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Review

The Role of Artificial Intelligence and Machine Learning in Advancing Civil Engineering: A Comprehensive Review

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Abstract

The integration of artificial intelligence (AI) and machine learning (ML) has revolutionised civil engineering, enhancing predictive accuracy, decision-making, and sustainability across domains such as structural health monitoring, geotechnical analysis, transportation systems, water management, and sustainable construction. This paper presents a detailed review of peer-reviewed publications from the past decade, employing bibliometric mapping and critical evaluation to analyse methodological advances, practical applications, and limitations. A novel taxonomy is introduced, classifying AI/ML approaches by civil engineering domain, learning paradigm, and adoption maturity to guide future development. Key applications include pavement condition assessment, slope stability prediction, traffic flow forecasting, smart water management, and flood forecasting, leveraging techniques such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), Support Vector Machines (SVMs), and hybrid physics-informed neural networks (PINNs). The review highlights challenges, including limited high-quality datasets, absence of AI provisions in design codes, integration barriers with IoT-based infrastructure, and computational complexity. While explainable AI tools like SHAP and LIME improve interpretability, their practical feasibility in safety-critical contexts remains constrained. Ethical considerations, including bias in training datasets and regulatory compliance, are also addressed. Promising directions include federated learning for data privacy, transfer learning for data-scarce regions, digital twins, and adherence to FAIR data principles. This study underscores AI 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.

Keywords: artificial intelligence; civil engineering; machine learning; predictive modelling; sustainability; infrastructure management

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1. Introduction

AI and ML are significantly transforming civil engineering by enhancing efficiency, accuracy, and decision-making across various domains. AI has undergone great technological changes with major influences across various sectors in the construction industry. From analysing the sensor data to detect anomalies and predicting the structural failure using real-time data in the field of structural health monitoring (SHM) to the predictive maintenance approach models to optimise maintenance schedules and resource allocation, AI has evolved as a starling innovation.

Rapid developments in AI have opened new fields in sustainable development. IEEE defined AI as the theory and development of computer systems that are able to perform tasks which normally require human intelligence, such as visual perception, speech recognition, learning, decision-making, and natural language processing [1]. AI is a distributed, statistical, and symbolic technique that prioritises modelling before focusing on simulating human functions, empathy, and acceptable communication. It also prioritises cognitive tasks before advancing into the realm of earlier approaches, like making analytical decisions [2].

The building industry faced a serious crisis in 2020 as a result of aging workers and declining productivity. The COVID-19 epidemic also has had a major impact on the construction sector, making it difficult to enhance worker safety and wellbeing [3]. Following the start of the pandemic, there was a serious decline in the available construction jobs and according to The National Bureau of Economic Research (NBER), the U.S. has experienced a high rate of unemployment, reaching 14.7% in April 2020 [4]. As a result, several options were put forth to address this issue. From a technical perspective, the best proposed solution was the projects for construction automation that were put into place, taking advantage of the potential of AI and the Fourth Industrial Revolution [5]. Specifically, basic studies were carried out in design automation using ML. Interest in generative design using AI models, a method that automatically produces algorithm-based design alternatives and drastically cuts down on human labour and time has increased because of this surge. The research concentrated on how generative design may increase architectural practices' efficiency and reduce pointless and superfluous work for an aging construction workforce [6,7].

In structural engineering, ML models are being applied in analysing structural design [8], reliability analysis [9], monitoring and inspecting structural health [10,11], failure detection of reinforced structures [12], resistance to fire [13], and resistance of different structural members under earthquake or various loads and conditions [14]. AI and ML techniques are increasing used in structural analysis and design optimisation [15]. Because of its capacity to manage intricate nonlinear structural systems under harsh conditions, AI offers a singular chance to increase the predictability of structural engineering. The findings in the literature highlight the value of adopting ML as a substitute prediction tool in fields where traditional physics-based approaches are too laborious and difficult [16].

ML models suggest optimal solutions for material engineering based on mechanical strength, durability, cost, and their environmental impact. Concrete is one of the leading construction materials utilised all over the world. Considerable attempts have been made for using ML techniques to anticipate the mechanical properties and mix design of different types of concrete including normal strength concrete [17], high performance concrete [18], fibre reinforced concrete [19], recycled aggregate concrete (RAC) [20], geopolymer concrete [21], self-compacting concrete [22], etc. The ML techniques used in most of the research publications include artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), SVM, Random Forest (RF), extreme gradient boosting (XGBoost), CNN, and Decision Tree (DT).

AI offers numerous benefits in construction management, transforming how projects are planned, executed, and monitored. Previous researches showed that ML and AI techniques can be beneficial in terms of improved cost estimation and budgeting by predicting the future expenses with the help of historical data [23], enhancing risk management during the project lifecycle [24], optimising project's planning, scheduling, monitoring, and control [25], optimising resource utilisation by predicting their demand [26], predictive analysis in making better and timely decisions, reducing uncertainties and improving project outcomes [27], personnel selection with the focus on hierarchical competency assessment [28], automating repetitive tasks and complex activities to enhance productivity [29], ensuring the safety measures and regulations at construction sites [30], and last but not the least, optimising the quality control by identifying early defects [31].

AI is playing an increasingly transformative role in transportation engineering by improving safety, efficiency, and sustainability across various systems. Traffic management and optimisation use AI algorithms to optimise signal timings based on real-time traffic conditions. ML models analyse historical and real-time data to predict congestion and adjust controls accordingly to predict traffic flow. Computer vision and sensor data can identify accidents, stalled vehicles, or dangerous conditions quickly, offering workable ideas to legislators and urban planners to promote more sustainable and effective transportation systems [32]. In smart urban planning, AI models can predict how infrastructure changes affect mobility patterns, helping planners make data-driven decisions. ML algorithms forecast public transport demand and ride-sharing needs, enabling better service allocation that are essential for intelligent planning of transportation [33]. Google maps, Tesla autopilot, and smart highways are the most used AI-driven applications in transportation worldwide.

In the field of geotechnical engineering, AI can estimate soil parameters that are otherwise expensive or time-consuming to obtain through laboratory or field testing. By incorporating laboratory test results, ML models can predict soil classification, shear strength, permeability, and bearing capacity [34]. AI helps in analysing and interpreting geotechnical data from multiple sources to recognise the pattern that can identify zones with similar geotechnical behaviour and map subsurface variability more accurately. Based on these patterns, a combined interpretation of the soil profiles with measured uncertainty can be provided [35]. Slope stabilisation and land sliding involve a key illustration of rock, soil, or mixed mass under different failures that cause moving detachable masses on a slope downstream. DTs, SVMs, and neural network techniques in AI enable real-time monitoring using sensor data from inclinometers, piezometers, and rainfall gauges to predict the factor of safety (FOS) and assess landslide risks based on terrain, rainfall, and soil properties [36]. AI can optimise the design of shallow or deep foundations and probabilistic risk analysis in uncertain conditions by analysing risks of ground failure, liquefaction, or settlement by reducing over-conservatism, learning from historical design and performance data and providing quick estimates for settlement, load-bearing, and uplift capacities [37]. During excavation, tunnelling, or piling, ML models can monitor ground behaviour in real time, predict ground movements, settlements, and collapses which can help in establishing preventative measures.

AI plays a vital role in environmental engineering to advance sustainability through smarter monitoring, resource management, pollution control, and climate adaptation. AI enables real-time monitoring and predictive analytics for various environmental parameters like air and water quality monitoring by using ML models to analyse sensor data to detect pollutants, predictive models for forecasting pollution events for early interventions and detecting contamination and illegal dumping in the field of waste water, and solid waste monitoring by optimise treatment plant operations for energy efficiency and regulatory compliance [38]. AI improves the efficiency and conservation of natural resources with smart irrigation systems using AI and sensors which can minimise water use in agriculture. Similarly predictive models help manage reservoirs and groundwater extraction sustainably. In terms of energy efficiency, AI optimises energy use in buildings, water treatment plants, and urban infrastructure, and supports the integration of renewables in energy grids like solar and wind forecasting. AI models and techniques are developing renewable energy sources and giving energy efficiency top priority to address energy sustainability and meeting the sustainable development goals (SDG) 7 and 13 [39]. By automating data analysis for quicker and more accurate evaluations, AI gives decision-makers practical insights for sustainability objectives and the execution of environmental impact assessments.

The use of AI and ML in civil engineering signifies a radical shift in the direction of safer, smarter, and more sustainable infrastructure. By supporting real-time monitoring and prediction, optimising resources, and bolstering data-driven decision-making, these technologies are not only improving efficiency and accuracy but also transforming the practice of civil engineering in the future. As the area grows, AI and ML will play an increasingly significant role in solving difficult engineering issues and furthering SDGs.

ML is a subfield of AI; however, they are so closely related that they are sometimes used interchangeably. We refer to AI as the whole collection of methods that makes machine behave intelligently like human being. This includes symbolic AI and nonsymbolic AI. ML, however, is used in AI systems to improve their performance through gathering experience from data and is considered within the nonsymbolic AI category [40,41].

Despite recent significant development, the current use of AI and ML in civil applications remains discrete and focused on narrow domains, with the basic shortcomings including limited interdisciplinary integration, attention to model interpretability, data availability and quality, and a lack of standardised frameworks. The aim of this review study is to provide a comprehensive assessment of how AL and ML techniques have been used in the main civil engineering disciplines to highlight their potential in addressing sustainability challenges and the difficulties in their general adaptation. To address this, the subsequent sections of the manuscript are structured as follows: Section 2 addresses the vital challenges in civil engineering that drive AI adoption across various fields; Section 3 presents a bibliometric analysis on the use of AL and ML in the recent research; Section 4 introduces AI and ML techniques and tools relevant to engineering; Sections 5–7 examine their applications in sustainable materials, structural engineering, and geotechnical and environmental engineering, respectively; and Section 8 concludes with a summary of findings and directions for future research.

2. Key Challenges in Civil Engineering Leading to AI Adoption

To create more intelligent, effective, and ecologically friendly solutions, AI is being used in civil engineering to address sustainability issues. The key issues that have spurred this change are listed below.

2.1. Construction and Demolition (C&D) Waste

Construction consumes massive amounts of raw materials like concrete, steel, and water, leading to depletion and waste [42]. With ever-increasing requirements and advancement in concrete construction, there is a huge demand for structures, which in turn produces a large amount of C&D waste in urban areas. Encouraging sustainable construction methods requires precise construction waste estimation. C&D waste, which includes trash produced during building construction, refurbishment, and demolition, is a major environmental concern [43]. It is concerning to note that about 10 billion tonnes of C&D waste is produced worldwide each year [44,45]. Conventional estimation methods use manual computations that consider variables like building type, floor space, and other pertinent elements. On the other hand, ML algorithms have significantly improved estimation accuracy, surpassing 90% [46]. The ability to estimate and accurately predict waste quantities is the primary benefit of utilising ML techniques. Several ML algorithms, such as autoregressive integrated moving average approaches for time-series analysis, SVM, regression trees, Gaussian process regression, and linear regression, can be applied to predict the accurate number and quantity of wastes [47]. By creating an intelligent waste management engineering system, these algorithms can be used to lessen the negative effects of trash on the environment, the economy, and society. When it came to estimating and classifying construction debris, deep CNNs scored an exceptional 94% accuracy rate. According to the authors' observations, ML algorithms are suitable for future sustainable waste management and are well suited for the prediction or classification of building debris [48]. A study comprising 98 journals pertaining to the use of ML in construction waste management were thoroughly examined between 2012 and 2023 to pinpoint hot subjects and new trends using different ML models [49]. The findings show that ML is used, and the suggested models show promise in various waste management procedures related to building and demolition. Adopting ML techniques optimises material usage through predictive modelling and structural optimisation, accurate waste prediction, trend forecasting, and automated categorisation from historical data, image analysis, and sensor data, reducing waste and environmental impact.

2.2. Carbon Emissions and Energy Consumption

The construction industry is one of the largest contributors to global carbon dioxide (CO_2) emissions [50]. CO_2 poses a significant challenge to sustainability in civil engineering due to its major role in climate change and the high carbon footprint associated with many constructions processes. Approximately 7–9% of global CO_2 emissions are ascribed to the production process of hydraulic cement only, which makes concrete responsible for adverse impacts on environment, human health, and plantations [51,52]. ML models help design low-carbon structures, concrete, predict energy consumption, and improve the efficiency of construction equipment and building operations. There is an utmost need to reduce carbon emission and accurately identify the threat levels of CO_2 on the environment. The risk point, point of no return, and other thresholds that represent the most critical CO_2 levels must be mapped. ML models are used to predict these values by using historical data of CO_2 emission and its consequences on the atmosphere. A study concludes that by 2047, the crucial CO_2 level of 500 ppm will be reached. This level is regarded as irreversible. To return the emissions to safe levels, a 6.37% decrease rate and a 23.38% reversal rate are needed [53]. A similar study was carried out by [54] by experimenting with a method known as the non-equigap grey model to predict the CO_2 emissions in 53 countries and other places. CO_2 emissions were used as the experiment's output and energy consumption as its input. To forecast greenhouse gas emissions, mainly the CO_2 from agricultural soil, nine distinct ML and deep learning models were developed and tested. When it came to predicting N_2O and CO_2, the LSTM model (a type of recurrent neural network (RNN)) performed the best [55]. Different AI techniques including ML, dimensionality reduction, and clustering by adopting methods like fuzzy neural networks and singular value decomposition (SVD) are used to forecast carbon emissions and energy consumptions [56]. Predicting energy consumption is a crucial component of building sector planning and energy control. To shed light on the viability of predicting building energy performance using ML-based techniques, Light Gradient Boosting Machine (LGBM) integrated with the SHAP algorithm was adopted which accurately forecasts residential structures' energy use and greenhouse gas emissions, finds the most important factors, and assesses their relative significance [57]. The wavelet enhanced extreme learning machine (W-EELM), a more advanced form of the extreme learning machine (ELM), is used to forecast CO_2 on weekly, monthly, and annual time frames. The model contributes to the basic understanding of the environmental engineering perspective by demonstrating that it is a reliable and useful computer-based technology for modelling CO_2 concentrations [58].

2.3. Aging Infrastructure and Maintenance

One of the biggest sustainability issues facing civil engineering worldwide is aging infrastructure and related maintenance cost. Many nations are dealing with aging water systems, roads, bridges, and buildings that were constructed decades ago but are now beyond their planned lifespan. There are social, economic, and environmental ramifications to maintaining or replacing these systems. Many structures globally are aging, requiring sustainable and timely maintenance to avoid collapse or environmental hazards. A modified deep hierarchical CNN architecture, based on 16 convolution layers and cycle generative adversarial network (GAN), was developed to predict pixel-wise segmentation in an end-to-end fashion to automatically detect corrosion and related damages to civil infrastructures like bridges, buildings, and roads [59]. In structural engineering, any damage to a bridge's structural elements will compromise its durability, safety, and integrity. Because bridge decks are subjected to extreme conditions such high traffic volumes, fluctuating temperatures, road salts, and abrasive forces, they are more likely to suffer from serious deterioration. A framework with a 91.44% prediction accuracy for assessing and forecasting deck conditions was created with two computational ML models of ANNs and kernel-nearest neighbours (KNNs) [60]. This can assist in guaranteeing the appropriate and efficient allocation of funds designated for bridge upkeep, rehabilitation, and repair. Deep hierarchical CNN architecture of 10 convolutional layers integrated with cycle GAN in utilised in [61] to assess the cracks in bridge structures. As compared to more conventional techniques like Segment Network Model (SegNet), Crack-BN (Crack Band), and Crack-GF (Crack Guided Filter), the researchers found that higher F-score, recall, and precision values are obtained. To determine the optimal set of input parameters that best capture the deteriorating phenomena of crack segments, two ML models, ANN and support vector regression (SVR), have been researched. The results can then be directly fed into optimisation algorithms [62]. In civil engineering, aging infrastructure is becoming a bigger danger to sustainability. It is less resilient to contemporary environmental issues, uses more resources, and presents safety hazards. A shift toward predictive maintenance utilising sensor data and ML, fewer needless repairs, green retrofitting, and more sophisticated monitoring systems is required to ensure the sustainability of infrastructure for future generations.

