

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING APPLICATIONS IN STRUCTURAL ENGINEERING: A COMPREHENSIVE REVIEW OF RECENT ADVANCES AND FUTURE DIRECTIONS

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Abstract

Artificial intelligence (AI) and machine learning (ML), including deep learning and evolutionary algorithms, are transforming traditional design, analysis, and maintenance processes in structural engineering (Kurcusz and Das, 2025). This comprehensive literature review synthesizes recent advances across five key application domains: structural health monitoring, damage detection, design optimization, computational mechanics, and seismic assessment. Machine learning techniques have demonstrated significant potential for improving computational accuracy and precision of simulations in structural system identification, structural design, and prediction applications (Etim et al., 2024). Artificial Intelligence-Aided Design (AIAD) has greatly alleviated challenges faced by structural design, showing great promise in design concept generation, enhancing efficiency while simplifying the workflow, reducing the design cycle time and cost, and achieving global optimal design (Ao, Li and Duan, 2025). However, widespread adoption remains constrained by data quality limitations, model interpretability challenges, validation framework gaps, and integration barriers with existing systems. While AI/ML adoption in civil engineering faces challenges including data availability, computational complexity, model interpretability, and integration with traditional systems (Jain et al., 2025), emerging solutions such as explainable AI (XAI), physics-informed neural networks (PINNs), and digital twin technologies offer pathways forward. This review integrates recent advances from 2020–2026, identifies critical research gaps, and outlines future directions for implementing trustworthy, efficient, and sustainable AI/ML systems in structural engineering practice.

1. Introduction

Structural engineering has undergone significant transformation with the integration of artificial intelligence and machine learning technologies

over the past decade. Artificial intelligence and its applications, encompassing machine learning, data analytics, and cognitive computing, can enhance various aspects of structural engineering

through analysis of computational data, identification of patterns within extensive data sets, and formulation of unique decisions (Varshney *et al.*, 2025). The traditional paradigm of structural engineering—characterized by iterative, manual design processes and empirical validation methods—has begun shifting toward data-driven, predictive, and automated approaches enabled by contemporary AI/ML frameworks.

Modeling and simulation have been extensively used to solve a wide range of problems in structural engineering, but many simulations require significant computational resources, resulting in exponentially increasing computational time as the spatial and temporal scales of the models increase (Etim *et al.*, 2024). This computational bottleneck has motivated the adoption of machine learning as a complementary tool. The integration of artificial intelligence and machine learning in civil engineering has revolutionized traditional approaches, enabling data-driven decision making, predictive modelling and process automation across diverse domains (Maheshwari, 2026).

The application spectrum of AI/ML in structural engineering has expanded considerably. The integration of AI with building information modelling (BIM), digital twins, and sensor-based monitoring systems is creating a more data-driven engineering environment (Kurcusz and Das, 2025). These integrations represent a fundamental shift from reactive, post-failure inspection methodologies to proactive, predictive maintenance strategies grounded in continuous monitoring data and pattern recognition algorithms.

Recent advancements in deep learning architectures—particularly convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based models—have demonstrated remarkable capabilities in processing complex structural data. Deep learning architectures including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and autoencoders have been widely used in structural damage detection, leveraging their ability to autonomously learn

damage-sensitive features and classify damage from complex datasets (Li *et al.*, 2025). These advances enable automated feature extraction and anomaly detection without requiring explicit feature engineering, a critical advantage in domains where damage signatures are heterogeneous or poorly understood.

However, the path toward comprehensive adoption of AI/ML in structural engineering faces substantial obstacles. Widespread adoption remains limited by issues such as data quality, model transparency, and a lack of validation frameworks (Kurcusz and Das, 2025). The "black box" nature of many deep learning models presents particular challenges in safety-critical applications where engineering judgment, interpretability, and regulatory compliance are essential. The "black box" nature of these models raises ethical and regulatory issues especially in decisions related to safety (Jain *et al.*, 2025).

Emerging technologies such as physics-informed neural networks (PINNs), explainable AI (XAI), and digital twins are beginning to address these interpretability and validation concerns. Advancements like physics-informed neural networks (PiNNs) integrate engineering principles with AI, providing models that are both reliable and interpretable (Satar *et al.*, 2025). These hybrid approaches combine physical domain knowledge with data-driven learning, thereby improving both model accuracy and trustworthiness.

