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Machine Learning-Driven Structural Health Monitoring in Civil Engineering: A Review of Algorithms, Sensor Networks, and Predictive Maintenance Frameworks

Dr. Alok Kumar Bhargava[1], Sanjay Kumar Tuddu[2], Tariq A Aljaafreh[3], Vinod Rathore[4], Dr. Vishal R. Sharma[5]

[1]Founder and Principal Researcher, Trayi Vani Foundation, India; Developer of The Inner Engine Framework™ for Conscious Leadership Assessment; Author of Trayi Vāṇī – Eternal Verses on Peace, Silence & Discernment; Saviour Green Isle, Crossing Republik, Ghaziabad – 201016, Uttar Pradesh, India. Email: founder@trayivani.in; ORCID: 0009-0009-1805-3075; GOOGLE SCHOLAR: https://scholar.google.com/citations?view_op=list_works&hl=en&user=XRzNh50AAAAJ, Scopus ID: 60698294500 ; ResearchGate: https://www.researchgate.net/profile/Alok-Bhargava-7?ev=hdr_xprf.
[2]Assistant Professor, Computer Science and Engineering, Dev Bhoomi Uttarakhand University, Dehradun, Uttarakhand, India. Email ID: sanjaytd98@gmail.com
[3]Assistant Professor, Civil Engineering/ Mutah University/Alkarak/ Jordan. Email ID: Tariq.aljaafreh@mutah.edu.jo. ORCID ID: https://orcid.org/0009-0006-0013-7244
[4]Assistant professor, Mechanical engineering department, ITM University Gwalior MP. Email ID. - vinod.me@itmuniversity.ac.in ; ORCID ID: 0009-0009-4826-3305
[5]Assistant professor, Mumbai University, Thakur Ramnarayan College of Arts and Commerce, Mumbai – 400068. Email ID. - Vishal.sharma@trcac.org.in

ABSTRACT
Structural health monitoring (SHM) plays an essential role in the safety, reliability and performance of civil engineering structures. The traditional method of monitoring structures has been revolutionized in recent years by new developments in machine learning, intelligent sensor networks, and predictive maintenance. This is a narrative review on the use, potential and drawbacks of machine learning algorithms, sensor technologies and predictive maintenance frameworks in civil engineering. Structural damage detection, anomaly identification, condition assessment and performance prediction are considered in the case of supervised, unsupervised and deep learning approaches. Wireless sensor networks, Internet of Things based monitoring systems and multi sensor data fusion for continuous data acquisition of structures are also discussed in the review. Beyond this, the concept of predictive maintenance using digital twins and intelligent decision support systems is also discussed to improve the planning of maintenance and infrastructure resilience. The use of bridges, buildings, dams, tunnels and civil structures are deemed to be areas that illustrate opportunities for implementation. Challenges include few labelled monitoring data, unreliable sensors, lack of understanding of the models, computational needs, and lack of real-world validation. These limitations can be addressed by new sensing paradigms such as explainable AI, physics-informed learning, and autonomous sensing and digital twin integration. Finally, the review highlights the promising prospects of SHM for more reliable, efficient, and sustainable infrastructure and structural systems using ML, intelligent sensing, and predictive maintenance systems.

Keywords: Structural Health Monitoring; Machine Learning; Sensor Networks; Predictive Maintenance; Civil Infrastructure

1. INTRODUCTION

Structural health monitoring (SHM) has become an essential component of modern civil engineering because of the increasing need to ensure the safety, reliability, and long-term performance of infrastructure systems. Mechanical loading, environmental changes, material degradation and ageing processes are all examples of phenomena constantly being applied to bridges, buildings, tunnels, dams and other civil engineering structures which can lead to the progressive degradation of the structural quality. Traditional methods of inspection, such as visual assessment and periodic non-destructive testing are still critical for the detection of structural defects. These methods, however, need significant manpower, time and funding and only give limited information on structural behavior in the intervening time. Hence, effective alternative monitoring techniques using intelligence have been brought into the fore to continuously assess the condition of structures. Machine learning (ML) has been identified as a promising method for enhancing the

analysis of monitoring data to detect damage and assess structural performance and infrastructure resilience (Dongre, 2025).

The use of data-driven techniques in structural engineering has been greatly extended in recent years due to the development of computational intelligence. Analytical models, numerical simulations and engineering judgment are traditionally used for structural assessment, where structural responses are evaluated based on various loading conditions. These methods yield valuable information but can be computationally intensive when dealing with complex structural configurations and with large amounts of monitoring measurements. The ML methods can identify the relationships between structural responses and damage conditions without the need for explicit mathematical description of each of the underlying mechanisms. Algorithms like artificial neural networks, support vector machines, random forests, and deep learning architectures have been explored for predicting structural response, identifying damages, and assessing performance (Etim et al., 2024). These developments are enabling a transition from the current structural evaluation to intelligent monitoring systems for structural information analysis and interpretation of complex structural data.

