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Application of advanced machine learning in civil engineering: A survey

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Abstract. Machine learning (ML) has been increasingly adopted across various disciplines, including civil engineering (CE), to address a wide range of complex problems. This study conducts a systematic literature review to examine recent trends in the ML applications within CE and to identify key challenges associated with its implementation. The review is proposed focusing on four research questions concerning data scarcity, efficient construction of learning datasets, overfitting mitigation, and the integration of CE's multidisciplinary nature. The analysis focuses on five major fields in CE— structural, geotechnical, transportation, water and environmental, and energy engineering—and evaluates the application of five prominent ML techniques: multilayer perceptron, convolutional neural network, recurrent neural network, generative adversarial network, and reinforcement learning. A total of 800 ML studies in CE were reviewed. Key subfields within each CE domain were identified, and domain-specific applications of ML were synthesized to address the predefined research questions. The findings of this study provide practical insights and methodological guidance for researchers aiming to apply ML to real-world CE challenges in a robust and informed manner.

Keywords: civil engineering; machine learning; systematic literature review

1. Introduction

Civil engineering (CE) involves designing and constructing infrastructure, such as buildings, dams, roads, and bridges, and ensuring their safety and efficiency. CE encompasses several domains, such as structural, geotechnical, transportation, water and environmental, and energy engineering, all of which address various issues that are closely related to human life. Structural engineering involves identifying appropriate structure members and materials and detecting their damage and defects. Geotechnical engineering addresses problems in determining geotechnical properties, optimal tunnel construction plans, and pavement property types. Transportation engineering deals with traffic congestion by predicting real-time transport conditions. Water and environmental engineering manage water-related issues such as flooding, pipe network accidents (e.g., pipe breaks), and drought. Energy engineering focuses on energy-related issues (e.g., power forecasting and air quality control) and solving climate change and pollution problems (e.g., air pollution).

Over the past few decades, machine learning (ML) models have been proven to be useful tools across multiple fields of study, including CE. Their ability to effectively solve complex issues through the analysis of large amounts of data (i.e., big data) has led to their growing and widespread application in many CE domains. The applications and purposes of ML models vary within each CE domain, and several state-of-the-art reviews have been conducted for each area. For example, Thai (2022) classified ML applications in structural engineering into five areas: structural components, materials, damage detection, analysis and design, and fire response. Similarly, Zhang *et al*. (2021) reviewed ML in geotechnical engineering, focusing on eleven application areas and highlighting models such as feedforward neural network (FNN), recurrent neural network (RNN), convolutional neural network (CNN), and generative adversarial network (GAN).

Some reviews focused on particular application topics in CE domains, such as energy analysis (Foucquier *et al*. 2013, Hong *et al*. 2020), energy management (Perera and Kamalaruban 2020, Zhang *et al*. 2022), renewable energy (Wang *et al*. 2019, Ahmad and Yan 2020, Aslam *et al*. 2021), underground construction (Zhang *et al*., 2020; Jong *et al*. 2021, Amaral *et al*. 2022), structural material (Chaabene *et al*. 2020), SHM (Hsieh and Tsai 2020, Flah *et al*. 2021, Avci *et al*. 2021, Spencer Jr *et al*. 2025), structural analysis (Sun *et al*. 2021, Mei and Wang 2021, Ramu *et al*. 2022, Afshari *et al*. 2022), pavement crack detection (Wang *et al*. 2019, Li *et al*. 2022), traffic state analysis (Silva *et al*. 2020, Gutierrez-Osorio *et al*. 2020), traffic control (Noaeen *et al*. 2022), hydrology (Zhu *et al*. 2020, Zounemat-Kermani *et al*. 2021, Mohammadi *et al*. 2021, Huang *et al*.

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Table 1 Research questions and their objectives

	Question	Objective
Research question 1	What efforts have been made to handle data scarcity in CE applications?	To analyze the extent of data availability across CE domains and examine the techniques employed to mitigate data scarcity issues.
Research question 2	What feature engineering techniques are used to improve learning performance?	To summarize recent methods for feature engineering techniques that enhance the effectiveness of ML models in CE.
Research question 3	What strategies are employed to prevent model overfitting?	To identify and evaluate approaches for improving model generalization and avoiding overfitting during ML model development and training.
Research question 4	How is the multi-disciplinary nature of CE incorporated into ML applications?	To investigate how the complex and interrelated characteristics of CE problems are integrated.

2021, Wee *et al*. 2021, Ahmadi *et al*. 2022, Tao *et al*. 2022), and urban water systems (Garzón *et al*. 2022). However, the scope, depth, and methodology of these reviews vary widely, and there remains a lack of consensus on model effectiveness and applicability across domains.

While domain-specific reviews provide valuable insights, they offer a fragmented understanding of ML's broader role in CE. To date, no comprehensive study has examined the cross-domain landscape of ML applications in CE, limiting our ability to generalize findings, identify common challenges, or synthesize best practices across disciplines.

In this study, a systematic literature review was conducted to comprehensively and comparatively examine the extent and depth of ML applications in CE. This review provides a clear and holistic perspective on the existing knowledge based on predefined research questions, guiding both practitioners and researchers. This study focuses on five different CE domains: structural, geotechnical, transportation, water and environment, and energy. By systematically reviewing 800 papers published between 2000 and 2024, the limitations of pre-ML methodologies, improvements brought by ML applications to various CE problems, and subsequent challenges encountered during ML model development were analyzed. The systematic examination of ML studies for the specific application fields of each CE domain enables us to address the research questions listed in Table 1.

The four research questions in this study were carefully formulated to reflect both the sequential process of ML model development and the unique characteristics CE problems. From a methodological standpoint, data availability is the foundation of any ML application, making

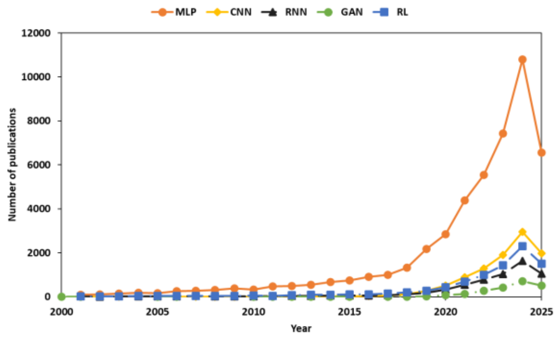

Fig. 1 The number of publications that applied ML in CE between the years 2000 and 2025; extracted from Scopus on May 06, 2025

the assessment of data scarcity a critical starting point (RQ1). Once data are secured, feature engineering becomes essential to ensure that the model can learn effectively from the available information (RQ2). The next natural concern is model generalization, prompting an investigation into strategies that prevent overfitting and improve robustness (RQ3). Finally, the inherently multidisciplinary nature of CE introduces additional complexity, requiring an exploration of how ML applications can integrate multiple interrelated domains and datasets (RQ4). Thus, the four research questions were designed not only to follow the logical progression of ML development but also to capture the multifaceted challenges specific to CE applications.

2. Machine learning techniques

The application of ML techniques in CE has been steadily increased since 2000, driven by the emergence and advancement of diverse models (Fig. 1). Among these, the most frequently adopted models in CE include multilayer perceptron (MLP), CNN, RNN, GAN, and reinforcement learning (RL). This section provides a concise overview of each model including its fundamental architecture, typical applications of each ML model.

Given the rapid evolution and diversification of ML models, definitions and categorizations can vary across the literature. To ensure clarity and consistency, this review adopts standardized definitions for each model as presented in Table 2. All subsequent analyses and discussions are based on these definitions to maintain a systematic and reproducible review process.

For brevity, detailed architectural explanations for individual ML models have been moved to the Appendix. In brief, MLPs consist of fully connected layers suitable for learning nonlinear relationships in tabular or vector data; CNNs specialize in spatial feature extraction for image or grid-like inputs; RNNs handle sequential or time-series data through recurrent connections; GANs generate synthetic data by pitting a generator against a discriminator; and RL models learn decision-making policies through iterative interaction with environments to maximize cumulative rewards.

Table 2 Definitions of ML models

ML model	Definition	Examples
MLP	ML model composed of input, hidden, and output layers with multiple nodes in each layer. The model consists of one or more hidden layers.	ANN DNN FFNN MLP RBF
CNN	ML model composed of convolutional and pooling layers. The former extracts unique features from the data and the latter reduces the size of the data provided by convolutional layer.	R-CNN Fast R-CNN Faster R-CNN Mask R-CNN ResNet YOLO
RNN	ML model composed of internal recurrent structure which uses output produced from the previous layer as the input for the following layer.	GRU LSTM Bi-LSTM ResLSTM Simple RNN
GAN	ML model composed of two components: discriminator and generator. The former distinguishes the real data from the data created by the latter.	cGAN cDC-GAN Tabular GAN
RL	ML model composed of agent and environment. The former learns a series of actions that interact with the latter to maximize rewards.	DRL Semi-cooperative Nash Q-learning

3. Systematic literature review approach

This section provides a detailed overview of the approach employed for the systematic literature review (Fig. 2). First, the research questions were defined, which serves as the main objectives of this review. As introduced earlier, four core questions were addressed to thoroughly explore the current landscape of ML applications in CE and to identify the challenges encountered during model development. Based on these questions, a review protocol was developed (Fig. 2a). The literature search and screening process followed predefined criteria (Fig. 2b). Searches were conducted using five major academic databases: Web of Science, Science Direct, Scopus, Springer Link, and Google Scholar. Keywords used for the search were grouped into two categories: CE-related and ML-related terms. CE-related terms include five CE domains—structural, geotechnical, transportation, water and environmental, and energy engineering—as well as specific application areas within each domain (e.g., structural materials and hydraulics). ML-related terms include specific ML models (e.g., RNN, CNN, GAN, RL) and their variants (e.g., R-CNN, Tabular GAN).