The structural engineering discipline is positioned at a critical juncture. On one side, the proven efficacy of AI/ML in complex pattern recognition and optimization tasks offers unprecedented opportunities to improve design efficiency, predict failures earlier, and optimize maintenance schedules. On the other side, the inherent conservatism of structural engineering practice—justified by safety considerations—necessitates rigorous validation, transparent decision-making frameworks, and seamless integration with existing codes and standards.

This review synthesizes recent advances in AI/ML applications across five major domains within structural engineering: (1) structural health monitoring and predictive maintenance, (2)

damage detection methodologies, (3) design optimization techniques, (4) computational mechanics and finite element analysis acceleration, and (5) seismic risk assessment and earthquake engineering. By integrating findings from peer-reviewed literature published between 2020 and 2026, this review identifies current methodological strengths, persistent research gaps, ethical considerations, and promising future directions. The review emphasizes that AI/ML should function as a complementary tool augmenting human expertise rather than replacing established engineering practice, while highlighting the critical importance of developing standardized validation frameworks, improving model interpretability, and addressing data scarcity challenges.

2. Methodology

2.1 Literature Search Strategy and Source Selection

This comprehensive literature review employed a systematic search strategy across peer-reviewed academic databases spanning the period 2020–2026. The search utilized multiple keyword combinations including "artificial intelligence," "machine learning," "deep learning," "neural networks," "structural health monitoring," "damage detection," "design optimization," "finite element analysis," "seismic assessment," and "structural engineering." The search strategy prioritized recent publications (2020 onwards) to ensure coverage of contemporary methodological developments, emerging technologies, and current challenges within the field.

Source selection criteria were established to ensure inclusion of peer-reviewed journal articles, conference proceedings, and review papers that directly addressed AI/ML applications in structural engineering contexts. Sources were systematically screened to exclude papers focused on tangential applications (e.g., solar panel defect detection, biomedical engineering, robotic kinematics) while retaining those with primary focus on civil and structural engineering systems. A total of 76 sources met inclusion criteria,

spanning multiple subdisciplines within structural engineering.

2.2 Thematic Organization and Synthesis Framework

Retrieved sources were organized into five primary thematic categories reflecting major application domains:

1. **Structural Health Monitoring (SHM) and Predictive Maintenance** (18 sources)
2. **Damage Detection and Classification** (20 sources)
3. **Design Optimization and Artificial Intelligence-Aided Design (AIAD)** (15 sources)
4. **Computational Mechanics and Finite Element Analysis Integration** (14 sources)
5. **Seismic Risk Assessment and Earthquake Engineering** (9 sources)

Within each thematic area, sources were further classified by methodology employed (e.g., supervised learning, unsupervised learning, deep learning architecture type) and application context (e.g., building structures, bridges, tunnels, pipelines).

2.3 Critical Analysis Framework

Each source was evaluated across multiple dimensions:

- **Methodological rigor:** Assessment of study design, sample size, validation strategy, and reported performance metrics
- **Technical sophistication:** Evaluation of ML/DL architecture complexity, algorithmic novelty, and computational efficiency
- **Practical applicability:** Consideration of real-world implementation feasibility, scalability, and integration with existing engineering workflows
- **Interpretability and transparency:** Examination of model explainability, feature importance analysis, and potential for black-box decision-making concerns
- **Data requirements and limitations:** Analysis of training data characteristics, data scarcity challenges, and generalization capabilities

Thematic Domain	Number of Sources	Primary Algorithms	ML Key Applications	Performance Range
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Thematic Domain	Number of Sources	Primary Algorithms	ML	Key Applications	Performance Range
Structural Health Monitoring	18	ANN, CNN, SVMs	LSTM,	Vibration-based monitoring, predictive maintenance	85-99% accuracy
Damage Detection	20	CNN, GRU, Transformers	ResNet,	Visual inspection, crack detection, localization	88-99.3% accuracy
Design Optimization	15	GA, PSO, Neural networks	RL,	Topology optimization, weight reduction, structural design	10-75% improvement
FEA Integration	14	ANN, LSTM, methods	DNN, ensemble	Stress prediction, fatigue analysis, surrogate modeling	$R^2 = 0.95-0.999$
Seismic Assessment	9	CNNs, Informed NNs, ML classifiers	Physics-	Earthquake damage assessment, response prediction	99.27% precision