2.4. Water Management and Pollution Control

One of the most important sustainability issues facing civil engineering today is water management and pollution control due to urbanisation and climate change. This problem has connections to population expansion, urbanisation, industrialisation, and climate change. Civil projects can cause water wastage, groundwater contamination, and poor stormwater management. ML modes monitor water quality in real time and optimise water distribution and treatment using AI-based decision systems. In [63], fifteen different ML techniques, RF, DT, SVM, and ANN are used to analyse the water quality and determine its potability in order to address the potential problem of water pollution brought on by increased urbanisation. SVM performed the best with an accuracy of 83% while the RF model achieved an accuracy of 81%. A wide range of ML techniques, using ANNs, fuzzy rule-based systems, reinforcement learning, and evolutionary algorithms, are studied in [64] to solve complex decision-making problems in the areas of real-time control of combined sewer systems for pollution reduction, integrated design and operation of storm water control systems for maintaining and repairing coastal aquatic ecosystems harmed by increased urbanisation and development, and integrated management of multipurpose river-reservoir systems. The water quality index is used to communicate water quality information to the public and decision-makers, which is a numerical representation that aggregates various water quality parameters into a single score, making it easier to assess the overall condition or "quality" of a water body (like a river, lake, or groundwater source). ML models like RT, RF and Reduced Error Pruning Tree (REPT) are used to predict water quality index [65]. In order to improve model robustness and prediction accuracy in water quality assessment, researchers present a novel hybrid approach that combines non-parametric kernel Gaussian learning (GPR), ANFIS, and DT algorithms. They also stress the importance of data quantity and quality in training to predict the water quality index of surface as well as ground water WQI and GWQI respectively [66].

2.5. Urbanisation and Land Use Pressure

Urbanisation and Land Use Pressure are indeed major challenges for sustainable civil engineering. As cities grow and populations increase, civil engineers face escalating demands to build infrastructure while minimising environmental impact, preserving natural resources, and ensuring resilience. Rapid urban growth strains infrastructure and leads to unsustainable land development. AI supports smart urban planning through land use modelling, traffic flow prediction, and green infrastructure design. Traditional urban planning techniques are being transformed by ML, which has the capacity to evaluate vast and intricate data, predict trends, and make better judgements. Various clustering, regression, and classification algorithms are used as effective tools for urban land use planning [67]. ML models are used to optimise the land use and land cover change (LULCC). LULCC classification is used to categorise land covers into different types according to their use and cover, such as crop, forest, road, residential, or industrial areas. LULCC modelling by incorporating models like DNN, RNN, SOM, and ANN-CA, uses information derived from forms, fringe, textures, and features to assess the cumulative effects of environmental and anthropogenic causes on landscape patterns [68]. The globe is rapidly becoming more urbanised; urban coverage is expanding twice as quickly as the global population, and the primary cause of the increasing urban encroachment into agricultural areas is the world's rapid population rise. An Urbanisation Risk Map (URM) can be created using ML algorithms like MLP-ANN, CA, and logistic regression models to let decision-makers know which districts are prioritised for sustainable planning [69]. Another factor that affects the expansion and changes of land use in urban areas is population increase. The pattern of industrial and rural land usage can be examined using ML techniques like Lasso Linear Regression (LLR), Random Forest Regression (RFR), and Multivariate Adaptive Regression Splines (MARS) [70]. AI technologies are helpful to handle land pressure and urbanisation through sustainable methods like Building Information Modelling (BIM) with GIS to effectively model land use and to use smart city technologies to maximise available resources.

2.6. Climate Change and Resilience

Climate change, driven by greenhouse gas emissions and environmental degradation, poses one of the most significant sustainability challenges of our time. For civil engineering, this means designing, building, and maintaining infrastructure that can withstand extreme weather events, changing environmental conditions, and long-term climate shifts while minimising ecological impact. Most of the non-renewable materials found in heritage sites and buildings in general face a new challenge because of the ongoing, cumulatively worsening effects of climate change. Climate change is one of the many domains where ML (ML) and deep learning (DL) techniques have become increasingly prominent because of technological advancements. ANNs are the most widely used ML approach for both mitigating and adapting to climate change [71]. In addition to already-existing issues including aging infrastructure, shifting regulations, and cybersecurity threats, climate change increases the risks facing electric power networks. Despite increasing energy efficiency and distribution, AI and ML also support conservation initiatives, provide dependable energy in the face of climate change, and strengthen power systems' resistance to catastrophic weather events brought on by climate change [72]. The results demonstrated the value of drone surveys in the context of automated heritage building monitoring as AI techniques were used to segment and classify data from a Digital Elevation Model DEM acquired by a photogrammetric drone survey [73]. In transportation engineering, it is concerning how climate change is affecting road maintenance systems since it increases their vulnerability to weather-related incidents and the resulting damage. This change can be mitigated by using Convolutional LSTM technique to optimise RMSDC (Road Maintenance Systems Using Deep Learning and Climate Adaptation) to enhance traffic safety, reduce costs, and improve environmental sustainability [74]. AI predicts climate risks, assesses vulnerabilities, and supports adaptive design strategies for resilient infrastructure.

The way sustainability is accomplished could be completely transformed by the combination of ML and civil engineering. Civil engineers can create and manage infrastructure that is not only robust and efficient but also reduces its environmental impact over time by utilising data-driven insights. By tackling these issues, AI and ML are enhancing civil infrastructure's sustainability, resilience, and readiness for the future in addition to enhancing engineering performance. Table 1 shows a summary of previous research addressing the sustainability challenges in civil engineering their respective solutions with ML techniques.

Table 1. Summary of ML techniques addressing sustainability challenges in civil engineering in literature.

Sustainability Challenge	Specific Problem	ML Adoption Technique	Reference
C&D Waste	C&D Waste	SVM, ANNs, RF, K-Nearest Neighbour (KNN), DCNNs	[48]
	Smart Solid Waste Management	Linear Regression, Regression Trees, Gaussian Process Regression, SVM, and Autoregressive Integrated Moving Average Method	[47]
	C&D Waste Classification	CVGGNet, VGGNet-11, VGGNet-13, VGGNet-16, and VGGNet-19	[75]
	C&D Waste Management	ANN, Deep Learning DL, CNN, and SVM	[49]
Carbon Emissions and Energy Consumption	CO_2 Emission	Linear Regression, Ridge Regression, k-nearest Neighbour (KNN) Regression, Polynomial Regression, Forest Regression, DT Regression, Gradient Boosting Regression, Support Vector Regression	[53]
	Forecasting the CO_2 Emissions	Non-equigap GM, CFNGM	[54]
	Greenhouse Gas Emissions	LSTM Model, Root Zone Water Quality Model (RZWQM2)	[55]
	Energy Consumption, Economic Growth, and CO_2 Emissions	ANFIS	[56]
	Short-, Medium-, and Long-Term Prediction of CO_2	W-EELM	[58]
	Building Energy Consumption	LGBM, SHAP, XGBoost, RF, and Support Vector Regression	[57]

Table 1. *Cont.*

Sustainability Challenge	Specific Problem	ML Adoption Technique	Reference
Aging Infrastructure and Maintenance	Civil Infrastructure Damage and Corrosion Detection	CNN, Cycle GAN, Conditional Random Fields (CRFs)	[59]
	Bridge Infrastructure, Deck Deterioration	ANNs and k-nearest Neighbours (KNNs)	[60]
	Crack Detection for Bridge	CNNs, Cycle GAN, DSN and Fully FCN	[61]
	Track Deterioration	ANN and Support Vector Regression (SVR)	[62]
Water Management and Pollution Control	Water Pollution Reduction	RFs, DTs, SVM, ANNs,	[63]
	Water Resources Systems Engineering	Reinforcement Learning, ANNs, Fuzzy Rule-Based Systems	[64]
	Water Quality Management	Random Trees (RT), RF, M5P, and Reduced Error Pruning Tree (REPT)	[65]
	Water Pollution and Groundwater Quality	Non-parametric Kernel Gaussian Learning (GPR), ANFIS, and DT	[66]
Urbanisation and Land Use Pressure	Urban Land Use	CNNs and SVMs	[67]
	Land use and Land Cover Change	DNN, RNN, SOM, and ANN-CA	[68]
	Urban Expansion	MLP-ANN, CA, and logistic regression models	[69]
	Land Use Change	Lasso Linear Regression (LLR), RFR, and Multivariate Adaptive Regression Splines (MARS)	[70]
Climate Change and Resilience	Climate Change Mitigation and Adaptation	Latent Dirichlet Allocation (LDA)	[71]
	Power System Resilience against Extreme Weather Events	Automated Meter Infrastructure (AMI), Supervisory Control and Data Acquisition (SCADA)	[72]
	Conservation of Built Heritage	CNNs, Digital Elevation Model (DEM), GSD Orthophoto	[73]
	Road Maintenance Systems	Convolutional LSTM	[74]

2.7. Civil-Specific Challenges in AI/ML Implementation

While data scarcity, interpretability, compliance, and computational cost are common challenges across AI domains, civil engineering presents several unique obstacles that make adoption particularly complex:

- Safety-critical decision environments: Unlike other fields, AI errors in civil engineering (e.g., misclassification of structural cracks or slope stability failures) can result in catastrophic consequences for public safety, requiring stricter validation and redundancy than typical AI applications.
- Long service life and lifecycle uncertainty: Civil infrastructure often spans decades. Models trained on short-term datasets may not generalise to long-term degradation, creep, or impacts of climate change.

- Integration with design codes: Current design codes (Eurocodes, ACI) provide no provisions for AI-based predictions. Therefore, AI outcomes must be reconciled with conservative physics-based approaches before regulatory acceptance.
- Heterogeneity of data sources: Unlike domains with standardised datasets (e.g., ImageNet in computer vision), civil data are fragmented (lab vs. field vs. sensor), non-standardised, and site-specific, which hampers model transferability.
- Liability and professional accountability: Engineers remain legally responsible for design decisions. This constrains the practical use of "black-box" AI models unless explainability methods (e.g., SHAP, LIME) can be shown to align with physical reasoning and code-based checks.

These aspects underscore the need for explainable, physics-informed, and code-compliant AI models in civil engineering.

3. Bibliometrics of AI and ML in Civil Engineering

The use of AI and ML in the field of civil engineering has undergone great technological changes, with major influences across various sectors. Recent studies confirm the critical role of AI technologies to improve structural analysis, construction management, geotechnical assessment, and infrastructure monitoring. The potential of AI and ML to enhance engineering processes' precision, effectiveness, and sustainability has been shown in numerous research. With an emphasis on how these advancements are influencing the field's future, this part provides a thorough analysis of the body of literature now in publication, highlighting significant advancements, approaches, and uses of AI and ML in civil engineering. This section presents a bibliometric analysis of a collection of research on the application of ML techniques to civil engineering applications. Based on literature searches, Scopus and Web of Sciences are the most successful scientific databases [76,77]. Therefore, only Scopus-indexed publications are included in the literature search. The following keywords were used in this search with Boolean search query as ("artificial intelligence" OR "AI") AND ("civil engineering" OR "geotechnical engineering" OR "structural engineering" OR "environmental engineering" OR "transportation engineering"). The total number of documents that resulted was 2074; however, after the application of various filters listed in the Table 2, the number of documents was reduced to 1206.

Table 2. Data mining in Scopus Database.

Data Type	Filters
Subject Area	Engineering Environmental Science Earth and Planetary Sciences
Document Type	Energy Conference Paper Article Review Conference Review Book Book Chapter
Language	English
Year	2000 to 2024

Figure 1 shows the subject area's annual trend which includes the data from year 2000 to 2024 and shows that the research trend in this field was nearly non-prominent and very low number of research papers were published until 2018. But starting in 2018, there has been a consistent rise in this field, which is intriguing and positive as it indicates that academics are concentrating on AI and ML-driven models for advancing in civil engineering. Figure 2 depicts the country data of the published documents in the said field. As of recent analyses, China leads globally in the number of publications related to AI and ML in civil engineering. As per digital science, in 2023, China published nearly 60,000 AI-related papers, surpassing the European Union and the United States. While China leads in publication volume, the United States remains influential in terms of citations and research impact.

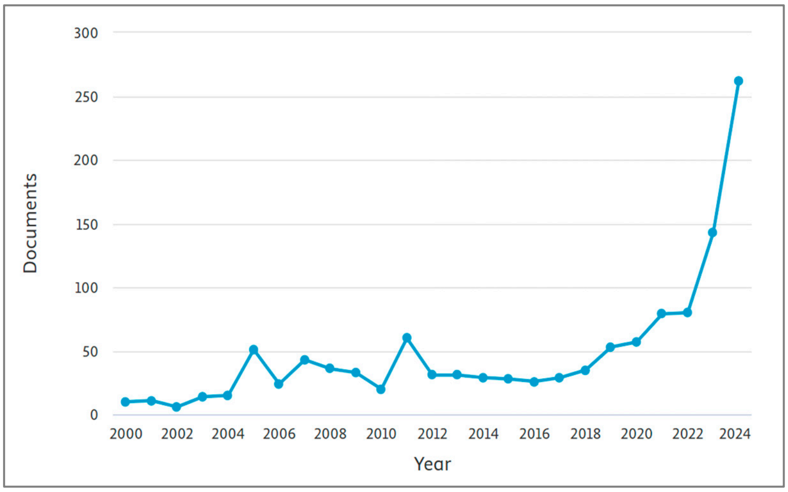

Figure 1. Annual publication trend (Scopus: 2000–2024) in AI-driven models.

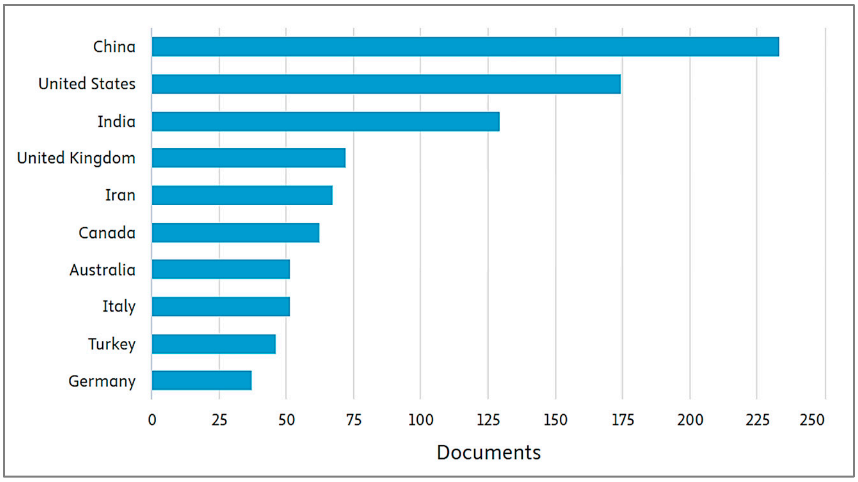

Figure 2. Published documents by country.

Engineering, Computer Science, Environmental Science, Earth and Planet Science and Material Science were the top five source types during data mining based on the document's density and relevance to the Boolean search of keywords. From 2000 to 2024, they contributed 38.1%, 14.9%, 10.6%, 8.7%, and 5% of documents, respectively, as Figure 3 illustrates. While each of the other individual sources account for less than 5% of the total volume of documents, these five fields account for 78%. Similarly, the contribution by document type is shown in Figure 4, with journal articles accounting for 37.1%, conference papers for 45.7%, reviews for 6.6%, conference reviews for 4.3%, and book chapter for 3.3%. Conference papers (45.7%) exceeded journal articles (37.1%), likely due to the interdisciplinary nature of AI research, where conferences serve as rapid dissemination venues. Conferences provide immediate feedback, collaboration opportunities, and visibility ultimately accelerates refinement and follow-up studies for journal submission.

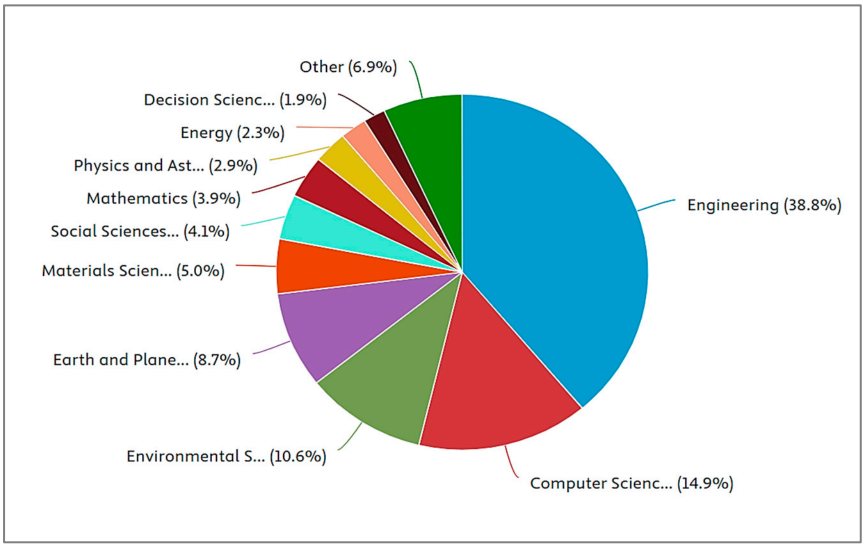

Figure 3. Published documents by subject area.