Articles were included if they met the following criteria: (1) published in Q1 or Q2 journals based on the 2024 Scimago Journal Rank (SJR), (2) published after 2000, (3) classified as primary papers rather than secondary papers (e.g., literature review), and (4) focused on at least one of the target ML models—MLP, RNN, CNN, GAN, and RL. Unlike a traditional SLR approach that employs a singular Boolean query followed by large-scale inclusion/exclusion filtering, the study used a domain-decomposed retrieval strategy. Papers were searched and selected iteratively based on specific application problems, target ML models, and CE subfields, to ensure relevance and depth in each technical area. As a result, the study focused more on topical coverage and model diversity than on filtering from an initially large dataset.

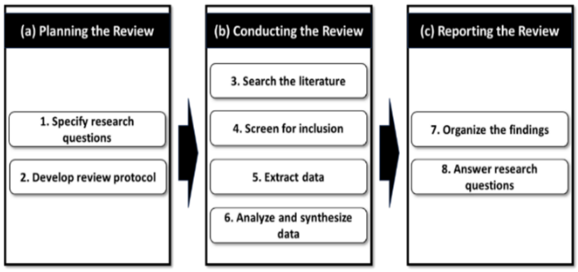

Fig. 2 Flowchart of literature review approach

From the selected literature, multiple data points were extracted to facilitate in-depth analysis (Fig. 2(b)). These included information on the topic, ML models used, dataset characteristics, and key challenges such as data scarcity or overfitting. The extracted information was then synthesized to evaluate the ML application across CE domains and subfield. Final results were organized according to the four guiding research questions, ensuring that each was comprehensively addressed based on the collected evidence (Fig. 2(c)).

4. Machine learning applications in civil engineering

4.1 Overview

This study conducted comprehensive analysis of ML applications across five major domains in CE. To enable a

Table 3 Subfields within each CE domain

Domain	Subfield	Research Topic
Structural engineering	Structural material	Physical properties and behaviors of materials that compose the structure such as concrete and steel
	Structural member	Properties (e.g., internal forces, loads and stresses) of the structure components to determine their size and shape
	Structural health monitoring (SHM)	Structural deformations and damages and structure's safety and lifespan
Geotechnical engineering	Soil mechanics	Physical and chemical properties of the ground and its constituents
	Pavement	Properties and damages of the pavement and its durability
	Tunneling and underground construction	Subsurface properties for underground construction and its safety
	Slope stability analysis	Stability of the slope considering topographical and geotechnical conditions
Transportation engineering	Traffic state analysis	Real-time traffic conditions based on transportation data (e.g., congestion)
	Traffic control	Transportation system optimization by controlling traffic facilities such as traffic lights, signs, and speed limits
	Traffic object	Objects that are installed along transportation infrastructures
Water and environmental engineering	Hydro-environment engineering	Hydrological and environmental factors involved in water cycle
	Hydraulic engineering	Behavior of fluids in water-related infrastructures such as dams and rivers
	Urban water systems	Water-related issues in urban area
Energy engineering	Energy analysis	Properties of energy and its consumption
	Energy management	Energy supply planning analysis
	Renewable energy	Energy production technologies using renewable resources such as solar and wind

detailed and holistic understanding, each domain was further divided into multiple subfields based on distinct problem types and application contexts. Table 3 presents an overview of these subfields along with their corresponding research topics. The following sections summarize the key findings in each subfield and highlight domain-specific challenges that should be considered when applying ML techniques.

4.2 Structural engineering

4.2.1 Structural materials

Structural engineering comprises three subfields: structural materials, structural members, and structural health monitoring (SHM) (Table 3). Structural materials studies mainly aim to predict the characteristics of the materials that compose a structure. Before ML techniques are implemented, the properties of these materials are typically analyzed through direct testing of the material. Several empirical formulas have been developed based on the data acquired from tests to investigate the characteristics of materials (Feng *et al*. 2020, Armaghani *et al*. 2021, Congro *et al*. 2021). However, experiment-based approaches are often limited in their ability to comprehensively consider the various factors that affect the performance of materials, making it difficult to examine the interrelationships between these factors. In response, several ML models have been developed to overcome these limitations.

Most ML studies (nearly 97%) in this subfield focus on concrete due to its dominant use in civil infrastructures. assess the properties and performance of concrete. Numerous ML models have been proposed to understand the behavior of both conventional and advanced concrete types (e.g., ultra-high-strength and recycled aggregate concrete), particularly under varying curing conditions, compositions, and loading types (Jang *et al*. 2019, Marani *et al*. 2020, Congro *et al*. 2021).

Recent literature reflects a shift from single-algorithm studies to more robust comparative analyses that benchmark a range of ML models using standardized datasets. Notably, ensemble methods such as XGBoost and AdaBoost consistently outperform linear models and traditional neural networks in terms of prediction accuracy for compressive strength, particularly on moderate-size datasets (typically ~1,000 samples) (Elhishi *et al*. 2023). These trends point to growing recognition that model selection must balance performance with computational efficiency, particularly for practical engineering applications.

Despite performance improvements, data scarcity remains a recurring challenge. A majority of studies (56%) still rely on 1D experimental data with limited sample sizes (often under 200 points), making models prone to overfitting. To overcome this, approximately 55% of the literature employed data aggregation strategies from prior studies (Nguyen *et al*. 2021 Wan *et al*. 2021), raising average dataset sizes to ~650 points. However, this is still significantly smaller than datasets in SHM, which benefit

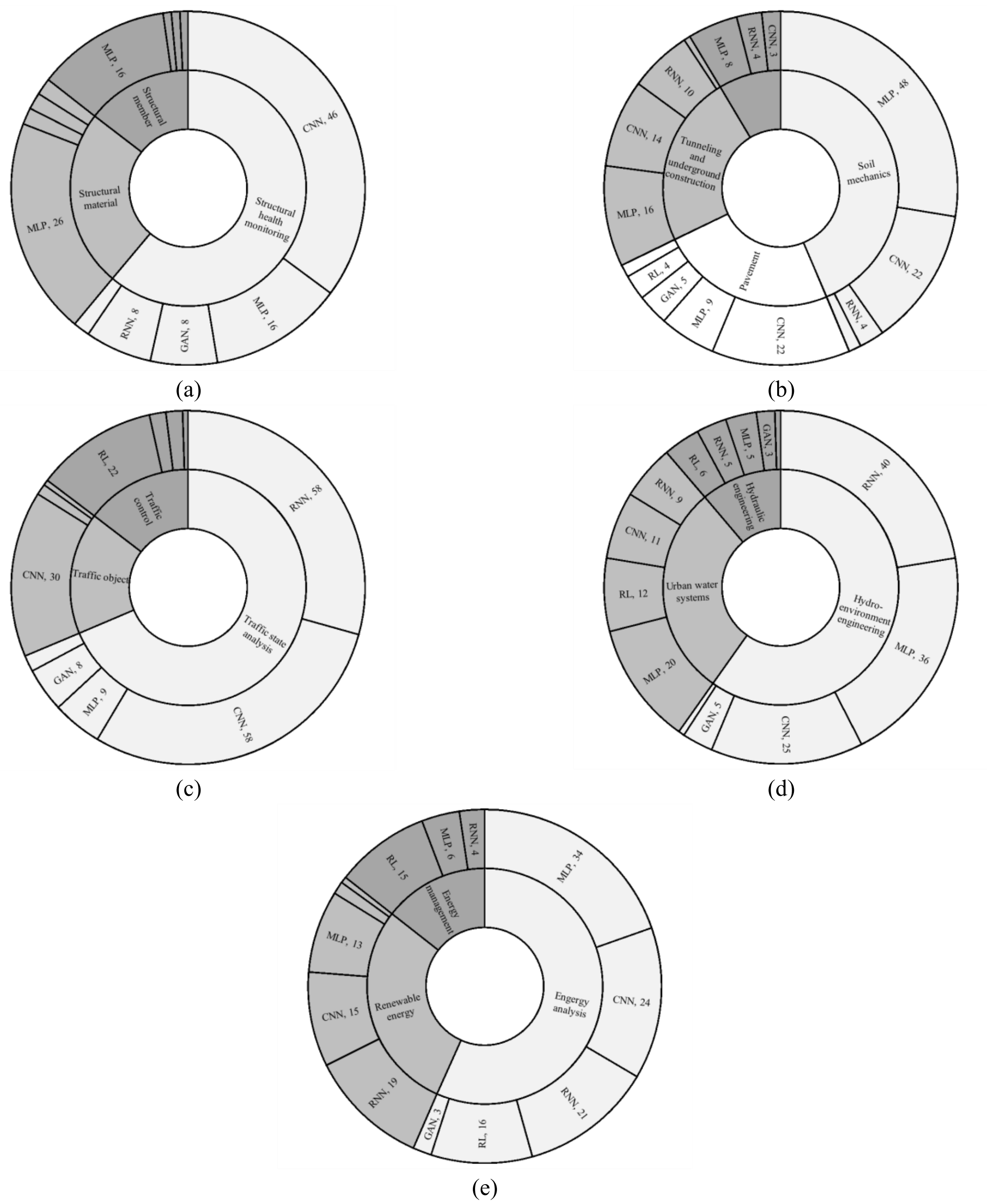

Fig. 3 The number of papers for different ML models used in the subfields of each domain: (a) Structural engineering, (b) Geotechnical engineering, (c) Transportation engineering, (d) Water and environmental engineering, and (e) Energy engineering

from continuous sensor data.