Table 1: Thematic Organization of Literature with Performance Metrics

2.4 Methodological Comparison Framework

To enable meaningful cross-study comparison, key methodological characteristics were extracted from each source and organized according to:

Study Characteristic	Description	Frequency of Reporting
Training dataset size	Number of samples/simulations used	92% of sources
Validation methodology	Cross-validation approach, test set separation	88% of sources
Algorithm comparison	Benchmarking against baseline/alternative methods	79% of sources
Hyperparameter tuning	Optimization strategy for model parameters	71% of sources
Computational requirements	Processing time, memory consumption, hardware specifications	64% of sources
Real-world deployment	Field testing or practical implementation evidence	47% of sources
Interpretability assessment	Explainability analysis using SHAP, LIME, or similar	38% of sources

Table 2: Methodological Reporting Frequency Across Literature

2.5 Performance Metric Standardization

Given heterogeneity in how different studies reported algorithm performance, a standardization framework was applied:

- **Classification tasks:** Reported metrics normalized to precision, recall, F1-score, and overall accuracy

- **Regression tasks:** Normalized to R^2 (coefficient of determination), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE)
- **Detection tasks:** Reported as sensitivity/specificity, damage localization accuracy, and false positive/negative rates

2.6 Research Gap Identification Methodology

Research gaps were identified through systematic analysis of:

1. **Methodological gaps:** Underexplored algorithm types, architectural combinations, or validation approaches
2. **Application gaps:** Structural typologies or engineering problems with minimal AI/ML literature
3. **Implementation gaps:** Disconnect between laboratory validation and real-world deployment
4. **Interpretability gaps:** Limited transparency analysis in deep learning models applied to safety-critical contexts
5. **Data gaps:** Scarcity of publicly available, high-quality datasets for training and validation

3. Results

3.1 Structural Health Monitoring and Predictive Maintenance Applications

Structural health monitoring represents one of the most mature and widely adopted application domains for AI/ML in structural engineering. AI and ML may enhance capabilities for real-time monitoring, anomaly detection, and optimization of maintenance schedules through processing of vast amounts of sensor data to provide actionable insights into the condition of infrastructure (Kulkarni, Deshvena and Samshoddin, 2025). Predictive analytics shows potential to forecast the remaining useful life (RUL) of components and support determination of optimal timing for repairs or replacements through machine learning models trained on historical inspection and operational data (Kulkarni, Deshvena and Samshoddin, 2025) (Shah, Ullah, Khoso, & Umali, 2026; Shah, Ullah, Khoso, Iqbal, et al., 2026).

Sensor network deployment and data acquisition have become increasingly sophisticated. IoT-based SHM platforms integrate multi-axis MEMS accelerometers and inclinometers, supported by on-site signal processing and cloud-based analytics backends, enabling comprehensive damage assessment through parameters such as frequency changes, inter-storey drift, roof displacement, torsional irregularities, and permanent tilt (Ergen and Zülfikar, 2026). Advanced signal processing combined with machine learning algorithms enables real-time condition assessment and early warning system activation.

AI significantly advances SHM capabilities across seven core areas: data acquisition and sensor networks, data processing and signal analysis, anomaly detection and damage identification, predictive maintenance, reliability and risk assessment, visual inspection and remote monitoring, and resilient and adaptive infrastructure (Plevris and Papazafeiropoulos, 2024). Wireless-enabled IoT fatigue damage sensors demonstrate potential for assessing remaining useful life (RUL) and fatigue state health monitoring of structures through sensor-integrated approaches (Kaplan et al., 2025).

3.2 Deep Learning Architectures for Damage Detection

Recent advances in deep learning have substantially improved structural damage detection capabilities. Deep learning architectures including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and autoencoders have been widely used in structural damage detection, with their ability to autonomously learn damage-sensitive features and classify damage from complex datasets (Li et al., 2025).

Convolutional neural networks have proven particularly effective for visual-based damage detection. Hybrid deep learning models combining ResNet50 and GoogLeNet, further enhanced by convolutional block attention modules (CBAM), significantly outperform standalone architectures for structural damage detection, with data augmentation techniques enhancing robustness (Singh et al., 2024). CNN-

based approaches achieve 88.4% accuracy in crack detection on reinforced concrete arch bridges, identifying damage points with effective localization within three-dimensional models generated from unmanned aerial vehicle imagery (Alfaro *et al.*, 2025).

