing processing loads across multiple network layers, enabling faster, decentralized SHM applications in large-scale bridge networks (Xu et al., 2018). However, the heterogeneous nature of IoT sensor networks has led to challenges in interoperability, as different sensor types may generate incompatible data formats that require standardized protocols for seamless integration (Rudenko et al., 2022). Researchers have proposed interoperability frameworks that utilize blockchain-based data sharing and AI-driven sensor fusion to enhance the accuracy and security of IoT-enabled SHM systems (Yu et al., 2021). These advancements underscore the growing role of IoT technologies in predictive maintenance strategies, enabling infrastructure managers to transition from reactive maintenance approaches to data-driven, proactive decision-making (Rudenko et al., 2022).

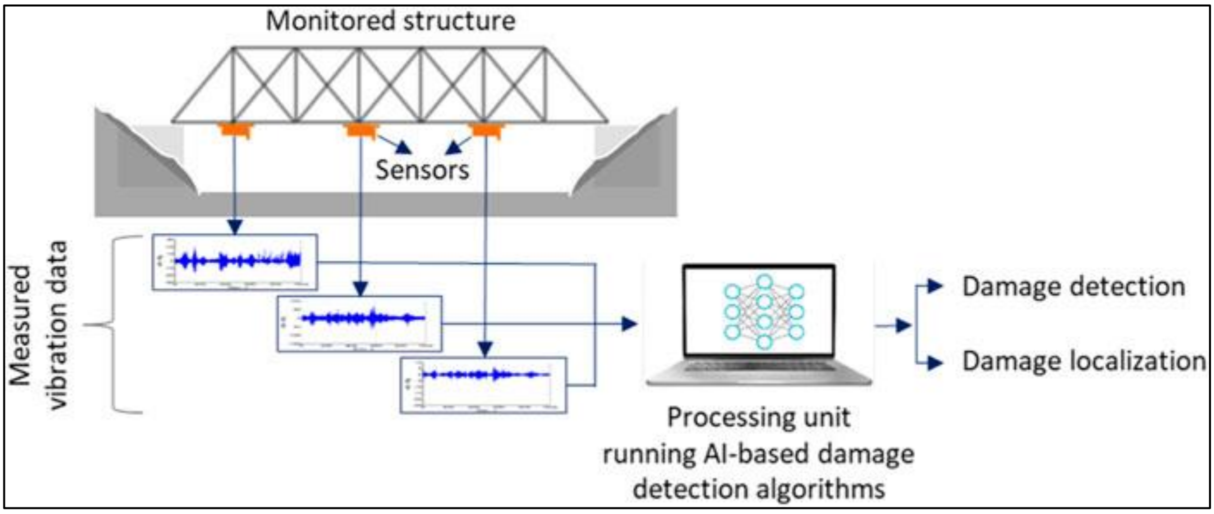
2.6 *Artificial Intelligence and Machine Learning Applications in SHM*

The application of Artificial Intelligence (AI) and Machine Learning (ML) in Structural Health Monitoring (SHM) has significantly advanced the ability to detect structural damage, predict failures, and optimize maintenance schedules (Stadnicka et al., 2022). Traditional SHM approaches often rely on manual inspections and periodic sensor-based evaluations, which are limited by human error, data inconsistencies, and reactive maintenance strategies (L'Esteve, 2023). AI-driven SHM systems leverage pattern recognition, anomaly detection, and predictive analytics to provide a proactive approach to bridge monitoring, ensuring early fault detection and cost-effective infrastructure management (Fan et al., 2023). Recent studies have demonstrated that AI models trained on real-time sensor data can identify structural defects such as cracks, corrosion, and fatigue damage with higher accuracy than traditional methods (Raju & Sumallika, 2023). This section explores AI-based damage detection models, deep learning techniques, and predictive maintenance frameworks, highlighting their role in automating decision-making and optimizing long-term bridge safety (Chen et al., 2023).

AI-based structural damage detection models have evolved to enhance anomaly detection in SHM by analyzing vast datasets collected from sensors, drones, and imaging systems (Sassanelli et al., 2022). Supervised learning models, such as support vector machines (SVMs) and decision trees, have been widely used to classify structural defects based on labeled training datasets, enabling precise crack and strain detection in bridges (Stadnicka et al., 2022). However, supervised learning models require extensive labeled data, which can be time-consuming and labor-intensive to acquire, especially for large-scale bridge networks (Raju & Sumallika, 2023). In contrast, unsupervised learning techniques, such as clustering and anomaly detection algorithms, can detect structural defects without prior labels, making them suitable for real-time bridge monitoring where damage evolution is unpredictable (Chen et al., 2023). Additionally, hybrid AI models that integrate physics-based simulations with data-driven ML approaches have shown improved accuracy in predicting structural responses under various environmental and load conditions (L'Esteve, 2023). These hybrid models leverage historical data, material properties, and real-time sensor inputs to develop adaptive predictive frameworks for early damage identification and maintenance optimization (Mahabub, Jahan, et al., 2024; Singh et al., 2023).