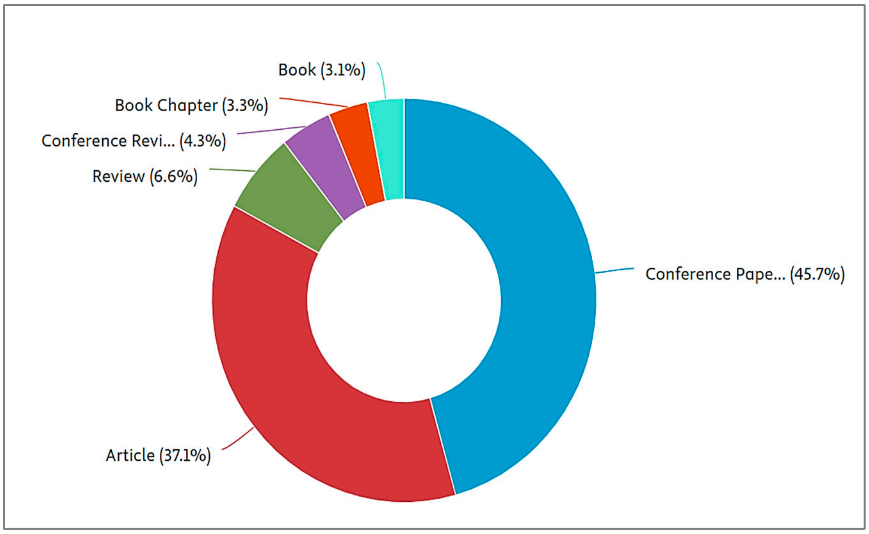

Figure 4. Type of published documents.

The bibliometric analysis presented in this review depicts the noteworthy surge of interest in AI and ML applications within civil engineering, particularly since 2018. This rapid growth reflects not only the increasing availability of computational resources and domain-specific datasets but also the urgency of addressing efficiency, resilience, and sustainability challenges in the built environment. This paper shows, by combining recent research trends through bibliometric assessment with current methods, that AI has moved beyond experimentation and is becoming a key tool for creating data-driven, adaptive, and sustainable civil infrastructure.

4. Overview of AI and ML in Engineering

To organise the diverse applications, we propose a conceptual taxonomy of AI/ML in civil engineering (Table 3), which maps methods across three dimensions: (1) engineering domain (e.g., structural, geotechnical, environmental, transportation, materials), (2) learning paradigm (supervised, unsupervised, deep learning, hybrid), and (3) adoption maturity (experimental, pilot-scale, operational integration). This taxonomy serves as a framework for comparing methods, identifying gaps, and guiding future adoption strategies.

Table 3. Conceptual taxonomy of AI/ML applications in civil engineering by domain, learning paradigm, and adoption maturity.

Domain	Supervised Learning (Adoption Maturity)	Unsupervised Learning (Adoption Maturity)	Deep Learning (Adoption Maturity)	Hybrid/Physics-Informed (Adoption Maturity)
Structural	SVM, RF for damage detection (pilot-scale)	PCA for SHM feature reduction (experimental)	CNN for crack detection (pilot-scale)	PINNs for seismic response (experimental)
Geotechnical	Regression, ANN for soil properties (pilot-scale)	Clustering for soil classification (experimental)	LSTM for slope stability (experimental)	ANN–PSO hybrids for slope FS prediction (experimental)
Environmental	DT, RF for water quality (operational)	Clustering for pollution source ID (pilot-scale)	CNN for waste classification (pilot-scale)	Hybrid ML + LCA for CO_2 emissions (experimental)
Transportation	SVM, RF for traffic flow (operational)	K-means for travel pattern clustering (pilot-scale)	RNN/LSTM for congestion forecasting (pilot-scale)	AI + CFD hybrid for wind/traffic modelling (experimental)
Materials	ANN, SVR for concrete strength (pilot-scale)	Feature clustering for mix optimisation (experimental)	CNN for microstructure analysis (experimental)	Hybrid ML + SHAP for embodied carbon optimisation (experimental)

4.1. Definitions and Techniques (Supervised, Unsupervised, Deep Learning)

AI and ML represent paradigm-shifting technologies that have fundamentally transformed the landscape of civil engineering applications. ML, as a subset of AI, encompasses computational methods that enable systems to automatically learn and improve performance from experience without being explicitly programmed for every scenario [78]. The integration of these technologies into civil engineering has opened unprecedented opportunities for data-driven decision-making, predictive modelling, and optimisation of complex engineering systems.

Rule-based systems use if/then rules created either by human experts or ML algorithms are widely used in civil engineering. As mentioned before, ML algorithms are designed to learn patterns from data. From the explainability point of view, rule-based systems are transparent and predictable. Modifying rules, needs human intervention that makes them inflexible, whereas ML systems although are dynamic and adaptable but complex and data dependent. Integration of ML, with rule-based systems has enabled refining the rules. On the other hand, rule-based systems can be used to initiate ML algorithms.

Supervised learning forms the backbone of predictive modelling in civil engineering applications. This approach utilises labelled training datasets to learn mapping functions between input features and target outputs. Common supervised learning algorithms extensively used in civil engineering include:

1. SVM: Particularly effective for classification problems such as soil type identification and structural damage classification. SVMs excel in handling high-dimensional data and nonlinear relationships through kernel functions [79].
2. RF: An ensemble method that combines multiple DTs, providing robust predictions for both regression and classification tasks. This technique has shown exceptional perfor-

mance in predicting concrete strength, structural health monitoring, and geotechnical parameter estimation [80].

3. Neural Networks: Multi-layered perceptrons capable of approximating complex non-linear relationships. Traditional neural networks have been successfully applied to structural response prediction, material property modelling, and optimisation problems [81]. Unsupervised learning techniques focus on discovering hidden patterns and structures within unlabelled datasets, making them invaluable for exploratory data analysis and feature extraction in civil engineering:
4. K-means Clustering: Widely used for grouping similar structural elements, identifying failure patterns, and segmenting infrastructure assets based on condition states [82].
5. Principal Component Analysis (PCA): Essential for dimensionality reduction and feature extraction, particularly useful in analysing large datasets from structural health monitoring systems and reducing computational complexity [83].
6. Hierarchical Clustering: Effective for creating taxonomies of structural systems, organising maintenance schedules, and identifying relationships between different infrastructure components [84]. Deep learning represents the most recent advancement in AI, utilising deep neural networks with multiple hidden layers to automatically extract hierarchical features from raw data. This approach has revolutionised computer vision applications in civil engineering:
7. CNNs: Specifically designed for image processing tasks, CNNs have become the gold standard for automated crack detection, structural damage assessment, and quality control in construction [85].
8. RNNs and LSTM: Particularly suited for time-series data analysis, these architectures excel in predicting structural responses, monitoring temporal changes in infrastructure condition, and analysing dynamic loading patterns [86].
9. GANs: Emerging applications in generating synthetic data for training purposes, creating realistic structural failure scenarios for testing, and augmenting limited datasets common in civil engineering research [78].

4.2. AI vs. Traditional Modelling Approaches

The transition from traditional modelling approaches to AI-driven methodologies represents a fundamental shift in civil engineering practice. Traditional approaches, while well-established and theoretically grounded, often face limitations when dealing with complex, multi-variable systems and large datasets characteristic of modern civil engineering challenges [87,88].

Traditional finite element analysis (FEA) has long been the cornerstone of structural analysis, providing detailed insights into stress distributions, deformation patterns, and failure mechanisms. However, FEA requires extensive computational resources, detailed material property definitions, and significant expertise for model setup and interpretation. The deterministic nature of FEA also limits its ability to handle uncertainty and variability inherent in real-world engineering systems [89–91].

AI methods can autonomously learn complex relationships from raw data without explicit physical modelling [92] and, once trained, they deliver rapid, scalable predictions in tasks like structural design and health monitoring [93]. Ensemble models with explainability also effectively quantify uncertainty [94]. However, traditional physics-based methods remain essential due to their interpretability and ability to generalise beyond training data. They continue to serve as the cornerstone of current design codes while AI awaits full regulatory integration [93,95].

Hybrid approaches emerge as the most promising direction, combining the strengths of both traditional and AI-based methods. Physics-informed neural networks (PINNs) represent a notable example, incorporating physical laws as constraints within neural network architectures, ensuring predictions remain physically consistent while leveraging the flexibility of AI [96].

4.3. Tools, Platforms, and Datasets

The rapid expansion of AI and ML tools, platforms, and datasets has significantly reduced the barriers to implementing these technologies in civil engineering practice. The increasing availability of accessible programming environments, cloud-based services, and domain-specific datasets has democratised AI/ML adoption, allowing civil engineers to leverage advanced analytics with minimal programming expertise [97].

Python has become the dominant programming language for AI/ML applications in civil engineering, primarily due to its extensive library ecosystem. Tools such as scikit-learn provide user-friendly implementations of traditional ML algorithms including classification, regression, and clustering [98]. For deep learning applications, TensorFlow and PyTorch offer scalable and flexible frameworks suitable for both research and production environments [99,100]. Complementing these, Pandas and NumPy serve as foundational tools for data preprocessing, manipulation, and numerical analysis [101]. In addition, R remains highly valuable for statistical analysis and visualisation tasks, offering packages specifically adapted to engineering datasets. Meanwhile, MATLAB continues to hold a strong position within academic and industrial settings due to its specialised toolboxes for optimisation, signal processing, and neural networks [102].

Beyond programming environments, cloud platforms have played a critical role in facilitating AI/ML adoption by offering scalable computational resources. Services such as Google Cloud AI Platform, Amazon SageMaker, and Microsoft Azure ML provide end-to-end pipelines for model development, training, and deployment. These platforms not only enable rapid scalability but also integrate with specialised AI services for computer vision, natural language processing, and predictive analytics [103].

The success of AI/ML applications in civil engineering heavily depends on the availability of high-quality, domain-specific datasets. In the field of SHM, datasets from the Los Alamos National Laboratory offer time-series data capturing controlled damage scenarios, providing a valuable resource for developing and validating AI-based diagnostic models [104]. For material behaviour modelling, datasets such as the widely used Concrete Compressive Strength Dataset available through the UCI ML Repository contain detailed records of concrete mix designs and associated strength outcomes, facilitating supervised learning approaches [105]. In the geotechnical domain, the National Geotechnical Database (NGDC) and USGS National Water Information System offer extensive data on subsurface soil, rock, and groundwater conditions, critical for data-driven modelling of underground infrastructure. Additionally, condition assessment datasets such as the FHWA Bridge Condition Database and various state-level pavement condition databases provide real-world inspection data for infrastructure asset management [106–108].

Open-source platforms have emerged that support AI integration for practitioners with limited coding expertise. OpenCV powers advanced image processing pipelines essential for crack detection in structural assessment [109], and deep learning extensions compound this capability through pixel-wise damage identification [110]. Tools such as WEKA and Orange provide intuitive, visual interfaces that facilitate ML workflows without extensive programming [111]. Together, these developments have democratised AI/ML in civil engineering, enabling professionals to harness data-driven insights on structural health that were previously limited by traditional methods [112].

5. Applications in Sustainable Materials

5.1. Sustainable Binder Alternatives

Cement concrete, being the most consumed material after water globally, has an annual production of approximately 30 billion tonnes. However, cement is the key ingredient in concrete which accounts for significant global CO_2 emissions, as producing 1 tonne of ordinary Portland cement (OPC) generates an equivalent of 1 tonne of CO_2 [113]. This is leading to serious environmental concerns, making low-carbon alternatives necessary. Several industrial and agricultural by-products are being considered partial or complete substitutes for cement. The most frequently used materials, however, are fly ash (FA), ground granulated blast furnace slag (GGBS), rice husk ash (RHA), metakaolin (MK), silica fume (SF), bagasse ash, and wood ash (WA) [114–119]. Such materials decrease the environmental impact of concrete, and in many cases, both strength and workability are also enhanced.

One of these alternatives is geopolymers, which have generated a lot of interest as a potential sustainable binder. Introduced in the late 1970s by Joseph Davidovits, geopolymers are derived from the activation of aluminosilicate-rich materials (e.g., FA, GGBS, MK) with alkaline solutions (e.g., sodium hydroxide, sodium silicate). This chemical reaction leads to a three-dimensional aluminosilicate structure that has compressive strength equivalent to or higher than OPC-based concrete [120].

Recent studies on industrial by-products and geopolymers have shown promise in utilising these materials in sustainable binders; however, we need to have a standardised mix design process and longer-term studies on durability. The following steps are to engage in a collaborative process to determine the specific testing methods, look to integrate AI lead optimisation following code-based provisions, and test when performance specifications are required in uncertain environments.

5.2. AI in Sustainable Concrete

The primary focus of this section is to use AI within environmental assessment and sustainable design practices, with an interest in how AI tools can help to alleviate environmental impact. It also focuses on ML models that optimise the mix design of geopolymer concrete, to further sustainability and performance. In civil engineering, AI is changing how environmental assessment is practiced, so sustainable development becomes the mainstream instead of an additional goal. AI tools such as Envision, developed by the Institute for Sustainable Infrastructure (ISI), allow engineers to analyse concrete designs against a wide range of sustainability indicators involving environmental, social and economic elements. Envision's decision-making process allows infrastructure professionals to evaluate their project performance across several sustainability standard measures that can support sustainable designs and aid in meeting their sustainability regulation obligations. Envision's flexible decision-making process allows AI models to anticipate and evaluate long-term environmental consequences of designs, such as CO_2 emissions and energy usage, and consequently, make decisions about alternatives that could mitigate future harms [121].

AI also allows for early anticipation of long-term environmental impacts during the design process, such as CO_2 emissions and energy consumption. This enables engineers to modify plans to minimise future damage. For instance, firms such as AECOM deploy AI models to simulate effects and manage environmental risks, thereby enabling their projects to achieve a high sustainability index because high sustainability has become more important [122].

Although geopolymer concrete offers environmental benefits, its widespread use remains limited due to a complex mix of design procedures and a lack of standardised formulations.

Many ML models have been created to estimate the compressive strength of FA-based geopolymer concrete with different levels of accuracy and complexity. Participants in the category of ensemble learning, including Boosting (R^2 = 0.96, RMSE = 2.04 MPa), Bagging (R^2 = 0.97, RMSE = 1.94 MPa), have always played a better role than single learners, such as ANN. Notably, Khalaf, A. constructed an efficient FLNN with an R^2 of 0.975 and RMSE = 3.87 MPa across a diverse dataset of 189 samples [123]. Dao, D.V. (2019) employed an ANFIS model and achieved relatively accurate predictions (R^2 = 0.879, MAE = 1.655 MPa) [124]. A recent hybrid model achieved the best results (R^2 = 0.983, RMSE = 1.712 MPa) by hybridising RF with GWO and XGBoost, demonstrating the capability of hybrid stacking models to predict the complex response of geopolymer mixtures [125]. These results demonstrate how ensemble and optimised AI methods can quickly, with a fast yet effective ROI, assist in the management of the pandemic, accurate prediction, and mix design of sustainable concrete systems. The LSTM–MPA and RF–GWO–Boost models all demonstrated the highest prediction accuracy of ensemble and hybrid models, with R-squared greater than 0.97 and the lowest RMSE values recorded. As predicted, traditional models like ANN and ANFIS performed lower than expected. The best-performing models incorporated nine or more input features with moderately to highly sized datasets, which highlights the value of high-quality, multi-variable datasets (as summarised in Table 4).

Table 4. Performance comparison of ML models for predicting compressive strength of geopolymer concrete.

Model Type	R^2	MAE (MPa)	RMSE (MPa)	Inputs	Dataset Size	References
Boosting	0.96	1.69	2.04	9.0	154	[126]
RFR	0.92	1.99	2.67	9.0	210.0	[127]
ANFIS	0.879	1.655	2.265	4.0	210.0	[124]
Optimised FLNN	0.975	-	3.87	10.0	189.0	[123]
RF–GWO–XGBoost	0.983	-	1.712	15.0	156.0	[125]
LSTM–MPA	0.994	-	0.8332	17.0	162.0	[128]
Gradient Boosting (AML)	0.9651	1.1891	-	9.0	132.0	[129]
AdaBoost	0.944	1.259	2.506	8.0	154	[130]
ANN	0.921	-	2.52	6.0	263.0	[131]

RFR = Random Forest Regression, ANFIS = Adaptive Neuro-Fuzzy Inference System, FLNN = Functional Link Neural Network, GWO = Grey Wolf Optimizer, XGBoost = Extreme Gradient Boosting, LSTM = Long Short-Term Memory, MPA = Marine Predators Algorithm, AML = Automated Machine Learning, AdaBoost = Adaptive Boosting, ANN = Artificial Neural Network.