Advanced architectures continue to emerge with enhanced capabilities. Novel hybrid wavelet-CNN-Transformer frameworks simultaneously extract localized damage signs and gradual changes in overall behavior of structural vibrations, achieving 98.85% accuracy on bridge datasets—representing 1.35% improvement over prior state-of-the-art methods (Najem *et al.*, 2025). Vision Transformer-based models with adaptive attention optimization achieve 99.27% precision, recall, and F1-score for fine-grained post-earthquake structural damage assessment, outperforming six traditional machine learning models, six deep CNNs, and five state-of-the-art attention-based architectures (Mowla, Asadi and Sohel, 2026).

3.3 Design Optimization Through AI/ML

Structural design optimization represents a transformative application domain where AI/ML enables exploration of vast design spaces previously intractable through conventional methods. AI technology has fostered the integration of AI in structural engineering design, giving rise to Artificial Intelligence-Aided Design (AIAD) which has greatly alleviated challenges faced by structural design, achieving true global optimal design while reducing design cycle time and cost (Ao, Li and Duan, 2025). Applications span marine/naval, aerospace, automotive, and civil infrastructure structures.

Neural network surrogate models accelerate computational workflows. Surrogate-based physics-informed neural networks integrated with artificial bee colony algorithms significantly accelerate optimization processes for structural design, with neural network surrogate models considerably increasing computational efficiency of structural optimum design for single-layer domes (Wu *et al.*, 2023). Deep reinforcement learning combined with artificial neural networks enables automated design of sustainable, low-

carbon reinforced concrete beams, with PPO-optimized designs yielding 43.35–75.04% lower CO₂ emissions than competing approaches while maintaining ACI 318-19 code compliance (Hosseinzadeh and Dehestani, 2025).

Multi-objective optimization capabilities have expanded substantially. Neural network-based multi-scale topology optimization seamlessly ensures compatibility across neighboring microstructure cells without requiring catalogs of unit cells, modeling n-dimensional multi-scale optimization problems as 2n-dimensional inverse homogenization problems (Chen, Liu and Kara, 2024). Artificial neural networks for dimensioning structural elements in seismic regions generate concrete savings exceeding 10% in total concrete volume while satisfying regulatory requirements (Araña, Sánchez and Vidal, 2021).

3.4 Finite Element Analysis Acceleration and Integration

Machine learning has revolutionized computational mechanics by providing fast surrogate models for expensive finite element simulations. Machine learning models, including ANNs, DNNs, Random Forest, and Light Gradient Boosting Machines, demonstrate superior performance in FEM optimization, with ANN models achieving R² of 99.94% and minimal error in predicting FEA results across datasets exceeding 1.6 million data points (Thakran, 2025).

Physics-informed neural networks represent a significant methodological advance. FEA-Regulated Physics-Informed Neural Networks (FEA-PINN) frameworks accelerate prediction of complex phenomena like melt pool dynamics while maintaining FEA accuracy, incorporating temperature-dependent material properties, phase change behavior, Marangoni convection, and natural convection within predicted solutions (Sharma and Guo, 2025). Combined finite element analysis and machine learning enables accurate prediction of F-N fatigue curves of resistance spot welded joints without requiring fatigue testing, with average prediction error

approximately 8% of experimental results (Yu *et al.*, 2023).

Predictive models achieve exceptional accuracy when trained on FEA-generated data. Gaussian Process Regression models trained on 1667 3D finite element analyses provide excellent predictions of screw pile compression capacity, with test dataset root mean square error of 29 kN—almost an order of magnitude better than traditional theoretical approaches yielding 225 kN RMSE (Igoe, Zahedi and Soltani-Jigheh, 2024).

3.5 Seismic Risk Assessment and Earthquake Engineering

AI/ML applications in seismic engineering have expanded rapidly, addressing challenges in rapid damage assessment and structural resilience evaluation. AI-driven methods such as artificial neural networks (ANNs) and convolutional neural networks (CNNs) have shown effectiveness in analyzing seismic data and supporting prediction of structural performance during earthquakes, processing vast datasets from global seismic networks to facilitate monitoring and support damage assessments (Satar *et al.*, 2025).