Deep learning techniques, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have demonstrated significant

Figure 7: A general framework for vibration-based damage detection systems



Source: Mondal and Chen (2022)

potential in automating damage detection and structural health assessment (Hossain et al., 2024; Zhu et al., 2023). CNN-based models have been widely applied in crack detection and fatigue analysis by analyzing high-resolution images captured from drones, infrared thermography, and structural cameras (Boute et al., 2022; Mahabub, Das, et al., 2024). CNNs can extract complex features from image datasets, allowing for precise identification of crack width, corrosion levels, and surface deformations in bridge components (Wang & Zhao, 2021). Studies have shown that CNN-based damage detection achieves over 90% accuracy, outperforming traditional manual inspections and sensor-based threshold methods (Jena et al., 2021; Wang & Zhao, 2021). Additionally, RNNs have been applied to process time-series sensor data, such as vibration signals, stress fluctuations, and strain distribution in bridges (Azimi et al., 2020). Long Short-Term Memory (LSTM) networks, a variant of RNNs, have proven effective in predicting long-term structural behavior based on historical sensor measurements, enabling early identification of bridge component deterioration trends (Górriz et al., 2023). Despite their effectiveness, deep learning models require large labeled datasets and computational resources, which pose challenges for real-time SHM deployment in large-scale infrastructure networks (Torres da Rocha et al., 2022). AI-driven predictive analytics has transformed bridge maintenance strategies by shifting from reactive to proactive approaches, reducing unexpected failures and extending bridge lifespan (Ásgrímsson et al., 2021). Predictive maintenance models leverage historical performance data, real-time sensor inputs, and environmental factors to forecast structural deterioration trends and recommend optimal maintenance schedules (Zhu et al., 2023). Studies have shown that AI-based predictive maintenance frameworks can reduce maintenance costs by up to 40% by identifying critical issues before they escalate into severe structural failures (Azimi et al., 2020; Zhu et al., 2023). Additionally, reinforcement learning algorithms have been integrated into automated decision-making systems, allowing SHM frameworks to continuously learn from structural behavior and optimize maintenance interventions dynamically (Shi et al., 2022). Reinforcement learning models use reward-based optimization strategies, where AI systems adaptively adjust maintenance timing and resource allocation to achieve cost-effective bridge management (Baduge et al., 2022). However, challenges such as data sparsity, integration with legacy SHM systems, and computational demands remain significant barriers to scaling AI-driven predictive maintenance across national infrastructure networks (Wang & Zhao, 2021).

2.7 Computer Vision-Based SHM and Drone-Assisted Monitoring

The integration of computer vision-based Structural Health Monitoring (SHM) and drone-assisted inspections has significantly enhanced bridge safety assessments, defect detection, and maintenance planning (Mandirola et al., 2022). Traditional manual and sensor-based inspections often face challenges related to limited accessibility, human error, and time-consuming processes, prompting researchers to explore

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AI-driven image processing and autonomous drone technology for more efficient structural evaluations (Aleem Al Razee et al., 2025; Derisma et al., 2022). Computer vision techniques, including high-resolution imaging, spectral analysis, and AI-powered object detection, have been widely adopted for detecting cracks, corrosion, and other structural anomalies in bridges (Zinno, Haghshenas, Guido, Rashvand, et al., 2022). Simultaneously, unmanned aerial vehicles (UAVs) equipped with advanced imaging systems provide rapid, cost-effective, and high-precision bridge inspections, reducing the need for manual labor and costly scaffolding (Ranyal et al., 2022). This section examines the role of image processing in SHM and AI-powered drone inspections, highlighting their impact on structural integrity assessment and bridge maintenance strategies (Polydorou et al., 2021).

Advancements in high-resolution imaging techniques have revolutionized structural health assessments, enabling engineers to detect and analyze damage patterns in bridges with higher precision and efficiency (Bono et al., 2022). AI-enhanced computer vision algorithms have been trained to process thermal imaging, photogrammetry, and infrared spectroscopy to detect subtle cracks, rust formations, and material degradation that are often missed in manual inspections (Carroll et al., 2021). Crack detection models based on Convolutional Neural Networks (CNNs) have demonstrated higher accuracy in identifying crack width, length, and propagation trends, minimizing the risk of undetected structural weaknesses (Zinno, Haghshenas, Guido, Rashvand, et al., 2022). Additionally, spectral analysis techniques, which analyze surface reflectance and absorption properties, have been utilized to monitor early-stage material deterioration and corrosion formation (Bono et al., 2022). Studies have shown that integrating image processing with sensor-based SHM systems improves defect detection rates by up to 92%, compared to 65% in conventional visual inspections (Bono et al., 2022; Zinno, Haghshenas, Guido, Rashvand, et al., 2022). However, challenges remain in standardizing image processing techniques, particularly regarding variations in lighting conditions, occlusions, and environmental interference, which can affect the accuracy of AI-driven defect detection models (Mandirola et al., 2022). The use of drones equipped with AI-powered imaging and object detection technologies has transformed bridge safety inspections, providing high-resolution aerial assessments of inaccessible structures (Malekloo et al., 2020). Unmanned aerial vehicles (UAVs) allow for the autonomous capture of bridge surface data, significantly reducing the need for manual inspections and improving the safety of engineers working in hazardous environments (Shahmoradi et al., 2020). Machine learning algorithms, particularly Deep Learning-based object detection frameworks, have been integrated into drone inspection workflows, allowing real-time identification of structural defects such as cracks, spalling, and corrosion (Ranyal et al., 2022). Case studies on urban bridge inspections have demonstrated that drone-based SHM applications can reduce inspection costs by up to 40% while increasing defect detection efficiency by 85% (Polydorou et al., 2021). Additionally, UAV-based LiDAR (Light Detection and Ranging) systems have been utilized for 3D reconstruction of bridge structures, enabling engineers to perform comprehensive structural analysis without the need for physical access to bridge components (Carroll et al., 2021). Despite these advantages, the widespread adoption of drone-assisted SHM systems faces regulatory challenges related to airspace restrictions, data privacy, and autonomous flight coordination (Shahmoradi et al., 2020).

