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Research Article

Integrating Artificial Intelligence in Structural Health Monitoring: A Path Toward Climate-Resilient Infrastructure

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A B S T R A C T

This paper explains how artificial intelligence (AI) is changing the way we check the safety and health of structures like bridges, buildings, and other constructions. Earlier, these AI-based inspections were done by people who took a lot of time, cost more money, and sometimes were not fully accurate. Now, AI-based systems use deep learning, the Internet of Things, and machine learning to find and predict damage automatically and in real time. AI technologies such as artificial neural networks (ANNs), convolutional neural networks (CNNs), and support vector machines (SVMs) are used to detect cracks, rusting, and other problems more accurately. These systems can also study environmental conditions like temperature and humidity, which affect the structure over time. Overall, AI has a structured structural health monitoring (SHM) promise system that only reacts after damage is seen, to one that can predict and prevent problems before they become serious. This helps in building safer, smarter, and more sustainable infrastructure for the future.

Keywords: Artificial Neural Network (ANN), Machine Learning (ML), Deep Learning (DL,) Internet of Things (IoT), Vibrational Analysis

Introduction

Structural Health Monitoring (SHM) has become very important in modern civil and mechanical engineering to keep structures safe, strong and long-lasting. As bridges, high-rise buildings, tunnels, and offshore platforms become more complex, traditional inspections that rely on manual checks are often slow, costly, and not very accurate. Now things are changing with the revolution of AI-based technologies such as machine learning (ML), deep learning, and the Internet of Things (IoT). These technologies allow data to be collected automatically for monitoring and analysis in real time. Problems are detected and predicted before becoming serious. More efficiency and accuracy are achieved by AI-based SHM systems, and the need for constant human inspection is reduced. Structural health is continuously being monitored under various conditions, including heavy rain and weather changes, to make infrastructure safer and smarter. Techniques such as Artificial Neural Networks (ANNs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Support Vector Machines (SVMs) are now being used for the analysis of data from sensors, accelerometers, and images to identify cracks, corrosion, and other structural issues. More accurate detection is achieved through the combination of different sensors, such as vibration sensors, acoustic devices, and optical tools. With the use of Edge AI and IoT systems, data is processed on-site more quickly, thus reducing the need for central computers. Inspection is made smarter and healthier by using technologies such as digital twins and drones. Due to the effects of climate change, monitoring is considered more important because materials can be weakened and structural behaviour can be altered by temperature, humidity, and extreme weather. Maintenance is now performed more efficiently, and structures are improved through AI systems. It has been shown by studies that bridges are the main focus of these AI systems (37%), followed by high-rise buildings (18.5%) and IoT-based infrastructure (11.1%). This demonstrates how safer and smarter cities are being created through the use of AI.

AI has changed SHM from a reactive approach to a proactive one. It allows early detection of faults, real-time analysis of data, and adaptive learning, all of which are important for building long-lasting and sustainable structures. However, there are still challenges, including limited data availability, the high cost of sensors, cybersecurity risks, and the complexity of integrating these systems. Overcoming these challenges requires teamwork between civil engineers, computer scientists, and material experts. SHM continues to develop, and AI will remain a key technology that connects automation, resilience, and sustainability for the next generation of smart infrastructure.

Literature Review on Climate Change Impacts and Structural Health Monitoring

Stewart, Wang, and Nguyen[22] were among the first researchers to study how climate change could affect reinforced concrete (RC) structures using probability-based methods. Their study, published in Engineering Structures in 2011, used Global Climate Models (GCMs) to predict changes in CO_2 levels, temperature, and humidity over the next hundred years in Australian cities. They found that the risk of carbonation-related corrosion in concrete could rise by more than 400% by the year 2100. Chloride corrosion, especially near coastal areas, could increase by around 15%. These findings show that climate change may speed up the deterioration of bridges, ports, and tall buildings. The authors stressed the need for durability models that consider uncertainty in environmental and material factors. Their work laid the foundation for later studies connecting climate-related damage with life cycle cost and sustainability analysis.

Following this, Lee, An, and Kim[23] expanded the research by focusing on the life cycle cost and environmental impact of bridges under different climate scenarios. Their 2025 study in Scientific Reports used Monte Carlo simulations to measure how temperature and humidity changes affect maintenance needs, repair expenses, and carbon emissions. Their results showed that both cost and environmental impact could increase by up to 12.4%. They also highlighted the importance of preventive maintenance and recycling to improve sustainability.