Damage detection is one important application of ML in the field of SHM. Structural defects may alter measurable properties, such as the natural frequencies, mode shapes, strain distributions, and vibration responses. These changes in these characteristics can be detected using ML algorithms; they can be used for classification, localization and assessment of structural damage. Both supervised and unsupervised learning approaches have been shown to provide potential tools for identifying key patterns in structural responses, especially when traditional analysis techniques are not able to capture the variation in complex responses. Despite this, issues with noise in the data, variability in the environment, a lack of labelled observations, and generalizability of the models remain a limiting factor in their effectiveness in practice (Numan, 2024). The limitations need to be addressed to design reliable monitoring systems for various infrastructures.

Relable structural measurements are also important in determining the effectiveness of intelligent SHM. The technology of sensors such as fiber-optic sensors, strain gauges, accelerometers and wireless sensors allows information describing structural responses over time to be collected. They can be used along with ML algorithms to enable continuous condition assessment, early detection of abnormal behaviour and/or better interpretation of structural performances. In addition, digital monitoring systems have enhanced opportunities to link sensing technologies to infrastructure management systems. These advancements emphasize how important integrated SHM approaches are for enhancing the safety and long-term performance of infrastructure systems (Riffat, Samaei, & Pastakkaya, 2025).

In addition to being able to identify damage, ML-powered monitoring can also be used to optimize infrastructure maintenance. Traditional maintenance methods are often based on periodic inspections or maintenance actions triggered by visible damage. Predictive approaches, however, rely on the information of the structural condition to predict the possible deterioration and timely planning of the maintenance. As AI becomes more prevalent in the civil engineering sector, intelligent management strategies for civil infrastructure are gaining traction by integrating automated data collection, predictive analytics, and informed decision-making processes (Sargiotis, 2024). These strategies could also enhance infrastructure resilience, aid in risk-informed assessment, and enhance prioritization of infrastructure maintenance interventions in the presence of uncertainty (Wang et al., 2022).

Yet, current state-of-the-art methods tend to consider ML algorithms, sensor networks, and predictive maintenance as stand-alone technologies. It is hard for their effective integration, due to the differences of data quality, computational requirement, prediction reliability and implementation condition. Hence, in this narrative review the connections among these technologies, their use in civil engineering and key challenges in establishing reliable and integrated framework for structural monitoring are explored.

Research Objectives

- To critically review machine learning algorithms used for structural damage detection, condition assessment, and performance prediction in civil engineering infrastructure.
- To examine sensor networks and intelligent data acquisition technologies and evaluate their integration with machine learning-based structural health monitoring systems.
- To assess predictive maintenance frameworks, their applications in civil infrastructure management, and the major challenges and research opportunities associated with integrated intelligent structural monitoring.

2. Fundamentals of Structural Health Monitoring in Civil Engineering

2.1. Principles and Components of Structural Health Monitoring

Structural Health Monitoring (SHM) is an essential component for the safety, integrity and long-term performance of civil infrastructures. This involves the data collection, processing and interpretation of the structural response measurements to reveal its deterioration and to assess its structural conditions. The vast majority of SHM systems consist of a configuration of sensors, data acquisition devices, communication

network and analytical models. Structural evaluation tools can be divided into two classes: traditional, based mainly on experimental tests; and advanced computational tools, which are more efficient in interpreting complex structural behaviour. The fusion of monitoring measurements with intelligent computational techniques enables a more comprehensive assessment of the structures' condition and automated condition assessment (Plevris et al., 2025).

2.2. Structural Damage Mechanisms and Monitoring Parameters

Cracking, corrosion, failure due to fatigue, excessive deformations, degradation of stiffness due to loading and environment are some of the ways in which civil engineering structures can deteriorate. These changes will impact upon measurable parameters such as vibration frequencies, strain distributions and displacement responses. SHM systems rely on the sensors used to detect the abnormal behaviour of the structure, including the use of acoustic emission devices, strain gauges, displacement sensors and accelerometers. Correctly interpreting these measurements can be crucial in detecting damage that can only be determined by measurement, and not by visual inspection during routine tests. Rekatsinas et al. (2023) propose computational diagnostic methods that can utilize structural models, in addition to monitoring data, to enhance damage identification in complex and composite structural systems.

2.3. Conventional and Intelligent Structural Monitoring Approaches

The standard method of structural monitoring involves visual inspections, non-destructive testing and regular measurements. These methods are valid for the detection of the visible damage, but have drawbacks related to the frequency of inspection, accessibility, and the need for expert interpretation. Structural health monitoring (SHM) is an important concept for the safety, integrity and long-term performance of civil infrastructure. This involves the collection, processing and interpretation of structural response measurements to give indications of deterioration and structural conditions. Typically, SHM systems include sensor, data acquisition, communication network and analytical models. Traditional methods used to evaluate structure behaviour are mainly experimental test and engineering intuition, while the advanced computer simulation method has higher interpretation efficiency of the complex structural behaviour. The use of monitoring measurements and intelligent computational techniques improves the assessment of structures, and it enables automated condition assessment (Plevris et al., 2025).