At this stage, AI models can predict the performance of a concrete mix with a sufficient level of accuracy; however, studies have mainly used small experimental datasets, and many have not been validated against code-based options. Thus, for the following stage of work, this involves creating large datasets and, in open-source form, assessing an explainable AI approach to get regulatory acceptance, and linking performance predictions back to concrete design via the provisions of Eurocode and ACI.

5.3. AI in Sustainable Mix Design Optimisation

This section considers the application of AI-based techniques to optimise the mixtures of geopolymer and conventional concretes, especially when recycled materials are available as supplementary cementing materials. Not only do AI models assist in improving mechanical performance, but they can also yield more cost-effective, durable, and environmentally beneficial outcomes by lowering raw material consumption and carbon emissions. Recent studies confirm the critical role of AI in optimising the mix design of geopolymer concretes, especially those incorporating recycled or industrial by-products. Golafshani et al. developed machine learning models to accurately predict the CS of geopolymer RAC [132]. They used ensemble learning techniques, especially XGBoost and light gradient boosting, and identified testing age, natural fine aggregate content, and recycled aggregate ratio as key predictors. Their approach, based on a comprehensive experimental synthetic database and SHAP analysis, enables reliable predictions and mix optimisation for sustainable concrete applications. Marathe S. focused on geopolymer pervious concrete, incorporating agro-industrial and construction demolition wastes. It employed hybrid AI models, particularly RF and Gradient Boosted Regression Trees, optimised with the Firefly Algorithm to achieve high prediction accuracy. The study emphasised the combined effects of GGBS, SF, W/B ratio, and alkaline activator dosage on strength development, highlighting the potential of intelligent models in designing sustainable and porous geopolymer concretes [133].

In the context of concrete technology, the value of AI models is demonstrated in predicting material properties. The study investigated the use of ensemble and deep learning models, including ANNs, CatBoost, and Extra Trees, for predicting the compressive strength of FA-based concrete. The ANN model achieved the highest accuracy ($R^2 = 0.93$), confirming its ability to capture complex, nonlinear relationships in concrete mix data. Key influencing variables included NaOH molarity, cement, and fine aggregate content. This research highlights how AI can support data-driven decision-making in concrete mix design, especially when incorporating industrial by-products like FA [134].

An intelligent optimisation framework was recently developed for mix design of alkali-activated (GGBS-FA) geopolymer concrete with a focus on compressive strength, cost-effectiveness, and carbon emission reduction. By utilising RF, Gradient Boosting, and BPNN models in conjunction with PSO, the authors have developed predictive models and observed that the GGBS and sodium hydroxide content are the most dominant factors. The platform efficiently produced mix designs providing a compromise between mechanical performance of the material and economic and environmental advantages, highlighting the role of AI in enabling sustainable, high strength geopolymer concretes [135].

In a new study on GGBS-based concrete, four models, DT, RF, Gradient Boosting, and XGBoost, were developed to predict the CS. XGBoost was the most accurate model ($R^2 = 0.97$), showing the best prediction performance and stability. The implications of the model results were also investigated through SHAP, which revealed that cement content, the curing age, and W/C had the most significant effect. This application of explainable AI increases the trust in model predictions or decisions and promotes transparency, making it a powerful tool for mix design in sustainable construction [136].

These studies show that ensemble and hybrid AI models not only improve prediction accuracy but also offer interpretability and flexibility for adjusting mix design parameters. The use of SHAP and optimisation algorithms like PSO and Firefly enables data-driven decisions that align mechanical performance with environmental and economic goals. AI can facilitate the efficient use of materials and decrease carbon footprints. However, current applications of AI tend to be case-specific in nature, often neglecting the trade-offs between performance and cost. Therefore, future research should look to build more multi-objective frameworks that evaluate materials based on strength, durability, price, and emissions, while also examining alignments with sustainability rating systems and building regulations.

5.4. ML in the Recycling and Reuse of Construction Waste

With the never-ending requirements and developments in concrete construction, the demand for structures continues to grow, which further generates a vast amount of C&D waste in cities. In the UK in 2022, around 59.4 Mt of C&D waste was produced, of which about 55.0 Mt was recovered. Most of that C&D waste was produced in England, accounting for about 53.9 million tonnes. Management and reduction are a global issue, particularly in densely populated city centres [137]. AI offers a scalable, accurate, and flexible solution to the complex nature of C&D waste management. Increasing accuracy compared to traditional methods, AI enables users to make data-driven decisions on the spot, assisting in shifting construction methods toward more sustainable, circular, and cost-effective building practices. Recent studies have demonstrated how ML techniques, more specifically deep learning (CNN, YOLOv7, Faster R-CNN) and traditional classifiers (SVM, RFs), have greatly increased the automated classification of C&D waste using image recognition and feature extraction. These models improve accuracy, speed, and sorting in real-time applications. From a computer vision and AI perspective, improvements in C&D waste management at a sustainable and scalable level are finally possible [48]. Alongside image-based systems, there are emerging studies that apply ML clustering (such as t-SNE and PCA) and chemical composition data to classify types of C&D waste, and to forecast the behaviours of contaminants. An ANN model was able to successfully predict hazard quotients from the chemical composition of basic oxides, illustrating that there are useful additional benefits for hazard assessment and sorting in risk assessment and sorting systems [138]. On an even larger environmental scale, semantic segmentation of remote sensing imagery has been employed to automatically identify illegal C&D waste landfills. One study utilising models such as DeepLabV3+ and HRNet detected 52 (illegal) landfills across Shenzhen, China, with 96.3% accuracy and an IoU of 74.6%. This study showcases the potential of AI for aiding in compliance and environmental oversight [139]. In addition to this work, Iyiola, Shakantu, and Daniel examined how digital technologies (DTs), including AI, ML, Blockchain, Internet of Things (IoT), Robotics, Building Information Modelling (BIM), and computer vision, could improve C&D Waste Management overall. They found that AI and ML supported three main roles, including: real-time monitoring, material classification, C&D waste prediction, lifecycle analysis, and design validation [139].

All these AI applications help contribute to sustainable construction with waste management and increased traceability. In addition, this research has built on these applications to develop intelligent optimisation of recycled aggregate concrete (RAC). As a result of AI ML models, data-driven design is possible and includes every aspect of compressive strength, durability, carbon footprint, and cost, unlike fixed mix design rules. The frameworks were often multi-objective approaches that combined improvements to the design used for RAC with optimised algorithms, also from an ensemble learning perspective, to develop a significant, sustainable approach toward being able to design concrete made using recycled materials and low-carbon binders [140]. One such approach was proposed by Zhang et al. [141] who developed a method to use big data analytics, including an LCA of RAC mix designs to evaluate environmental performance. The findings concluded that transportation distance is a significant factor influencing total carbon emissions in RAC, and strength categories C30 performed the best in the trade-off between sustainability/structural performance. In contrast, Liu et al. [142] applied a multi-objective Particle Swarm Optimisation (CMOPSO) approach to the simultaneous optimisation of compressive strength, cost, emissions, and energy intensity, pointing to inherent trade-offs between mechanical and environmental objectives. Further work explored hybrid ML models (e.g., ANN–SVR, GWO–SVR) for predicting mechanical properties of RAC. Among these, the GWO–SVR model demonstrated the best performance ($R^2 = 0.9056$), indicating that the potential for using explainable AI tools to support accurate and sustainable RAC mix design is a reality [143].

ML techniques can enhance waste classification systems and the design process for RAC; nonetheless, any research that focuses on field-scale projects with verified RAC classification systems and lifecycle assessments is scarce. Future work should focus on large-scale pilot projects, databases of RAC, and hybrid models incorporating AI and environmental impact models.

5.5. Scalability of AI in Resource Constrained Environments

In developing and underdeveloped countries, the data regarding the computational infrastructure is very limited, which require various tailored and scalable approaches to validate the data. Recent research studies have signified practical applications that can help regarding these constraints. Using light weight and parameter efficient models such as adapter modules or low rank adaptations applied to foundation models like SAM for crack detection can enable powerful inference using minimal computational data [144]. The research showed that CrackSAM performs significantly better than all state-of-the-art models on datasets with generated noise and datasets that have never been seen before. Particularly in difficult situations like low light levels, shadows, road markings, construction joints, and other interfering issues, CrackSAM shows exceptional performance. These cross-scenario results offer fresh concepts for creating vision models in civil engineering and highlight the exceptional zero-shot capacity of foundation models. Another work regarding built resistant infrastructure, a MEC (mobile edge computing) was introduced that can store data and improve the applications of federate learning to detect and improve the defects [145]. The model allows decentralisation and privacy-preserving model training using smart phones which can be helpful for providing insightful information for projects like road-condition digital twins in Sri Lanka. Similarly, in countries like Africa, local AI manufacturing techniques like ECI (edge computing infrastructure) is advancing to process the data sources and reducing latency and reliance on cloud services. These ML techniques for developing countries focus on transfer learning that may be helpful, but they must account for the biases in pertaining data and high adaptation costs. While AI holds promise for sustainable development, its scalability must be considered to ensure the extension of their benefits on a global level.

Artificial intelligence applications in sustainable materials research have shown significant potential for mix design and mechanical performance prediction, especially with the use of ensemble and hybrid models for geopolymer concretes and recycled aggregate concretes. However, many of these models are still limited by the small size of laboratory datasets. In many cases, they have not been validated outside of the laboratory to demonstrate performance across different environments. As a result, the motivation to test these models on-site has not been realised because there is no standard formulation, material specification, or regulatory guideline for large-scale adoption, like practices in geotechnical engineering. Additionally, the reliability of these models is constrained by the relatively small datasets available. Material design is also trust-based; practitioners need access to larger databases and explainable models to regain confidence. Continuing to bridge sustainability goals with structural performance and lifecycle carbon assessments, AI in material engineering will provide a foundation for interconnected applications in civil engineering fields.

While AI models such as ensemble and hybrid approaches achieve high predictive accuracy for compressive strength and mix optimisation, most studies remain limited to small laboratory datasets without validation against large-scale field projects. This gap questions the immediate transferability of results to practice, highlighting the need for open-access, standardised databases and explainable models linked to code-based provisions.

6. Applications in Structural Engineering

6.1. Structural Health Monitoring

SHM is significantly enhanced by AI advancements in the form of real-time condition monitoring through various sensor technologies such as vibration-based sensors, strain gauges, wireless sensor networks, and optical fibre sensors [146]. Technology makes it possible to obtain accurate, continuous data required for monitoring structural health. AI and ML algorithm-based predictive maintenance with such methods as anomaly detection procedures, autoregressive integrated moving average (ARIMA), and LSTM models gives reliable predictions of structural degradation and enhances anticipatory interventions [147]. In addition to the use of AI for real-time monitoring, sensor optimisation and strategic placement play a critical role in improving data quality and cost-efficiency of SHM systems. Optimisation algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimisation (PSO) have been extensively applied to determine optimal sensor locations, minimising the number of sensors required while maximising monitoring effectiveness [148]. These metaheuristic approaches account for multiple objectives, including sensitivity to damage, redundancy, and environmental robustness, ultimately enhancing both monitoring accuracy and economic feasibility [149–151].

Most studies rely on laboratory datasets or controlled experiments, which limit generalisation to large-scale field applications. Sensor placement optimisation and data fusion techniques remain underdeveloped. Future research should focus on integrating SHM with digital twins for continuous monitoring, validating ML models on long-term field datasets, and developing low-cost, energy-efficient sensor networks to enable scalable deployment.

6.2. Damage Detection and Structural Diagnostics

Deep learning, i.e., CNNs, improved structural damage detection markedly by automating image-based inspection using images taken by drones and advanced computer vision algorithms [152]. Figure 5 illustrates a representative CNN architecture for crack detection, where image input passes through successive convolutional, pooling, normalisation, and activation layers before final classification using softmax [153]. Reported performance in key studies includes F1 scores above 0.85, with precision and recall frequently exceeding 0.80 [154–156]. Nonetheless, CNNs can suffer from overfitting, especially when trained on small or homogeneous datasets, which limits their generalisation to new conditions. To mitigate this, dataset diversity and augmentation techniques such as rotation, flipping, and synthetic data generation are often employed to enhance robustness [155,157]. AI-enabled non-destructive testing (NDT) techniques, including ultrasonic testing, infrared thermography, and ground-penetrating radar, provide faster and more accurate structural diagnostics compared to traditional manual inspection methods [158,159]. ML-based regression models and deep regression CNNs are also used to quantify damage severity and identify the location of defects. This capability supports targeted maintenance planning, helping reduce both maintenance downtime and associated costs [156,157].

CNN-based approaches require large, diverse image datasets, but available datasets are often small or site-specific. Transferability across different structures and environmental conditions remains limited. Research should prioritise dataset standardisation, transfer learning to improve cross-structure applicability, and explainable AI methods to ensure that automated diagnostic tools are accepted in practice.

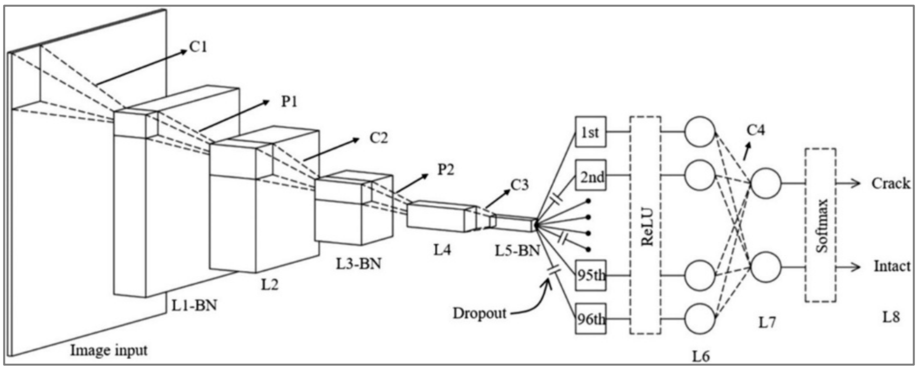

Figure 5. Overall architecture: L#: layers corresponding to operations (L1, L3, L5, and L7: convolution layers; L2 and L4: pooling layers; L6: ReLU layer; L8: softmax layer); C#: convolution; P#: pooling; BN: batch normalisation [153].

6.3. Load and Response Prediction

AI techniques notably improve load and response prediction capabilities, particularly in seismic response modelling through hybrid simulation methods and deep learning models that simulate earthquake-induced structural responses [147]. Advanced approaches, such as physics-informed machine learning (PIML), integrate domain knowledge with data-driven algorithms, resulting in models that uphold physical consistency while improving generalisation. In wind engineering, ML-driven computational fluid dynamics (CFD) analyses facilitate precise wind load predictions and aerodynamic assessments, enhancing structures resilience against extreme weather. Similarly, AI-based fatigue life prediction using recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) architectures significantly improve the accuracy of structural lifespan estimation, supporting optimal resource allocation and proactive maintenance planning [160].

To ensure alignment with design codes and regulatory standards, AI models are validated using benchmark datasets, cross-validation techniques, and comparison against analytical solutions or high-fidelity finite element models. Additionally, uncertainty quantification and sensitivity analyses are employed to assess robustness, while compliance checks with Eurocode or ACI guidelines help confirm that AI-predicted responses meet structural safety criteria [161].

Many ML models neglect physics-based constraints, leading to predictions that may not align with structural safety codes. Benchmarking against traditional FEA or code provisions is often insufficient. Physics-informed ML models (PINNs) and hybrid approaches should be developed to combine computational efficiency with physical interpretability, ensuring compliance with Eurocodes and other regulatory standards.

6.4. Optimisation of Structural Design for Sustainability

AI and ML algorithms optimise structural designs for sustainability by aiding the selection of eco-friendly materials and techniques, significantly reducing carbon footprints through accurate embodied carbon assessments and integrated lifecycle analyses [162]. These models allow engineers to evaluate multiple mix designs incorporating supplementary cementitious materials such as fly ash, ground granulated blast furnace slag (GGBS), silica fume, or recycled aggregates. They enable direct estimation of embodied carbon impacts during the early design phase. Figure 6 illustrates a generative approach that automatically proposes novel concrete formulations based on targeted strength, age, and environmental performance criteria [163]. Generative design algorithms using reinforcement learning can explore extensive design spaces to recommend optimal structural configurations that balance mechanical performance, cost efficiency, and sustainability goals [164,165].