AI and ML have been recognised as major advancements in SHM under changing climate conditions. Figueiredo et al.[25] investigated how AI-based damage detection in bridges is influenced by rising temperatures as per a 2025 study. They used the Z-24 Bridge data set from Switzerland and tested AI models under future climate conditions based on RCP 2.6, RCP 4.5, and RCP 8.5 scenarios. They found that if AI models are trained only on old climate data, they may give wrong results or alarms in the future. This shows the need for AI models that can continuously learn and adapt to changing environmental conditions, similar to Stewart et al.'s call for adaptive reliability models. A global analysis by Colpari-Pozzo et al.[24] reviewed over 6,000 research papers on climate-related deterioration of concrete structures. Published in 2025, the study shows grooming international collaborations on AI and predictive analytics for coll and durability monitoring. However, most research focused on developed countries like China and the United States, while developing regions were less represented.

Physical damage is observed to extend beyond the impact of climate change. They force an in-house structure on how it should be designed and governed. In 2025, Hellenic Open University, Martzaklis,[26] observed that current design codes dependent on old climate data are not prepared for extreme events like heat waves, floods, or hurricanes. Combined case studies with risk analysis were conducted, and the use of materials like self-healing, Ultra-High-Performance Concrete (UHPC), and AI-based monitoring systems was suggested. It was argued that these technologies can extend the structure's lifespan while minimising maintenance costs. In other research, Akturk and Hauser[27] in Natural Hazards (2025) emphasised cultural heritage protection. Disaster Risk Reduction (DRR) and Climate Change Adaptation (CCA) practices were explored as being commonly done in isolation. It was discovered that even though frameworks such as the Paris Agreement and the Sendai Frameworks advocate for resilience, their executions at localities are weak. Strengthened cooperation, risk-based insurance, and combining policy responses were advised to safeguard heritage destinations from floods, heatwaves, and other climate-related vulnerabilities.

Overall, these studies illustrate the way research has developed – from corrosion risk forecasts[22] to sustainability and life cycle cost analysis[23] then AI-based monitoring[25] and finally policy and cultural protection.[27] All the research points to the same general point: to safeguard infrastructure and heritage from climate change. Therefore, a requirement

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of an adaptive, data-driven, and multidisciplinary approach integrating engineering, AI, and effective policy planning is required.

As shown in Fig. 1 above, the bar graph clearly indicates how AI is being implemented in SHM. Maximum usage of AI technologies is in bridge monitoring (37%), followed by high-rise buildings (18.5%), IoT-based smart infrastructure (11.1%), and a smaller share in health care applications (3.7%). The main objective of this chart is to demonstrate that AI is mostly being applied to upgrade infrastructure safety and support predictive maintenance.

Fig. 2. The aforementioned figure predicts the percentage share of various application domains in the research study. Bridges account for a huge portion at 37.0%, followed by building high-rise buildings, each comprising 18.5%. IoT sectors represent 11.1%, while healthcare shows a smaller share at 3.7%. SHM research methodology is highlighted in different domains through the pictorial presentation of a pie chart.