3. Machine Learning Algorithms for Structural Health Monitoring

3.1. Supervised Machine Learning Algorithms

Supervised machine learning algorithms have been widely used for structural health monitoring (SHM) for damage detection, classification and condition prediction. This is usually done using Support Vector Machines (SVM), Random Forest (RF), Decision Trees (DT), and Artificial Neural Networks (ANN). These algorithms recognize relationships between the measurements of structure and known damage conditions using observations with labels. They rely on training data quality, feature selection and model validation for their effectiveness. Machine learning applications focused on classification and regression have proven to have potential in fault detection and condition prediction of engineering systems, which can be translated to civil infrastructure monitoring (Soomro et al., 2025).

3.2. Unsupervised and Semi-Supervised Learning Approaches

Unsupervised learning methods such as K-means clustering, Principal Component Analysis (PCA), and autoencoders can be used to detect abnormal structural response patterns without necessarily having to rely on labelled damage observation data. Semi-supervised methods utilize a small amount of labelled data with unlabelled data to enhance the condition assessment. These methods are especially helpful in situations where there is limited actual structural damage observations. The accuracy of anomaly detection, however, can depend on variations in the environment, noise in the measurements, and changes in operational conditions. The ability to extract reliable features from an image and interpret data obtained from the image is a key aspect in recent advancements related to AI-assisted machine monitoring for continuous condition assessment (Sufi, 2025).

3.3. Deep Learning Algorithms for Structural Damage Assessment

In the context of complex measurements for structural monitoring, deep learning methods offer powerful capabilities. To extract spatial features from the images and vibration signals, Convolutional Neural Networks (CNN) are used, and Long Short-Term Memory (LSTM) networks are used to analyse temporal response patterns. The relationships between sequential monitoring information can also be modelled using a transformer-based architecture. While building operational monitoring is different from structural damage assessment, applications of deep learning in intelligent building systems provide opportunities for automated pattern recognition and performance prediction (Arun et al., 2025). AI methods are used in civil infrastructure, such as bridges, to aid vibration-based damage identification and assessment of the structural condition. However, they require representative training data and testing in the real environment (Tang et al., 2025).

3.4. Hybrid and Physics-Informed Machine Learning Approaches

Hybrid methods combine machine learning with the use of signal processing and structural mechanics for better damage identification. Frequency characteristics of structural vibration measurements are obtained by these techniques like Fast Fourier Transform (FFT) and Short-Time Fourier Transform (STFT). The use of STFT-based feature extraction along with machine learning can aid in damage related variations in the structural responses (Katam et al., 2025). Physics-informed methods also utilize engineering principles in predictive models, which could increase the reliability of models and the need for training observations.

3.5. Comparative Performance and Limitations of Machine Learning Algorithms

The performance of machine learning algorithms will vary based on monitoring objectives, structural complexity, availability of data and computational needs. Supervised methods work well if the observations are labeled, while unsupervised methods can be used for anomaly detection with limited information regarding damages. Deep learning can use a complex measurement but need a lot of computational resources and proper validation. In the field of aerospace structural monitoring, other challenges exist that are transferable to other areas, such as model generalizability, model interpretability, and prediction uncertainty (Scarselli & Nicassio, 2025). Thus, the algorithm evaluation should consider the accuracy, precision, recall, F1 score, computational efficiency and reliability under different operational conditions. Table 1 provides a summary of the main applications, advantages, and limitations of machine learning approaches to structural condition assessment. The principal machine learning approaches used for structural damage assessment are illustrated in Figure 1.

Table 1. Comparative Assessment of Machine Learning Algorithms for Structural Health Monitoring

ML approach	Main techniques	SHM applications	Advantages	Limitations	References
Supervised learning	SVM, RF, DT, ANN	Damage classification, fault detection, condition prediction	Effective with labeled observations; supports quantitative prediction	Requires representative training observations; risk of overfitting	(Soomro et al., 2025)
Unsupervised learning	PCA, K-means, autoencoders	Anomaly identification, feature extraction, structural condition monitoring	Useful when damage labels are limited	May confuse operational variations with damage	(Sufi, 2025)
Deep learning	CNN, LSTM, RNN	Automated feature extraction, response prediction, pattern recognition	Processes complex spatial and temporal measurements	High computational requirements; limited interpretability	(Arun et al., 2025)
AI-based bridge monitoring	ML and deep learning models	Bridge damage identification and structural response assessment	Supports analysis of complex monitoring information	Performance depends on structural and environmental conditions	(Tang et al., 2025)
Hybrid learning	STFT with ML classifiers	Vibration-based damage identification	Combines signal features with automated classification	Sensitive to feature selection and signal quality	(Katam et al., 2025)
Cross-domain ML approaches	Supervised and deep learning models	Structural anomaly detection and condition assessment	Offers transferable diagnostic approaches	Requires validation before transferring between structural domains	(Scarselli & Nicassio, 2025)