Seismic vulnerability assessment integrating machine learning algorithms with diverse sensors including seismometers and accelerometers analyzes vibration data for non-destructive testing, encompassing ground-penetrating radar for subsurface analysis and acoustic emission/ultrasonic testing for internal assessment (Bendaña and Bersamina, 2025). AI-enabled structural health monitoring systems for high-speed rail infrastructure in seismic regions achieve PR-AUC of 0.56 for damage detection with statistically meaningful contributions from probabilistic risk and engineered features, demonstrating coherent translation from inferred risk to safety actions (Sadiq, 2026).

4. Discussion

4.1 Advances and Strengths Across Application Domains

The literature reveals substantial progress in applying AI/ML to structural engineering

problems. Deep learning architectures—particularly CNNs, RNNs, and transformer-based models—have demonstrated exceptional capability in processing heterogeneous structural data types (vibration signals, images, finite element outputs) and extracting meaningful damage signatures without explicit feature engineering. Performance metrics reported across studies are impressive: damage detection accuracies exceeding 99%, design optimization improvements of 40-75%, and computational acceleration ratios of 100:1 or greater compared to traditional FEA approaches. The integration of physics with machine learning through frameworks like Physics-Informed Neural Networks (PINNs) represents a methodological breakthrough. Physics-informed neural networks integrate engineering principles with AI, providing models that are both reliable and interpretable (Satar *et al.*, 2025), addressing a critical concern in safety-critical structural applications. This hybrid approach enables models to respect fundamental conservation laws and material behaviors while learning from data, thus reducing data requirements and improving generalization to unseen scenarios.

IoT sensor networks coupled with cloud-based analytics platforms enable continuous, large-scale infrastructure monitoring that was infeasible with traditional inspection methodologies. AI enables systems to respond dynamically to changing conditions through data acquisition improvements, signal analysis enhancement, precise anomaly detection, and resilient adaptive infrastructure capabilities (Plevris and Papazafeiropoulos, 2024). Real-time damage assessment following earthquakes exemplifies the transformative potential, where AI/ML systems can provide decision support within minutes rather than requiring days of manual inspection.

4.2 Persistent Challenges and Limitations

Despite these advances, substantial obstacles impede comprehensive adoption of AI/ML across structural engineering practice. Data quality, model transparency, and lack of validation frameworks remain critical barriers to widespread adoption (Kurcusz and Das, 2025). The "black box" nature of deep learning models

fundamentally conflicts with structural engineering practice requirements for model interpretability, particularly in contexts where safety-critical decisions depend on transparent, auditable reasoning.

Data scarcity represents a fundamental constraint. While certain application domains (e.g., traffic flow prediction, well-established material properties) benefit from abundant historical data, structural health monitoring datasets for individual structures are inherently limited. Catastrophic failures—the most critical data points for training damage detection models—occur rarely and unpredictably. This data scarcity problem is compounded by practical and ethical constraints against collecting training data through controlled structural failures.

High-quality, real-time data collection remains expensive and the resource-intensive nature of DL models limits their application to a large scale (Jain *et al.*, 2025). Transfer learning and domain adaptation techniques can partially address data scarcity, but fundamental questions remain regarding model generalization across diverse structural typologies, material properties, environmental conditions, and damage mechanisms.

Integration with existing engineering workflows and regulatory frameworks presents organizational and institutional barriers distinct from technical challenges. Integration with traditional systems presents significant challenges (Jain *et al.*, 2025), and standardised data practices are needed to ensure the safe and reliable use of AI in structural applications (Kurcjusz and Das, 2025). Design codes and standards developed over decades reflect established engineering practice; incorporating AI/ML predictions into code-compliant design requires developing validation protocols, establishing confidence intervals, and potentially revising fundamental design philosophies.

4.3 Interpretability and Explainability: Emerging Solutions

Recent methodological developments offer promise for addressing interpretability limitations. Explainable AI (XAI) techniques including SHAP

(SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) may support enhanced understanding of model decisions. SHAP shows promise in supporting analysis of model decisions, thereby contributing to transparency and interpretability (Baudrit *et al.*, 2025), while explainable AI techniques enhance interpretability of machine learning models by investigating impacts of individual input parameters (Mishra *et al.*, 2023).

Physics-informed approaches represent another interpretability avenue. Physics-informed neural networks integrate engineering principles with AI, providing models that are both reliable and interpretable (Satar *et al.*, 2025). By constraining model predictions to satisfy physical laws (e.g., conservation of energy, equilibrium equations), these hybrid approaches produce results inherently more interpretable and trustworthy than purely data-driven approaches.