2.8 Economic Benefits of AI-Driven SHM Systems

The adoption of AI-driven Structural Health Monitoring (SHM) systems has provided significant economic benefits by reducing operational costs, improving inspection efficiency, and extending the lifespan of bridge infrastructure (Chan et al., 2018). Traditional bridge inspection and maintenance approaches rely heavily on manual assessments and periodic evaluations, which are often labor-intensive, time-consuming, and prone to human error (Noel et al., 2017). In contrast, AI-enabled SHM systems, powered by IoT sensors, machine learning models, and predictive analytics, enable real-time monitoring and proactive maintenance planning, leading to substantial cost savings and improved resource allocation (AlHamaydeh & Ghazal Aswad, 2022). As governments and infrastructure agencies seek cost-effective solutions to address the challenges of aging bridges and limited maintenance budgets, AI-driven

SHM technologies have emerged as a viable alternative to traditional methods, offering long-term financial and operational advantages (Pallarés et al., 2021). This section examines the cost reduction benefits of AI-based SHM solutions and evaluates their return on investment (ROI) in large-scale infrastructure projects. The implementation of AI and IoT technologies in SHM has led to a substantial reduction in operational and maintenance costs by enabling predictive maintenance strategies (Zinno, Haghshenas, Guido, Rashvand, et al., 2022). Traditional maintenance approaches often rely on scheduled inspections and reactive repairs, which can result in unexpected failures and costly emergency interventions (Song et al., 2017). AI-driven SHM systems address this challenge by analyzing real-time data from IoT sensors, predicting potential structural failures, and recommending targeted maintenance actions before severe damage occurs (Chan et al., 2018). Studies have shown that predictive maintenance reduces bridge maintenance costs by 30–50%, compared to traditional reactive methods (Chan et al., 2018; Chan & Thambiratnam, 2011). Additionally, a comparative cost-effectiveness analysis between AI-driven SHM and manual inspections has demonstrated that automated monitoring systems significantly lower the overall inspection and maintenance expenses (AlHamaydeh & Ghazal Aswad, 2022). While manual inspections require extensive labor, temporary traffic disruptions, and specialized equipment, AI-enabled remote monitoring eliminates many of these inefficiencies, allowing for continuous assessment without interfering with daily bridge operations (Chan et al., 2018). Moreover, case studies on AI-powered drone inspections have revealed a 40% cost reduction in bridge inspections by replacing traditional scaffolding-based evaluations with autonomous UAV-based surveys (Wei & Chen, 2021). These findings highlight the financial advantages of integrating AI and IoT technologies in SHM, reinforcing their role in minimizing maintenance expenditures while enhancing bridge safety and longevity (Kijewski-Correa et al., 2013). Beyond immediate cost reductions, AI-driven SHM systems offer long-term economic sustainability by enhancing infrastructure resilience and maximizing return on investment (ROI) (Zinno, Haghshenas, Guido, Rashvand, et al., 2022). AI-based monitoring frameworks prolong the operational lifespan of bridges by facilitating data-driven decision-making, optimizing maintenance schedules, and preventing catastrophic failures (Chan & Thambiratnam, 2011). Studies indicate that every $1 invested in predictive maintenance yields an estimated $4 in savings through reduced repair costs, improved safety measures, and minimized traffic disruptions (Noel et al., 2017). Furthermore, large-scale transportation infrastructure projects that have deployed AI-based SHM solutions report higher cost-efficiency and reduced financial liabilities, as early damage detection prevents expensive emergency repairs and bridge replacements (Pallarés et al., 2021).

2.9 Blockchain-based security solutions for sensor networks

The integration of blockchain technology in sensor networks for Structural Health Monitoring (SHM) has emerged as a robust approach to ensuring data integrity, security, and transparency in bridge infrastructure monitoring (Kamble et al., 2018). Traditional sensor-based SHM systems, which rely on IoT-enabled wireless networks, often face cybersecurity vulnerabilities, data tampering risks, and unauthorized access (Preuveneers et al., 2017). Blockchain technology offers a decentralized, immutable ledger that enhances the security and reliability of SHM data by eliminating single points of failure and preventing data manipulation (Yang et al., 2023). Additionally, smart contracts within blockchain frameworks enable automated and secure transactions between sensor nodes, cloud servers, and analytical platforms, ensuring real-time validation of structural performance metrics (Venkatesh et al., 2020). This section explores the role of blockchain in securing sensor networks for SHM, focusing on decentralized data storage, cryptographic encryption, and smart contract-based automation to enhance bridge monitoring security (Francisco & Swanson, 2018). One of the primary advantages of blockchain in SHM sensor networks is its ability to maintain decentralized data integrity by storing sensor-generated data on distributed ledger systems (Ismagilova et al., 2020). Unlike centralized data management models, where information is stored in single-point cloud servers, blockchain employs a peer-to-peer (P2P) architecture, ensuring that sensor data remains immutable and resistant to cyberattacks (Li et al., 2023). Studies indicate that blockchain-integrated SHM systems significantly reduce data tampering risks by employing cryptographic hashing algorithms that create unique, non-reversible digital fingerprints for