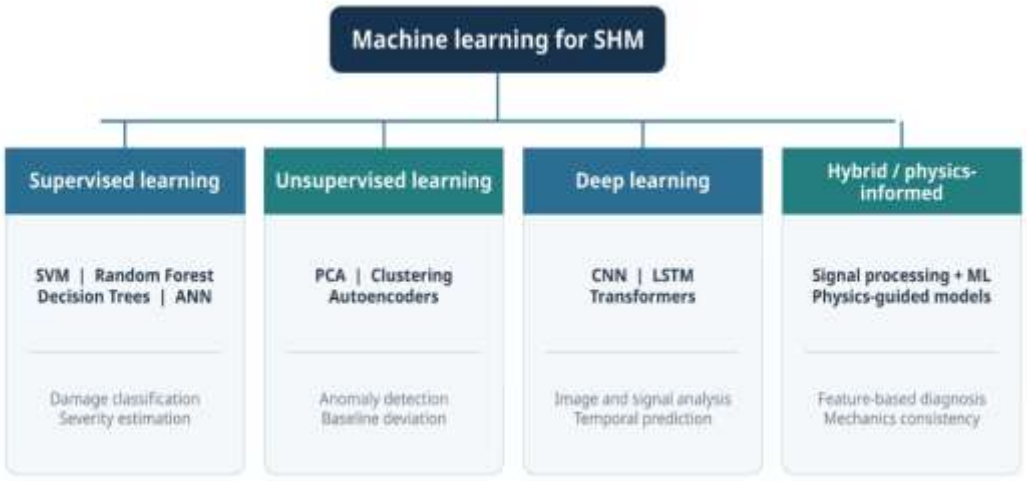


Figure 1. Classification of Machine Learning Algorithms for Structural Health Monitoring

4. Sensor Networks and Intelligent Data Acquisition Technologies

4.1. Conventional Sensors for Structural Health Monitoring

In the field of structural health monitoring (SHM), sensor technologies are vital to the collection of measurements associated with the behaviour, damage, and environment of a structure. Examples of common sensing devices are accelerometers, strain gauges, displacement sensors, fibre-optic sensors, and acoustic emission sensors. The technologies are useful for identifying structural changes by measuring continuously or periodically. There has also been some work on using smart sensing for underground infrastructure where data-driven techniques can be used to assist with leak detection, or to detect abnormal operational conditions. These applications highlight the need for choosing suitable sensors for various infrastructure monitoring needs (Chadalawada, 2024).

4.2. Wireless Sensor Networks for Structural Monitoring

Wireless sensor networks (WSNs) allow the measurements to be taken in and on the structure and sent to other points without the need for extensive wired connections. They typically include distributed sensor nodes, communication interfaces and centralized or distributed processing systems. Their benefits are that they can be installed almost anywhere, accessed remotely, and, in very large infrastructure systems, may be scaled up. Wireless monitoring systems with machine learning algorithms can monitor and analyses sensor readings to detect changes in the structure's response. In practical implementation, however, reliability of wireless communication, power consumption, synchronization, and the impact of environmental interference are all important factors to consider (Pop et al., 2024).

4.3. Internet of Things-Based Intelligent Monitoring Systems

This is enabled using the Internet of Things (IoT) technologies, which help to connect the sensing devices to communication networks and analytical platforms to enable remote monitoring and automated condition assessment. Real-time measurements can be combined with machine learning models to aid in early fault detection and forecasting in IoT-based systems. Industrial predictive maintenance dashboards showcase the practical application of ongoing sensor data to present information in a digestible way for equipment monitoring and decision-making purposes (Bristy et al., 2025). In healthcare monitoring, IoT sensors combined with deep learning can help with automated interpretation of measurements continuously collected from the sensor, with similar concepts under investigation. While there are differences in the application of healthcare and civil infrastructure, both of their sensing and analytical architectures give insights for the development of intelligent monitoring systems (Deepak, 2025). The integration of sensing devices, wireless communication networks, and machine learning-based analytical systems is presented in Figure 2.