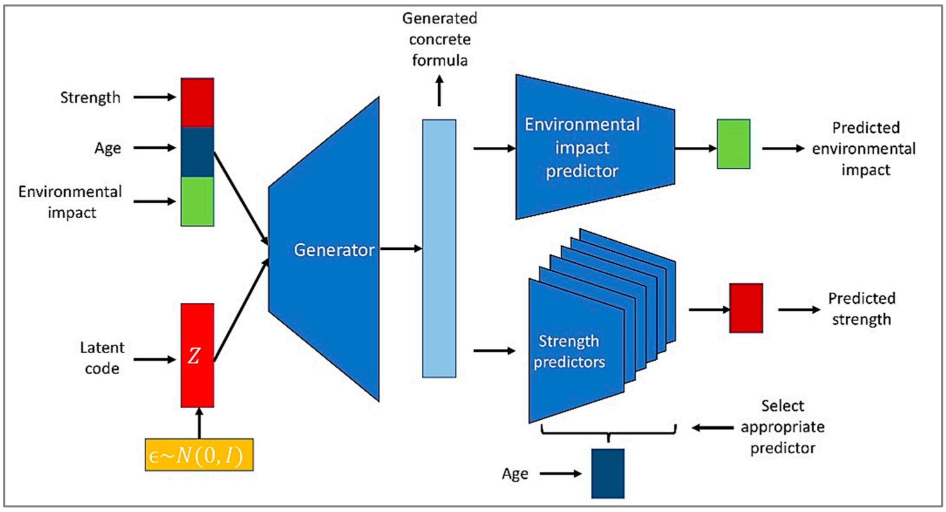

Figure 6. Generating new concrete formulas and evaluating their properties [163].

Cost-effectiveness analyses using multi-objective optimisation algorithms like NSGA-II and SPEA2 ensure sustainable designs meet both structural performance targets and economic viability [166]. Lifecycle cost analysis (LCCA), combined with embodied carbon optimisation, enables long-term sustainability goals that consider both embodied and operational carbon emissions over the structure's lifespan [167]. Table 5 illustrates a comprehensive comparison of embodied carbon and cost for different concrete mix designs using data from the Inventory of Carbon and Energy [168].

Table 5. Embodied carbon, cost, and strength trade-off for various cement replacements in concrete mixes [168].

Concrete Mix	Cement Replacement	Embodied Carbon ($kgCO_2e/m^3$)	Material Cost (£/m^3)	Compressive Strength (MPa)
C30/37	0% (ordinary Portland cement)	320	£110	37
C30/37	30% GGBS	260	£105	36
C30/37	50% GGBS	220	£100	34
C30/37	70% GGBS	180	£98	32
C30/37	20% Fly Ash	270	£106	36
C30/37	10% Silica Fume	250	£108	38
C30/37	40% Recycled Aggregate	290	£102	35

Existing optimisation frameworks often overlook the trade-off between embodied carbon, cost, and structural safety. Many models remain theoretical and lack real-world case validation. Future work should emphasise multi-objective optimisation validated on real construction projects, integration with Building Information Modelling (BIM), and frameworks that explicitly balance sustainability with long-term durability.

6.5. Risk Assessment and Resilience

AI methodologies are highly useful in probabilistic risk analysis with Monte Carlo simulations and Bayes' networks for evaluation and mitigation of uncertainties in structural performance. Digital twin technology integrated with AI simulation ensures better scenario analysis, which enhances structural resilience by pre-emptively responding to potential disaster scenarios [169,170]. Structural risk management is increasingly enhanced by AI-driven decision-support systems, which integrate predictive analytics, probabilistic modelling, and real-time data processing. These systems leverage ML algorithms, Bayesian networks, and scenario-based simulations to evaluate multiple risk scenarios under uncertainty, allowing engineers and decision-makers to proactively identify vulnerabilities, optimise maintenance strategies, and improve operational resilience. By reducing uncertainties associated with structural performance, environmental conditions, and aging infrastructure, AI-supported frameworks significantly strengthen the reliability and sustainability of long-term structural asset management [171,172].

Current AI-based risk frameworks are often tested under simulated scenarios rather than actual hazard events, and uncertainty quantification is still underdeveloped. Future studies should explore probabilistic ML approaches, integrate climate change projections into resilience modelling, and enhance the use of digital twins for real-time risk management.

6.6. Automated Construction and Robotics

AI-driven robots revolutionise construction productivity with computer vision-based automated additive manufacturing and robotic assembly cells. Notable case studies include the 3D-printed pedestrian bridge in Madrid, developed by Acciona, which demonstrated the feasibility of large-scale printed concrete infrastructure [173], and robotic rebar tying systems employed by Skanska in the United States, which have improved reinforcement efficiency and reduced labour-intensive tasks [174]. Additionally, computer vision-enabled systems and wearable sensors enhance on-site safety by enabling real-time hazard detection, reducing accident rates, and ensuring regulatory compliance. Autonomous inspection robots and drones enhance inspection with quick, frequent, and accurate analyses [153].

While promising, robotic construction applications remain limited to experimental projects. High implementation costs, lack of skilled operators, and safety regulations restrict wider adoption. Future research should focus on cost-effective robotic systems, AI-driven safety compliance checks, and integration of robotics into mainstream construction workflows supported by real-world case studies.

6.7. Advanced Structural Analysis and Design

AI-assisted finite element analysis (FEA) and modelling techniques enhance structural analysis and design processes by providing accurate parameter identification, surrogate modelling, and optimisation capabilities that significantly reduce computational costs while improving accuracy [147]. ML-enhanced structural dynamics analyses can effectively predict complex modal behaviours under varying loading scenarios and optimise vibration control systems. Reinforcement learning algorithms allow for adaptive structural design strategies that respond to changing performance demands in real time [175–177].

Furthermore, AI-powered topology optimisation methods enable the generation of structurally efficient geometries by minimising material usage while maintaining safety and serviceability The use of surrogate modelling techniques, such as Kriging and support vector regression (SVR), further accelerates parametric design optimisation by approximating high-fidelity finite element (FE) models. As shown in Figure 7, SVR can effectively approximate structural displacements across different parameter settings, with demonstrated accuracy in predicting probabilistic constraints under varying uncertainties. In their proposed SVR-TO-APMA framework, SVR models were trained using Latin Hypercube Sampling and integrated with an accelerated performance measure approach (APMA) to improve computational efficiency in reliability-based topology optimisation (RBTO). The results confirm that optimal SVR parameters significantly influence prediction accuracy, with the model yielding relative errors below 7% and strong agreement with FE analysis across multiple reliability levels. Such hybrid approaches not only reduce computational burden but also ensure robust structural performance under uncertainty [178]. Table 6 illustrates a simplified comparison of conventional design versus AI-assisted optimisation outcomes for a reinforced concrete beam.

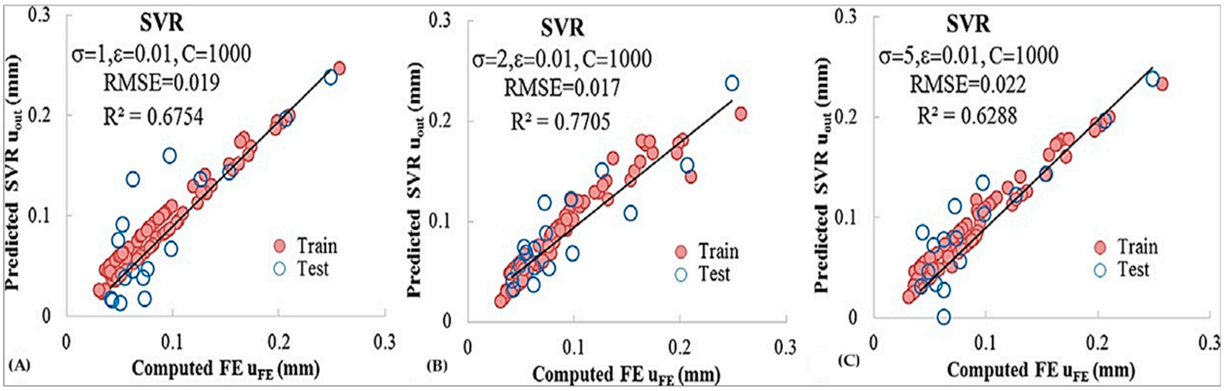

Figure 7. Scatter points of predicted SVR model and computed FE for three different shape parameters of SVR (**A**) σ = 1, (**B**) σ = 2, and (**C**) σ = 5 for structure [179].

Table 6. Comparison of conventional versus optimised beam design. Optimisation (via shape and prismatic beam algorithms) yields a 38% reduction in embodied carbon with ~24% less concrete and ~22% less steel relative to standard design practices, actuated through AI-informed parametric strategies [180].

Design Type	Concrete Volume (m^3)	Reinforcement (kg)	Embodied Carbon (kg CO_2e)	CO_2 Reduction (%)
Conventional Beam	12.5	1800	12,500	–
Optimised Prismatic	9.5	1400	7750	38%

By integrating AI-driven optimisation and adaptive analysis tools, structural engineers are empowered to generate innovative, resource-efficient, and sustainable designs that would be impractical or impossible with traditional trial-and-error approaches. Modern AI frameworks leverage surrogate-assisted optimisation to explore vast, multidimensional design spaces, allowing rapid evaluation of structural performance, cost, and environmental sustainability during the design phase. As shown in Figure 8, AI applications support both design and operational stages across different sustainability tiers, enabling smart control, fault detection, and load prediction in addition to early-stage optimisation [181,182].

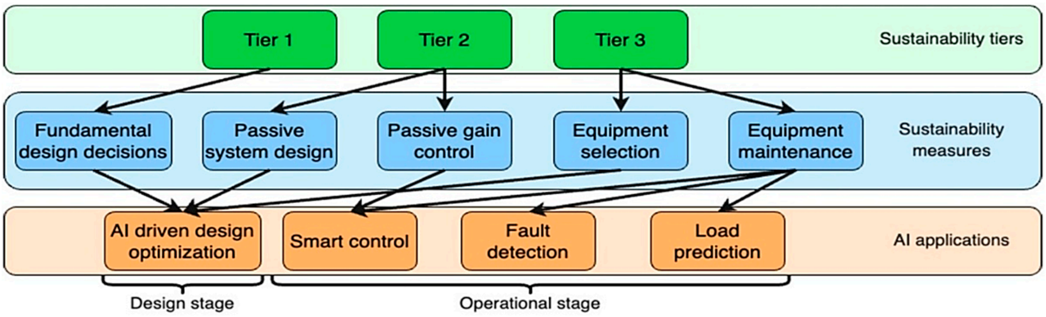

Figure 8. AI integration in building sustainability. AI is applied during both design and operational stages. Design stage focuses on optimising decisions from the three tiers, while operational stage includes smart control, fault detection, and load prediction [182].

Significant progress has been made in structural engineering through advancements in crack detection with CNN, sensor-based SHM, and hybrid simulations guided by SHM for load prediction. These techniques are generally automated, reducing the need for manual inspections with high accuracy, and they also enhance safety. However, a key issue is the limited transferability of models trained on narrow datasets to real-world applications. When relying on models for standards like Eurocode or ACI, their poor performance transferability can be a critical problem. Another challenge is that machine learning methods are often seen as "black boxes," offering little interpretability, especially when safety is involved. Regardless of technical, regulatory, or ethical hurdles, transparency in AI systems that indicate safety remains essential, much like in environmental monitoring, where regulatory oversight is crucial for addressing biosphere and climate change issues. Future progress depends on developing explainable AI and physics-informed AI, which will help bridge research models and practical design, ensuring consistency in safety and sustainability practices.

Many AI applications in structural engineering, particularly CNN-based crack detection and SHM, demonstrate excellent accuracy in controlled settings but lack generalisation to diverse real-world conditions. Without harmonisation with Eurocode or ACI design requirements, their adoption will remain constrained.

7. Applications in Geotechnical and Environmental Engineering

7.1. Slope Stability Analysis Using ML

Slope stability evaluation plays an important role in the geotechnical engineering field, with traditional approaches relying on limited equilibrium, finite element, or statistical methods. However, these approaches are problematic in their ability to account for the non-linear feedback loops between geological and environmental conditions that influence slope behaviour [178]. Since the late 1990s, increasing applications of AI have been considered. The early work by Ni et al. using fuzzy ANN models incorporated thirteen input variables related to topography, geology, meteorology, and environment, yielding promising results [183]. In more recent years, several researchers have explored various ML models (primarily ANN, SVMs, DTs, RFs, ELMs, ANFIS, and hybrid approaches) to predict the factor of safety and slope failure. Primary predictive features include slope angle, cohesion, internal friction angle, pore water pressure, and seismic loading. Recent models had some limitations that can affect the generalizability of the models, such as dataset imbalance and size. Additionally, because these are synthetic datasets, they do not encapsulate all the real-world geotechnical conditions, which could influence discrepancies in the predictions. There is also the risk of overfitting, specifically with complex models such as ANNs that will perform well on training data but likely struggle with new unobserved data. To combat these issues, geotechnical validation is necessary; verification of the model predictions is essential to ensuring reliable and applicable predictions in real-world engineering scenarios by seeking out comparisons to field data and subject matter expertise [184–194].

As an example, Meng et al. proposed a 3D slope stability prediction model based on an ANN-based software called "SlopeLab". This software is valuable to engineers because it provides the ability to estimate FS3D or FS2D in addition to incorporating geometric and material variables (Figure 9). Because the model was found to be very accurate ($R > 0.999$, $RMSE < 0.15$) and because it was implemented on a GUI-based software, slope stability can be evaluated promptly and taking into consideration 3D aspects so that engineering decisions can be made easily [189].

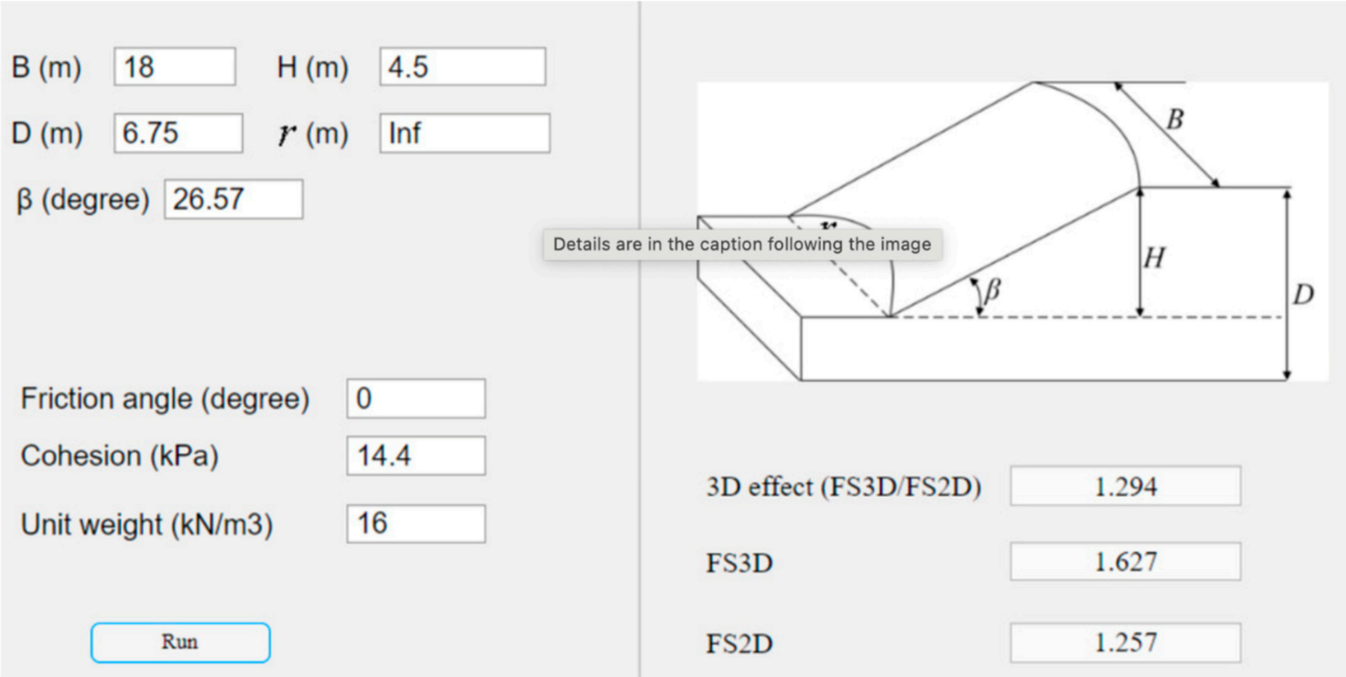

Figure 9. Results data for undrained slope [189].

