

Resilient Infrastructure Systems: From Seismic Damage Evaluation to AI-Enabled Quality Assurance and Digital Design

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WoS ID: HKV-8282-2023

Scopus Author ID: 59380815100

ARTICLE INFO

Keywords:

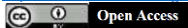
artificial intelligence,
resilient infrastructure,
seismic damage assessment,
structural health monitoring,
digital twins.

Vol.01, No.04, 2026

<https://doi.org/10.5281/zenodo.22974358>

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ABSTRACT

Intelligent technologies are playing an important role in the development of resilient infrastructure that builds the ability to identify structural weaknesses, provide quick and accurate assessments, and enhance decisions across the infrastructure life cycle. This review explores the use of AI and machine learning in three related fields: seismic damage assessment, construction quality assurance, and digital design. After an earthquake, computer vision and deep learning based. AI can help identify cracks, spalling, corrosion, deformation, etc. and help process the information rapidly; earthquake regional scale models can help with portfolio level damage assessment and recovery planning. Automated imaging and sensor systems can provide continuous quality monitoring during construction, thus improving the ability to detect defects early in reinforcement, concrete and welding and minimize potential rework, all of which can be expensive. In digital design, generative AI can analyze several design options, and Building Information Modeling and digital twins can synchronize design data with real-time operational data to enable predictive maintenance and life cycle performance management. The applications are connected to each other by vibration, strain, imaging and other sensors that are used for structural health monitoring, giving a crucial link between these applications, allowing continuous condition assessment. While there has been significant progress, there are still practical limitations in using the models, such as the availability of limited datasets for rare and high consequence events, poor generalization across structure types and environmental conditions, interoperability issues, uncertainty, and the need for robust validation.

1. Introduction

Machine learning and artificial intelligence are becoming real tools in assessing structures, in quality assurance of the built environment, in monitoring structures and in digital design, and this trend is now beginning to be part of civil infrastructure. AI techniques can handle and make sense of vast and complex datasets that are often hard to analyze, such as accelerometer streams, strain measurements, drone images, point clouds, Building Information Modeling (BIM) data, and historical inspection records, across seismic damage assessment, construction inspection, and infrastructure planning [1]. Therefore, the marriage of AI and SHM has evolved into a growing discipline that involves automated assessment, anomaly detection, predictive analysis and data-informed decisions. Resilient infrastructure is infrastructure that can withstand disruptive events, continue to perform critical functions and recover quickly after a hazard or a gradual deterioration. AI and machine learning play a role in resilience across the LCA of an infrastructure asset [2]. In the design phase, predictive and generative approaches can aid in assessing alternative configurations, detecting conflicts in the design, and enhancing decision making prior to the construction phase. In construction period defects, dimensional inconsistencies and quality

problems can be identified by computer vision and sensor based systems during the construction process. Operating systems with structural health monitoring can continuously analyze measurements of vibration, strain, displacement, imagery, etc., and alert to abnormal behavior, and support proactive maintenance [3]. AI based approaches enable features to be automatically extracted, anomalies detected, classified and fault predicted. Structural images, videos and time series data are increasingly being processed using deep learning architectures, such as convolutional neural networks, recurrent models or transformer models. These can allow the automatic detection of cracks, deformations, corrosion, damage patterns and other structural anomalies, limiting the need for intensive manual inspections [4]. After the seismic catastrophe, AI systems can help quickly classify and prioritize the damage to the structures. Computer vision and sensor fusion can identify defects in constructions before the pieces are put in place. For digital design, AI can be used in conjunction with BIM and simulation platforms to assess the performance of structures and to make better design decisions [5]. Two key technological shifts are helping to make these applications a reality. First, with the advancement of the deep learning, models can learn complex patterns from images, videos, and sensor measurements directly without relying solely on manually engineered features. Second, as the technology of sensing and imaging infrastructure has become more widely available, at relatively low cost, the quantity and variety of infrastructure data has grown, including unmanned aerial vehicles, strain gauges, LiDAR, etc., and accelerometers [6]. The shift from traditional periodic inspections, to modal based assessment, and finally towards more continuous and data driven approaches to structural health monitoring has therefore been made.