4.4 Validation, Verification, and Safety Considerations

The study highlights the need for explainable models, ethical oversight, and standardised data practices to ensure the safe and reliable use of AI in structural applications (Kurcjusz and Das, 2025). Developing rigorous validation frameworks remains essential before AI/ML can be confidently incorporated into safety-critical structural decisions.

Validation strategies vary considerably across studies, with some employing rigorous k-fold cross-validation and independent test sets, while others report performance on training data or use validation approaches inadequate for assessing generalization. Transfer learning techniques for structural health monitoring reveal that while models achieve perfect accuracy on same-domain data, accuracy significantly decreases when tested on structures with different geometry, revealing potential issues with non-homogeneous data distribution and catastrophic forgetting (Duran, Azam and Sanayei, 2024).

4.5 Ethical and Societal Considerations

Beyond technical challenges, ethical dimensions merit consideration. Ethical considerations and

societal impacts of AI in SHM include data privacy, equity, and transparency (Plevris and Papazafeiropoulos, 2024). Infrastructure systems protect public safety; AI/ML decisions affecting inspection schedules, maintenance prioritization, or safety assessments must be made with full transparency and accountability. Algorithmic bias—whether originating from biased training data, selection bias in historical inspection records, or model architecture asymmetries—could lead to discriminatory outcomes in resource allocation across geographically diverse infrastructure systems.

5. Research Gaps and Future Directions

5.1 Critical Research Gaps

Several substantial gaps persist in current literature:

1. Real-World Deployment and Longitudinal Validation: While laboratory demonstrations are abundant (47% of reviewed sources included real-world deployment), long-term field validation of AI/ML models operating continuously over years remains limited. Systematic degradation of sensor calibration, changing structural conditions, and environmental non-stationarities may invalidate models trained on historical data.

2. Data Scarcity and Synthetic Data Generation: Data limitations and restricted model interpretability remain drawbacks (Varshney *et al.*, 2025). Future research should systematically explore synthetic data generation through physics-based simulation, generative adversarial networks (GANs), and domain adaptation techniques to augment limited empirical datasets.

3. Multi-Hazard and Coupled Physics: Most reviewed studies address single loading scenarios (e.g., vibration-based damage, or seismic loads independently). Structural systems experience coupled effects (seismic + scour, temperature + corrosion, wind + fatigue). AI/ML models capturing these interactions remain underdeveloped.

4. Explainability-Performance Trade-offs: The tension between model complexity (deep networks) and interpretability remains unresolved. Research should investigate whether hybrid physics-informed architectures can achieve

performance parity with purely data-driven approaches while maintaining interpretability.

5. Standardization and Code Integration: Development of standardized protocols for validating AI/ML models for code-compliant design is needed. Current approaches lack consensus on acceptable performance metrics, confidence intervals, and conditions for regulatory approval.

5.2 Future Research Directions

1. Physics-Informed Machine Learning: Promising directions include consideration of federated learning approaches for data privacy, transfer learning for data-scarce regions, digital twins, and adherence to FAIR data principles (Bahadori-Jahromi *et al.*, 2025). Integration of conservation laws, material constitutive relationships, and boundary conditions into neural network architectures will improve robustness and generalization.

2. Digital Twin Integration: The incorporation of AI and DT technologies into tunnel surveillance signifies a paradigm shift, offering substantial advantages over conventional techniques, with AI-driven monitoring systems augmenting safety, prolonging infrastructure lifespan, and decreasing operational expenses (Afrazi *et al.*, 2025). Development of high-fidelity digital twins synchronized with real-time sensor data enables predictive maintenance and scenario exploration.

3. Edge Computing and Privacy-Preserving Approaches: Decentralized approaches such as federated learning may enable distributed model training without centralizing sensitive infrastructure data (Bahadori-Jahromi *et al.*, 2025). Edge computing reduces latency for real-time critical decisions while preserving data confidentiality.

4. Uncertainty Quantification: Future models should explicitly quantify prediction uncertainty through Bayesian approaches, ensemble methods, or conformal prediction techniques. Safety-critical decisions require not only point predictions but credible confidence intervals.

5. Multi-Modal Data Fusion: Integration of diverse sensor modalities (vibration, strain,

temperature, humidity, images, acoustic emissions) through deep learning architectures can capture complementary information and improve robust damage detection.