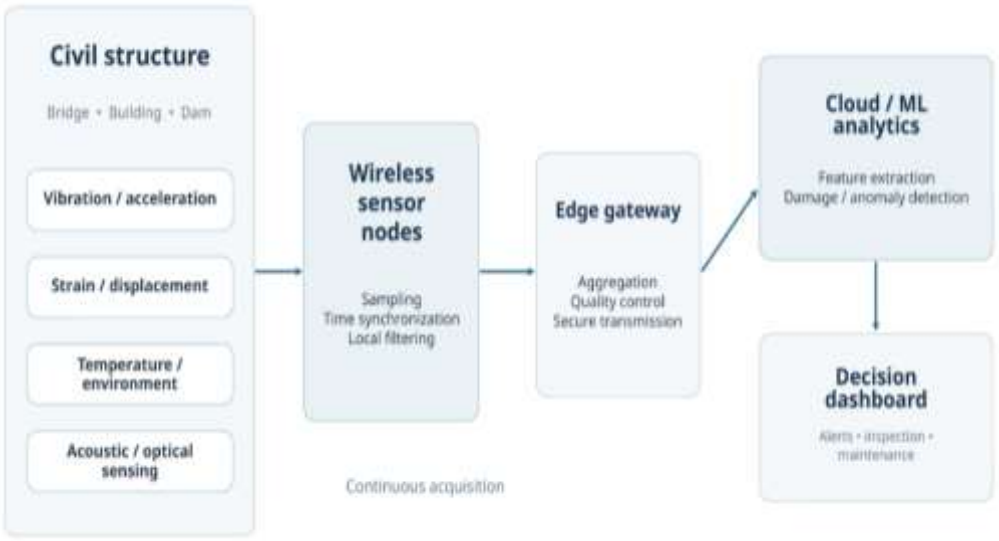


Figure 2. Architecture of an Intelligent Sensor Network for Structural Health Monitoring

4.4. Sensor Data Processing and Multisensor Data Fusion

The accurate structural condition assessment is crucial and depends on the effective preprocessing and interpretation of sensor measurements. Raw monitoring signals can include signals from environmental factors that affect damage detection reliability, noise and missing values. To make measurements suitable for machine learning analysis, signal filtering, normalization, feature extraction and data synchronization are thus essential. Multisensor data fusion is the process of using multiple sensor data to create a more complete picture of structural behaviour. In engineering, the use of AI-assisted sensor fusion has been explored in the context of pressure vessel monitoring for predictive failure analysis and reliability assessment, highlighting its potential for safety-critical scenarios. These can also be adapted to structural response characteristics and civil infrastructure operational conditions to support civil infrastructure monitoring (Fazle et al., 2023).

4.5. Challenges and Advances in Intelligent Sensor Networks

Challenges to the implementation of intelligent sensor networks include measurement accuracy, sensor lifetime, energy usage, communication reliability, and calculation requirements. Another important feature of the sensors for long-term structural monitoring is the ability to operate with consistent performance in varying environmental and mechanical conditions. These limitations can be addressed by recent advances in smart sensing materials. Conductive polymer composites were explored with machine learning and IoT technologies for strain monitoring and interpretation of real-time responses of the structure. These systems showcase the flexibility of sensing materials and embedded intelligence in enhancing adaptability in monitoring and facilitating distributed structural assessment (Nagaraj et al., 2025). Table 2 compares the monitoring functions, advantages and implementation limitations of conventional and emerging intelligent sensing systems.

Table 2. Comparison of Sensor Technologies and Intelligent Data Acquisition Systems for Structural Health Monitoring

Sensor technology or system	Monitoring function	Application	Advantages	Limitations	References
Pipeline monitoring sensors	Leak identification and abnormal condition detection	Underground infrastructure	Supports remote condition assessment	Performance depends on installation and monitoring conditions	(Chadalawada, 2024)
Wireless sensor networks	Structural response acquisition and transmission	Distributed structural monitoring	Flexible deployment and reduced cabling	Energy consumption and communication reliability	(Pop et al., 2024)
IoT-based monitoring	Continuous data collection	Industrial predictive	Facilitates real-time	Requires reliable	(Bristy et al., 2025)

dashboards	and visualization	maintenance	monitoring and decision support	connectivity and data integration	
IoT and deep learning sensing systems	Continuous measurement and automated prediction	Healthcare monitoring; transferable sensing architecture	Supports automated interpretation of measurements	Requires domain-specific validation for civil SHM	(Deepak, 2025)
Multisensor fusion systems	Integration of multiple sensor measurements	Pressure vessel condition monitoring	Provides complementary information for fault prediction	Synchronization and data quality challenges	(Fazle et al., 2023)
Conductive polymer composite sensors	Strain and structural response monitoring	Intelligent SHM	Potential for flexible and distributed sensing	Long-term durability and field validation requirements	(Nagaraj et al., 2025)

5. Machine Learning-Based Predictive Maintenance Frameworks

5.1. Evolution of Infrastructure Maintenance Strategies

Infrastructure maintenance has evolved from reactive to preventative and now to condition based and predictive maintenance. Reactive maintenance: maintenance activities are carried out when the structure becomes inoperable; preventive maintenance: periodic inspections and interventions. Predictive maintenance means using data from measurements combined with the analytical models to predict deterioration and optimise maintenance tasks. Machine learning can facilitate this change by identifying trends of the degradation of the structure and possible failures. The use of their application in building services has showcased potential for enhancing maintenance efficiency, operational reliability, and infrastructure lifecycle management (Adhikari et al., 2025). Furthermore, AI-powered maintenance strategies help in automating building condition assessments and making informed decisions (Yaqi et al., 2025).