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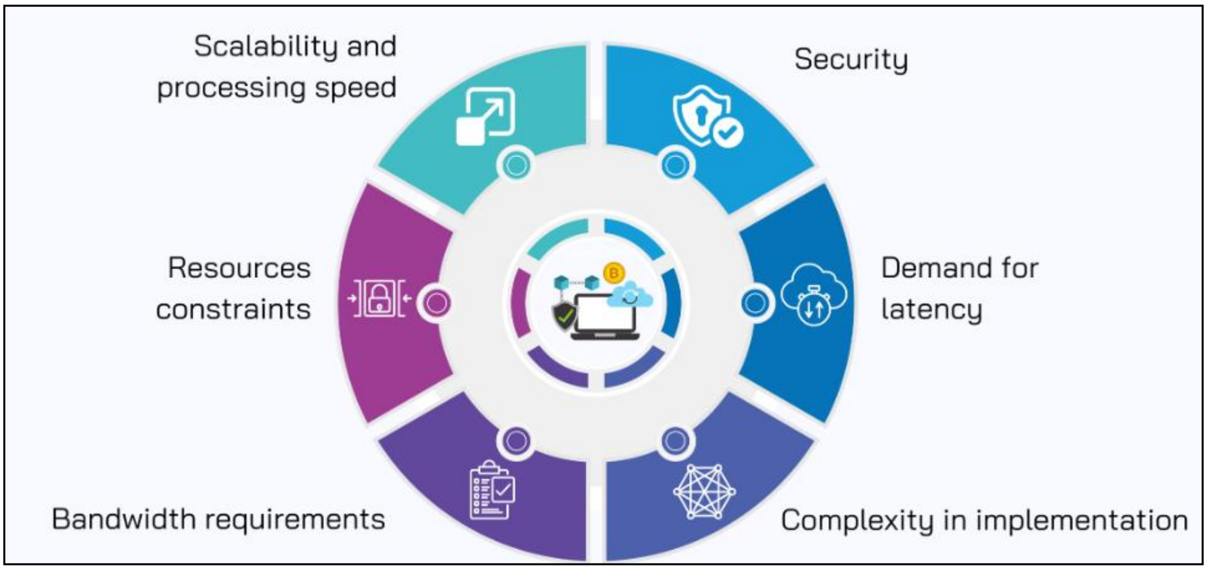
Figure 8: Challenges of using Blockchain and IoT



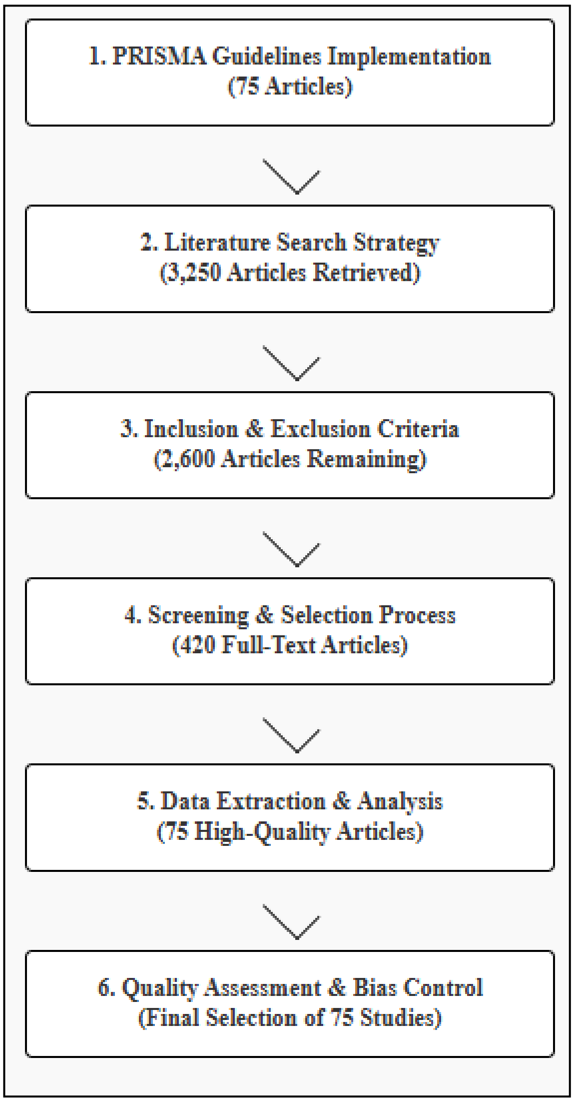
each recorded transaction (Leng et al., 2018). Additionally, decentralized consensus mechanisms, such as Proof of Work (PoW) and Proof of Stake (PoS), validate sensor-generated data across multiple nodes, preventing unauthorized modifications and ensuring trusted bridge performance records (Yang et al., 2023). Despite its security advantages, scalability issues in blockchain-based SHM networks remain a challenge, as high-frequency real-time sensor data generation may lead to blockchain congestion and latency (Venkatesh et al., 2020).