2. Foundational Methods: From Signal Processing to Deep Learning

The majority of AI use cases within resilient infrastructure have a relatively small number of fundamental techniques, each used in unique ways depending on the type of input data—whether it be a vibration signal, an image, or a structured dataset. CNNs are still quite popular for image and video related applications such as image classification of crack patterns in concrete and corrosion detection on steel members [7]. Once trained with labeled samples of good and bad, supervised CNN based inspection can detect defects quickly, which is suitable for the real time quality control during the production or construction process. When a large amount of data of defects is not available, as in structural engineering where severe failures are rare, the anomaly detection approach can be adopted to detect the deviations from a set baseline. Another approach which is being investigated is few shot and zero shot learning, as it is costly and time-consuming to label rare defect types [8]. The methodological toolbox is wider in the field of vibration and signal based damage detection. Seismic signal data has been directly used with random forest, XGBoost and artificial neural networks as automated solutions to replace the manual monitoring which are complex and time consuming for critical infrastructure. Other approaches rely on structural dynamics architectures [9]. To perform these tasks, filter bank and hybrid deep learning architectures have been designed to enhance the performance of seismic assessment of bridges; pattern recognition approaches have been devised to use with Bayesian optimization for seismic damage detection in highway bridge systems. Interest is also growing in physics-informed models, which combine learned representations with known ideas of structural mechanics, that can facilitate generalization over structures that are not represented in the training set [10].

3. AI Enabled Seismic Damage Evaluation

A critical use of AI in resilient infrastructure is the quick and automated evaluation of buildings and bridges after an earthquake. The priority is to ascertain whether any buildings are immediately suitable for re-occupancy, or if they are required to be evacuated, either partially or completely, or if they need to be inspected in detail or rehabilitated [11]. There have been significant developments in image based methods. End to end deep learning frameworks are developed for structural damage

detection after extreme events such as cracks, spalling and others. The previous Region Based Deep Learning (RBDL) approaches proved the feasibility of visual inspection without human intervention by detecting multiple types of damage from post disaster images (Figure 1). Specifically, these systems are applicable to post-disaster reconnaissance, where large amounts of field imagery can be captured using drones, mobile phones, and other imagery platforms and processed much faster than manual, on-foot inspection (Table 1) [12]. The limited availability and geographical focus of post earthquake labelled imagery can also be overcome by using multi class damage detection frameworks and transfer learning. One of the most significant factors is assessment speed, as the usefulness of automation for assessment relies on the speed it can deliver results to guide evacuation, shelter in place and emergency response decisions [13]. Shear wall building rapid health assessment models based on the artificial intelligence have been developed, using different ground motion records, and have shown that the model can predict the health condition of the structure within less than 1 minute, which means that the health assessment of the structure can be carried out in near real time. These systems can be integrated into wider emergency response and disaster risk reduction contexts to leverage the use of structural information with other data for timely decision making [14].

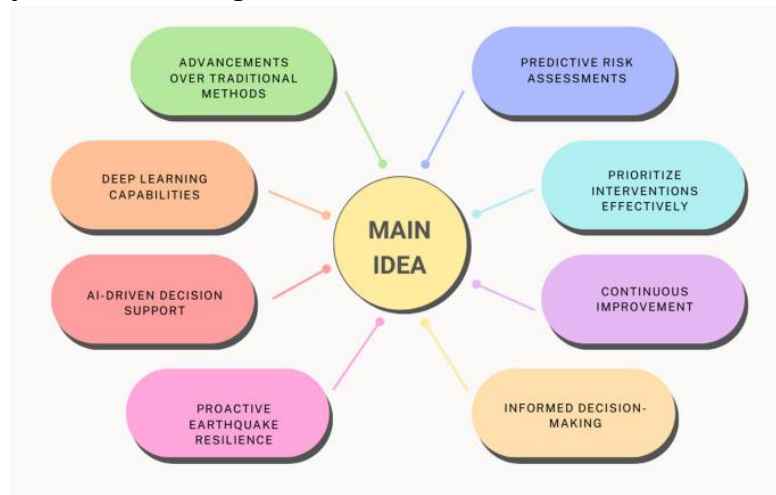


Figure 1. AI and ML tools for earthquake damage assessment and retrofiting strategies [36]