5.2. Machine Learning-Based Structural Deterioration Prediction

The main idea behind predictive maintenance is to use data from past monitoring activities and real-time data to detect deterioration patterns and to predict the condition of structures using machine learning algorithms. Damage progression assessment, anomaly detection and remaining useful life (RUL) estimation are possible by regression models and intelligent algorithms like neural networks. The latter techniques may help the engineer to determine which components must be addressed before bigger problems occur. Automated fault prediction and continual condition monitoring are further improved using Artificial Intelligence (AI) and connected sensing technologies. AI of Things (AIoT) frameworks showcase the synergy of interconnected devices and intelligent analytical models in strengthening predictive maintenance in engineering systems (Bitam et al., 2025).

5.3. Integration of Sensor Data with Predictive Maintenance

Reliable sensor measurements, appropriate analytical models and constant assessment of structural conditions are all basis for effective predictive maintenance. Information pertaining to vibration, strain, displacement and other performance indicators are captured using so called Internet of Things (IoT) sensors. These measurements are then fed into the machine learning algorithms to identify an abnormal pattern; they also aid in maintenance planning. The study highlights the importance of integrating IoT sensing technologies with AI algorithms in the field of industrial automation for enhanced fault detection and condition monitoring (Haque et al., 2024). However, data quality and reliability of the models, together with implementation constraints, are significant challenges to be addressed when using signal processing techniques and hybrid analytical models to complement monitoring information (Garcia et al., 2025). The sequential processes involved in machine learning-based predictive maintenance and continuous feedback are illustrated in Figure 3.

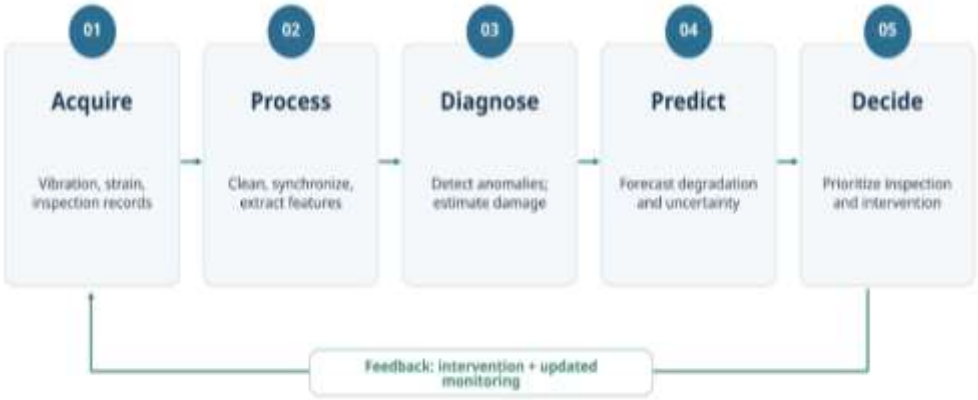


Figure 3. Machine Learning-Based Predictive Maintenance Framework for Civil Infrastructure

5.4. Digital Twins and Intelligent Maintenance Decision-Making

Digital twin technology offers opportunities to bridge the gap between the physical and the virtual, which is constantly updated. Digital twins can be used to aid in the structural condition assessment and maintenance decision making by combining sensor measurements, computational models and predictions from machine learning. Proper City information modelling along with AI-driven predictive maintenance can help in the management of urban infrastructure assets by aiding in coordinated monitoring and planning of interventions (Lawal et al., 2025). In the same vein, another digital twin application used for high-speed railway systems, with the assistance of machine learning, shows how to monitor the condition of the infrastructure and predict maintenance needs. Their effectiveness, however, relies on proper model calibration, accurate measurements and proper validation under real operating conditions (Nwamekwe & Chikwendu, 2025).

5.5. Benefits and Limitations of Predictive Maintenance Frameworks

The potential benefits of machine learning based predictive maintenance are: Structural reliability, Unplanned maintenance reduction, More efficient resource allocation, Longer life of infrastructure services. By combining IoT technologies with intelligent analysis systems, urban infrastructure managers can better detect early signs of issues and schedule maintenance work based on the state of the infrastructure and its operational needs (Sanusi, 2025). However, there are challenges to predictive maintenance frameworks, such as incomplete monitoring records, sensor failure, computational needs, model uncertainty, and cost of implementation. There are also limitations in directly transferring predictive models due to infrastructure type differences. Thus, it is necessary to have reliable data acquisition, the proper model validation, and to be compatible in engineering maintenance practices. Table 3 illustrates the comparative analysis of the predictive maintenance frameworks considering their technologies, engineering applications, operational benefits, and implementation challenges.