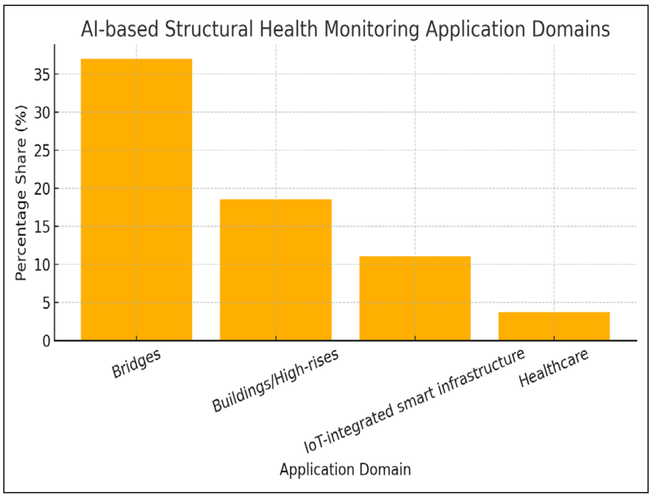

Figure 1.AI-Based Structural Health Monitoring Application Domains

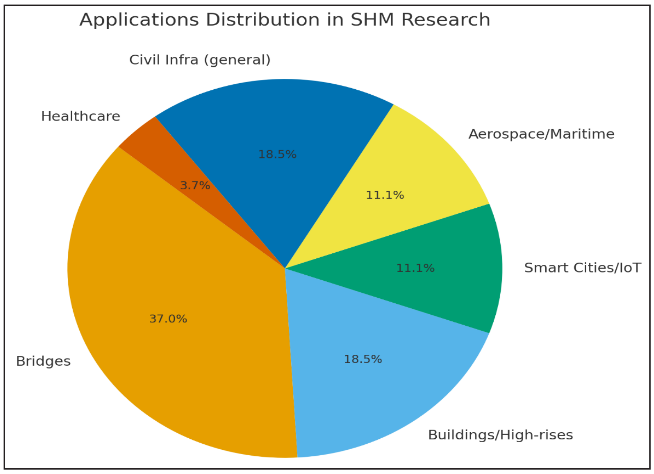

Figure 2.Application Distribution in Structural Health Monitoring

Comparative Study on AI-Based Structural Health Monitoring and Climate-Resilient Infrastructure

Methodological Approaches

Two major methodological directions are evident in the reviewed studies: AI-based monitoring systems and climate-adaptive design frameworks. AI-based SHM methodologies vary and are largely reliant, both for actively monitoring real-time damage and recognising patterns within monitoring data, on ML, deep learning, and ANN. Most approaches are integrated with the IoT and other big data methodologies. For example, Shibu et al. (2023) utilised multimodal sensing technologies – fibre-optic and ultrasonic sensors – which have been shown to detect cracks with a high level of real-time reliability. Other examples of advanced deep learning architectures applied to SHM include CNN, RNN, and edge AI specifically designed for autonomous structural inspection. Conversely, researchers such as Stewart et al. (2011) and Lee et al. (2025) used probabilistic models, life-cycle assessments (LCA), and Monte Carlo simulations to assess deterioration and climate-induced risk over longer timeframes. While the former study types focused on adapting during real time, the latter methodologies focused on future risk (multi-timeframe) and sustainability.

Experiments with AI-based SHM showed notable improvement in operational effectiveness and detection accuracy. Multi-stage ANNs showed 94% accuracy for composite T-joint degradation prediction, while ML methods like SVM and Random Forest attained up to 88–92% precision in damage prediction. Real-time monitoring achieved using edge-AI applications reduced the inference time from three seconds to twenty milliseconds. Conversely, climate research indicated alarming patterns—carbonation-induced corrosion can increase by over 400% by 2100 (Stewart et al., 2011), and the cost of bridge maintenance could rise by 12.4% with climate change (Lee et al., 2025).[10]

Advantages and Applications

AI-based SHM gives automation, scalability, and huge precision, incorporating infrastructure such as buildings (18.5%), bridges (37%), and smart infrastructure (11.1%). Predictive maintenance, safety, and data collection are improved by combining IoT-enabled sensors with UAV-based monitoring. On the contrary, climate-resilient design studies promote sustainable materials (such as self-healing concrete and UHPC) for long-term resilience. Future smart and climate-adaptive infrastructure systems can be approached holistically by integrating environmental modelling and AI-driven monitoring.

Challenges and Research Gaps

Both domains encounter operational and technical difficulties. High sensor cost, data heterogeneity, and

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interoperability problems are the limitations of AI-driven SHM, while model uncertainty, data generalisation, and lack of regional calibration are problems with climate-based investigations. Furthermore, even if AI models are very accurate, they frequently lack industry standardisation and explainability. A cohesive framework that integrates climate-adaptive modelling with AI intelligence is necessary to create future infrastructure solutions that are autonomous and sustainable.