Table 1: Core AI Application Domains in Resilient Infrastructure

Domain	Key AI Techniques & Technologies	Primary Functions & Use Cases	References
Seismic Damage Evaluation	Region-Based Deep Learning (RBDL), computer vision, transfer learning, multi-class damage frameworks	Rapid post-disaster reconnaissance using drone/mobile imagery, crack/spalling detection, and near-real-time structural health assessment	[2]
Construction Quality Assurance	Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), automated cameras, sensor fusion	Continuous defect detection in concrete, reinforcement, and welds; early identification of dimensional inconsistencies and surface anomalies	[3]

Digital Design & Management	Generative design, Building Information Modeling (BIM), simulation platforms, digital twins	Exploring large design envelopes, evaluating cost/sustainability options, synchronizing design data with real-time operational performance	[5]
Structural Health Monitoring (SHM)	Deep multiple instance learning, variational autoencoders, physics-guided neural networks	Distinguishing structural damage from environmental noise, sensor fault management, and data-informed predictive maintenance	[8]

4. AI Enabled Construction Quality Assurance

For seismic assessment, most of the time it is a post event process, but AI based quality assurance can be used on site throughout the construction process, enabling defects to be discovered before they become hidden or expensive to correct. Traditionally, construction quality control relied mainly on manual and manual checking processes. They can be time consuming, sporadic and may be prone to inconsistencies between inspectors and defects are likely to go undetected until they are harder and more costly to address [15]. Computer vision is an important alternative since it allows automated and continuous inspection. Patterns linked to construction defects like surface anomalies, cracks, corrosion, dimensional inconsistencies, and irregular finishes can be identified with deep learning models like convolutional neural networks (CNN) and vision transformers (ViT). Automated image analysis can thus be of assistance for better and timely quality assessment. AI powered cameras and sensors could also be integrated into the process of active construction. Deviations are detected early and corrected prior to the inclusion of them in completed structural elements [16]. These same technologies can help to monitor construction progress and to predict completion times, thus making quality assurance, site monitoring and project management more closely interwoven. Data scarcity is another technical challenge as defects are much less frequent than construction which meets the standards. Therefore, enhanced and expanded training datasets with synthetic image generation, data augmentation, and image processing techniques can be used to increase the diversity of training datasets and boost model performance on rare defect categories [17]. Continuous learning is also gaining ground as a new method, where deployed systems can gain insights into uncertain or wrong classifications and inform future model refinement. These methods shift inspection systems from static to adaptive, with opportunities to enhance the system as more construction data is collected.

5. Digital Design: BIM, Digital Twins, and Generative Engineering

The third pillar, digital design, links AI to pre- and post-physical construction planning, modeling and operational management of infrastructure. Digital design is growing at the fastest pace of the three domains as AI has the potential to be combined with generative design, BIM, simulation, and digital twin technologies to support decisions across the infrastructure lifecycle [18]. Generative design is changing the landscape of infrastructure development by creating the ability for AI systems to assess a vast array of design scenarios and options, considering a multitude of factors such as cost, structural performance, constructability, energy consumption, and sustainability. This is not the same as just drafting or documentation automation. The main benefit is in increasing the design envelope that can be explored in a reasonable amount of time, and determining if there are any viable options to be considered by engineers (Figure 2) [19]. AI powered predictive models can also help detect potential risks, schedule

delays, cost overruns and performance issues early in the design process, guiding the design process with anticipated project conditions. While BIM and digital twins are similar, they are not the same. Digital representation, coordination and management of information during design and construction are at the center of BIM, while digital twinning brings digital representation into the operational phase by continuously updating the information and monitoring the performance. They are becoming more and more integrated, making it possible to link the design assumptions to the real conditions of operation and past performance [20]. The trend, then, is the integrated digital ecosystems where the design, construction, operation and maintenance are going together in one and not in separate platforms. Together, cloud-based environments, BIM, digital twins, embedded sensors and AI analytics can ensure infrastructure models are continually updated. These kinds of systems enable to monitor the performance of infrastructure over time and find out issues before they escalate into major failures. This is a change from this traditional step of static digital documentation to responsive infrastructure management, in which decisions are made across the entire life cycle of an asset with the help of digital information [21].