Table 3. Comparative Assessment of Machine Learning-Based Predictive Maintenance Frameworks

Maintenance approach	Technologies or framework	Main applications	Advantages	Limitations	References
ML-based predictive maintenance	Supervised learning and predictive models	Building services	Supports deterioration prediction and maintenance planning	Requires historical monitoring records	(Adhikari et al., 2025)
AIoT-enabled maintenance	Artificial intelligence and connected sensors	Intelligent engineering systems	Enables continuous monitoring and automated fault prediction	Connectivity and system integration challenges	(Bitam et al., 2025)

Signal-based predictive maintenance	Signal processing and hybrid models	Industrial equipment	Improves fault identification using condition measurements	Sensitive to signal quality and model selection	(Garcia et al., 2025)
IoT-integrated maintenance	IoT sensors and ML algorithms	Industrial automation	Supports early fault detection and condition assessment	Sensor reliability and data management requirements	(Haque et al., 2024)
Cognitive predictive maintenance	AI and city information modeling	Urban infrastructure assets	Supports coordinated asset management	Requires interoperable information systems	(Lawal et al., 2025)
Digital twin-based maintenance	ML and virtual asset modeling	High-speed rail networks	Supports condition prediction and maintenance decisions	Requires model updating and calibration	(Nwamekwe & Chikwendu, 2025)
Smart infrastructure maintenance	IoT and AI-driven monitoring	Urban facilities	Supports maintenance prioritization and resource allocation	Deployment costs and technical complexity	(Sanusi, 2025)
Intelligent building maintenance	AI-assisted condition assessment	Building management systems	Improves maintenance planning and operational management	Data availability and implementation barriers	(Yaqi et al., 2025)

6. Integration and Civil Engineering Applications of Intelligent Structural Health Monitoring Systems

6.1. Integration of Machine Learning and Sensor Networks

Machine learning (ML) can be combined with sensor networks to achieve automated data collection and real-time evaluation of structures with early damage detection. Intelligent structural health monitoring (SHM) systems use sensors, communication technologies, and prediction algorithms to detect unexpected structural behaviour and enhance the reliability of structures. The application of AI-based condition monitoring strategies for industrial control systems shows the promise of ongoing sensing and automated fault detection, which can be applied to intelligent civil infrastructure monitoring with some transferable principles (Arifeen, 2025).

6.2. Applications in Bridge Structural Health Monitoring

Bridges are the subject of constant traffic loads, environmental conditions and degradation of their structures, and are thus an important area for intelligent SHM. Detecting damage and assessing the structural conditions is done by ML algorithms that analyse vibration, strain and displacement measurements. In concrete bridge decks, the use of deep learning algorithms for fusing multiple sensor data shows how combined monitoring data can aid in damage detection and predictive maintenance decisions (Hakimi et al., 2025).

6.3. Applications in Buildings and Urban Infrastructure

Intelligent SHM systems can aid in building safety by providing continuous monitoring of structural vibrations, deformation and deterioration. Sensors and ML algorithms can enable the automated condition assessment and maintenance planning for IoT. The examples of integrated condition monitoring approaches, created for electrical power plant systems, confirm the potential of multiple condition monitoring parameters combined for predictive analysis. These principles can be used in the same manner to build infrastructure management, which can be validated by applying structural measurements (Islam, 2025).

6.4. Applications in Dams, Tunnels, and Complex Infrastructure

The continuous monitoring of dams, tunnels, and underground structures is necessary in view of the complicated loading conditions and environmental influences. Intelligent systems can be used to analyse data obtained from measurements of displacement, strain, temperature and seepage to detect abnormal structural behaviour. Through data-driven environmental monitoring and predictive risk mapping,

opportunities for integration between real-time monitoring and spatial risk mapping are shown. These analytical methods have environmental applications but can also be applied to infrastructure monitoring (Rajesh et al., 2025).

6.5. Digital Twin-Enabled Monitoring and Real-Time Predictive Assessment

Digital twin technologies combine physical infrastructure, sensor readings, and computational models to aid in the assessment of the condition of structures and to enable predictive maintenance. Digital twins can be used to enhance structural response prediction and reliability assessment under uncertain environmental conditions with artificial intelligence. The use of uncertainty-aware monitoring in applications like offshore wind turbines shows how such monitoring can be used to assess structural performance and inform maintenance decisions (Riffat, Doudran, et al., 2025). But the accurate implementation requires accurate measurements from the sensors, model calibration and long-term validation. The use of integrated intelligent monitoring systems in the civil infrastructure and related engineering fields is listed in Table 4. The integration of intelligent sensors, machine learning, digital twins, and maintenance decision-making is illustrated in Figure 4.