To address both data limitations and generalizability, a promising direction involves integrating domain knowledge into ML pipelines. This includes incorporating physics-informed constraints, empirical equations, and pre-existing engineering rules into the model architecture or training process. The review of knowledge-informed ML frameworks reveals that such hybrid approaches improve model robustness, reduce data dependency, and enhance interpretability—especially for predicting concrete strength and modulus of elasticity under varied material conditions (Li *et al*. 2023).

The development of ML models based on limited datasets can easily cause overfitting problems (Hilloulin and Tran 2022, Tran *et al*. 2022, Imran *et al*. 2022). Roughly 34% of reviewed studies explicitly report implementing regularization strategies such as k-fold cross-validation, dropout layers, and early stopping (Naderpour *et al*. 2010, Ahmad *et al*. 2021). Yet, many publications still lack a comprehensive validation framework, underlining the need for standardized evaluation protocols in ML applications for structural materials.

4.2.2 Structural members

Approximately 17% of the structural engineering studies were related to structural members. The primary application of ML models is the stable design of structural members and predictive modeling of structural performance. Historically, empirical testing and finite element-based numerical simulations dominated this task. However, such approaches face limitations in accounting for the high-dimensional and nonlinear nature of real-world structural behavior (Elshafey *et al*. 2011).

ML models have emerged as a viable solution to this limitation, as they can effectively account for complex nonlinear relationships among multiple variables. Among the many ML models, MLP was the most frequently used (70% in the subfield; Fig. 3(a)) model, showing exceptional performance. For instance, Elshafey *et al*. (2011) developed an MLP model to predict the punching shear strength of slabs and achieved a high predictive accuracy of R2 = 0.997. Wang *et al*. (2021) developed a CNN model to detect the shear loading of through-bolts via a percussion-based method.

A growing number of studies have demonstrated that ML models can go beyond black-box prediction to derive simplified design formulas. These formulas, extracted from trained models, have shown greater accuracy than traditional empirical equations. For example, Sharifi *et al*. (2019) developed an MLP-based equation to predict the lateral torsional buckling of steel I-beams, which outperformed seven existing formulas. This trend is reinforced in recent studies that used SHAP and sensitivity analysis tools to extract interpretable relationships, producing compact yet accurate design expressions (Su *et al*. 2024, Sidvilasini and P.T. 2024).

Limited experimental data remains a challenge in this subfield. For instance, Sharifi *et al*. (2019) trained their model on just 99 samples. To address this, several studies have adopted hybrid approaches that combine synthetic and numerical datasets. Naser *et al*. (2022) expanded their dataset using the Synthetic Minority Oversampling Technique (SMOTE) alongside numerical simulations. Similarly, Ferreira *et al*. (2022) and Zrringol *et al*. (2021) employed finite element models to generate 768 and 720 synthetic samples, respectively, enabling robust training of MLP models for buckling and strength prediction.

Recent investigations confirm that hybrid datasets—combining physical testing, literature data, and simulations—substantially improve ML model accuracy and robustness for predicting flexural and shear performance in FRP-retrofitted and reinforced concrete members (Gao and Lin 2020, Alhusban *et al*. 2023).

ML is also being used as a surrogate model for resource-intensive simulations. This approach, demonstrated in Ferreira *et al*. (2022), allows rapid yet accurate prediction of structural performance, making it ideal for real-time design iterations. Recent studies reinforce this strategy. For example, ML models have successfully replaced traditional FE models to estimate buckling and fire-induced failure in steel members with high fidelity (Chen *et al*. 2023, Wei *et al*. 2024).

4.2.3 Structural health monitoring

SHM involves analyzing the condition of a structure and diagnosing its defects. ML-based SHM models are generally classified into two categories: (1) vibration-based methods that use fixed sensor data, and (2) vision-based methods that rely on images captured by static devices.

The first category predominantly uses MLP models with data gathered from sensors mounted on structures, such as accelerometers. These models predict structural performance indicators such as such as structural stiffness and mass (Zhang *et al*., 2019), strain (Weinstein *et al*., 2018) and flexural stiffness (González-Pérez *et al*. 2011). Vibration-based methods are becoming more data-intensive and accurate, particularly with the use of advanced signal-processing and time-frequency transformation techniques, which enhance ML's ability to distinguish between damage and noise (Dang and Nguyen 2023, Kumar *et al*. 2023).

Vision-based SHM predominantly uses CNNs and their variants—accounting for over half of the reviewed SHM studies (Fig. 3(a)). These models now go beyond simple crack detection and handle complex tasks such as damage localization, semantic segmentation, and severity assessment (Dinh *et al*. 2018, Gulgec *et al*. 2019, Ali *et al*. 2021). Recent research has significantly advanced this field by incorporating 3D vision systems and motion magnification to measure submillimeter structural vibrations, offering non-contact precision diagnostics even in dynamic environments (Shao *et al*. 2022, Chen *et al*. 2022).

Since these models typically require large datasets and substantial training time, transfer learning (TL) has emerged as a key technique to reduce training time and mitigate overfitting. Eleven out of the 80 SHM studies applied TL to reduce model to boost convergence efficiency. For example, Yu *et al*. (2022) enhanced concrete surface crack detection by combining the CNN, TL, and data fusion techniques, while Teng *et al*. (2023) achieved an improvement of approximately 47% while reducing the convergence time of the model through TL-based model fine-tuning.

While SHM models benefit from large datasets—Kim *et al*. (2021) used over 40,000 images for crack detection—data quality remains a concern. Real-world data often contain noise, variable lighting, and complex backgrounds. Several studies have explored noise mitigation, showing that robustness improves significantly when applying denoising filters, morphological operations, and robust feature extractors during preprocessing (Kalfarisi *et al*. 2020, Hou *et al*. 2021). This direction continues to evolve with the use of graph neural networks and sensor fusion architectures that integrate spatial and temporal correlations for more stable predictions (Bao and Li 2020, Naresh *et al*. 2023).

4.3 Geotechnical engineering

4.3.1 Soil mechanics

Geotechnical engineering comprises four subfields: soil mechanics, pavement, tunneling and underground construction, and slope stability analysis (Table 3). Among these, soil mechanics accounts for approximately 45% of the ML studies (Fig. 3(b)). This subfield focuses on understanding the physical properties (e.g., soil moisture and permittivity) and behavior of soils as construction materials, and their interactions with structures. ML techniques in this subfield have been introduced to address the limitations of existing traditional approaches (e.g., field or laboratory experiments and statistical methods), which often rely on limited datasets and struggle to make long-term predictions (Park and Lee 2011, Hao *et al*. 2020, Han *et al*. 2022).

The most widely used model in this subfield is MLP, appearing in approximately 65% of the studies (Fig. 3(b)). MLP models are typically built on 1D experimental data, but data limitations remain a significant problem. For example, Azarafza *et al*. (2022) trained an MLP on only 120 samples for predicting rock geomechanical properties—a size insufficient for generalizable modeling.

CNNs also play a critical role in soil mechanics, accounting for 28% of the studies (Fig. 3(b)). They are favored for their ability to handle spatially distributed data, such as ground-penetrating radar (GPR) or satellite imagery. While, manual investigation of GPR data is time-consuming and labor-intensive, CNN models enable successful automatic detection in various tasks, such as identifying subsurface voids. Models are developed for target detection (Hou *et al*. 2021, Zhang *et al*. 2021, Yamaguchi *et al*. 2022) and permittivity estimation (Wang *et al*., 2022) using GPR images. Moreover, CNNs trained on satellite imagery were successfully used to classify soil texture and moisture levels in expansive zones (Hegazi *et al*. 2021, Wang *et al*. 2022).

A growing number of studies are leveraging multi-source data integration—combining satellite imagery, lab data, and climatic or topographic variables—to improve generalization and predictive power. This approach is exemplified by Celik *et al*. (2022) and Jarray *et al*. (2022), who enhanced soil moisture prediction by combining satellite and in situ data using LSTM and hybrid models. More recently, interpretable ML frameworks have also emerged for consolidation settlement analysis and soil model selection. Tian and Wang (2024) introduced a sparse dictionary learning model that not only improved settlement prediction accuracy but also allowed geotechnical interpretability by identifying the most influential soil constitutive models using real project data.

