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Artificial intelligence in the design, optimization, and performance prediction of concrete materials: a comprehensive review

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Artificial Intelligence (AI) is transforming concrete research. This review explores various AI techniques that drive cutting-edge solutions across all stages of concrete lifecycle, from material, mixture, and process optimization to quality control and performance prediction. Meta-analysis shows that XGBoost model excels in predicting workability ($R^2 = 0.98$), while ensemble models provide the best strength predictions ($R^2 = 0.93$). The study highlights trends, gaps, and future AI opportunities in concrete technology.

By strategically integrating materials such as cement, coarse aggregate (ca), fine aggregate (fa), etc., economically affordable concrete can be produced with sufficient strength and durability for infrastructure construction, making concrete the most widely used construction material. The global annual consumption of concrete is estimated at approximately 30 billion tons, and this demand is expected to keep rising in the coming decades, driven by increasing population, ongoing industrialization, and rapid urbanization^{1,2}. The rapid expansion of the concrete industry requires increasingly complex prediction models for different types of concrete. The accurate prediction ensures the safety and quality of various structures throughout their entire life cycle, tailored to particular applications³.

There are three primary methods for designing and ensuring the quality of concrete: the prescriptive method, the performance-based method, and the computational method⁴. The perspective method follows step-by-step design methodologies, such as the arbitrary 1-2-3 (cement-sand-aggregate) volumetric ratio method⁵, the absolute volume method^{6,7}, etc. While these methods are suitable for large-scale and general construction projects, they lack the flexibility needed to meet specific requirements for custom mix proportions in particular cases. Unlike traditional methods with linear and non-iterative features, the performance-based method places greater emphasis on laboratory trial batches. This approach offers greater flexibility in the proportioning mixture to meet diverse design specifications. However, it requires significant investments of time and labor due to the trial-and-error nature of the iterative proportioning process⁸. The computational method for optimizing concrete mixtures involves using mathematical models. These models normally encompass problem formulation, the relationships being modeled, and the optimization algorithms employed⁴. However, the complex mechanisms governing the development

of concrete properties make it challenging for computational methods to precisely represent the relationship between mixture constituents and concrete performance objectives⁹.

Artificial intelligence (AI) refers to the field of computer science dedicated to creating systems or machines that can perform tasks typically requiring human intelligence¹⁰. AI has been widely used in concrete technology during the past years¹¹. As shown in Fig. 1, the number of publications on AI used in concrete technology has increased dramatically since the early 1990s, especially after 2020. AI technique has been the most advanced computational method for optimizing concrete mix design^{12,13} and predicting its fresh properties^{14,15}, mechanical^{16–18} and durable performance^{19,20}. Moreover, the reliable optimization and prediction results produced by AI techniques enable them to outperform traditional experimental and mathematical methods in concrete technology²¹. Therefore, AI technique, which enables to analyze vast amounts of data, identify complex patterns, and make accurate predictions, has been applied in the concrete field to enhance efficiency, accuracy, sustainability, and performance while simultaneously reducing costs and environmental impact²². Their ability to handle complex, non-linear relationships and provide real-time monitoring makes them indispensable tools for advancing concrete technology and infrastructure development. For instance, the use of AI to predict concrete properties can significantly enhance the accuracy of reinforced concrete structure designs, effectively mitigating issues of underestimation and overestimation. Traditional models may underestimate strength or durability, leading to overly conservative designs, while overestimation can result in unsafe structures. Analyzing large datasets and real-time data, AI enhances accuracy, leading to safer, more efficient designs and optimized material use. Alhalil and Gullu²³ developed a machine learning (ML) model employing five distinct algorithms to predict key characteristics of

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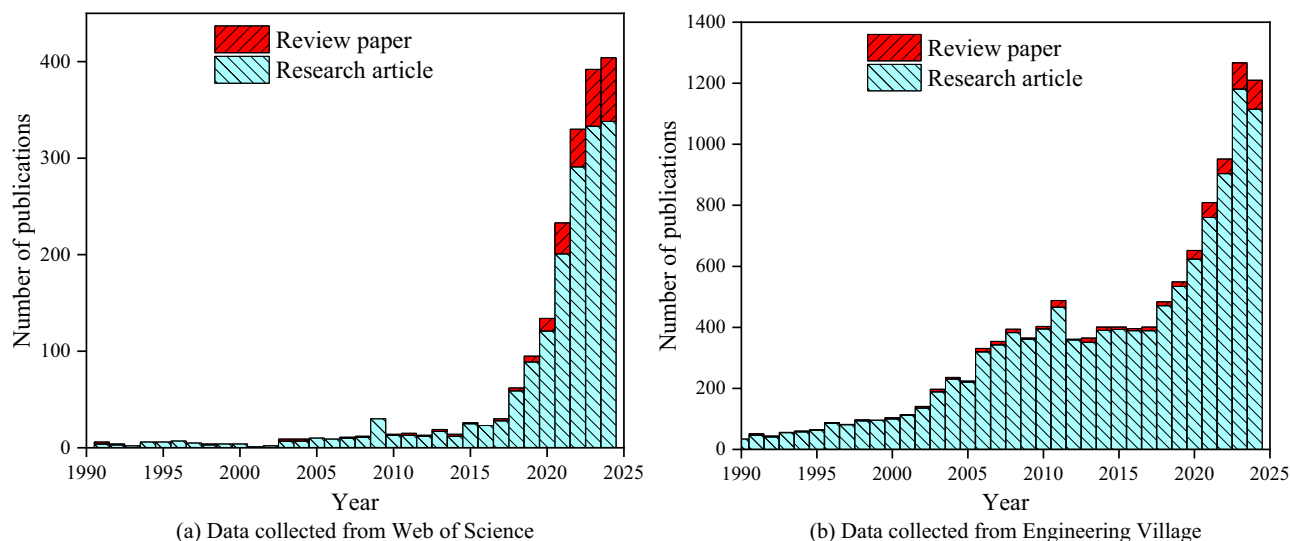