Table 1.Existing methodologies for Structural health monitoring using AI

Reference No.	Methodologies	Results	Advantages	Applications	Challenges
[1]	AI with IoT and big data for SHM in bridges; non-destructive testing (NDT), vibration analysis, image-based monitoring	AI enhances monitoring accuracy, damage detection and predictive maintenance of bridges	High efficiency, early damage detection, improved safety, long-term sustainability	Bridge construction, management, and maintenance within Intelligent Transportation Systems	Human errors in traditional methods, the cost of sensors, integration issues, and limited accessibility in some bridge parts
[2]	AI/ML algorithms with multimodal sensors (eddy current testing, UPV, fiber optic sensing, image processing)	Crack width avg. 2.38 cm, length avg. 63.36 cm; model predicts crack propagation in multiple directions	Real-time monitoring, predictive maintenance, and climatic factor analysis	Buildings and bridges under varying climatic conditions	Economic cost of fiber optic sensors, dependency on high-resolution imaging, and data analysis complexity
[3]	Systematic review of AI in SHM; ML (SVM, Random Forest), DL (CNN, RNN, RL)	AI enables real-time damage detection, anomaly classification, and predictive maintenance	Automation, scalability, and enhanced accuracy in anomaly detection	Bridges, high-rise buildings, offshore platforms	Data scarcity, model interpretability, computational complexity, scalability across structures
[4]	Deep learning-based SHM; CNN, RNN, GANs, Transformers, UAV integration, digital twins, physics-informed learning	DL achieves robust damage and defect detection; potential for automation of SHM	Non-destructive, scalable, integrates UAVs/digital twins, and accurate fault detection	Infrastructure monitoring, UAV-assisted inspections, defect classification	Early-stage development, cost, reliability, and integration of DL models into field applications
[5]	Supervised machine learning techniques (SVM with linear, RBF, polynomial, sigmoid kernels; Naïve Bayes; Feed-Forward Neural Network; Ensemble methods: Random Forest, AdaBoost	- SVM (Linear & Sigmoid): Highest precision (87–88%), fastest classification (~0.1 ms) - Random Forest (75 estimators): High precision (82–92%) but slower - Naïve Bayes: Moderate precision (78%) - FNN: Poor precision (58–74%) - AdaBoost: Worst (57%)	- SVM: High precision, low computation time - Random Forest: Reliable with large estimators - Ensemble learning provides diversity	- Structural Health Monitoring (SHM) in aircraft and metallic structures - Identifying the type and severity of damage via acoustic emission signals	- AdaBoost underperformed significantly - Random Forest required higher computation time - Limited dataset (60 samples) - PCA did not improve much - Classifier performance varied across scenarios

[6]	AI-based methods: ML, deep learning, feature extraction, system identification, diagnostics, big data analytics	Demonstrated superior performance in system identification, damage detection, and prediction of structural behavior	Handles large datasets, improves feature extraction, and enables real-time monitoring	Structural health monitoring (SHM), intelligent infrastructure, smart cities	Data heterogeneity, integration across domains, and scalability
[7]	Artificial Neural Networks (ANN), GNAISPIN model, FEA simulations, DRAT algorithm,	94.1% damage prediction accuracy for T-joint composites; up to 82% improvement with GNAISPIN	High accuracy, independent of load variations, and the capability for multiple damage detection	Composite T-joints in maritime structures, beams with delamination	Complexity of ANN training, sensor configuration dependency, need for extensive validation
[8]	Multi-stage ANN, statistical ANN, finite element modeling, guided wave propagation, spectral element modeling, clonal selection algorithm (CSA)	More reliable damage prediction; accurate detection of cracks, debonding, and shear slip	Reduces noise influence, improves reliability, and combines local & global detection	Damage identification in concrete-steel rebars, structural vibration analysis, and debonding detection	Measurement noise, modeling error, and limited sensitivity of global methods
[9]	AI + IoT-enabled sensors, predictive analytics, generative design, UAVs, robotics integration	Real-time monitoring of SHM, predictive maintenance, and optimized construction resource allocation	Efficiency, safety improvements, reduced downtime, smart adaptive buildings	AEC industry: smart buildings, infrastructure monitoring, predictive maintenance, automation	Cybersecurity, interoperability, cost of adoption, and workforce training requirements
[11]	AI & ML (neural networks, SVM, genetic algorithms, digital twins, predictive analytics)	Demonstrated applications in SHM, disaster management, predictive maintenance, and sustainable construction	Enhances efficiency, reduces material waste, and increases infrastructure longevity	Civil engineering: SHM, smart infrastructure, disaster response	Data quality, interoperability, high computational demands, and ethical concerns
[12]	Edge-AI, optimized CNN (quantization, pruning, weight clustering), Kneron KL520 chip testing	Real-time crack detection with 92.4% accuracy; inference time reduced from 3s to 20ms	Low latency, reduced bandwidth, improved security, cost optimization	Real-time SHM (bridges), robotics, surveillance, automation	Limited device operator support, need for optimized models, and generalization issues