4.3.2 Pavement

Road pavements deteriorate under the combined impact of traffic loading and environmental factors (e.g., precipitation, temperature variation, and freeze–thaw cycles). Monitoring and maintaining pavement performance requires reliable tools for assessing both current and projected deterioration. ML-based approaches have emerged as powerful tools in this context, providing efficient and scalable solutions for damage detection and predictive maintenance (Zhang *et al*. 2018, Ma *et al*. 2022, Yao *et al*. 2020, Botella *et al*. 2022, Dong *et al*. 2022).

Notably, CNN were used in 84% of the studies for image-based pavement analysis (Fig. 3(b)). Huyan *et al*. (2020) developed "Crack U-net" for pixel-level crack detection on pavement surface. Hsieh *et al*. (2021) applied 3D sensing for concrete pavement slab health monitoring, and Kyriakou *et al*. (2019) combined onboard smartphone sensor data with ANN models to detect potholes via acceleration and rotation parameters. These early efforts have evolved into more robust CNN-based systems with enhanced crack detection accuracy. Recent models, such as a novel U-Net variant (CrackHAM) and GoogleNet-based frameworks, achieved high pixel-level segmentation performance and resistance to noise (He and Lau 2024, Lin 2024).

Although data acquisition has become easier with the use of advanced equipment such as UAV, obtaining high-quality labeled data remains challenging (Maeda *et al*. 2021, Dong *et al*. 2022). Manual labeling is costly and time-consuming. For instance, Zhang *et al*. (2018) manually labeled 6,000 images for crack detection of pavement. Pixel-level annotations especially for segmentation tasks, demand extensive labor (Xu and Liu 2022). To address this, studies employ pre-trained models, active learning, and data augmentation (Ma *et al*. 2022, Dong *et al*. 2022). GAN-based frameworks have proven especially effective in generating diverse, high-resolution crack imagery, leading to significant improvements in model training and generalization (Han *et al*. 2024, Ijari and Paternina-Arboleda 2024).

In addition to supervised learning, RL is gaining momentum in optimizing pavement maintenance schedules. These models consider long-term condition forecasting and feedback mechanisms, using pavement characteristics, historical repair data, and traffic patterns to generate dynamic maintenance policies. For example, a Q-learning-based RL system developed using real-world airport pavement data reduced maintenance costs while improving long-term surface conditions (Yao *et al*. 2020, Barua and Zou 2021). These advancements underline the shared relevance of geotechnical and transportation engineering in pavement ML applications. Models benefit from considering not only pavement materials and structures but also vehicle behaviour, traffic volume, and operational environments.

4.3.3 Tunneling and underground construction

Securing stability is essential for underground excavation. This is generally achieved by monitoring underground features such as internal pressure, groundwater behavior, and surrounding rock conditions while adjusting excavation speed and equipment, setting. However, due to the non-linear and interdependent nature of geotechnical parameters during excavation, predicting ground responses in real-time challenging (Shen *et al*. 2022, Wu *et al*. 2023). In particular, tunnel boring machine (TBM) operations, require adaptive control of excavation parameters to optimize cost, safety, and efficiency (Zhang *et al*., 2022). ML models have become valuable tools for replacing oversimplified traditional prediction methods and capturing the complexities of real-time excavation behavior (Lu 2005, Qin *et al*. 2021).

Recent studies have emphasized the use of temporal models to capture time-dependent behavior in TBM operations. About 35% of ML studies in this subfield employ RNN or its variants (Fig. 3(b)). In particular, studies highlight the significance of dynamic factors evolving over time which subsequently influence operational decisions (Gao *et al*. 2019, Shen *et al*. 2022). Subsequently, RNN, LSTM, and GRU models have outperformed traditional regressors in real-time prediction of TBM thrust, torque, and advance rate (Gao *et al*. 2019).

Moreover, TBM operations rely on spatiotemporal modeling to understand how both time and location affect machine behavior. Elbaz *et al*. (2022) successfully modeled cutterhead drive energy consumption using spatially and temporally linked TBM parameters. More recently, attention-based graph convolutional networks (att-GCN) have enabled multi-output prediction of TBM energy and penetration rate with superior accuracy and online learning capability (Pan *et al*. 2022, Zou *et al*. 2024).

Given the importance of direct onsite applications, most studies use field-acquired excavation data, as shown in 12 studies in this subfield. Gao *et al*. (2019) and Zhang *et al*. (2022) used data collected from subway projects in Shenzhen, China, while Zhou *et al*. (2020) used data from a tunnel project in Malaysia. These data often contain missing or inconsistent entries due to operational conditions, requiring robust preprocessing and feature selection algorithms to ensure model reliability.

4.3.4 Slope Stability Analysis

Analyzing slope stability is crucial in CE as unstable slopes can result in landslides that endanger nearby structures and infrastructure. Traditionally, slope stability is assessed using sensitivity maps and expert-driven evaluation which can be subjective and fail to reflect the complex, dynamic nature of slope movement (Li *et al*. 2021, Ullo *et al*. 2021). To address these limitations, ML models have been introduced to improve the accuracy and objectivity of landslide prediction.

Although ML accounts for only about 8% of all geotechnical studies (Fig. 3(b)), it has shown strong potential for advancing slope stability analysis. Time-dependent features, such as soil moisture and electrical resistivity, play a critical role in slope failures. RNNs have demonstrated effective prediction of landslide displacements using such temporal patterns. For example, Lee and Yoon (2021) used RNN to predict the electrical resistivity of soil and its temporal pattern, while Ma *et al*. (2022) developed a GRU-based framework integrating multi-sensor monitoring data for real-time landslide displacement forecasting.

In addition to temporal analysis, spatial analysis is essential, as landslide susceptibility is affected by the heterogeneous distribution of geomechanical and hydrological factors (Wang and Goh 2021). Hence, approximately 60% of the studies in this subfield have built spatial databases considering spatially varying geotechnical parameters (Wang and Goh 2021, Ullo *et al*. 2021) and spatial resolution (Pradhan and Lee 2009, Wang *et al*. 2020). Recent studies have used CNNs and spatial correlation indices to capture the interaction between terrain units and past landslide events (Wang and Goh 2021, Ullo *et al*. 2021, Liu *et al*. 2022) (Fig. 3(b)). Liu *et al*. (2022) trained Mask R-CNN model to extract pertinent landslide information from interferometric synthetic aperture radar, while Wang and Goh (2021) demonstrated the effectiveness of CNN as a surrogate model for the slope reliability analysis of spatially variable soils.

Modern ML research in slope stability is increasingly multi-source and multi-dimensional, combining temporal, spatial, and environmental variables. For instance, Xiong *et al*. (2024) proposed a spatiotemporal ML framework using dual landslide inventories and rainfall data to model regional susceptibility in Pennsylvania with an AUC score of 0.86. Likewise, Zhang *et al*. (2022) developed an ensemble learning model (i.e., XGBoost and Random Forest) to predict slope stability in China, achieving high accuracy across 786 case studies.

4.4 Transportation engineering

4.4.1 Traffic State Analysis

Transportation engineering comprises three subfields: traffic state analysis, traffic control, and traffic objects (Table 3). Traffic state analysis is the most explored subfield in transportation-related ML research (Fig. 3(c)). It involves collecting and analyzing traffic flow, speed, volume, and vehicle type to assess current traffic conditions and predict congestion. Owing to the high complexity and dimensions of traffic datasets with complex spatiotemporal dependencies and dynamics, ML techniques are increasingly used to address nonlinear, time-dependent patterns.

Many studies have focused on predicting specific traffic parameters, such as traffic flow (An *et al*. 2019, Chen *et al*. 2020, Li *et al*. 2021, Tang *et al*. 2021), traffic density (Chung *et al*. 2018), traffic speed (Ma *et al*. 2015, Zhang *et al*. 2020), and travel time (Ran *et al*. 2019). For example, MLPs have been applied using flow-sensing data (Chen *et al*. 2020), while CNNs and CNN-LSTM hybrids have been used to model spatiotemporal traffic features for travel time and congestion forecasting (Tang *et al*. 2021, Li *et al*. 2021). Recent work has refined these hybrid methods by integrating incremental learning to reduce update latency (Zhao *et al*. 2023).

Approximately 53% of the studies developed CNNs to extract spatial and temporal features by reshaping time series traffic data into 2D matrices or images (Ma *et al*. 2017, Jo *et al*. 2019) (Fig. 3(c)). This strategy remains widely used, and new studies have introduced advanced attention mechanisms and graph-based convolution to enhance spatial dependency modeling. For instance, a recent dual-attention 3D CNN captured lane-level traffic flow propagation with high precision on Shanghai expressway data (Tang *et al*. 2023), while a spatiotemporal transformer model outperformed graph-based CNNs in multi-step forecasting accuracy across multiple road networks (Li *et al*. 2024).

Another key advancement is the modeling of nonstationary traffic behavior, acknowledging that real-world traffic is often irregular, nonlinear, and influenced by unpredictable events. (Cheng *et al*. 2022, Kuo and Kunarsito 2022). While older methods smoothed out nonstationarity to fit ML assumptions (Ma *et al*. 2022), recent studies embrace it directly (Zang *et al*. 2024, Wang *et al*. 2024). For instance, Zang *et al*. (2024) proposed AdaRNN-DCORAL, which combined domain adaptation and adaptive recurrent networks to learn from temporally disordered datasets with minimal labeling.

