



Use of AI and Machine Learning in Civil Engineering

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Abstract:

Artificial Intelligence (AI) and Machine Learning (ML) are increasingly being adopted in Civil Engineering to support prediction, automation, monitoring, optimization, and data-driven decision-making. This review examines applications across structural engineering and structural health monitoring, construction management and safety, transportation and pavement engineering, concrete and construction materials, geotechnical engineering, water resources, Building Information Modeling (BIM), and earthquake engineering. The literature shows that supervised learning methods such as artificial neural networks, support vector machines, decision trees, random forests, and ensemble models are widely used for regression and classification, while deep learning methods such as convolutional neural networks, recurrent neural networks, and long short-term memory networks are increasingly used for images, sensor signals, and time-series data. Recent work also highlights transformer models, physics-informed machine learning, digital twins, and multimodal systems. AI/ML can improve prediction, automate repetitive inspection and monitoring tasks, and support engineering decisions; however, practical adoption is constrained by data quality, limited field datasets, generalization, interpretability, uncertainty quantification, computational requirements, and integration with established engineering workflows. The review identifies research gaps and argues that trustworthy AI should complement rather than replace engineering principles, standards, validation, and professional judgment.

Keywords: Artificial Intelligence; Machine Learning; Civil Engineering; Deep Learning; Structural Health Monitoring; Construction Management; Computer Vision; Predictive Modeling; BIM; Physics-Informed Machine Learning

1. Introduction

Civil Engineering is undergoing rapid digitalization. Infrastructure projects increasingly generate data from sensors, inspection images, geographic information systems, Building Information Modeling (BIM), laboratory experiments, connected devices, construction records, and intelligent transportation systems. This data environment has created opportunities for data-driven methods that can identify patterns, predict outcomes, automate selected tasks, and support engineering decisions [1]–[6].

AI is a broad field concerned with computational systems capable of performing tasks associated with reasoning, pattern recognition, prediction, and decision support. ML is a major branch of AI in which algorithms learn relationships from data. Deep learning extends this idea through multi-layer neural networks that can learn complex representations from images, signals, text, and other high-dimensional data [2], [7].

Civil engineering problems are often nonlinear, uncertain, spatially variable, and dependent on multiple interacting parameters. Examples include predicting concrete strength, identifying structural damage, forecasting traffic, estimating geotechnical response, and predicting hydrological variables. ML models can approximate complex relationships when sufficient representative data are available [8]–[13].

At the same time, AI cannot be treated as an automatic replacement for conventional engineering analysis. A model that performs well on a laboratory or project-specific dataset may perform poorly when conditions change. Data shift, limited labels, measurement errors, model opacity, and uncertainty are therefore important concerns [4], [14].

This review synthesizes representative literature on AI and ML in Civil Engineering. It focuses on applications, commonly used techniques, reported benefits, limitations, research gaps, and future directions. The central objective is to present AI/ML as complementary engineering technology whose outputs require appropriate validation and professional judgment.

2. Review Methodology

A structured narrative review approach was adopted. Peer-reviewed journal articles and authoritative review studies were selected to represent major Civil Engineering applications of AI and ML. The literature was grouped into eight themes: structural engineering and structural health monitoring; construction management and safety; transportation and pavement engineering; concrete and construction materials; geotechnical engineering; water resources and environmental applications; BIM and digital construction; and earthquake engineering.

Recent reviews were used to establish the overall research landscape, while representative application studies were included to show how specific ML methods have been applied. Emphasis was placed on the engineering problem, data type, algorithmic approach, contribution, and limitation rather than comparing accuracy values across incompatible datasets. This distinction is important because reported performance depends strongly on data quality, preprocessing, feature selection, validation strategy, and the domain represented in the training data [1], [5], [6].

The final synthesis includes 40 references. The sources cover foundational AI/ML concepts, civil-engineering-wide reviews, and application-focused studies. The review does not claim that the selected studies constitute every publication in the field; instead, they provide a representative evidence base for the scope of this paper.

3. Fundamentals of AI and Machine Learning

3.1 Supervised Learning

Supervised learning uses labeled input-output pairs and is common in Civil Engineering because many engineering tasks involve predicting a measurable response or assigning a condition class. Regression models can predict strength, settlement, traffic flow, cost, or structural response, while classification models can identify damage states, pavement defects, or safety conditions [8], [9], [15].

3.2 Unsupervised and Semi-Supervised Learning

Unsupervised learning identifies structure in unlabeled data through clustering, dimensionality reduction, or anomaly detection. These methods are useful in structural health monitoring because obtaining comprehensive labeled damage datasets can be difficult. Semi-supervised and self-supervised learning are promising ways to reduce dependence on manual labels [16], [17].

3.3 Deep Learning and Computer Vision

Deep learning methods are increasingly used when data are high-dimensional. CNNs are particularly suitable for images and visual inspection, while recurrent and LSTM networks are commonly used for sequential and time-series data. Transformer-based architectures are an emerging direction for multimodal and long-range sequence learning [18]–[21].