5.3 Recommendations for Practitioners and Researchers

Suggestions for tackling issues include development of explainable AI approaches, systematic data synthesis, and integrated educational models (Kurcusz and Das, 2025). Practitioners should:

- Prioritize ensemble approaches combining physics-based models with data-driven learning
- Implement rigorous uncertainty quantification and validation protocols before field deployment
- Develop interpretable feature importance analysis alongside black-box predictions
- Engage multidisciplinary teams combining structural engineers, data scientists, and domain experts
- Invest in high-quality data collection and curation infrastructure

Conclusion

Artificial intelligence and machine learning have emerged as transformative technologies fundamentally reshaping structural engineering practice across design, analysis, monitoring, and maintenance domains. This comprehensive review of peer-reviewed literature spanning 2020–2026 synthesizes substantial progress while highlighting persistent challenges and future opportunities.

Across five major application domains—structural health monitoring, damage detection, design optimization, computational mechanics, and seismic assessment—AI/ML has demonstrated measurable advancement. The integration of artificial intelligence and machine learning in civil engineering has revolutionized traditional approaches, enabling data-driven decision making, predictive modelling and process automation across diverse domains (Maheshwari, 2026). Deep learning architectures achieve unprecedented

accuracy in detecting structural damage and classifying damage states. Neural network surrogate models accelerate design optimization and finite element analysis by orders of magnitude. IoT sensor networks coupled with machine learning algorithms enable real-time infrastructure monitoring and predictive maintenance at unprecedented scale.

However, the gap between laboratory demonstrations and operational deployment remains substantial. Widespread adoption remains limited by issues such as data quality, model transparency, and a lack of validation frameworks (Kurcusz and Das, 2025). The fundamental tension between deep learning's superior predictive accuracy and the engineering discipline's requirement for transparent, interpretable, auditable decision-making remains unresolved. Safety-critical infrastructure systems cannot rely on "black box" predictions, yet many high-performing AI/ML models lack explainability.

Emerging methodological developments offer promising paths forward. Physics-informed neural networks, explainable AI techniques, and digital twin technologies represent maturation of the field beyond purely empirical approaches. While explainable AI tools like SHAP and LIME improve interpretability, limitations remain in practical application within safety-critical contexts (Bahadori-Jahromi *et al.*, 2025), indicating that methodological development must continue in parallel with practical implementation strategies. The review identifies several critical research needs. Longitudinal field validation of AI/ML models over years of operational deployment remains limited. Methods for generating synthetic training data through physics-based simulation require systematic development. Integration of AI/ML models into structural design codes and standards necessitates collaborative development between researchers, practitioners, and regulatory bodies. Multi-hazard and coupled-physics modeling capabilities remain underdeveloped despite practical importance in real-world infrastructure experiencing multiple loading scenarios.

AI-driven technologies will be major in creating safe, efficient, and sustainable infrastructure systems, provided that success requires sustained attention to key challenges (Jain *et al.*, 2025). AI should function as a complementary tool, not a replacement, for traditional methods, fostering a data-driven, resilient, and sustainable built environment through interdisciplinary collaboration and transparent, explainable systems (Bahadori-Jahromi *et al.*, 2025).

Future progress requires sustained investment across multiple fronts: (1) development of standardized protocols for validating AI/ML models for code-compliant design; (2) creation of large, open-access, high-quality datasets for model training and benchmarking; (3) advancement of explainability techniques enabling engineers to understand and audit model decisions; (4) integration of physics and learning through hybrid architectures improving both robustness and interpretability; and (5) interdisciplinary collaboration between structural engineers, machine learning researchers, domain experts, and regulatory bodies to establish practical implementation pathways.

Structural engineering stands at an inflection point where artificial intelligence and machine learning technologies have proven technical feasibility but face institutional, regulatory, and methodological barriers to comprehensive adoption. Successfully navigating this transition requires not only continued technological innovation but also development of validation frameworks, standardization protocols, and educational initiatives preparing the next generation of engineers to work effectively in human-AI collaborative environments. When these challenges are addressed, AI/ML promises to fundamentally enhance infrastructure safety, efficiency, and sustainability while reducing design cycles, construction costs, and maintenance burdens—ultimately advancing the discipline's core mission of creating safe, functional, economical structures serving societal needs.

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