4.4.2 Traffic control

Traffic control represents approximately 15% of the ML studies in transportation engineering (Fig. 3(c)). This subfield focuses on using intelligent systems to optimize traffic flow, reduce congestion, and manage intersection operations. The interest in ML for traffic control has increased dramatically in recent years, with 80% of studies published between 2018 and 2023.

Among these, the dominant focus is traffic signal control, accounting for 21 of 30 studies. The dynamic nature of real-world intersections—changing demand, unpredictable arrival patterns, and time-varying congestion—necessitates adaptive strategies (Aziz *et al*. 2018, Chu *et al*. 2019). RL is particularly well-suited to this context. RL agents interact with the environment, learning adaptive control policies by optimizing reward functions under varying traffic conditions (Zang *et al*. 2020, Genders and Razavi 2020, Wang *et al*. 2021).

Key elements in RL model design include states, actions, and rewards (Wang *et al*. 2021). For states, variables representing traffic conditions are dominantly used (e.g., vehicle queue lengths and accumulative delay). For example, Liu *et al*. (2021) used vehicle queue lengths at intersection entrances to define the state, while Chu *et al*. (2020) incorporated cumulative delay and total vehicle count along incoming lanes. For actions, 46% of studies focused on adjusting green phase durations, while another 46% modified phase transitions.

For the reward function, the most common metrics are vehicle queue length (46%) and cumulative delay (38%). These parameters enable the model to determine the optimal policy for traffic control minimizing congestion. For instance, Liu *et al*. (2021) derived rewards from the number of vehicles waiting in entry lanes, whereas Genders and Razavi (2020) defined the reward function as the negative square of the queued vehicles. Moreover, recent models integrate multi-objective criteria, including safety and emissions. Wang *et al*. (2023) introduced a D3QN-based controller that optimized both delay and carbon emissions at mixed traffic intersections, reducing CO_2 output and average waiting time.

4.4.3 Traffic object

The transportation system consists of numerous visual components—such as traffic signs, crosswalks, pedestrians, and lane markings—which are critical for safe traffic management and intelligent vehicle guidance. With the rising development of autonomous vehicles and advanced driver assistance systems, research in traffic object detection has expanded, representing 31 of 167 transportation ML studies (Fig. 3(c)).

As in SHM, most studies in this domain utilize image data, employing CNN and their variants to detect objects with varying sizes and types. About 93% focused on image-based detection of signs (Liu *et al*. 2022), road objects (He *et al*. 2021), or lines (Li *et al*. 2019). For example, YOLOv5 based architectures have been commonly adapted for small object detection, such as traffic signs and lights, achieving significant speed and precision gains under real-time constraints (Mahaur and Mishra 2023).

A major challenge in traffic object detection is handling environmental uncertainties, such as low-light conditions, rain, snow, and fog. Image degradation in these environments significantly reduces the effectiveness of CNN models. Recent studies have made progress in this area: Gao *et al*. (2024) proposed a CNN-based detection system with adverse condition classifiers and image enhancement modules to achieve over 95% accuracy in fog, dirt, and blur scenarios, while Zheng *et al*. (2023) integrated visual synthesis and image-to-image (I2I) augmentation to improve object recognition performance in rainy and nighttime conditions.

Another crucial issue is data imbalance (19 of 31 studies) common in multiclass datasets where some object types are underrepresented. Studies have addressed this through data augmentation and feature-weighting techniques (Lee and Kim 2018, Kamal *et al*. 2020). For example, Kamal *et al*. (2020) balanced classes by generating 4,200 images by augmenting the 600 training images through techniques such as shifting and adjusting.

4.5. Water and environmental engineering

4.5.1 Hydro–environment engineering

Water and Environmental Engineering consists of three subfields: hydro-environmental engineering, hydraulic engineering, and urban water systems (Table 3). The first subfield explores the movement of water in relation to land (Subramanya 2008) influenced by key hydrological processes such as precipitation, evaporation, surface runoff, and groundwater flow. Traditionally, rainfall-runoff modeling has relied on conceptual and physically based models to simulate these processes. However, the limited adaptability of such models under real-time, complex, and nonlinear conditions has often resulted in poor prediction accuracy (Behzad *et al*. 2010). Consequently, ML models have gained significant attention and are emerging as robust alternatives.

ML studies in this subfield account for approximately 56% of the water and environmental engineering applications (Fig. 3(d)). Due to the inherently temporal nature of hydrological variables (e.g., streamflow, precipitation, water level, contaminant concentration), RNN variants such as LSTM, and GRU have been the most commonly applied models (45% of all ML studies in this area, Fig. 3(d)). Early studies, such as Bodri and Čermák (2000), used sequential precipitation data to predict extreme events. Later, Hu *et al*. (2019) examined temporal changes in flood characteristics such as the free surface height, water depth, and quantity of flow or velocity obtained from specific sensor locations.

Building on these foundations, recent research has advanced hybrid deep learning architectures for improved performance. For example, a hybrid Transformer–LSTM model combined with an adaptive random search algorithm (AGRS) achieved superior accuracy for 1–6 hour lead-time flood forecasting, outperforming conventional LSTM and MLP models (Li *et al*. 2024, Hosseini *et al*. 2025).

Given that most ML models rely on field observational data, addressing uncertainty and noise in raw time-series has become a central concern. Among available denoising methods, signal transformation has emerged as the preferred choice for enhancing model performance by reducing the effect of noise present in the time series (Hu *et al*. 2019, Song *et al*. 2021, Ibañez *et al*. 2022). Several studies have validated the efficacy of wavelet-enhanced models. For instance, Miau and Hung (2020) combined wavelet filtering with a CNN-GRU model to accurately predict fluctuating water levels. Song *et al*. (2021) improved dissolved oxygen forecasting by mitigating randomness and nonlinearity using wavelet-enhanced LSTM architecture.

This trend continues in more recent applications. Houénafa *et al*. (2025) combined stochastic rainfall–runoff simulations with wavelet-enhanced GRU and XGBoost models, showing improved prediction for both low- and high-discharge scenarios, with an NSE increase of up to 29% over standalone ML models

4.5.2 Hydraulic engineering

Hydraulic engineering focuses primarily on the design, construction, and management of systems related to the movement and storage of water. Various ML models have been employed depending on study objectives, with no particular model emerging as dominant in this domain (Fig. 3(d)).

Even simple models, such as the MLPs, have shown considerable effectiveness in examining hydraulic characteristics (e.g., water quality, wave force, and peak flow). For example, Latif *et al*. (2022) used MLP model to predict reservoir water quality from five quality parameters while, Xu *et al*. (2018) developed MLP models to estimate the solitary wave force on a costal bridge deck accurately modeling the nonlinear interactions between wave height and structural geometry.

Notably, 57% of ML studies in this domain focus on streamflow forecasting and reservoir operation. These problems require understanding the nonlinear behavior of water systems under variable hydrological and meteorological conditions (Wegayehu and Muluneh 2021, Apaydin *et al*. 2020). Short- and long-term streamflow forecasts are critical for managing reservoir release, power generation, and flood control.

Recent studies have significantly enhanced forecasting capability. For instance, Herbert *et al*. (2021) introduced an LSTM encoder–decoder model trained on 30 years of data for the Upper Stillwater Reservoir in Utah, achieving long-term forecasting accuracy comparable to the Ensemble Streamflow Prediction (ESP) system—a gold standard in hydrologic modeling. Similarly, Li *et al*. (2021) developed a hybrid ensemble model combining Bidirectional LSTM (BiLSTM) with variational mode decomposition (VMD) and energy entropy analysis. This model achieved an NSE of 0.957 for daily inflow predictions at Baozhusi Reservoir in China, outperforming traditional and other hybrid ML methods.

In terms of operational decision-making, RL is now actively replacing rule-based or stochastic programming approaches. Several studies have developed RL models trained for objectives such as allocation, water quantity, water quality, and power generation. For instance, Castelletti *et al*. (2014) proposed an RL model for the optimal operation of a multipurpose water reservoir, accounting for both quantity and quality targets. Similarly, Xu *et al*. (2021) employed RL methods to determine optimal operations and achieve high-performance hydropower generation.

Recent studies show a surge in sophisticated RL applications for real-time and multi-objective optimization (Luo *et al*. 2025, Sadeghi Tabas and Samadi 2024). Luo *et al*. (2025) proposed a Soft Actor-Critic (SAC) RL model integrated with Evolutionary Hindsight Experience Replay (EVHER) to optimize power generation and flood control in a cascade hydropower system. The model achieved a load deviation of less than 3% and a success rate above 99.8% in Monte Carlo simulations, proving its robustness under inflow and grid uncertainty.

4.5.3 Urban water systems

Intelligent water meters and sensor networks are increasingly deployed across cities to manage urban water systems. These devices generate vast volumes of time-series data related to related to water flow, pressure, and quality. Advances in ML have made it possible to analyze this data for real-time insights, improving efficiency, safety, and sustainability. Approximately 30% of the ML studies in water and environmental engineering have focused on urban water systems (Fig. 3(d)).