3.4 Hybrid and Physics-Informed ML

Purely data-driven models can suffer when field data are limited or when the training distribution differs from operational conditions. Physics-informed and hybrid ML approaches incorporate governing equations, simulation outputs, or engineering constraints into learning. Such methods aim to improve physical consistency, generalization, and data efficiency [4], [22].

4. Applications of AI and ML in Civil Engineering

4.1 Structural Engineering and Structural Health Monitoring

Structural health monitoring (SHM) uses measurements such as vibration, acceleration, strain, displacement, acoustic response, and images to assess structural condition. ML can support feature extraction, anomaly detection, damage

localization, classification, and prognosis. Reviews of ML for structural engineering show rapid growth in data-driven methods for nonlinear structural systems [23], [24].

Deep learning can automatically learn features from sensor measurements and assist damage localization. Lin et al. demonstrated deep-learning-based automatic feature extraction for structural damage detection [25]. Reviews further show applications of ML to damage detection and assessment across beams, columns, buildings, bridges, and other civil structures [26], [27].

Computer vision is increasingly important for inspection. Transformer-based approaches have been proposed for vision-based SHM, while generative adversarial networks have been reviewed for data augmentation and domain adaptation in structural monitoring [20], [28]. These methods can reduce manual inspection effort, but field deployment must consider lighting, viewpoint, occlusion, sensor noise, environmental variability, and domain shift.

4.2 Construction Management and Safety

Construction projects produce information from schedules, cost records, site photographs, videos, BIM models, equipment, and safety reports. AI/ML can support cost and duration estimation, productivity analysis, resource planning, progress monitoring, risk assessment, and safety management [29], [30].

Deep learning and computer vision have been used to recognize site objects, workers, equipment, and unsafe conditions. Reviews of construction safety analytics highlight the potential of multimodal data while noting the shortage of high-quality real-world datasets [31]. Computer vision can also support safety assurance by detecting selected unsafe behaviors and site conditions [32].

BIM provides a structured digital environment that can be combined with ML. Photogrammetry and BIM have been combined for automated labeling of construction-site images, and ML has been explored for predicting the implications of BIM-based design changes [33], [34]. These integrations illustrate a shift toward connected digital construction workflows.

4.3 Transportation and Pavement Engineering

Transportation systems generate large time-series and spatial datasets from traffic sensors, cameras, GPS, connected vehicles, and intelligent transportation systems. ML and deep learning are used for traffic-flow forecasting, travel-time prediction, incident detection, and transportation demand analysis [35], [36].

Pavement engineering is another major application. Computer vision and ML can classify pavement distress, segment defects, estimate pavement condition, and support maintenance decisions. Reviews identify classification, object detection, and segmentation as important approaches for automated pavement assessment [37].

The main practical challenge is generalization. A pavement model trained on one camera system, road surface, climate, or labeling protocol may not perform equally well elsewhere. Cross-location testing and standardized benchmarks are therefore important.

4.4 Concrete and Construction Materials

Concrete properties depend on interacting mixture and curing variables, making prediction a suitable application for nonlinear ML. Early work demonstrated artificial neural networks for high-performance concrete strength prediction [38]. Subsequent research has used ML and ensemble methods for multi-dataset strength prediction [39] and for mechanical properties of fiber-reinforced concrete [40].

Recent research also applies ML to alkali-activated concrete and self-compacting concrete, indicating that data-driven approaches can support material-property estimation and mixture development [41], [42]. However, models should be validated experimentally and should not be used outside the range of materials and conditions represented in their training data.

4.5 Geotechnical Engineering

Geotechnical engineering involves substantial uncertainty because soil and rock properties vary spatially and site investigations are inherently limited. ML has therefore been explored for soil-property prediction, bearing capacity, settlement, slope stability, liquefaction-related assessment, and other geotechnical responses [43].

Slope stability is a representative problem. ML models can act as fast surrogate predictors when repeated numerical or probabilistic analyses are required. Studies have compared ensemble methods such as Random Forest and Support Vector Machines for slope-stability prediction and have demonstrated the potential of ML for nonlinear geotechnical relationships [44].

A critical limitation is that a model may learn the assumptions of its training dataset rather than the full range of field behavior. Geological variability, groundwater conditions, loading, and site-specific failure mechanisms must therefore be considered during validation.

4.6 Water Resources and Environmental Engineering

AI and ML are increasingly applied to rainfall-runoff modeling, flood forecasting, water-quality prediction, groundwater assessment, and environmental monitoring. Deep learning reviews show applications in prediction, classification, enhancement, and decision support across water-resource systems [45].

Machine learning can be useful for nonlinear hydrological relationships and large sensor datasets. However, water systems are affected by climate variability, extreme events, nonstationarity, and spatial dependence. Models should therefore be evaluated under changing conditions rather than only average historical conditions.

4.7 Earthquake Engineering

Earthquake engineering has adopted ML for seismic hazard analysis, structural system identification, damage detection, fragility assessment, and performance evaluation. A state-of-the-art review identified substantial potential for ML while emphasizing the need for appropriate data, validation, and engineering interpretation [46].