Another comparison of models was done by Huang et al. involving SVM, RF, CNN, and LSTM models. They reported LSTM to have the best modelling accuracy (0.9827) and lowest RMSE (4.45%) (Figure 10). This showcases LSTM's potential to be able to extract temporal and spatial features better than traditional models [193].

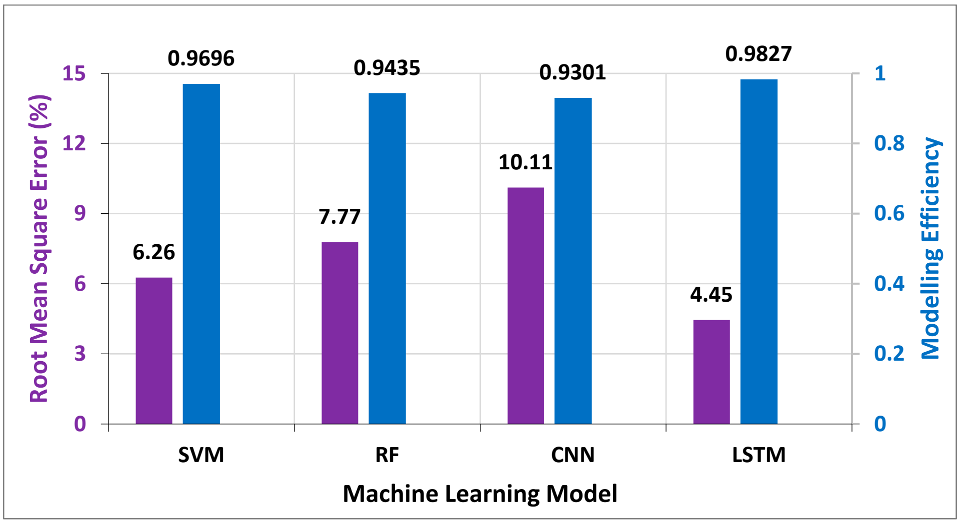

Figure 10. Comparison of various ML models [193].

Hybrid models were also very interesting. For instance, Lei et al. proposed a PCA-PANN model that assimilates ANN and PSO optimisation by Principal Component Analysis, resulting in a $R^2 = 0.971$ [192]. In ANN models with PCA, high accuracy usually means lower interpretability. ANN is a black-box model, which makes it difficult to understand how individual features, that is, slope angle, cohesion, and so on, make contributions to predictions. To improve interpretability without losing accuracy, we can employ interpretability models such as SHAP, LIME, and sensitivity analysis, which can explain how each input affects the decision of the model. This provides transparency and usability in practice. In civil engineering practice, the feasibility of explainable AI tools such as

SHAP and LIME remains mixed. While they successfully identify influential variables in lab-scale datasets (e.g., water–cement ratio in concrete mix design, or soil cohesion in slope stability), practitioners often require that these insights correspond directly to code-based provisions or physical models. For instance, a SHAP ranking of features may highlight curing age as dominant, but unless this aligns with Eurocode-based durability models, practitioners may be hesitant to adopt the tool. Therefore, explainability methods should not only improve transparency but also demonstrate regulatory alignment and physical plausibility before they can be widely adopted in practice. There is also the AN-MPA model, which incorporates ANN and the Marine Predators Algorithm, and was performed for probabilistic slope analysis during seismic loading and resulted in a R^2 = 0.9931 [194]. The ensemble models, and primarily the RF and Gradient Boosting models, were demonstrated to work in the studies by Yadav et al. and Karir et al. with classification accuracies up to 96% and good regression results ($R^2 \approx 0.84$), meaning they are robust models for predicting slope stability for natural and man-made slopes [195,196].

Slope stability prediction has seen various ML models applied, with their performance and strengths depending on model architecture, input features, and dataset characteristics (Table 7). For example, the hybrid models ANN-ICA and ANN-MPA achieved the highest prediction accuracy. In contrast, tree-based models like RF and XGBoost performed well when the dimensionality was limited. Deep learning architectures such as CNN and LSTM have also been used on large datasets to analyse complex soil behaviour. Notably, LSTM models have the advantage of retaining memory over time steps, making them ideal for modelling events like progressive slope instability across different variables. The literature suggests that ML models are particularly useful, especially when employing ensemble or hybrid methods, in enhancing slope stability prediction. From modelling nonlinearity to integrating various data types and delivering timely, accurate predictions, they represent a significant advancement for geotechnical engineering practice. Future work should focus on constructing large, open-access databases of slope stability, integrating explainable AI tools, and combining ML with physical models to enhance their trustworthiness and acceptance in the engineering practice context.

Table 7. Various ML models for slope stability prediction.

Study	Model Used	Performance	Advantages	Limitations	Notes
Meng et al. [189]	ANN	$R^2 > 0.999$, RMSE < 0.15	Accurate 3D slope stability prediction; GUI support	No pore pressure considered; homogeneous slopes only	Trained on dimensionless parameters using classical charts
Ahangari Nanehkaran et al. [190]	MLP, SVM, KNN, DT, RF	MLP: R^2 = 0.9	Comparison of multiple ML models; MLP showed best results	Limited to 100 slope cases	Applied to real slope data from Iran's Fars, Isfahan, and Tehran provinces
Kardani et al. [191]	Hybrid Stacking Ensemble	AUC = 90.4%	Combines multiple optimised ML models for better performance	Model complexity; optimisation cost	Used synthetic and field datasets; applied LVQ for feature ranking
Lei et al. [192]	PCA-PANN	R^2 = 0.971	Feature reduction via PCA; optimised with PSO	Limited dataset size (307 cases)	Slope angle, cohesion, and pore pressure most sensitive
Bardhan and Samui [194]	ANN-MPA	R^2 = 0.9931, RMSE = 0.0233	Probabilistic analysis; strong in seismic analysis	Search space selection critical for MPA	Used for Indian Railways embankment slope
Kasa and Mohd [197]	ANN, ANN-ICA, ANFIS	ANN-ICA: R^2 = 0.998, RMSE = 0.041	Hybrid model improved ANN performance	ANN without optimisation underperformed	PLAXIS used to generate dataset for ML training
Kumari et al. [198]	ANN, ANFIS	ANFIS: R^2 = 0.9999, RMSE = 0.0308	Very high accuracy; real soil data	High data requirements for ANFIS	Used TIC, RAE, RRSE, and LMI as performance metrics

Table 7. *Cont.*

Study	Model Used	Performance	Advantages	Limitations	Notes
Lei et al. [199]	Improved SVR	R^2 = 0.901, RMSE = 0.133	Hyperparameter tuning via grid search	Needs more development for field use	γ found to be most influential variable
Yadav et al. [195]	RF, Bagging, Boosting	Accuracy = 96%, R^2 = 0.84	Robust under dimensionality reduction	High computational cost	Compared classification and regression perspectives
Karir et al. [196]	SVR, ANN, RF, GB, XGBoost	XGBoost best, SVR worst	Compared models on natural and man-made slopes	Natural slopes harder to model accurately	Tree-based models outperformed others
Tien Bui et al. [200]	MLP, GPR, MLR, SLR, SVR	MLP: R^2 = 0.9939, RMSE = 0.7039	Comprehensive model comparison	Single-layered slope case	Used WEKA and Optum G2 for simulation
Huang et al. [193]	LSTM, CNN, SVM, RF	LSTM best (lowest RMSE)	Captures global temporal features	High training data requirements	LSTM showed higher accuracy than CNN, SVM, RF

7.2. AI and ML Applications in Groundwater Modelling

Groundwater resources are essential for agriculture, industry, and drinking water, and they also greatly influence environmental and socioeconomic systems [199]. Groundwater level (GWL) indicates water availability but is difficult to forecast because of its reliance on complex climatic and hydrogeological interactions. AI has become a very useful alternative to traditional numerical models for predicting GWL, as these models face challenges like data shortages, complex calibration needs, and boundary condition issues [200]. AI methods, especially using machine learning and soft computing techniques, are potentially better at capturing the nonlinear and high-dimensional aspects of these systems [201,202]. AI models need fewer input parameters and tend to deliver more accurate results than numerical models, making them valuable tools for practical water resource management. Recently, AI has been increasingly applied in groundwater modelling across various climates and geological conditions. Despite these advances, many regions still lack AI-based studies [201–204]; therefore, further application and corroboration of AI-based models are warranted [205].

Many studies have effectively used ANN models to perform groundwater level forecasting in different regions on a global scale. In India, for instance, a study used ANN with a large training dataset with the Levenberg–Marquardt (LM) training algorithm to contend with historical rainfall (Raf) and antecedent GWL to make long-term monthly predictions [206]. Similar success in Tunisia, where researchers have evaluated groundwater forecasting with a few input variables (Raf, EVP, and antecedent GWL) for monthly GWL predictions [207]. In Pakistan, there was a strong daily groundwater-level prediction performed with a large ANN based on meteorological data (temperature, solar radiation, humidity, wind speed) despite complex interconnectedness within the groundwater system correlation with hydro accumulated historical datasets, particularly when the training networks employed tangent sigmoid transfer functions and optimal partitioning recursive statistical analysis of datasets. Studies within the United States also employed both feed-forward and RNNs to relate hour and daily groundwater level estimates, showing that ANN was effective, particularly given the ability to identify cycles and lags effectively [208,209].

In this context, tree-based machine learning models, especially RF, are highly effective at estimating groundwater contamination levels. These models can identify the most critical factors that influence contaminant concentrations; they may also help trace pollution sources and pinpoint hotspots. Additionally, unlike time-series prediction models such as ANN, RF models can classify and predict contamination risks, providing practitioners with early warning signals and potential strategies for mitigation [210]. Deep learning techniques like LSTM networks are increasingly popular and reliable for long-term groundwater level (GWL) forecasting. LSTM models have consistently outperformed traditional models, offering higher accuracy by capturing both temporal dependencies with monthly and hourly data; case studies have been conducted in South Korea, Italy, and Virginia. Hybrid models have also been developed to enhance prediction accuracy. By combining ANN with Genetic Algorithm (GA) or SVM with Particle Swarm Optimisation (PSO), improved results were achieved through optimised internal parameters. Studies in India and Canada have validated these hybrid frameworks as practical methods for attaining greater prediction accuracy compared to standard models [205].

Current groundwater studies related to AI do demonstrate the predictive power and even generalisable powers of AI; however, the level of application is regional, and the studies are currently restricted by incomplete datasets (in terms of the length and extent of study), short (temporal) observations, and a lack of validation at the field scale. Future studies should develop global datasets for groundwater, expand long-term forecasting models of groundwater flow and storage, and explore hybrid application frameworks that use AI-based predictions and adhere to hydrogeological principles that can also facilitate design and the provision of solutions.

7.3. AI in Flood Prediction and Resilience Modelling

For efficient flood control and prompt public warnings, urban flood prediction is essential. Issues associated with conventional mechanistic models which rely on detailed physical and mathematical representations of hydrological and hydraulic processes, include their restricted real-time capabilities and hefty processing costs. ML can significantly complement traditional approaches by handling data uncertainty, reducing model complexity, forecasting real-time floods, adapting better scalability and enhancing decision-making tools. The main causes of flooding include climate change and urbanisation. Due to the interdependence between temperature and precipitation, climate change-induced extreme rainfall and temperature events can lead to urban pluvial floods [211]. The 1D and 2D models combined with machine learning (ML) techniques to thoroughly investigate flood dynamic features and hazard analysis in metropolitan locations, particularly near the River Thames in London [212]. This study showed how a hybrid hydrodynamics-ML model can increase the accuracy of flood predictions and hazard analyses. Flood scenarios were simulated for the River Thames in West London using high-resolution Lidar photos and advanced modelling. The socioeconomic information was used to precisely map areas that were at risk. The 1D and 2D hydrodynamic models integrated with high-resolution Lidar data and calibrated with exact parameters showed remarkable accuracy in forecasting flood dynamics. High predicted accuracy was demonstrated by the 1D model validation using 2008 flood data, with an RMSE of 0.960 m^3/s and an MAE of 0.332 m^3/s. Error measurements were greatly impacted by the 2D model's sensitivity to computational time steps. The advanced ML models, such as the Extra Trees–Principal Component Analysis (ET-PCA) model further bolstered confidence in the validity of the study findings by exhibiting nearly perfect predictive validity with an R^2 of 0.999. This project aims to improve flood dynamics forecast accuracy, analyse hazards and perform flood risk zoning, evaluate flood risk based on frequency analysis, and incorporate socioeconomic data into flood hazard analysis by using hybrid technique of integrating hydrodynamic models and ML predictive.

The rise in temperature is causing a significant increase in rainfall intensity and snow melting rates, ultimately resulting in higher evaporation and groundwater levels. Similarly, many environmental issues such as population growth, land use changes, rising water demand, and excessive groundwater extraction are worsened by rapid urbanisation [211].

The rate and amount of water that reaches drainage systems are ultimately impacted by these land use changes, which also modify soil retention and drainage capacity and interfere with hydrological connection. A typical flowchart used for ML modelling for urban flood forecasting control system is shown in Figure 11 [213].

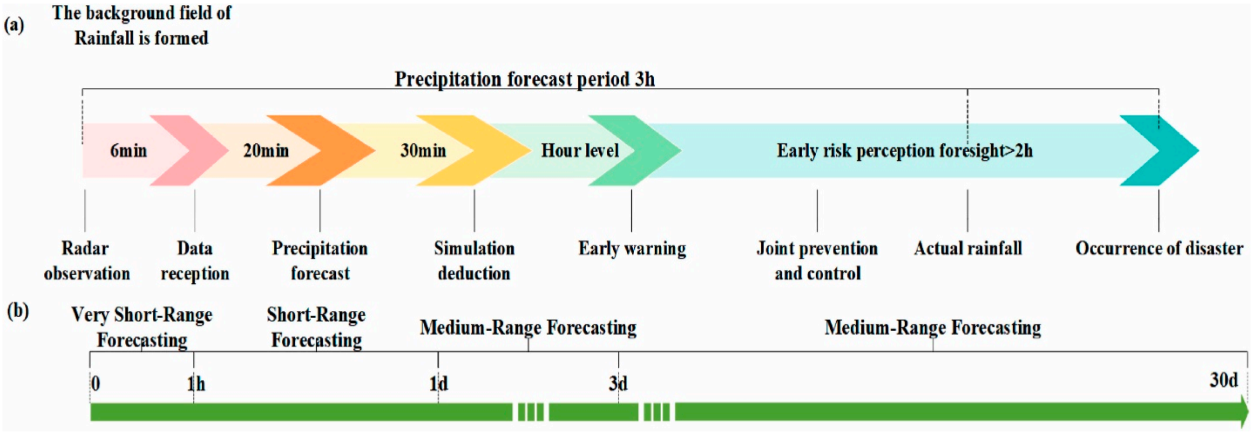

Figure 11. Diagram of urban flood forecasting control system (license no. 6075870216257) [213]. (**a**) Implementation process; (**b**) foreseeable period.