ML has been applied across a wide range of urban water challenges, including flood prediction, pipe leakage detection, water quality analysis, and component operations control.

For flood prediction, MLP and CNN have traditionally been used to estimate quantitative parameters, such as water depth and elevation fluctuations models (Radmehr *et al*. 2014, Chang *et al*. 2014, Park *et al*. 2021, Huang *et al*. 2023). More recently, RL models have been used for real-time flood mitigation through drainage system control. Tian *et al*. (2023) introduced a framework for safe and trustworthy RL in urban drainage systems, incorporating safe learning and uncertainty quantification to ensure stable performance across varying rainfall and system states.

Pipe leakage detection in water distribution systems (WDS) has evolved significantly with ML. Earlier work relied on rule-based and model-based methods, but modern studies apply ML to detect nonlinear signal features. For instance, Lee and Yoo (2021) used sensor data for real-time leak detection, and Zhang *et al*. (2023) improved location prediction with CNN-SVM fusion. Elshazly *et al*. (2024) proposed a spatial ML framework combining Geographically Weighted Regression (GWR) and Local Outlier Factor (LOF), achieving over 90% leak detection accuracy using live pressure and flow sensor data in a real-world network.

RL models are increasingly applied for operations control in WDS. Tasks like pump scheduling (Hajgató *et al*. 2020, Xu *et al*. 2021), valve control (Mosetlhe *et al*. 2021, Hu *et al*. 2022), and sensor placement (Song *et al*. 2022) have been framed as sequential decision-making problems. Recent work has extended this to interpretable DRL systems. For example, Tian *et al*. (2024) developed a method for interpreting DRL behavior in real-time drainage system control using sensitivity analysis and surrogate modeling, improving transparency and trust in AI-driven WDS optimization.

The success of these applications depends heavily on sensor infrastructure. Sensor-derived data—covering flow rate, demand, water quality, and pressure—is foundational for ML models to function in real time. Studies like Mounce *et al*. (2003) and Kang *et al*. (2018) have shown that integrating time-series data with ML enables predictive management of leaks and flow anomalies. These systems are now supported by large-scale deployment and real-time feedback capabilities.

4.6 Energy engineering

4.6.1 Energy Analysis

Energy engineering comprises three subfields: energy analysis, energy management, and renewable energy (Table 3). The increasing threat of global warming, limited fossil fuel energy resources, and growing environmental pollution emphasized the importance of designing and operating optimal energy systems. Accurate predictions of energy loads, consumption, and performance metrics are critical to ensure reliability, efficiency, and sustainability. Energy analysis problems constitute approximately 61% of energy engineering ML studies (Fig. 3(e)), with most published in the last five years (2019-2024), indicating a rapidly recent development.

ML models have shown considerable potential in analyzing large and complex energy datasets. Various ML models, including MLP, CNN, and RNN, have been widely applied—comprising roughly 30% of the studies (Fig. 3(e)). These models effectively estimate critical energy parameters such as heat and cooling load (Ekici *et al*. 2009, Fan *et al*. 2017), energy consumption (Luo *et al*. 2020, Mustapa *et al*. 2020, Elbeltagi and Wefki 2021), irradiance (Huang *et al*. 2018), and thermal comfort (Zhang *et al*. 2018, Gao *et al*. 2020).

Because energy consumption patterns are inherently temporal and nonlinear, time-series ML models have been widely adopted. Traditional forecasting relied on ARMA and ARIMA models, but deep learning approaches like LSTM and GRU have proven more effective, especially when managing large-scale smart grid data (Amalou *et al*. 2022). These RNN-based models are now standard in electricity load forecasting applications (Sendra-Arranz *et al*. 2020, Chaturvedi *et al*. 2022).

Recent advances in hybrid CNN–LSTM models further enhance prediction accuracy by combining spatial feature extraction with temporal pattern learning. For example, Asiri *et al*. (2024) introduced a hybrid CNN–BiLSTM–Autoencoder model with Beluga Whale Optimization (BWO) for short-term load forecasting in smart grids. The model significantly outperformed standalone deep learning approaches, reducing error rates below 3.5%. In another real-world application, Hasanat *et al*. (2024) developed a parallel multichannel 1D-CNN and BiLSTM model to capture spatial and temporal load features independently. Their approach achieved a MAPE of 0.56% for one-hour-ahead forecasts, outperforming stacked CNN–LSTM models and providing reliable forecasts under smart grid conditions.

4.6.2 Energy management

In the energy engineering domain, approximately 16% of the ML studies address energy management problems (Fig. 3(e)), with a focus on optimizing building energy consumption and grid-scale power coordination. Applications range from HVAC control and indoor thermal comfort to multi-resource dispatch in distributed energy systems (Li and Du 2023, Fang *et al*. 2022, Foruzan *et al*. 2018, Hua *et al*. 2019).

Energy management challenges are typically divided into two subcategories: grid-level energy management and indoor building-level control. Among the 24 studies reviewed in this subfield, 13 focus on grid-scale applications—such as energy scheduling, power flow regulation, and energy storage management—while 11 center on building systems aimed at balancing energy use and occupant comfort.

In both domains, RL has gained strong traction, with approximately 63% of the studies employing RL models (Fig. 3(e)). RL's adaptability to high-dimensional, uncertain, and dynamic environments makes it well suited for replacing rule-based or model-based control strategies. For example, Li and Du (2023) used RL to optimize microgrid retail pricing, where the model's action space represented hourly price signals and its reward reflected profit and demand smoothing. In indoor environments, Wu *et al*. (2022) introduced an RL model with LSTM integration for HVAC control, demonstrating improved generalizability and thermal regulation under continuous action spaces.

Recent studies further expand the capability of RL in energy systems. Zhuang *et al*. (2023) proposed a Soft Actor–Critic (SAC) RL framework integrated with LSTM and attention mechanisms for smart HVAC control in IoT-enabled buildings. Their model achieved 17.4% energy savings and a 16.9% improvement in thermal comfort under real-time operational scenarios. Further advancing RL-based coordination, Homod *et al*. (2022) developed a cooperative multi-agent RL algorithm (DCCMARL) for optimizing multi-chiller HVAC systems. Their hybrid clustering and multi-objective control strategy achieved up to 44.5% energy savings, highlighting the model's ability to balance thermal performance with minimal energy expenditure in high-dimensional control spaces.

In addition to RL, MLP and RNN models remain useful in supporting Model Predictive Control (MPC) methods. For instance, Yang *et al*. (2021) applied an RNN to approximate the building's thermal dynamics and optimize cooling power setpoints based on historical disturbances and feedback states. Similarly, Elnour *et al*. (2022) developed an MLP-MPC hybrid to regulate HVAC systems and improve energy performance with minimal modeling assumptions.

4.6.3 Renewable energy

The global surge in energy demand, the depletion of fossil fuel reserves, and growing climate change concerns underscore the need for robust and intelligent renewable energy forecasting systems. Accurate prediction of energy generation —especially from intermittent sources like solar and wind—is crucial for real-time power dispatch, storage control, and overall energy system reliability (El Alani *et al*. 2021, Zheng *et al*. 2023).While earlier forecasting approaches were based on statistical and physics-driven models, the advent of large datasets from SCADA systems has accelerated the shift toward ML-based methods (Li *et al*. 2019, Kisvari *et al*. 2021, Dong *et al*. 2022).

No single ML model dominates the renewable energy forecasting space. Commonly applied methods include MLP, CNN, and RNN (Fig. 3(e)), with applications ranging from wind and solar power prediction to wave force estimation and reservoir inflow modeling (Ahmad and Hossain 2019, Gómez-Orellana *et al*. 2022, Chen and Yuan 2023).

Hybrid deep learning models—particularly those combining CNN and LSTM—have gained attention for their superior handling of nonlinear and temporal dynamics. For instance, Zhang and Wang (2023) developed a multi-head attention-based probabilistic CNN–BiLSTM model for day-ahead wind speed forecasting. This model not only improved prediction accuracy but also quantified uncertainty using ensemble methods and scoring rules. Similarly, Babay *et al*. (2025) evaluated hydrogen production using various solar panel technologies and implemented MLP and CNN–LSTM models to forecast energy output under fluctuating irradiance and environmental conditions. Their results demonstrated over 94% R^2 in most forecasting scenarios, reinforcing the suitability of deep learning for optimizing hybrid solar-hydrogen systems.

Uncertainty is an inherent challenge in renewable energy forecasting due to the stochastic nature of environmental inputs such as solar irradiance, wind speed, and cloud cover. These variabilities introduce nonlinearity and noise into datasets, which complicate both short- and long-term predictions. Approximately 53% of ML studies in the renewable energy domain explicitly account for both data-driven and system-level uncertainties during model development. Recent research has gone beyond passive modeling to actively estimate or mitigate uncertainty within the forecasting process. For instance, Yin *et al*. (2020) designed an RNN-based approach that estimates lumped, unknown uncertainties in real time, improving the robustness of controller design and decision-making in fluctuating environments. Similarly, Rahman *et al*. (2021) incorporated uncertainty bounds into solar power prediction to evaluate model reliability under rapidly changing weather conditions. El Alani *et al*. (2021) proposed an ensemble learning method that integrates meteorological uncertainty into photovoltaic forecasting, enhancing resilience to prediction errors. These approaches highlight a shift from deterministic ML to probabilistic and uncertainty-aware forecasting strategies.