[13]	Statistical ANN, sub-structuring ANN, vibration + guided wave analysis, spectral finite element modeling	Improved reliability of damage identification; efficient crack & debonding detection	Reduces computational cost, identifies both local & global damage	Bridge and infrastructure SHM, steel rebar crack detection, vibration monitoring	Sensitive to data quality, requires extensive training, and complexity of hybrid models
[14]	AI/ML (data-driven & model-driven SHM), IoT integration, finite element analysis, pattern recognition, ANN models	Effective for monitoring, controlling, and evaluating bridge health; demonstrated ANN success	Enables automated pattern recognition, real-time assessment, and improves damage localization	Bridge SHM, decision-making in maintenance, NDT/NDE inspections	Sensor installation & cost, data fusion issues, uncertainty in modeling, noise sensitivity
[15]	Wireless Smart Sensor Networks (WSSN), AI/ML integration, acoustic emission, GPS monitoring, smart paints, piezoelectric smart aggregates	Reduced cost/time compared to wired systems; accurate crack/corrosion detection; real-time displacement and strain monitoring	Economical, scalable, flexible, autonomous functionality, suitable for large structures	Bridges, high-rise buildings, chimneys, offshore platforms, nuclear reactors	Power supply limitations, environmental sensitivity, hardware damage, lack of standards for field execution
[16]	Vibration-based and strain-based SHM systems, load rating with finite element models, and reliability analysis for service life estimation	Effective in detecting damage, real-time structural capacity estimation is possible; reliability algorithms predict service life	Tracks structural changes over time, integrates codified frameworks, and enables real-time monitoring	Highway bridges, load capacity estimation, damage detection, service life prediction	Lack of validated SHM using ambient data; difficulty in long-term service life estimation
[17]	Wireless Sensor Networks (WSNs) for SHM, MEMS accelerometers, strain sensors, LVDTs, fiber optic sensors, distributed data processing, Tiny OS/Contiki OS	Efficient for vibration-based damage detection, real-time bridge monitoring, and scalable deployment across hundreds of nodes	Low-cost, scalable, reduced installation/maintenance cost, easier deployment in remote locations	Bridges, railroads, buildings, seismic monitoring	Power efficiency, high data rate/throughput, time synchronization, fault tolerance, and limited computation in sensor nodes

[18]	Case studies SHM: dams, bridges, platforms, buildings, tunnels; AI, MISTRAL, DAMSAFE	Real-time monitoring feasibility; anomaly detection; validated models (Humber Bridge, Singapore bridges)	Continuous, automated, real-time safety data; maintenance decisions; resilience	Civil infrastructure: dams, bridges, offshore platforms, tall buildings, nuclear plants, tunnels	Lacking baselines, high sensor density, cost, environmental variability, and limited localization[1]
[19]	IoT smart health monitoring (AI, DL, sensor-based, smartphone-based, microcontroller)	Improved patient monitoring, reduced hospitalizations, real-time disease tracking, anomaly detection	Remote access, reduced costs, personalized care, smart city integration	Remote healthcare, chronic management, elderly care, telemedicine, smart cities	Security/privacy, device management, operator training, noisy data, energy requirements[1]
[20]	Statistical pattern recognition: operational evaluation, acquisition, feature extraction, modeling; NN, novelty detection	Lack of rigorous statistical validation; effective unsupervised novelty/outlier detection	Data-driven, reduces model dependence, scalable advances	Aerospace, infrastructure: bridges, buildings, composite plates, beams	Environmental/operational variability, big data, validation limits, statistical rigor[1]
[21]	Statistical process control, autoregressive modeling, feature reduction (PCA, discriminant projection), and integrated sensor systems	Detect trends, improve diagnosis accuracy, enable automated monitoring, enhance damage classification, and reduce data dimensions	Quantitative, scalable, enhances discrimination, condenses data, supports automation	Structural health monitoring, vibration analysis, automated and wireless infrastructure monitoring, and real-time damage identification	Model choice, false positives, info loss, operational variability, sensor/ environment integration
[22]	Probabilistic and reliability-based analysis using General Circulation Models (GCMs) and climate projection tools like OZClim to predict CO2, temperature, and humidity effects on concrete corrosion.	Carbonation-induced corrosion risk in concrete may rise over 400% by 2100; chloride-induced corrosion risk may increase by ~15%. Results are most sensitive to CO2 concentration changes.	Quantitative assessment supports long-term infrastructure planning and cost-effective adaptation strategies; incorporates uncertainty modeling	Bridge, building, and port infrastructure durability forecasting; design adaptation for urban and coastal regions under high CO2 emission scenarios.	High uncertainty in GCM projections and variability in material/environmental data; need for localized adaptation frameworks.