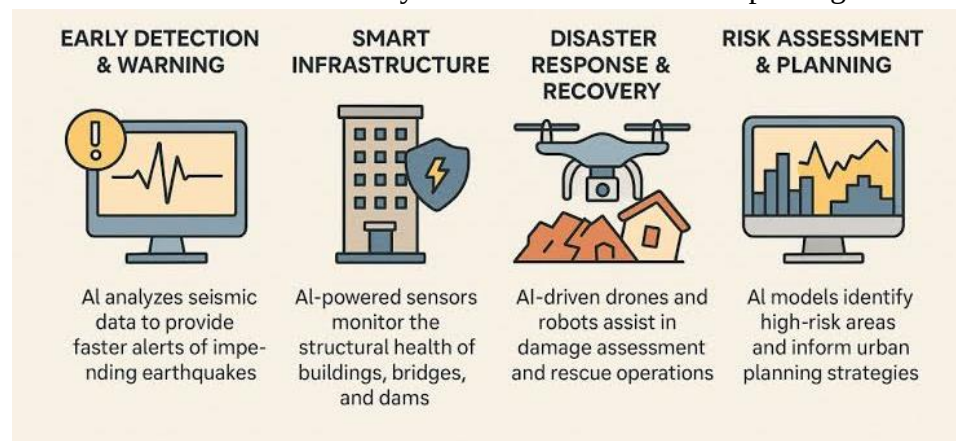


Figure 2. Harnessing AI for Earthquake Mitigation [37]

6. Structural Health Monitoring and Predictive Maintenance

Structural health monitoring is one of the most “mature” application areas of AI in resilient infrastructure, that bridges seismic assessment and construction quality assurance. A key question is whether it is a true structural damage or only due to the measurement noise, the sensor fault, or the normal variation of the environment and operation. To be reliable, damage identification models must be able to interpret complex monitoring data and be robust with imperfect measurement conditions [22]. Newer methods focus on the reliability of sensors, such as deep multiple instance learning algorithms, which are able to continue to function in order to detect damage when some sensors in a monitoring network are damaged or malfunction (Table 2). For monitoring datasets that are too unlabeled, clustering and classification techniques are also being used. For structural damage detection and clustering, a variational autoencoder architecture with multiple loss functions is developed to include the use of modal information, and for Lamb wave based monitoring, physics guided neural networks are used to help consider boundary reflection effects that can affect automated damage identification [23]. Besides the technical aspects of damage detection, the value of SHM is great. Monitoring information can be of measurable economic value, when it is used for decision making for infrastructure safety, maintenance and post disaster response. The value of seismic monitoring information for post earthquake evacuation decisions and the value of bridge monitoring for structures subject to flood induced scour have been looked at in some studies. This represents the value of information perspective, and offers a way to assess the monitoring investments in terms of their potential contribution to improved decisions, as well as in terms of added infrastructure costs [24].

Table 2: Methodological Approaches and Practical Implementation Challenges

Category	Specific Methods	Limitations & Practical Barriers	References
Signal & Vibration Processing	Random forest, XGBoost, artificial neural networks, filter bank architectures, Bayesian optimization	Complex and time-consuming data streams, handling uncertainty, and managing sensor network reliability	[12]
Data Strategies for Rare Events	Synthetic image generation, data augmentation, anomaly detection, few-shot and zero-shot learning	Scarcity of training data for rare high-consequence failures and class imbalance between standard and defective construction	[14]
Generalization & Validation	Physics-informed models, continuous learning adaptive systems	Poor generalization across unfamiliar structure types or changing environmental conditions, plus rigorous validation needs	[18]
Ecosystem Integration	Cloud-based environments, integrated digital ecosystems, hierarchical decision processes	Interoperability issues between separate platforms, incomplete information flow across project lifecycles	[19]