5. Discussions

This section addresses the four predefined research questions by synthesizing insights from the literature across CE domains and subfields. The discussion highlights common strategies, methodological trends, and domain-specific challenges that have emerged in applying ML to CE problems.

5.1 Research question 1: What efforts have been made to handle data scarcity in CE applications?

Many CE studies face difficulties collecting sufficient high-quality data due to the cost, time, and complexity of physical experiments and field monitoring. In ML contexts, data scarcity can significantly hinder model performance and generalization. Although no strict guidelines exist for required dataset size, prior studies suggest that a sample-to-feature ratio between 10 and 100 is generally acceptable, depending on task complexity (Zhu *et al*. 2023). Several key strategies have been adopted to address this issue.

(1) Data accumulation from previous studies

Many studies construct datasets by compiling experimental data from earlier research, particularly in subfields like structural materials and soil mechanics. This allows broader coverage of case variations and improves dataset diversity. In some areas—such as structural health monitoring (SHM) and computer vision-based inspections—well-established public datasets (e.g., Structural ImageNet, PEER Hub ImageNet) have been instrumental in accelerating model development.

(2) Data augmentation

Data augmentation increases the size of datasets by modifying them, thereby creating various forms of data that may not exist in the original dataset. In subfields using image data (e.g., SHM, pavement analysis, traffic object detection), data augmentation techniques such as flipping, rotation, blurring, and cropping are commonly used to synthetically increase the training dataset. Irrespective of the domain or subfield of CE, when image data are employed, multiple data augmentation techniques are actively used to ensure comprehensive learning from enriched datasets (Zhang *et al*. 2020, Acquaah *et al*. 2021). These methods enrich the model's learning capacity without requiring additional data collection efforts.

(3) Data generation

Synthetic data generation using generative models (e.g., GANs) is gaining popularity as a way to augment limited labeled datasets (Zhang *et al*. 2021, Dewi *et al*. 2021). Despite its potential, GAN-based studies constitute only 5% of the ML studies in CE, indicating its relatively recent adoption in the field. However, as shown in Fig. 7, the proportion of studies utilizing GANs has steadily increased. Data generation via GAN has great potential as a solution to limited labeled data.

While still emerging in CE, these techniques have demonstrated strong potential in replicating complex distributions. Additionally, numerical simulation models (e.g., finite element models, hydrologic simulations) provide an alternative means of generating abundant labeled data, especially in structural, geotechnical, and energy engineering. Simulation-generated datasets are also used to create dynamic learning environments for RL, enabling effective decision-making in real-time systems such as traffic control, flood response, and energy dispatch.

5.2 Research question 2: What feature engineering techniques are used to improve learning performance?

The way input data is structured and represented plays a critical role in determining ML performance. Effective feature representation facilitates the extraction meaningful patterns, thereby enhancing both training efficiency and prediction accuracy. In CE, several feature engineering strategies have been widely employed, including feature selection, feature extraction, scaling, signal transformation, and dimension transformation.

(1) Feature selection

Feature selection involves identifying and retaining only the most relevant attributes from the dataset to improve model accuracy and reduce computational complexity. This approach is particularly beneficial when working with datasets that include a large number of variables, such as those obtained from experiments or multi-sensor systems. In CE applications, feature selection is frequently used in conjunction with MLP models to predict target outcomes. Common methods include correlation-based analysis (Botella *et al*., 2022; Kouadri *et al*., 2022; Jiang *et al*., 2022) and Shapley additive explanation (SHAP)-based sensitivity analysis (Asghari *et al*. 2020, Woldesellasse and Tesfamariam 2022). SHAP, in particular, has been effectively applied in subfields such as structural materials, structural members, and soil mechanics —where data are typically one-dimensional and structured—demonstrating its utility in improving model interpretability and efficiency.

(2) Feature extraction

Feature extraction aims to derive new, lower-dimensional features from original data while preserving essential information. Principal component analysis (PCA) is widely adopted to reduce the dimensions of multiple features while preserving maximum information (Kouadri *et al*. 2022, Taloba 2022). In SHM, for instance, PCA is used to condense thermal and vibration signal data, improving the quality of extracted features and enabling more robust learning (Tian *et al*. 2021). This dimensionality reduction facilitates faster training and enhances generalization by removing noise and redundancy.

(3) Scaling

Scaling transforms input features into a consistent numerical range, which is critical for accelerating convergence during training and ensuring balanced learning across features. Normalization—typically scaling features between 0 and 1—is among the most commonly employed preprocessing techniques in CE (Tampubolon *et al*. 2019, Khalaf *et al*. 2020). This approach is widely applied to both 1D and 2D data formats, ensuring uniformity across variables and improving the stability of optimization processes.

(4) Signal transformation

Signal transformation is extensively used in CE subfields that involve time-series sensor data (Hao *et al*., 2020). The primary goal is to filter noise and emphasize significant temporal patterns in the signal. Wavelet transformation, in particular, is a widely adopted method for this purpose (Sendra-Arranz and Gutiérrez 2020, Yue *et al*. 2022).

(5) 1D to 2D matrix transformation

Transforming one-dimensional data into two-dimensional matrices allows ML models—especially CNNs—to better capture spatial dependencies in data with inherent spatial structure (Zhao *et al*. 2021, Wu *et al*. 2022). For example, Wu *et al*. (2022) used data generated using the random field method in an image-like format as input data to account for the spatial variability of soil parameters for predicting wall deflection using a CNN.

A growing research trend involves converting time-series data into two-dimensional image representations to retain temporal dynamics while enabling spatial feature learning. The Gramian Angular Field (GAF) method, for instance, encodes time-series data into polar coordinate systems to reveal correlations between time steps. This technique has been applied across various CE problems, including damage localization using damage index sequences (Deng *et al*. 2023, Demirel *et al*. 2022, Liao *et al*. 2023). Such hybrid representations allow ML models to leverage both spatial and temporal patterns, offering new opportunities for more advanced forecasting and diagnostic tools.

5.3 Research question 3: What strategies are employed to prevent model overfitting?

Overfitting is a significant concern in CE ML applications, especially when training data is limited, noisy, or highly variable. A well-generalized model should perform effectively on unseen data, and CE studies have adopted several strategies to prevent overfitting.

(1) Regularization

Common methods include dropout (randomly disabling neurons during training), early stopping (terminating training based on validation performance), and cross-validation (rotating data subsets for training and testing) (Abdollahi *et al*. 2021, Adams *et al*. 2020, Yin *et al*. 2021). Among these, cross-validation is the most frequently used, particularly for tabular or 1D data.

(2) Transfer learning (TL)

In studies using image data, especially in SHM, pavement, and slope stability analysis, TL is commonly used to leverage pretrained CNN models on large public datasets (Liang 2019, Lork *et al*. 2020, Chaiyasarn *et al*. 2022). This allows smaller CE-specific datasets to benefit from generalized feature representations, improving training efficiency and model accuracy. These strategies are often used alongside data transformation and augmentation techniques discussed earlier, forming a comprehensive approach to improving model robustness.

5.4 Research question 4: How is the multi-disciplinary nature of CE incorporated into ML applications?

CE is inherently multidisciplinary and many real-world challenges require integrating knowledge and data from multiple domains. For instance, structural health depends not only on material degradation but also on external loads such as traffic, linking structural and transportation engineering (Ge *et al*. 2020, Sarwar *et al*. 2021). Similarly, geotechnical problems often overlap with water-related issues due to interactions between soil and groundwater (e.g., in slope stability or tunneling under saturated conditions) (Alsharari *et al*. 2020, Orakoglu and Atila 2021).

Studies increasingly reflect this interconnectivity. For example, Liu *et al*. (2022) integrated geotechnical and traffic data to improve pavement failure predictions. Other studies have combined structural and environmental data to assess flood vulnerability of infrastructure, reflecting the growing importance of interdisciplinary ML models.

Additionally, researchers are adopting "Divide & Conquer" strategies to break down complex CE problems into smaller, manageable tasks. For instance, Li *et al*. (2022) split the leakage detection problem in water supply networks into two stages: identifying the presence of a leak and localizing it. Similarly, Kang *et al*. (2020) separated concrete crack analysis into detection and pixel-level segmentation. These modular pipelines simplify problem-solving, improve interpretability, and allow parallel processing—contributing to more scalable and adaptable ML systems.

Despite these advances, the current literature tends to be descriptive within each domain, with limited critical synthesis that spans across the multidisciplinary spectrum. There remains a notable methodological gap in unifying models or frameworks that seamlessly integrate heterogeneous data types and domain knowledge across CE subfields. Future research should thus emphasize developing integrative ML frameworks that bridge these domain boundaries, leveraging physics-informed models, transfer learning, or federated learning approaches to capture complex interactions. Moreover, establishing standardized datasets and benchmarking protocols across CE disciplines would foster comparability and accelerate innovation. Overall, a more analytical, cross-domain perspective in CE ML applications will unlock deeper insights and guide the design of robust, multidisciplinary solutions.