A study conducted by [214] shows that in coastal cities, regions with urbanisation rates exceeding 80% face a flood risk 2.5 times higher than those with urbanisation levels below 20%. CNN are among the most extensively studied algorithms for urban flood prediction, particularly effective in processing image and spatial data. RF demonstrate high robustness against noisy data and outliers. LSTM networks are well suited for time-series forecasting due to their ability to capture temporal dependencies. SVMs generally perform well when working with smaller datasets [213]. K-means clustering algorithm and RF models were trained employing the flood type derived from clustering as the dependent variable and the rainfall associated with past flood episodes as the independent variable [215]. They deciphered the flooding mechanism using a hybrid approach that combined ML techniques with physically based modelling. Parameters of the hydrological model were modified in response to dynamic rainfall data. The results of the proposed method indicate its effectiveness in simulating the flood process, with probabilistic integration yielding more accurate flood forecasts than ensemble averaging. The datasets were used to train ANN and DT algorithms to classify the precipitation at the same time when RNN and ES-LSTM models were used to forecast hourly rain measurement [216]. The results showed positive outcomes of all the models with accurately predict the precipitation rate of 96.5% and 84% by ANN and DT models, respectively. The suggested model could predict the rain incidence well in time. A rapid urban flood inundation forecasting model was developed by integrating ML algorithms with a hydrodynamic-based urban flood model [217]. The data outputs from the hydrodynamic model and the rainfall characteristics were applied to train the ML models like RF and K-nearest neighbour KNN. By predicting the flood water volume with 10% of the mean relative errors, a hybrid model of these algorithms allowed decision-makers to take more suitable and timely precautions against flooding. ANN and LR models were trained using available data to create a connection between the historical flood record from impacted areas and specific factors such the local terrain, climate, and land use planning [218]. The focus of the study was to develop a flood prediction chart. The results showed that the ANN model predicted the flood with an accuracy rate of 76.4% compared to the LR model whose accuracy rate was 62.5%. According to the research, places with significant flood susceptibility are primarily found in areas with high levels of human activity, such as agricultural and populated land areas. A comparison of performance evaluation of different ML models including RF, NB and XGBoost for flood prediction was established by [219]. The historical data was collected from 50 different topographic areas and analysed considering the factors like precipitation, sediments and their transport, land use and coverage, and topography of the area. The higher accuracy of 84.7 was achieved by RF model followed by the 83.1% accuracy of XGBoost model. The efficiency of the NB model was 82.1%. All possible flooding scenarios must be fully covered by the training data to guarantee the accuracy of prediction results. Table 8 shows a summary of previous research as mentioned above.

Table 8. Studies on use of AI techniques in flood control prediction.

Study	Research Focus	Study Area	ML Applied Techniques	Ref.
Flood Risk Assessment	Comparison b/w Hydrodynamic Models and ML Models	River Thame West London	ET-PCA Extra Trees–Principal Component Analysis Model	[212]
Coastal Flood Risk Assessment	Adaptation Strategies to mitigate Coastal Flooding	Coast Line of South Korea	RF, ANN, KNN	[214]
Flood Forecasting Based on Precipitation	Hybrid Combination of Physical Models with ML models	Jingle, Yellow River Basin, China	K-means cluster, RF	[215]
Rainfall Prediction to Control Floods	Rain Prediction with ML Models	Australia (Multiple Locations with heavy rainfall)	AN, DT	[216]
Rapid Forecasting of Urban Flooding	ML prediction model with Hydrodynamic model simulation	Fengxi New Town China	RF, KNN	[217]
Flood Mitigation and Control	Flood Susceptibility Map by ML models	Nigeria Coastlines	ANN, LR	[218]
Flood Susceptibility Planning	Comparison b/w ML models	Silabati River India	RF, NB, XGBoost	[219]

7.4. AI in Soil Classification and Texture Prediction

Soil classification is the main factor that governs the design criteria of foundation for any structure. To define the different components discovered during ground investigation, a formal system of soil description and categorisation must be adopted which entails expensive and time-consuming tasks, such as sample collection and laboratory testing. Different ML models have proved to be efficient in soil classification over the traditional methods in terms of accuracy, analysing large datasets and most importantly saving time without extensive field work and laboratory testing. A dataset comprising 805 soil samples was developed and analysed by [220] and the model was trained and tested with Python libraries. The missing data values were imputed by using KNN imputer and balanced by synthetic minority oversampling technique SMOTE. The data was tested by XGBoost, Light GBM, and Cat Boost. The ML models performed well with an accurate rate of 90%. The results were compared with the ANN, DT, SVM, and naïve Bayes results that previously showed an accuracy of 70%.

A comparative performance of different ML methods to evaluate soil texture classification was assessed by [221]. The focus of the study was to predict the soil classification and contents of clay, silt, sand and gravels by using ANN, Kriging, Co-Kriging, and IDW models in MATLAB software. The root means square error (RMSE), and correlation coefficient R values result showed that the ANN method performed well compared to the other three methods. The IDW method had the lowest values for MSE and R for all three parameters, including sand, silt, and clay. SVM models were trained using digital images of different areas to classify these images using linear kernel [222]. The results showed that the proposed model has an accuracy of 91.37% as an overall average with 97.7%. 96.21%, and 93.25% average percentage of accuracy of clay, sand, and silt, respectively. The suggested method for classifying the soil is precise and quick. With the aid of smart phones and an SVM, it provides a quick and precise result for soil categorisation as compared to a simple hydrometer test that requires 24 h to give accurate results. Digital mapping for soil classification and prediction using DT, RF, and SVM was performed including the use of Landsat 8 OLI science products and DEM (digital elevation models) to evaluate environmental variables' capacities [223]. The results showed that the majority of the dataset was overestimated by the SVM model. However, in terms of both accuracy and abundance index, RF maps performed the best.

The best environmental covariate for predicting the spatial distribution of texture classes was the TWI (topographic wetness index) generated from the DEM and the remote sensing-derived covariates were more significant than TWI. Kappa index, overall accuracy, area under the ROC curve (AUC), and receiver operating characteristics (ROC), were employed to identify the soil texture classification and analyse a comparison between three ML algorithms, including ANN, SVM, and classification trees [224]. The performance of SVM model was more accurate than the other deployed models with values of 0.943, 0.79, and 0.944 for overall accuracy, kappa index, and SVM polynomial function, respectively. The accuracy rates were 0.794, 0.992, and 0.661 for the classification criteria for clay, loam and sand. The findings demonstrated the viability and dependability of SVM for classifying soil textures.

AI models like ANNs, SVMs, and LSTMs can predict slope stability, soil classification, and foundation performance. These models excel at predicting nonlinear behaviours that traditional models struggle with and offer real-time predictive capabilities. However, they often suffer from limited model fidelity because they are mainly developed using synthetic or small datasets, which reduces their robustness under diverse field conditions. Furthermore, issues with field validation, explanation, and interpretability decrease trust in purely data-driven outputs, causing concerns among practitioners. These biases and limitations are like those found in structural and environmental research, where uncertainty and data scarcity are common. Integrating hybrid, physics-informed models and addressing data scarcity and uncertainty through shared datasets could significantly advance geotechnical AI research, leading to deeper insights and potentially strengthening connections to structural resilience and climate adaptation. Although ML models for slope stability and water management outperform conventional approaches in predictive accuracy, they are highly dependent on site-specific datasets and suffer from overfitting. The real challenge lies in validating these tools under heterogeneous geological and environmental conditions, where physical consistency is as important as predictive power.

8. Applications of AI in Transportation and Infrastructure

The use of AI in transportation and urban infrastructure is transforming how we understand and manage urban mobility. Challenging issues associated with complex urban transport planning, traffic management, and infrastructure maintenance are currently addressed using AI. This section highlights the use of AI in transportation and infrastructure from the literature and enlists the use of various AI techniques. Table 9 summarises various studies using AI techniques in the fields of transportation and built environment.

Table 9. Studies on use of AI techniques in transportation and infrastructure.

ML Technique	Purpose	Key Findings	Advantages	Disadvantages	Ref.
Field experiment with AI controllers (RL supervised)	Assessing AI integration in smart city service operations (Industry 5.0)	AI improved service efficiency, user satisfaction, and operational uptime	Real-world deployment; adaptive responsiveness; context-aware	Operational complexity; integration with legacy systems	[225]
Sustainable deep radial function network	Enhance traffic intelligence in smart cities	Improved prediction accuracy over baseline CNN/RNNs	High modelling fidelity; sustainability considerations	Possible scalability constraints; computational load	[226]
Chaos theory inverse modelling	Traffic flow forecasting using chaotic dynamics	Achieved RMSE comparable to traditional statistical models	Handles nonlinearities; novel theoretical framework	Methodological complexity; niche domain	[227]
Spatiotemporal Graph Attention Network (GAT)	Short-term road traffic flow prediction	Outperformed LSTM/CNN baselines acros25test scenarios	Captures spatial–temporal dependencies; high precision	Requires rich graph-structured input; heavy computation	[228]
ATT-CONV-LSTM (Attention + Conv + LSTM)	Freeway traffic flow forecasting	Achieved about 5–10% lower forecasting error vs. standard LSTM	Integrates spatial feature extraction and temporal memory	More parameters, risk of overfitting; slower training	[229]
T-GCN (temporal graph convolutional)	Forecast traffic under extreme weather events	Effective in extreme conditions; better than GRU/LSTM	Models spatiotemporal correlations; robust to anomalies	Needs high-quality weather and graph data	[230]
CNN-based video processing	Detect parking occupancy in smart systems	>95% accuracy in daylight; lower at night	Real-time detection; high accuracy in ideal conditions	Sensitive to occlusion and lighting changes	[231]
Federated learning for traffic forecast	Privacy-aware, distributed traffic modelling	Comparable accuracy to centralised models with privacy benefits	Protects data privacy; leverages multi-agent data	Network overhead; slower convergence	[232]
Chaos theory inverse modelling (non-ML but computational)	Predict urban traffic flow	RMSE comparable to traditional models	Captures chaotic, nonlinear behaviour	Complex and less generalisable model	[227]
Pattern-based regression (linear/logistic regression)	Short-term urban traffic prediction in India	Acceptable accuracy in short-term forecasts	Computationally light, interpretable	Limited in capturing complex nonlinear patterns	[233]
Intelligent control system (possibly fuzzy logic or ML classification)	Intelligent pedestrian traffic light optimisation	Reduced average waiting time and queue length	Improves pedestrian wait times; real-time adaptation	Lack of clarity on ML algorithms used	[234]
Route optimisation via AI (GA, RL)	Minimise congestion via route planning	Significant reductions in travel time and delays	Adaptive to dynamic traffic; scalable	Computational complexity; data-dependency	[235]

Table 9. *Cont.*

ML Technique	Purpose	Key findings	Advantages	Disadvantages	Ref.
Review of deep learning for edge analytics	Survey edge computing in ITS	Edge deployment is promising but network and compute limits persist	Highlights DL approaches on-device	Does not present new model; identifies latency concerns	[236]
AIoT traffic management (IoT + ML/AI)	Develop a smart, integrated traffic system	Demonstrates improved traffic flow in simulations	Real-time sensor fusion; scalable control	Integration complexity; device constraints	[237]
AI-based ITS benchmark (likely ML classification/regression)	Provide benchmark for intelligent traffic control systems	Offers reference metrics for ML in ITS	Establishes a baseline; allows future comparison	Specific algorithms not deeply detailed	[238]
SVM with hybrid Particle Swarm Optimisation	Predict traffic fatalities	Accuracy improved over base SVM; PSO tuning critical	Improves SVM performance via PSO	SVM + PSO can be slow to train; data-intensive	[239]

8.1. Pavement Condition Monitoring and Maintenance

Monitoring and maintenance of pavement infrastructure is a labour intensive and subjective problem which leads to inconsistencies in assessing pavement conditions. However, the use of AI and image processing techniques has emerged as a more efficient and reliable alternative to conventions techniques. A study conducted on classification of various types of pavement distress has achieved significant accuracy using deep learning method, CNN [225].

Moreover, predictive modelling methods for the prediction of pavement citation index and estimation of required repair and maintenance with ANNs has been used. A study illustrated that models utilising ensemble learning yield improved predictive reliability compared to methods using single predictive techniques, which shows the benefits of combining multiple techniques to enhance accuracy and decision-making in infrastructure maintenance [226].

The use of AI in pavement condition monitoring not only facilitates timely interventions but also enhances maintenance schedules. Consequently, municipalities can assign resources more purposefully and lifecycle of pavement materials can be prolonged, eventually leading to cost-effective and enhanced services. This predictive competence aligns with the broader objectives of sustainable urban planning, where proactive maintenance strategies are of paramount importance.

8.2. Bridge SHM

Bridges are critical components of transportation infrastructure due to their vital role in connectivity, complex construction processes, and high costs associated with construction and maintenance. As a result, ensuring their long-term serviceability and safety requires robust, proactive approaches to SHM and maintenance.

SHM of bridges benefits significantly from the capacity of AI to quickly process and interpret large datasets obtained from various sensors installed in the bridge system. By using learning algorithms, researchers can automatically detect the anomalies and potential structural failures in advance thus reducing the risk of major damage or collapse [227]. Recent developments in the use of AI techniques for anomaly detection improves the precision and reliability of these monitoring systems, allowing for timely mitigation techniques. For instance, a study demonstrated the efficiency of unsupervised AI learning methods in detecting anomalies in bridge systems by classifying delicate sensor behaviour changes prior to structural issues [240]. Such methodologies not only improve the reliability of SHM systems but also address the need for an automatic infrastructure monitoring system and providing real-time details that conventional methods normally overlook.

The use of AI-based SHM methods ensure public safety and resource management. By ensuring that structural anomalies are detected quickly, necessary repair and maintenance can be done before structural collapse.

8.3. Traffic Flow Prediction and Management

Traffic congestion is a persistent issue to urban development due to continued increase in vehicles, and complex road structures. Typical statistical methods like autoregressive integrated moving average (ARIMA) mostly falls short to forecast the traffic flow due to its linier approach [228,233]. Similarly, another study reported that conventional statistical methods struggle with the large-scale data processing and sophisticated nonlinear relationships required for precise traffic prediction [229]. On the other hand, AI methods application especially deep learning techniques has better performance. For example, the LSTM networks method has demonstrated significant efficiency in predicting traffic attributes. A study conducted on traffic flow prediction reported better performance using LSTM networks compared to conventional methods due to the model's ability to extract temporal correlations from data [230].

Similarly, another study reported improved predicting capabilities required for improving real-time traffic management systems using hybrid models integrating CNNs with LSTMs for extracting both temporal and spatial attributes from traffic data [234]. The use of hybrid models in urban traffic management indicates a shift towards data-driven methodologies; however, ML algorithms are used to analyse huge datasets obtained from various traffic monitoring and sensors systems. The use of robust predicting models is not limited to only congestion management, they are used for optimising urban systems resource allocation, reducing delays, and improved experience for the commuters. The development and use of these predictive models shows the potential of AI in creating responsive and smarter transportation systems, positioning with broader trends toward smart urban development [235].

8.4. Intelligent Transportation Systems (ITS)

ITS use AI to improve the effectiveness and safety of the transportation networks. It facilitates route optimisation, adaptive signal control, vehicle detection, and autonomous navigation. Reinforcement learning (RL) has appeared as an effective methodology in developing real-time adaptive traffic signal systems. A study suggested a multi-agent traffic signal control system with Q-learning, considerably outperform static rule-based systems by vigorously adapting to the traffic conditions [231]. This methodology features the versatility of RL in operating complex urban traffic conditions. AI-based computer vision applications contribute to improving road safety by enabling automatic vehicle and incident detection. The growing reliance on big data and ML to resolve real-time traffic monitoring issues through sophisticated analytical techniques with the increasing data volume from sensors and cameras has a potential for AI applications [236].

The rapid advancements in ITS demonstrate the use of AI in urban transportation, which is transforming the systems from reactive to pre-emptive approach, emphasising safety, operational efficiency, and ways for further exploration and implementation.

8.5. Urban Mobility and Infrastructure Planning

The urban mobility and infrastructure planning has very important role in the development and construction sector which affect the landscape of the whole built environment. The use of AI in this sector has significant applications for infrastructure planning and policy evaluation. Using agent-based models supplemented with ML algorithms, urban planners can simulate the infrastructures in conformity with the built environment. A study proposed a hybrid methodology combining spatial analysis with deep learning to optimise public transit routes, indicating the efficiency of predictive analysis in urban planning [237]. Additionally, GANs have been used as tools for generating artificial urban traffic data. This approach is used in situations where historical data is limited, allowing for scenario testing under uncertain future conditions. A study validates the accuracy of the synthetic traffic data benchmarked against real-world data, offering insights into the model's strengths and limitations and enabling realistic simulation of traffic scenarios for urban planning purposes [241]. The use of GANs in urban mobility planning demonstrates the advanced approach to tackle the uncertainties in urban systems traffic scenarios so that planners can create strategies that align with preventative measures rather than reactive measures [238]. As data becomes more readily available from a various source, it can be used effectively for urban planning to cater for how cities respond to the complex modern transportation challenges. Thus, integrating AI in urban mobility planning constitutes a critical evolution in the development of smarter infrastructure influencing long-term decisions impacting city growth, sustainability, and quality of life for residents.

8.6. Comparison of AI Techniques in Transportation and Infrastructure

AI methodologies vary significantly in their applications, advantages, and limitations across different fields within the transportation sector. A comparison of various ML techniques for various applications in the field of transportation has been made in Table 10. For instance, LSTM networks are best suited for traffic flow forecasting due to their ability to model temporal dependencies intricately. However, they require large, labelled datasets for efficient training, which can slow the training process [229]. Similarly, CNNs are preferred for tasks like pavement image-based crack detection due to their accuracy and real-time operational abilities; however, they are sensitive to environmental factors such as lighting [242].