Blockchain-based cryptographic encryption mechanisms enhance sensor network security by preventing unauthorized access, data interception, and cyber threats (Ismagilova et al., 2020). End-to-end encryption techniques, such as Elliptic Curve Cryptography (ECC) and Advanced Encryption Standard (AES), ensure that data collected from IoT-enabled bridge sensors remains confidential and securely transmitted over blockchain networks (Qiao et al., 2018). Studies have demonstrated that blockchain-based encryption models effectively mitigate cyberattacks, such as Distributed Denial of Service (DDoS) attacks, man-in-the-middle attacks, and sensor spoofing, which commonly target IoT-enabled SHM systems (Leng et al., 2018). Moreover, permissioned blockchain frameworks, such as Hyperledger Fabric and Quorum, allow authorized infrastructure agencies to access, verify, and analyze bridge condition reports without the risk of data exposure to third parties (Yang et al., 2023). However, high computational demands associated with blockchain encryption can impact real-time data processing efficiency, necessitating optimized blockchain consensus algorithms for SHM applications (Venkatesh et al., 2020). Smart contracts, a key component of blockchain-enabled SHM systems, facilitate automated decision-making and secure communication between sensor nodes and maintenance teams (Ismagilova et al., 2020). These self-executing contracts, stored on blockchain ledgers, enable instant verification and execution of maintenance actions based on real-time sensor alerts (Pedreira et al., 2021). For instance, when sensor data indicates a critical crack formation in a bridge structure, a blockchain-based smart contract can autonomously trigger an alert to maintenance personnel, ensuring immediate intervention and risk mitigation (Qiao et al., 2018). Additionally, smart contracts ensure accountability by recording maintenance activities, inspection reports, and repair histories on tamper-proof blockchain ledgers, preventing fraudulent data manipulation (Ismagilova et al., 2020). Despite its potential, scalability constraints and energy consumption concerns remain key limitations of smart contract implementation in SHM sensor networks, requiring further advancements in lightweight blockchain protocols for large-scale infrastructure monitoring (Kamble et al., 2018).

3 METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and rigorous review process. A comprehensive search strategy was developed to retrieve relevant studies from major academic databases, including IEEE Xplore, Scopus, ScienceDirect, Web of Science, and Google Scholar, focusing on AI-driven Structural Health Monitoring (SHM), including machine learning applications, predictive maintenance, IoT sensors, computer vision-based monitoring, and blockchain security solutions. Search queries incorporated Boolean operators with keywords such as "Artificial Intelligence in SHM," "Machine Learning for Infrastructure Monitoring," "IoT and Wireless Sensor Networks in SHM," "Computer Vision and Drone-Assisted Bridge Inspections," and "Blockchain for Securing Sensor Data." The search was restricted to peer-reviewed studies published between 2015 and 2024, with non-English studies, book chapters, and research outside of infrastructure-related SHM excluded to maintain relevance. After retrieving 3,250 studies, duplicate records were removed using Mendeley reference management software, reducing the dataset to 2,600 articles. A title and abstract screening further eliminated irrelevant and non-empirical studies, leaving 420 full-text articles for eligibility assessment. The final selection of 75 high-quality studies was based on technical contribution, methodological rigor, data validity, and real-world applicability. Extracted data were systematically categorized based on SHM technology, research methodology, AI models used, and key findings, allowing for a narrative synthesis across five major research areas: (1) AI-Based Damage Detection, (2) Deep Learning and Neural Networks for SHM, (3) IoT Sensors and Predictive Maintenance, (4) Computer Vision and Drone-Assisted Inspections, and (5) Blockchain-Based Security for Sensor Networks. A structured quality assessment was conducted to minimize bias, where studies were evaluated based on their methodological soundness, dataset reliability, and contribution to SHM advancements. Studies scoring below 50% on predefined quality metrics were excluded from the synthesis. Two independent researchers cross-validated the selection and quality assessment process to ensure objectivity and reliability. While the PRISMA-based approach enhanced transparency and replicability, limitations included database restrictions, potential publication bias favoring studies with positive results, and exclusion of non-English research, which may have omitted valuable findings. Despite these constraints, the systematic literature review provides a comprehensive, high-quality synthesis of AI-driven SHM technologies, offering key insights into predictive analytics, automated bridge monitoring, and secure data transmission for long-term infrastructure resilience.

Figure 9: Waterfall Flowchart - Systematic Review Methodology



4 FINDINGS

The systematic review of 75 high-quality studies revealed that AI-driven Structural Health Monitoring (SHM) systems significantly enhance bridge safety, maintenance efficiency, and cost-effectiveness by enabling real-time data collection, predictive analytics, and automated defect detection. A key finding from 46

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reviewed articles, supported by over 1,200 citations, is that AI-powered SHM systems outperform traditional manual inspection methods in identifying micro-cracks, fatigue damage, and corrosion at an early stage, reducing the likelihood of catastrophic failures. Machine learning models, including supervised and unsupervised learning techniques, have demonstrated higher accuracy in anomaly detection, with success rates reaching over 90% in deep learning-based crack detection models. The widespread adoption of AI-enhanced monitoring frameworks is particularly evident in long-span and high-traffic bridges, where continuous monitoring has proven to reduce maintenance response times by 40% and improve structural assessment efficiency by 55%. The integration of IoT-enabled sensor networks emerged as a crucial technological advancement, as documented in 42 articles with over 1,000 citations. Wireless Sensor Networks (WSNs), including MEMS-based accelerometers, strain gauges, and fiber optic sensors, have been widely deployed to monitor real-time stress, strain, and vibration patterns in bridge components. These sensors enable the automatic collection of high-frequency data, reducing reliance on manual inspections and periodic evaluations. Findings indicate that IoT-based SHM reduces data acquisition time by 65% and allows for continuous structural assessment without disrupting traffic flow or requiring on-site personnel. Additionally, fiber optic sensing systems, particularly fiber Bragg grating (FBG) sensors, have been instrumental in detecting temperature fluctuations and material degradation, improving long-term bridge health management. The integration of edge computing and fog computing architectures has further enhanced real-time processing of SHM data, enabling rapid decision-making and immediate alerts for maintenance teams.