Table 4. Applications of Intelligent Structural Health Monitoring Across Civil Engineering Infrastructure

Application area	Intelligent monitoring approach	Monitoring objective	Potential benefits	Key limitations	References
Civil engineering bridges	Deep learning and multisensor data fusion	Damage identification and condition assessment of concrete bridge decks	Supports integrated damage assessment and maintenance prediction	Requires reliable multisensor measurements	(Hakimi et al., 2025)
Electrical infrastructure	AI-based fault detection and condition monitoring	Detection of abnormal system behavior	Provides transferable approaches for intelligent infrastructure monitoring	Electrical faults differ from structural damage mechanisms	(Arifeen, 2025)
Building service infrastructure	Integrated condition monitoring and predictive modeling	Operational condition assessment and maintenance prediction	Supports monitoring of complex infrastructure systems	Requires structural validation before use in building SHM	(Islam, 2025)
Environmental and urban monitoring	ML-based real-time assessment and risk mapping	Identification of environmental abnormalities and spatial risks	Demonstrates integration of monitoring data with predictive analytics	Does not directly establish structural damage detection capability	(Rajesh et al., 2025)
Offshore wind turbine structures	AI-enabled digital twins and reliability modeling	Structural condition prediction under environmental uncertainty	Supports uncertainty-aware reliability assessment	Requires calibrated models and representative monitoring information	(Riffat, Doudran, et al., 2025)



Figure 4. Integrated Intelligent Structural Health Monitoring Framework

7. Challenges, Research Gaps, and Future Directions

7.1. Data Availability, Quality, and Standardization

The machine learning-derived structural health monitoring (SHM) depends on dependable and standardized monitoring information. But damage observations are limited and may be incomplete, and sensor measurements and environment variations may decrease the accuracy of the damage predictions. The methods of data collection also limit the ability to compare models and to transfer across models. In the aerospace sector, predictive maintenance studies also face issues related to data quality, model reliability, and implementation challenges, with stress on the necessity of standardization in monitoring practices (Li, 2025).

7.2. Model Generalizability, Interpretability, and Prediction Uncertainty

The models developed using machine learning under certain structural conditions could be sub-optimal for other infrastructure systems. The reliability of predictions may vary depending on material, loading, and/or environment. Also, complex deep learning models are not very interpretable and thus not accepted well in engineering decision making. AI-based fault detection systems also suffer from similar issues related to transparency, uncertainty in prediction, and reliability (Rana, 2025).

7.3. Technical, Economic, and Implementation Challenges

Intelligent SHM systems need investments on the sensors, communication networks, computational infrastructure and maintenance platforms. Long-term implementation is also impacted by sensor durability, energy use, cybersecurity, and cost of operating the sensors. Financial and regulatory issues related to smart city technologies have been identified as challenges in the research of smart city monitoring (Singh & Nayyar, 2024). In addition, one of the significant challenges of data-driven predictive systems is the high computational burden, data integration issues, and the reliability of the models (Strielkowski et al., 2023).

7.4. Research Gaps in Real-World Deployment

Even though many machine learning monitoring methods have been developed, many of these are not sufficiently validated in actual infrastructure environments. Laboratory tests cannot fully capture the in-service, environmental and aging conditions. Model transferability is further constrained by variations in the configuration of the sensors and the type of monitoring needed. Preventive maintenance studies in the industry sector highlight the need for application-dependent validation and trustworthy operational measurements, pointing to the need for long-term field evaluations, specifically in the civil engineering sector (Suwatcharachaitiwong et al., 2025).

7.5. Future Research Directions

Future research will be directed towards explainable, reliable and transferable machine learning models for structural condition assessment. Prediction performance could be improved with limited information from monitoring using physics-informed learning, transfer learning, and self-supervised approaches. Continuous monitoring can potentially be further bolstered by autonomous sensor networks, edge computing and energy efficient sensing technologies. Combining digital twins with data-driven predictions using machine learning for predictive maintenance could enable real-time evaluation of the structure, prediction of the evolution of damage, and decisions based on risk. The future research should focus on standardized monitoring schemes, field validation over long-term period, low cost and easy implementation, and interoperability to achieve scalable and sustainable intelligent SHM system.

8. Conclusion

Structural health monitoring (SHM) is one of the most important applications of machine learning for

enhancing the safety, reliability and service life of civil engineering structures. In this review, the application of machine learning algorithms, intelligent sensor networks and prediction maintenance systems for structural health monitoring and infrastructure management were explored. Automated Damage Detection, Anomaly Identification and Structural performance prediction can be great opportunity for Supervised, Unsupervised and Deep learning techniques. Combining computational intelligence and structural engineering principles via hybrid and physics-informed approaches further enhances monitoring capabilities. The advanced sensor technologies, wireless sensor networks and IoTs allow data to be collected continuously from the structures and monitored in real-time. The machine learning features help them to assess conditions and detect failures in structures more accurately. Predictive maintenance solutions, along with digital twins and intelligent decision-support systems, can assist with optimising maintenance plans, minimize maintenance costs and improve the resilience of infrastructure. These, however, are still constrained by the challenge of obtaining labelled information, sensor reliability, model interpretability, computational demands, and real-world validation. To overcome these drawbacks, it is needed to standardize the methods of monitoring, to develop reliable models for prediction and to have more dialogue and collaboration among the computational researchers and the civil engineers. Explainable artificial intelligence, autonomous sensing technologies and integrated digital monitoring platforms are future research and development areas. The scope of application of smart sensor networks, predictive maintenance and machine learning in civil infrastructure systems is highly promising for safe, efficient, sustainable and resilient systems.

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