Table 10. Application of various ML techniques in transportation.

AI Technique	Application Area	Advantages	Limitations
CNN (ResNet, VGG)	Pavement image-based crack detection	Accurate feature extraction from images; real-time capability	Sensitive to lighting and shadows; needs extensive training data
LSTM/RNN	Traffic flow forecasting	Captures complex temporal dependencies; high prediction accuracy	Requires large, labelled datasets; slow training
Reinforcement Learning	Adaptive signal control	Learns policies from environment; handles non-stationary traffic	Difficult convergence; computational cost
Ensemble ML (XGBoost)	Pavement condition prediction	Improved generalisation; combines multiple models	Requires careful feature engineering; risk of overfitting
Autoencoders/LSTM-AE	Bridge SHM anomaly detection	Handles unlabelled data; effective in early fault detection	Can produce false positives; complex architecture
Agent-Based + ML Models	Urban mobility simulation	Represents individual-level interactions; supports dynamic planning	High complexity; data-intensive
GANs	Traffic data simulation for urban planning	Generates realistic synthetic data; helps in planning under uncertainty	Training instability; interpretability issues

On the other hand, reinforcement learning has potential in adaptive signal control systems by learning optimal traffic plans in dynamic environments. Although it effectively handles non-stationary traffic patterns, challenges associated with convergence and computational demands persist [239]. By leveraging ensemble learning techniques, researchers have improved the reliability of pavement condition predictions, though careful feature engineering is required to mitigate overfitting risks [230].

GANs are effective in simulating urban traffic data for planning, although they face challenges like interpretative difficulties and training instability [232]. Agent-based models paired with ML offer insights into individual-level interactions, providing dynamic responses for urban mobility simulations. However, their complexity and data intensity can pose practical challenges [243].

In conclusion, while the integration of AI in transportation and infrastructure offers significant benefits and promotes sustainability in planning, designing, and prevention. It can improve traffic management and enhance the prediction of required maintenance. However, the challenges associated with each AI technique highlight the need for continued research in the field. Challenges such as model interpretability, real-time integration, and consideration of long-term sustainability impacts are still underexplored. Therefore, future work should prioritise large and diverse datasets, develop explainable AI frameworks to build trust, and explore integration with IoT infrastructure and autonomous vehicle systems to enable more adaptive and sustainable transportation networks. As transportation continually evolves through the interplay of practical applications and technological advancements, ongoing innovation is essential to fully realise the potential of AI.

9. Intrinsic Connections Across Civil Engineering Domains

AI applications in civil engineering are frequently cited in different spaces, and there is overlap, if not clear and close connections between them. Material selections and mix designs are determined by sustainability targets, which also influence structural performance and geotechnical design considerations. Data from environmental monitoring informs water management and resilience planning. Transportation systems and urban mobility are tied directly to water management, resilience to climate impacts, structural performance, and geotechnical considerations. Transportation infrastructure relies on road-building innovations and the development of materials. Material optimisation influences sustainability targets. Figure 12 depicts the interconnectedness of these types of contributions. Sustainability, infrastructure performance, geotechnics, water management, transportation systems, and urban mobility are not entities in and of themselves. Each of these connections feeds the best practices of another. At the same time, we consider regulatory and code standards to be at the core as the primary requirement for AI and civil engineering research to be applied in design practice. This interconnectedness aims to illustrate that AI in civil engineering is not a collection of connections, but a connected ecosystem dedicated to delivering safer, more sustainable, and code-compliant infrastructure.

To provide a cross-cutting synthesis, Table 11 compares the main AI/ML methods used across civil engineering. It highlights their strengths, weaknesses, and representative applications. This framework shows that while methods such as CNNs and LSTMs excel in monitoring and forecasting, their adoption in practice is limited by data requirements and a lack of code integration. Hybrid and physics-informed models, though less mature, offer a promising pathway toward regulatory acceptance.

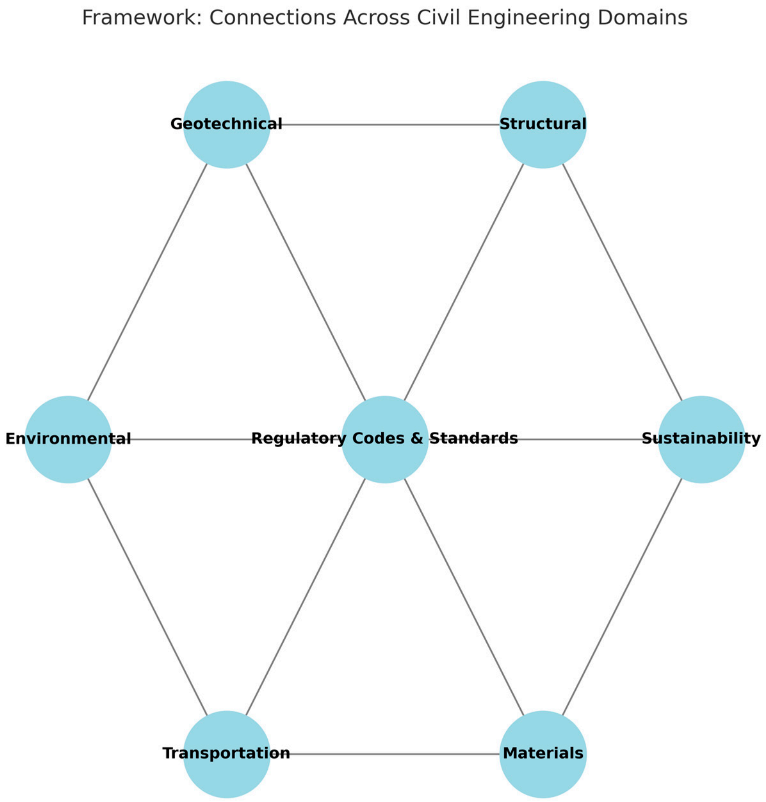

Figure 12. Overlaps and interdependencies between six civil engineering domains.

Table 11. Comparison of AI/ML methods in civil engineering: strengths, weaknesses, and typical use cases.

Method	Strengths	Weaknesses	Typical Use Cases in Civil Engineering
ANN [131,138,189,194,208,209]	Captures complex nonlinear relationships; good for prediction	Black-box, prone to overfitting, needs large datasets	Concrete strength prediction, slope stability, groundwater forecasting
CN [153,156,157,225,226]	High accuracy in image recognition; automates visual tasks	Requires large, labelled datasets; computationally heavy	Crack detection, traffic intelligence, waste classification
RNN/LSTM [229,230]	Handles sequential and time-series data well	Training complexity; sensitive to data quality	Traffic flow forecasting, SHM time-series
SVM [207,223]	Works well with small datasets; effective for classification	Limited with large datasets; struggles with high noise	Soil type classification, Rain prediction
RF [195]	Robust, handles nonlinearities; interpretable feature importance	Can be computationally heavy; less effective with very high-dimensional data	Slope stability, material property prediction
DT [218,223]	Simple, interpretable, fast	Lower accuracy than ensemble methods; prone to overfitting	Preliminary soil classification, Rain Prediction
Ensemble Models (XGBoost, Bagging, Boosting) [126,129,130,196]	High accuracy; reduce overfitting; flexible	Require tuning; less interpretable	Geopolymer mix design, CO_2 emissions forecasting, slope stability
GA [148,241]	Generates synthetic data; augments limited datasets	Complex training; risk of instability	Structural failure simulation, traffic data
Hybrid Model [179,191,212]	Combine data-driven and physics-based accuracy; better reliability	Still experimental; requires domain expertise	Structural load prediction, geotechnical modelling, flood forecasting

10. Challenges and Limitations

Despite the promising advancements of AI in civil engineering, several cross-disciplinary limitations hinder its widespread adoption

10.1. Data Limitations and Fragmentation

Across domains such as geotechnical engineering, environmental modelling, and recycled concrete design, the lack of unified, high-quality, and openly accessible datasets hampers generalizability and transferability. Particularly in slope stability prediction, groundwater modelling, and CDW classification, sparse or non-standardised data limits model robustness. Similarly, the fragmented data, arising from the inconsistency in collection format, lack of standard protocols also limits the model performance.

10.2. Model Interpretability and Trust

Deep learning models like LSTMs, CNNs, and hybrid stacks achieve high accuracy but often lack explanations. In safety-critical applications such as flood prediction, SHM, and damage detection the "black-box" nature of these models presents significant challenges to adoption by engineers and regulators. To address these issues, the integration of human-in-the-loop (HITL) systems is a promising approach, enabling expert oversight and improved accountability. However, employing HITL frameworks dependably across all these domains remains an evolving and complex challenge, requiring cross-disciplinary collaboration, tailored solutions, and supportive regulatory frameworks.

10.3. Regulatory and Code Compliance Gaps

AI integration in design and monitoring practices e.g., in SHM is complicated by a lack of alignment with current building codes and standards. This is especially problematic in domains with high public safety and liability concerns.

10.4. Computational Complexity and Cost

Hybrid models like RF–GWO–XGBoost or ANN–MPA used in materials or geotechnical predictions offer superior accuracy but require heavy computational power and careful parameter tuning. This makes real-time deployment or use on mobile inspection devices impractical without simplification.

10.5. Generalisation and Overfitting and Physical Inconsistencies

AI models trained on localised, narrow datasets (e.g., from a specific soil region or building type) may not perform well in new environments. Overfitting reduces model scalability for applications like urban land use modelling or energy forecasting. Additionally, many models overlook domain-specific physical constraints, leading to predictions that are statistically valid but physically not viable. This is a key concern in critical areas of applications like structural load estimation, SHM, and slope stability models. Addressing both overfitting and physical inconsistency is important for developing reliable, real-world AI applications in the built environment.

10.6. Integration and Real-Time Responsiveness

While AI can enhance real-time decision-making in traffic control, flood response, and maintenance scheduling, real-time integration with IoT devices, sensor networks, and digital twins remains limited and technically demanding.

These limitations must be addressed through interdisciplinary collaboration, regulatory reform, interpretable AI development, and investment in open data infrastructure. For instance, the development of open benchmark datasets for the researcher to test and compare AI models easily could arise a viable solution. Additionally, using hybrid methods that combine physics-based models with ML can improve accuracy by blending expert knowledge with data-driven insights. It is important for experts from different fields to work together and share knowledge. Rules and standards should be updated regularly to ensure AI models are safe, transparent, and respect privacy, with pilot projects to try new ideas carefully. Finally, investing in open data platforms and encouraging companies to share their data will help everyone build better and more reliable AI systems.

10.7. Regulatory Acceptance and Integration with Codes

A major obstacle is that it is not codified in engineering standards such as Eurocode, ACI, and various national codes. These standards are deterministic and transparent, while AI models are probabilistic and data-driven, which makes integrating AI into design practice difficult. Achieving practical and realistic AI integration requires hybrid verification methods, including isoquant-based code calculations, certified benchmarking datasets, explainable AI outputs useful for regulatory compliance, and pilot studies as essential intermediaries. The process of integration will likely be gradual, starting with lower-risk applications like sustainability assessments and material optimisation, before gradually expanding into full design processes. Ultimately, codes may evolve over time to include AI-based criteria that formalise AI-assisted design, similar to current allowances for numerical methods.

11. Future Research Directions

Integrating digital twins with AI promises transformative impacts on civil engineering by enabling predictive modelling, performance monitoring, and lifecycle management. When combined with real-time data and advanced analytics, digital twins can support dynamic simulation and optimisation, thereby improving structural resilience and operational efficiency [244–246]. Recent case studies have already demonstrated their potential in proactive maintenance and disaster preparedness [169,170,247]. However, most current applications remain focused on simulation and monitoring. A key research priority lies in developing hybrid AI–physical models that can operate in real time for complex infrastructure systems such as bridges, dams, and transportation networks.

Explainable AI (XAI) is another critical direction. Techniques such as SHAP and LIME enhance trust by clarifying model decisions, which is crucial for regulatory compliance and industry acceptance [248]. Scholars increasingly highlight the importance of XAI in ensuring ethical use, reliability, and practical integration of AI into civil engineering workflows [249]. However, there is a critical need for interpretability techniques that incorporate engineering principles, regulatory requirements, and structural safety constraints, ensuring AI recommendations are practically possible and trustworthy for practitioners.

Open datasets and reproducibility standards are foundational for credible AI research. Publicly available datasets allow benchmarking, validation, and transparency, promoting collaboration and innovation [250]. Initiatives such as FAIR (Findable, Accessible, Interoperable, Reusable) data principles advocate for enhanced data sharing, significantly improving the reproducibility and quality of research outcomes [251].

Deep learning (DL) continues to show great promise in areas such as flood forecasting and emergency management. However, its limited interpretability and challenges with real-time deployment restrict widespread adoption. Future research should focus on integrating diverse data sources, improving DL transparency, and enabling real-time analytics. Promising directions include the development of hybrid DL–physics models and scalable architectures for early warning systems and disaster response.

The future adoption of AI in civil engineering will also depend heavily on interdisciplinary collaboration. Combining expertise from engineering, computer science, environmental science, and materials science is vital for addressing complex sustainability challenges holistically. Such collaboration fosters innovation and ensures solutions are technically robust, environmentally responsible, and socially acceptable [252].

Finally, emerging approaches such as federated learning and transfer learning hold strong potential. Federated learning enables privacy-preserving collaboration by allowing institutions to train models without sharing sensitive datasets, while transfer learning allows knowledge gained from well-instrumented sites to be applied to data-scarce regions. At the same time, advancing AI ethics, fairness, and bias mitigation is critical to ensure equitable, transparent, and trustworthy deployment of AI in infrastructure systems.

In summary, future research should focus on hybrid and explainable models, robust data governance, scalable real-time applications, interdisciplinary collaboration, and ethical AI adoption. Collectively, these directions will move AI from experimental studies to reliable, field-ready tools that enhance the resilience, sustainability, and equity of civil infrastructure.

12. Conclusions

This review provides an overview of the growing applications of AI and ML in civil engineering, spanning sustainable materials, structural engineering, geotechnical and environmental assessment, and transportation systems. Many studies have highlighted the benefits of predictive accuracy, resource optimisation, and automation. However, the fragmented and domain-limited landscape of the existing research highlights the need for a more inclusive framework. Beyond compiling existing applications, this review critically evaluates the limitations of current approaches, emphasising gaps in data quality, code integration, and real-world feasibility that must be addressed for AI/ML to transition from promising research to reliable engineering practice.

Unlike generic AI reviews, this study highlights civil-specific barriers such as safety-critical requirements, lifecycle uncertainties, and the absence of AI provisions in design codes, ensuring that the feasibility of interpretability methods is critically assessed in the context of real-world engineering practice.

By combining bibliometric mapping, a structured taxonomy, and critical evaluation, this review moves beyond a descriptive listing of applications. It establishes a conceptual framework that highlights unique challenges in civil engineering, including limited domain-specific datasets, absence of AI provisions in codes, and the integration with physical models, thereby providing novel insights not addressed in earlier reviews.

AI and ML are redesigning civil engineering across sustainable materials, geotechnical and environmental systems, structural engineering, and transportation systems by enabling precise predictions, intelligent monitoring, and resource optimisation. Despite clear development such as better concrete mix design, structural health monitoring, slope stability prediction, flood modelling, and traffic flow forecasting, the existing research remains fragmented, case-specific, and restricted by small datasets, weak generalizability, and lack of model interpretability. Future work should focus on developing large, standardised datasets, advancing hybrid and explainable AI approaches, and integrating these technologies with digital twins, IoT, and sustainability frameworks. By bridging disciplinary gaps and aligning with codes, resilience goals, and carbon reduction strategies, AI can move civil engineering from isolated applications toward holistic, adaptive, and low-carbon infrastructure solutions.

Building on the insights of this review, three key directions emerge as fundamental for advancing AI and ML in civil engineering. First, explainability and trust remain critical bottlenecks, underscoring the need to integrate interpretable methods such as SHAP and LIME to increase transparency and accelerate adoption in safety-critical domains. Second, hybrid approaches that combine data-driven models with mechanics-based principles offer a powerful pathway to overcome the limitations of both traditional and purely AI-based methods, ensuring predictions remain robust and physically consistent. Finally, interdisciplinary integration of AI with IoT, digital twins, and sustainability frameworks can shift civil engineering practice from reactive problem-solving toward proactive, adaptive, and resilient infrastructure systems that align with long-term sustainability goals.

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