7. Discussion

The use of AI and machine learning in resilient infrastructure is a more fundamental paradigm shift in the way structural performance is assessed, controlled and managed. The three main application areas explored in this review (seismic damage evaluation, construction quality assurance, and digital design) are becoming more intertwined and are being increasingly linked by the concepts of structural health monitoring and digital information management for the whole life of the structure [25]. While the methods and approaches for each domain vary, they all employ various data collection and processing techniques with the common goal of detecting risk before it happens, enhance the quality of engineering decisions, and minimize the impact of structural failure. One important computational capability made possible by AI is that it can process large amounts of the heterogeneous infrastructure data that is necessary for achieving these goals faster than traditional manual methods [26]. Seismic damage evaluation shows how usefulness of AI-driven infrastructure evaluation is immediately apparent in terms of safety. After an earthquake, assessment of large buildings and bridges may be needed within a short time frame and access to damaged areas may be limited. Reliance on the conventional assessment method is heavily reliant on expert visual assessment which may be difficult to undertake during a large disaster [27]. The opportunity exists to speed up the process of identifying and categorising visible and measurable damage through the use of image based deep learning, computer vision and sensor based models. Photographs, drone imagery and sensor measurements can be used to identify damage patterns, including cracks, spalling, deformation and more. In conjunction with structural response data and ground motion information, these methods can help in a rapid estimation of conditions of buildings and bridges [28]. The potential contribution of AI can be extended even further to the regional scale seismic assessment. While individual building evaluation gives an asset-specific answer, a portfolio level assessment can be used to estimate a pattern of damage for a large number of assets. Machine learning and probabilistic seismic fragility methods can be used to assist in providing estimates of probable

damage distributions throughout communities. The information can be directly applicable to emergency planning, prioritization of inspections, resource allocation and recovery management [29]. So an automated individual assessment and regional scale modeling may create a hierarchical decision process, where the automated system first identifies areas and buildings that need to be addressed, and then progressively more detailed engineering evaluation establishes a decision process. The second instance is construction quality assurance, which is another use case because AI can continuously work in the construction of infrastructure, rather than just in an aftermath of a disruptive event [30]. Traditional quality control is often based on planned inspections, manual records, and personal judgment. This is still relevant, but may allow defects to survive in between inspections. Cameras and other sensors introduced into the world of computer vision can offer more continual monitoring on building works and completed building components. The key benefit of an AI powered continuous inspection is not just an increased level of automation [31]. Defects can have different economic implications when detected early. A defect found during the time the structural element is still accessible is likely to be resolved by less extensive action, whereas a defect found after the installation of additional layers is likely to require demolition and/or reconstruction or extensive repair. AI-driven QA can thus help in ensuring structural reliability and construction efficiency. Additionally, progress monitoring and schedule prediction can be merged with defect detection, so that quality information can be embedded in the construction management systems [32]. The third main domain is Digital design, which takes AI from inspection to creation and management of infrastructure. Generative design can test a great many design options for structure, cost, environmental impact and constructability. Engineers are then able to consider the alternatives in a manner that incorporates known analysis and professional judgment. AI is a key enabler for this evolution, when combined with BIM. Geometric, material, component and project data can be organized using BIM during design and construction, and AI can analyze this information to determine conflicts, predict risks, assess alternatives, and aid in project planning [33]. The long term value of these systems is, however, dependent on whether information accumulated in the design and construction phase of the system is available during all its operating phases. Information flow between project delivery systems and operational management is incomplete in many projects. This is a huge obstacle to lifecycle-based resilience. The overarching structural health monitoring is crucial to this movement as it links physical infrastructure with digital analytical systems [34]. The basic problem it faces is the differentiation between true deterioration and errors, environmental influences and changes in operation, and measurement noise. To tackle these challenges, AI techniques such as autoencoders, recurrent neural networks, classification models, clustering and physics-informed models have been developed. Physics informed models are also significant, because of the possibility that if a purely data driven model is able to work well with familiar structures and environments, it fails when applied to structures or environments that are not part of the training set [35].

8. Conclusion

AI is reshaping resilient infrastructure by connecting seismic damage evaluation, construction quality assurance, digital design, and structural health monitoring within increasingly integrated workflows. Deep learning, computer vision, generative design, digital twins, and physics informed models can improve the speed, consistency, and predictive capability of infrastructure assessment and management. However, data scarcity, limited model generalization, interoperability problems, uncertainty, and validation requirements remain important barriers to reliable deployment. Future progress will depend on representative datasets, stronger integration of engineering knowledge with AI, interoperable digital platforms, continuous validation, and effective data governance. Human engineering judgment will remain essential for safety critical infrastructure decisions.

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