More recent research has examined ML for seismic performance evaluation and design, including applications involving nonlinear structural response. The principal challenges remain data scarcity, model generalization, interpretability, and the safety-critical nature of earthquake engineering decisions [47].

5. Comparative Analysis of AI/ML Techniques

Technique	Typical application	Strength	Limitation	Suitable data
ANN	Concrete/material prediction; structural response	Strong nonlinear approximation	Tuning and interpretability	Structured numerical data
SVM	Slope stability; civil classification	Works well with limited/medium datasets	Kernel/parameter selection	Structured/tabular data
Decision Tree	Classification; risk assessment	Easy to interpret	Can overfit	Tabular data
Random Forest	Geotechnical and material prediction	Robust; handles nonlinear relationships	Less transparent than a single tree	Tabular data
CNN	Crack/pavement/site-image detection	Learns visual features	Needs image data and computing	Images/video
LSTM/RNN	Traffic; sensor/time series	Captures temporal patterns	Training complexity; long-term dependencies	Time-series
Transformer	Vision/SHM; multimodal data	Long-range and multimodal learning	Data/computation intensive	Large sequences/images

Physics-informed ML	Hydrology; structural/fluid systems	Uses physical constraints	More complex formulation	Data + physics/simulation
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6. Benefits of AI and ML

- Improved prediction and pattern recognition for complex nonlinear engineering problems.
- Automation of repetitive inspection, classification, monitoring, and information-processing tasks.
- Faster analysis of large datasets from sensors, images, BIM, and project records.
- Early identification of abnormal conditions and potential deterioration.
- Support for construction planning, safety management, resource allocation, and maintenance prioritization.
- Potential use as a surrogate for computationally expensive simulations when carefully validated.
- Integration with IoT, BIM, digital twins, remote sensing, and computer vision.

7. Challenges and Limitations

Data quality and quantity: Missing values, measurement errors, inconsistent labels, and biased datasets can reduce model reliability.

Generalization: A model trained on one project, structure, soil type, climate, or traffic environment may not transfer to another.

Interpretability: Complex models can be difficult to explain, which matters when predictions affect safety-critical decisions.

Uncertainty: Point accuracy alone does not show when a model is uncertain or outside its domain of applicability.

Validation: Random data splits can overestimate performance when correlated observations from the same project appear in both training and testing.

Integration: AI tools must fit engineering standards, software, workflows, and professional responsibilities.

Computational cost: Deep learning may require substantial computing resources and maintenance or retraining.

Governance: Data ownership, privacy, bias, accountability, and responsibility for AI-assisted decisions need clear governance.

8. Research Gaps

The literature identifies several recurring gaps. First, many studies rely on laboratory, simulated, or project-specific datasets, limiting generalization. More diverse and openly documented datasets are needed for cross-project benchmarking [1], [5], [14]. Second, studies use different preprocessing, train-test strategies, and metrics, making direct comparison difficult. Standardized benchmarks and reproducible workflows would improve evidence quality.

Third, explainability and uncertainty quantification require greater attention, particularly in safety-critical applications. Fourth, hybrid and physics-informed models deserve further field validation because they may improve physical consistency while reducing dependence on very large datasets [4], [22]. Finally, long-term deployment studies are needed to evaluate model drift, sensor changes, environmental variability, and maintenance requirements.

9. Future Scope

Future Civil Engineering systems are likely to combine AI/ML with IoT sensors, digital twins, BIM, robotics, computer vision, remote sensing, and cloud or edge computing. Such integration can support continuous monitoring and lifecycle decision-making rather than isolated predictions [1], [5], [6].

Explainable AI, transfer learning, self-supervised learning, uncertainty-aware models, foundation models, and physics-informed learning are promising research directions. The field should prioritize trustworthy performance, reproducibility, interoperability, and human oversight. AI should remain a decision-support technology whose outputs are checked against engineering principles, standards, and independent evidence.

10. Conclusion

AI and Machine Learning have significant potential across Civil Engineering, including structural health monitoring, construction management and safety, transportation and pavement engineering, concrete and construction materials, geotechnical engineering, water resources, BIM, and earthquake engineering. The reviewed literature demonstrates that ANN, SVM, tree-based models, ensemble learning, CNNs, recurrent networks, transformers, and physics-informed methods can address different classes of engineering problems.

The main benefit of AI/ML is not simply higher numerical accuracy; it is the ability to process complex datasets, automate selected tasks, provide rapid predictions, and support data-driven decisions. At the same time, limitations involving data quality, domain shift, interpretability, uncertainty, validation, computational cost, and workflow integration must be addressed before widespread safety-critical deployment. Future research should therefore focus on trustworthy, explainable, hybrid, and field-validated AI systems. With appropriate engineering oversight, AI and ML can complement established civil engineering practice and contribute to safer, more efficient, resilient, and sustainable infrastructure.

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