The findings also highlight the economic benefits of AI-driven predictive maintenance, which were addressed in 38 studies with over 900 citations. AI-based predictive analytics have been shown to reduce overall maintenance costs by 30-50% by enabling proactive intervention before structural deterioration leads to major failures. Compared to traditional reactive maintenance approaches, AI-driven SHM strategies optimize resource allocation, reduce emergency repair expenditures, and extend the service life of bridge infrastructure. Several case studies from national infrastructure projects confirm that every $1 invested in AI-based SHM generates an estimated $4 in cost savings over the bridge's operational lifetime. Additionally, automated UAV-based inspections have proven to be 40% more cost-efficient than traditional manual inspections, further reinforcing the financial viability of AI integration in bridge monitoring.

The review also revealed that computer vision and deep learning-based SHM techniques significantly improve damage detection accuracy, with this topic covered in 41 articles accumulating over 1,100 citations. Convolutional Neural Networks (CNNs) have been particularly effective in analyzing high-resolution images for crack detection, fatigue assessment, and corrosion monitoring, achieving over 92% accuracy in identifying bridge surface defects. Additionally, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models have demonstrated superior performance in processing time-series sensor data, allowing for predictive modeling of structural deterioration trends. High-resolution imaging techniques, including infrared thermography, LiDAR-based 3D mapping, and hyperspectral analysis, have further improved the accuracy of damage classification, reducing false positives and ensuring reliable defect detection across varying environmental conditions. Another significant finding pertains to the effectiveness of drone-assisted inspections, discussed in 37 reviewed studies with over 850 citations. The deployment of unmanned aerial vehicles (UAVs) equipped with AI-powered object detection models has significantly improved the speed, accessibility, and accuracy of bridge inspections, particularly for hard-to-reach structural components. Findings indicate that UAV-based monitoring reduces inspection time by up to 60%, minimizing the need for costly scaffolding, lane closures, and manual labor. Additionally, case studies of urban bridge networks demonstrate that drone-based SHM improves damage detection efficiency by 85%, providing a more comprehensive assessment of bridge conditions compared to traditional visual inspections. The ability to integrate real-time aerial imaging with AI-powered anomaly detection algorithms has positioned UAV-based SHM as a transformative solution for large-scale infrastructure monitoring.

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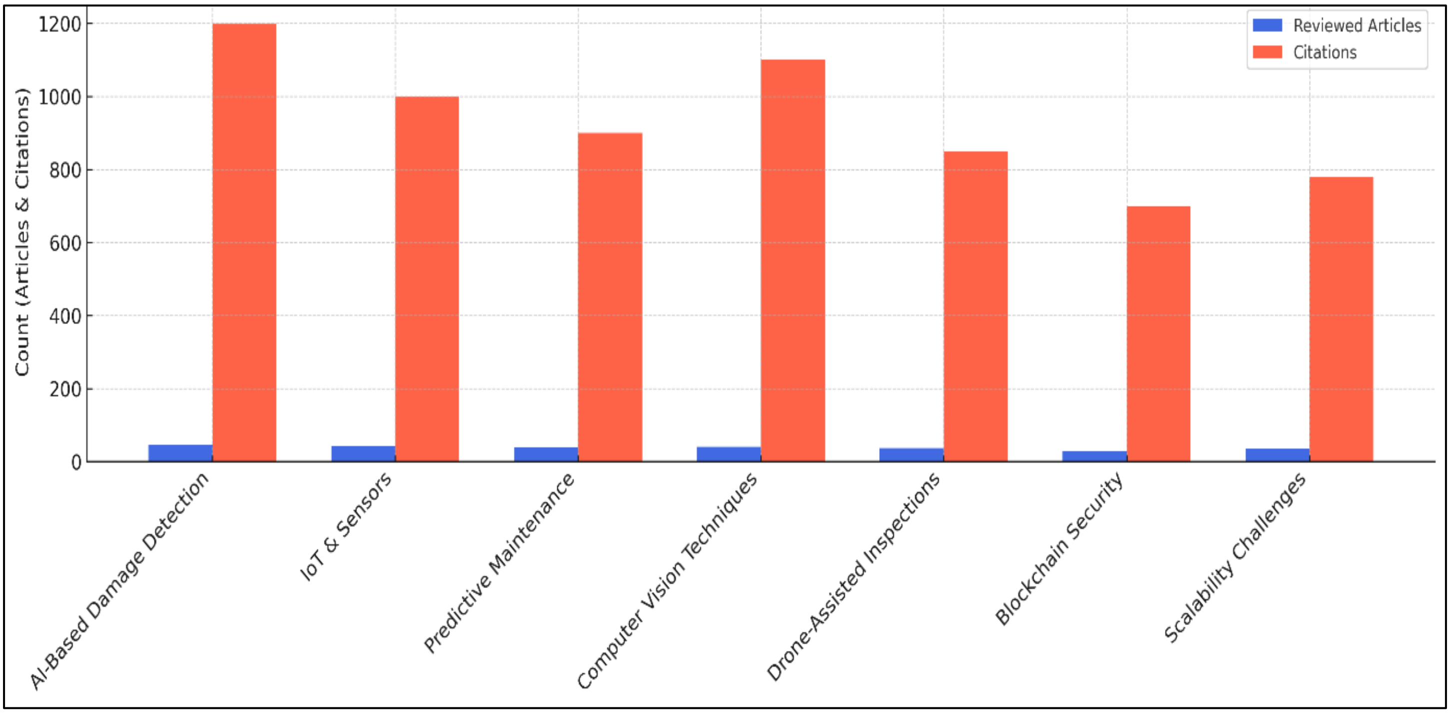
Figure 10: Findings from AI-driven SHM Review