Furthermore, this review identified that certain ML techniques—especially CNN-based methods for vision tasks like crack detection—appear repeatedly across multiple CE domains with only minor variations. While this reflects the versatility of these models, it also suggests opportunities for reducing redundancy through cross-domain collaboration, shared frameworks, and consolidated knowledge bases. Developing unified modeling pipelines and comparative studies across disciplines could streamline research efforts and promote methodological consistency.

6. Conclusions

This study conducted a systematic literature review to examine the application of ML across five major disciplines in CE: structural, geotechnical, transportation, water and environmental, and energy engineering. Guided by four research questions, the review aimed to assess current status, emerging trends, and practical challenges associated with ML implementation in CE.

The findings reveal that ML techniques are being widely and effectively applied to diverse problem domains within CE. These applications often target predictive modeling, decision-making, and optimization tasks, while also addressing domain-specific challenges such as limited data availability, overfitting, and the complex, multidisciplinary nature of CE systems. Although many ML studies focus on tasks such as forecasting or anomaly detection, these efforts frequently serve as foundational elements for broader management and operational strategies in CE domains—for instance, guiding pavement maintenance scheduling, infrastructure health management, or water resource policy development. This reflects the practical nature of CE, where the ultimate goal often converges on effective and sustainable system management.

Furthermore, the review highlights a growing interest in hybrid models, real-time applications, and methods that account for uncertainty and interpretability. However, the ethical, regulatory, and safety-critical aspects of deploying ML in CE deserve further attention. In particular, explainable AI (XAI) techniques—including SHAP, surrogate modeling, and uncertainty quantification—are crucial for building trustworthy and transparent ML systems in civil infrastructure applications, where decisions can have significant societal and safety implications.

Given the breadth and complexity of CE research, the scope of this review was intentionally focused on major subfields and widely adopted ML models. As such, newer model architectures—such as Transformers, physics-informed neural networks, federated learning, and large foundation models—were not included despite their increasing relevance. These emerging technologies, along with the need for standardized CE datasets and model benchmarking, represent promising directions for future research.

For future research, this study suggests several avenues. First, critical reviews focused on specific technical challenges (e.g., model generalizability, real-time control, explainability) can offer deeper insights for targeted applications. Second, quantitative meta-analyses could be conducted on frequently studied ML problems in CE to identify model performance trends, best practices, and data-related limitations. Finally, interdisciplinary research combining ML with domain knowledge, regulatory requirements, and sustainability goals will be essential to ensure that ML tools deliver safe, transparent, and socially responsible solutions for civil engineering challenges.

Despite its limitations, this study contributes a comprehensive and methodical review across CE's main domains. By bridging the perspectives of both ML and CE, it offers valuable guidance for researchers aiming to develop or adopt ML methods in CE contexts—supporting more robust, scalable, and informed research in this rapidly evolving field.

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APPENDIX A

A.1 Multilayer Perceptron

MLP is among the earliest and most extensively applied neural network architectures. MLP is composed of three types of layers: input, hidden, and output. Similar to the neurons in the human brain, each layer has fully interconnected nodes. Each node has its own input value and generates an output through signal computing operations using the node weights and biases. The model parameters (weights and biases) are optimized through a supervised learning process using backpropagation, which iteratively updates the parameters to minimize prediction error until convergence is achieved (Rumelhart *et al*. 1986). Examples of the MLP models are summarized in Table 2.

The architecture of an MLP—including the number of hidden units and the choice of activation function (e.g., sigmoid or rectified linear unit (ReLU))—is determined based on the problem's complexity, data characteristics, and performance objectives. For example, increasing the number of nodes may better capture the interactions between the input and output, thereby improving model accuracy; however, this increases the computational time and the risk of overfitting. The selection of activation functions is guided by the learning objective: ReLU is commonly employed for regression tasks, while the sigmoid functions are more frequently utilized in binary classifications (Nwankpa *et al*. 2018).

Since their first publication by McCulloch *et al*. (1943), MLPs have been extensively used across various disciplines. Models are favored for their ability to effectively solve complex problems through their remarkable features of self-learning, adaptability, and nonlinearity (Abiodun *et al*. 2018). Notable applications include the prediction of solar collector systems (Ghritlahre *et al*. 2018), the assessment of tumor responses on MRI (Kickingereder *et al*. 2019), and the analysis of vulnerability within the rice industrial chain (Song *et al*. 2021).

A.2 Convolutional Neural Network

CNN (LeCun *et al*. 1998) is a well-known ML model for image-based tasks. A typical CNN operates in two stages: (1) feature extraction through convolutional and pooling layers, and (2) prediction via fully connected layers. Convolutional layers apply learnable filters to detect local features, while pooling layers reduce spatial dimensions and emphasize salient information. The resulting feature maps are flattened and processed by fully connected layers to produce the final output.

Several CNN variants have been developed by modifying its basic structure. A region-based CNN (R-CNN; Girshick *et al*. 2014), identifies regions of interest (RoIs) for targeted feature extraction. Its successors—Fast R-CNN (Girshick 2015), Faster R-CNN (Ren *et al*. 2015), and Mask R-CNN (He *et al*. 2017)— introduce improvements in speed and accuracy. You Only Look Once (YOLO) (Redmon *et al*. 2016) achieves real-time object detection using a single-stage approach.

Due to their ability to learn spatial hierarchies, CNNs have been successfully applied in diverse domains, including urban land classification using aerial images (Zhang *et al*. 2018), joint face detection and pose estimation (Ranjan *et al*. 2017), and real-time objects recognition in videos (Maturana *et al*. 2015).

A.3 Recurrent Neural Network

RNNs differ from feedforward models such as MLP and CNN by incorporating recurrent feedback loop, enabling the modeling of sequential data, such as speech, text, or time series (Rumelhart *et al*. 1986). RNNs capture temporal dependencies by processing input sequences one step at a time, maintaining a hidden state that encodes information from previous steps (Yu *et al*. 2019). The architecture comprises three layers: input, recurrent hidden, and output. The recurrent hidden layer consists of a series of hidden states composed of a hidden layer activation function, input vector, weighted connections, and bias vector of the hidden units. Training is performed through backpropagation through time (BPTT) which unfolds the network across time steps and propagates error gradients backward (Salehinejad *et al*. 2017).

Despite their ability to model sequences, RNNs suffer from the vanishing gradient problem when learning long-term dependencies (Yu *et al*. 2019). To mitigate this, Long-short term memory (LSTM) was proposed (Hochreiter and Schmidhuber 1997). LSTM units use gating mechanisms to selectively retain or discard information, allowing the model to capture dependencies across extended sequences. Gated recurrent unit (GRU) (Cho *et al*. 2014) has offer a simplified architecture with fewer parameters than LSTM, while maintaining comparable performance in learning long-term pattern.

RNNs have been applied in tasks such as automatic writing (Wang *et al*. 2020) and language recognition (Gao *et al*. 2021). LSTM, in particular, are widely used for time-dependent predictions, including fault diagnostics in engineered systems (Wu *et al*. 2018), and electricity price forecasting (Chang *et al*. 2019).

A.4 Generative Adversarial Network

GANs are widely used for generating synthetic data that closely resemble real (Goodfellow *et al*. 2020). A GAN consists of two competing neural networks: a generator and discriminator. The former learns to generate new data samples that mimic the training data, while the latter learns to distinguish between real and fake synthetic input. Training proceeds in an adversarial manner—first updating the discriminator using both real and generated samples, then updating the generator to produce outputs that increasingly resemble real data. Random noise is fed into the generator to introduce variability and enhance output diversity. This iterative process continues until the discriminator can no longer reliably distinguish between real and synthetic data.

Owing to its ability to produce high-quality, realistic data, GANs have been employed in diverse applications, including photorealistic human face generation (Karras *et al*. 2017), image-to-image translation (Isola *et al*. 2017), road traffic states estimation (Xu *et al*. 2020) and text-to-image translation (Zhang *et al*. 2017).

A.5 Reinforcement Learning

RL trains the model through a trial-and-error interactions with an environment to learn decision-making strategies that maximize cumulative rewards. The RL framework involves two core components: an agent and an environment. At each time step t, the agent observes state (st) and takes action (at). As the agent follows the policy π(a_t |s_t), the agent learns from the new state (st+1) and reward (rt) obtained from the environment (Li, 2017). Over time, the agent seeks to learn an optimal policy π* that maximizes the expected discounted return (Perera *et al*., 2021).

The discount factor $\gamma \in [0,1)$ is used to balance immediate and future rewards, prioritizing near-term outcomes while still accounting for long-term gains. The expected return under a given policy is estimated using a value function, which evaluates the quality of a state or state-action pair. Through iterative interactions and value updates, the agent progressively refines its policy to improve performance.

Following the introduction of deep RL models incorporating CNN (Mnih *et al*. 2017), RL has been successfully applied across diverse domains, including abstractive summarization (Paulus *et al*. 2017), robotics (Zhao *et al*., 2020), recommendation systems (Tang *et al*. 2019), and game playing (Silver *et al*. 2018).