[23]	Two-phase framework: (1) risk-based life cycle assessment (LCA) for steel and PSC girder bridges; (2) integration of environmental impact, cost, and maintenance data under climate scenarios (AR6). Monte Carlo simulations for reliability.	Climate change increased environmental impact & cost by ~12.4%. Preventive maintenance frequency and recycling rate most influenced sustainability outcomes.	Provides a quantitative model linking deterioration, cost, and environmental impact. Promotes sustainable bridge design and adaptive maintenance.	Applicable to highway bridge design and climate-resilient infrastructure management.	Requires detailed climate projections; uncertainty in corrosion modeling and data generalization.
[24]	Requires detailed climate projections; uncertainty in corrosion modeling and data generalization.	Identified major research clusters (durability, sustainability, corrosion). China and the USA lead global research. Increasing integration of AI for predictive maintenance.	Provides global overview and data-driven insight on emerging trends in climate-resilient concrete research.	Useful for researchers & policymakers in AI-based monitoring, RC durability, and sustainable materials.	Limited participation from developing regions; lack of unified global framework; data bias toward English publications.
[25]	Machine learning algorithms applied to bridge Structural Health Monitoring (SHM), trained on historical data (Z-24 Bridge), and tested under climate	Climate change significantly alters temperature-dependent bridge dynamics, reducing the accuracy of machine learning-based damage detection over time	Provides early insight into SHM vulnerabilities under climate change; helps design adaptive learning algorithms for infrastructure monitoring	Long-term SHM system optimization; adaptive maintenance scheduling for bridges and transport structures under changing environmental conditions	Machine learning models become outdated due to climate shifts, lack of temperature-robust training datasets, and adaptive algorithms

[26]	Mixed-method approach combining qualitative case studies (Netherlands, New York, Australia) and quantitative risk modeling (hydrological, thermal stress, material failure) for infrastructure resilience.	Conventional design codes are inadequate under current climate extremes; adaptive engineering using UHPC, self-healing concrete, and predictive models enhances structural resilience.	Combines environmental, structural, and economic dimensions; provides a comprehensive framework for climate-resilient infrastructure.	Urban infrastructure, coastal defense systems, and transport networks; engineering education and climate policy integration. Limited global standardization of climate-resilient design codes; financial and implementation barriers in developing regions.	Limited global standardization of climate-resilient design codes; financial and implementation barriers in developing regions.
[27]	Systematic literature review integrating Disaster Risk Reduction (DRR) and Climate Change Adaptation (CCA) frameworks to assess resilience of cultural heritage sites, using policy and scientific data sources.	Integration of DRR and CCA strengthens resilience planning for cultural heritage; identified lack of local-scale implementation and weak policy–science coordination as major gaps. Climate change increased environmental impact & cost by ~12.4%. Preventive maintenance frequency and recycling rate most influenced sustainability outcomes.	Promotes holistic resilience strategies by linking heritage preservation with global climate and disaster risk frameworks (Sendai, SDGs, Paris Agreement).	Cultural heritage management, disaster-preparedness planning, and international policy design for resilience of UNESCO heritage sites.	Lack of integration between cultural policy, climate science, and disaster risk management; insufficient funding and coordination for heritage resilience.

Conclusion and Future Scope

The study emphasises that AI has significantly revolutionised SHM by transitioning it from traditional manual methods to intelligent, automated, and predictive systems. Through the integration of ML, deep learning, and IoT-based sensing, AI enhances fault detection, real-time assessment, and damage prediction in infrastructures such as bridges, buildings, and smart cities. Also, the integration of climate-adaptive algorithms helps to meet the increasing challenge of changing environments and global warming. However, challenges such as limited data availability, sensor costs, and cybersecurity challenges are being faced.

In the future of AI-based SHM, there will be a focus on developing adaptive AI models that include explainable AI, climate resilience, digital twins, and big data analytics to support smart and sustainable infrastructure systems. Interdisciplinary cooperation between civil engineers, data scientists, and policymakers is critical to develop autonomous, energy-efficient, and climate-resilient monitoring frameworks for the future of infrastructure

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