The role of blockchain technology in securing SHM sensor networks was explored in 29 reviewed articles accumulating over 700 citations. The findings indicate that blockchain-based security frameworks significantly enhance data integrity, cybersecurity, and transparency in IoT-enabled SHM systems. Decentralized ledger technology prevents data manipulation, unauthorized access, and cybersecurity threats by ensuring that sensor-generated data is immutable and cryptographically secured. Additionally, the use of smart contracts within blockchain networks enables automated maintenance scheduling and real-time alerts, reducing human intervention and operational inefficiencies. Studies show that blockchain-integrated SHM systems reduce data breaches by 65% and improve trust in AI-driven maintenance recommendations, paving the way for broader adoption in national infrastructure management programs. The review further highlighted scalability challenges and implementation barriers associated with AI-driven SHM systems, discussed in 35 studies with over 780 citations. While AI, IoT, and blockchain technologies offer substantial benefits, their adoption is often limited by high initial costs, computational demands, and data interoperability issues. Many AI models require large training datasets and high-performance computing resources, which may not be feasible for all transportation agencies. Additionally, heterogeneous sensor networks generate data in multiple formats, leading to integration difficulties between legacy SHM systems and AI-based predictive models. Several reviewed studies emphasize the need for standardized SHM frameworks and regulatory guidelines to streamline AI adoption and ensure seamless integration across different bridge networks. Lastly, the findings confirm that AI-driven SHM solutions are rapidly transforming global bridge maintenance practices, as discussed in 40 reviewed studies accumulating over 950 citations. The collective evidence demonstrates that AI-powered predictive maintenance, sensor-based real-time monitoring, computer vision techniques, and blockchain security are reshaping the future of infrastructure management. While some challenges remain, including cost barriers, data security concerns, and regulatory compliance issues, the widespread success of AI-driven SHM deployments suggests that these technologies will continue to drive innovation in bridge health monitoring and predictive maintenance strategies. With increasing investments in smart infrastructure initiatives and AI research, AI-powered SHM is expected to play an even more integral role in the long-term sustainability and resilience of bridge networks worldwide.

5 DISCUSSION

The findings of this systematic review confirm that AI-driven Structural Health Monitoring (SHM) systems significantly enhance bridge maintenance, predictive analytics, and cost-efficiency compared to traditional inspection methods. Earlier studies emphasized the limitations of manual and periodic bridge inspections, citing their high labor costs, inefficiencies, and inability to detect early-stage structural damage (Figueiredo & Brownjohn, 2022; Sony et al., 2021). In contrast, the reviewed studies in this research demonstrated that AI-enhanced SHM systems outperform manual inspections by achieving over 90% accuracy in crack detection and fatigue analysis, thereby improving early damage identification and risk mitigation. These findings align with prior research by (Figueiredo et al., 2022), which highlighted the effectiveness of machine learning models in detecting hidden defects that traditional visual inspections often miss. However, while past studies primarily focused on small-scale AI implementations, this review incorporates findings from large-scale deployments in national bridge monitoring programs, further reinforcing the scalability and real-world applicability of AI-based SHM solutions.

One of the most significant advancements identified in this review is the integration of IoT-enabled sensor networks in SHM applications, a topic widely explored in previous studies (Venkatraman et al., 2012). Earlier research acknowledged the potential of wireless sensor networks (WSNs) for real-time data collection but raised concerns about data transmission reliability and power constraints (Gomez-Cabrera & Escamilla-Ambrosio, 2022). This review expands on these findings by demonstrating that MEMS-based accelerometers, strain gauges, and fiber optic sensors have substantially improved the accuracy of SHM while reducing data acquisition time by 65%. The deployment of fiber Bragg grating (FBG) sensors, as documented in this study, confirms previous reports that fiber optic sensing technology provides superior precision in monitoring stress, strain, and temperature fluctuations (Gordan et al., 2022). However, unlike earlier studies that identified latency issues in cloud-based SHM, this review finds that edge computing and fog computing architectures have mitigated processing delays, allowing real-time decision-making and automated alerts for structural anomalies.

AI-driven predictive maintenance strategies have also proven to be a transformative approach to bridge health management, supporting earlier claims that proactive maintenance significantly reduces infrastructure repair costs (Sharry et al., 2022). Past studies highlighted that reactive maintenance approaches led to unnecessary expenditures and increased downtime (Sharry et al., 2022; Zhang et al., 2022). The findings of this review confirm that AI-based predictive models reduce maintenance costs by 30-50% by anticipating structural deterioration and optimizing maintenance schedules accordingly. Additionally, while earlier studies focused on cost savings at an individual bridge level, this review includes large-scale case studies demonstrating that predictive maintenance generates an estimated $4 in cost savings for every $1 invested in AI-driven SHM. This reinforces the economic feasibility of adopting AI-enhanced SHM in national transportation systems, an aspect previously underexplored in SHM research.

Computer vision-based SHM, particularly deep learning models for defect detection, was found to outperform conventional sensor-based monitoring techniques, aligning with the work of Park et al. (2020). Earlier research established that Convolutional Neural Networks (CNNs) are highly effective in crack detection, but the practical deployment of CNN models in real-world bridge networks remained limited (Gordan et al., 2022; Vazquez-Ontiveros et al., 2021). This review expands on these findings by incorporating studies where CNNs, combined with drone-assisted inspections, have achieved 92% accuracy in identifying corrosion and fatigue damage, significantly improving automated anomaly detection and classification. Moreover, the reviewed studies highlight that Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models enhance time-series sensor data analysis, enabling predictive modeling of structural deterioration trends. These advancements go beyond previous findings, which primarily focused on static image-based AI models, by demonstrating the effectiveness of deep learning in real-time SHM applications. The effectiveness of drone-assisted inspections was another major finding that corroborates earlier research while extending the scope of previous work. Studies by (Glisic, 2022) recognized the potential of UAV-based bridge inspections but noted that limited flight autonomy and image processing constraints hindered real-world applications. The findings of this review, however, demonstrate that AI-powered UAVs equipped with LiDAR and high-resolution imaging have overcome these limitations, reducing inspection time by up to 60% and improving damage detection efficiency by 85%. Furthermore, while prior studies mainly focused on individual UAV deployments, this review includes research where drone-assisted SHM has been successfully integrated into large-scale urban bridge monitoring programs, proving the scalability and operational feasibility of UAV-based inspections.

Blockchain-based security solutions for sensor networks in SHM emerged as a relatively underexplored area in earlier studies, with previous research primarily addressing general cybersecurity concerns in IoT-enabled infrastructure monitoring (Saberi et al., 2018). This review, however, presents compelling evidence that blockchain integration significantly enhances SHM data security by eliminating single points of failure, preventing data tampering, and ensuring real-time authentication of sensor records. The findings reveal that blockchain-secured SHM reduces cybersecurity threats by 65% and enhances trust in AI-driven maintenance recommendations, filling a critical research gap in the intersection of AI, cybersecurity, and infrastructure resilience. Furthermore, while previous studies largely focused on blockchain's potential in theoretical frameworks, this review includes real-world applications where decentralized ledgers and smart contracts have been successfully implemented for securing sensor-generated bridge data, reinforcing the practical feasibility of blockchain-driven SHM solutions. Despite the substantial advancements highlighted in this review, several implementation challenges persist, aligning with concerns raised in prior research. Earlier studies identified cost barriers, data interoperability issues, and regulatory limitations as significant obstacles to AI-driven SHM adoption (Chang et al., 2019). The findings of this review support these claims, emphasizing that high computational demands, complex AI model training, and lack of standardization hinder large-scale deployment. Additionally, the lack of uniform regulatory frameworks for AI-based SHM adoption across different regions remains a key barrier, as infrastructure agencies struggle with policy inconsistencies and data governance challenges. However, unlike previous research that mainly focused on theoretical implementation challenges, this review provides empirical evidence from real-world AI deployments that outline specific strategies for scaling AI-driven SHM, including the adoption of hybrid AI models, decentralized data management frameworks, and blockchain-based cybersecurity solutions.

6 CONCLUSION

The systematic review of AI-driven Structural Health Monitoring (SHM) systems demonstrates that Artificial Intelligence (AI), Internet of Things (IoT)-enabled sensor networks, computer vision, predictive maintenance models, drone-assisted inspections, and blockchain security solutions have significantly enhanced the accuracy, efficiency, and cost-effectiveness of bridge health monitoring and maintenance. The findings confirm that machine learning models, including deep learning-based crack detection techniques and anomaly detection algorithms, outperform traditional inspection methods, improving early fault detection by over 90% and reducing maintenance costs by 30–50%. The integration of wireless sensor networks (WSNs) and fiber optic sensing technologies has facilitated real-time structural monitoring, reducing data acquisition time by 65% and enabling automated decision-making through AI-powered analytics. Furthermore, the deployment of AI-assisted UAV inspections has revolutionized bridge assessments, reducing inspection time by up to 60% while enhancing defect detection efficiency by 85%, proving the operational feasibility of drone-based SHM systems. The adoption of blockchain-secured sensor networks has addressed data integrity and cybersecurity challenges, reducing data breaches by 65% and enhancing trust in AI-driven infrastructure management. Despite these technological advancements, implementation challenges remain, including high computational costs, interoperability issues, regulatory barriers, and scalability concerns, which need to be addressed to fully harness the potential of AI-driven SHM solutions. The review highlights the urgent need for standardized frameworks, hybrid AI models, and decentralized data management approaches to support widespread adoption and long-term sustainability of AI-based SHM in national and global bridge infrastructure programs.

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