Fig. 1 | Number of publications on AI used in concrete technology since 1990 with searching keywords of “artificial intelligence” and “concrete”. a Data from Web of Science and **(b)** data from Engineering Village.

reinforced concrete structures in a 3D environment. These characteristics included the torsional irregularity, the modal participating mass ratio, and the fundamental period, achieving R^2 values of 0.977, 0.997, and 0.923, respectively. The stiffness modifiers in concrete²⁴ and its compressive strength²⁵ were also accurately predicted by ML techniques, enabling more precise material selection and mix design. This approach significantly reduces the risks associated with underestimating or overestimating concrete properties.

It can be seen from Fig. 1 that review papers related to the use of AI techniques in concrete technology have also increased significantly since 2020. Most of the existing review papers have only focused on narrow aspects of this topic. Specifically, (1) some reviews have concentrated on the use of a single AI technique in concrete, such as ML⁹; (2) others reviewed the application of AI techniques in specific types of concrete, including self-compacting concrete (SCC)²⁶, ultra-high-performance concrete (UHPC)²⁷, and UHP fiber reinforced concrete²⁸; and 3) some have examined AI applications in relation to specific properties of concrete, such as compressive strength (CS)^{29,30}, corrosion of reinforced concrete³¹, and frost resistance³². Although few recent review papers have examined AI techniques used in concrete¹¹, they still focused on a limited number of aspects as listed above. Kazemi¹¹ primarily conducted a scientometric analysis and presented an updated summary of various AI techniques used in concrete technology. The review did not address the applications of these techniques for optimizing and predicting concrete properties, which may limit its utility for beginners seeking comprehensive and detailed information.

To address the above-mentioned gaps, this study introduces the following novel contributions:

- (1) **Comprehensive Scope:** Unlike prior reviews that often focus on specific AI techniques, particular types of concrete, or isolated properties, this work provides a holistic examination of AI applications across all key aspects of concrete research. These include mix design optimization, performance and durability predictions, microstructural performance evaluation, automated inspection, and the discovery of innovative materials.
- (2) **Systematic Comparison:** This paper systematically evaluates the strengths, limitations, and effectiveness of various AI techniques, such as ML, FL, NLP, ES, Rb, and CV, in addressing diverse concrete-related challenges, with a critical analysis to guide researchers and practitioners (i.e., Fig. 3, Tables 1 and 2).
- (3) **Meta-analysis:** A comprehensive meta-analysis is conducted to compare the accuracy of different AI models in predicting concrete properties, with valuable insights into model performance provided in Table 4 and Figs. 9 and 11.

Figure 2 shows the schematic diagram of the research methodology used in this study. Firstly, the applications of different AI techniques in concrete technology (Section “AI techniques used in concrete technology”) were summarized. Then, the focus of this study extends beyond specific areas to cover a wide range of topics, including the optimization of concrete mix design using AI techniques (Section “Concrete mix design”), the prediction of fresh properties, namely, workability, rheology, setting (Section “Prediction of fresh properties of concrete”), various hardened properties, such as CS, flexural strength, and splitting tensile strength (Section “Prediction of hardened properties of concrete”), durability characteristics, including shrinkage and creep, freeze-thaw, chloride penetration, sulfate attack, alkali-silica reaction (ASR), and fire resistance (Section “Prediction of durability characteristics of concrete”). The application of AI in micro-performance prediction, automatic inspection and innovative materials investigation was also included in this study (Section “Other applications”). In the end, Section “Conclusions and Future Perspectives” summarizes the key findings of this study and future perspectives. Various types of concrete, including normal concrete, UHPC, SCC, alkali-activated concrete (AAC), steel fiber-reinforced concrete (SFRC), and 3D-printed concrete (3DPC), among others, have been considered and analyzed in this study. This comprehensive review aims to provide clear and practical guidance, especially for newcomers interested in the application of AI techniques in concrete technology.

AI techniques used in concrete technology

AI is increasingly applied in concrete technology to predict the properties and performance of concrete and optimize mix design, helping to enhance sustainability and extend the service life of concrete structures. Several AI methods have been successfully applied in concrete technology, including ML, Expert System (ES), Fuzzy Logic (FL), Natural Language Processing (NLP), Robotics (Rb), and Computer Vision (CV), as shown in Fig. 3. The main procedures to be followed for each AI method were also presented. It can be seen from the figure that the key procedural differences are driven by their distinct approaches to problem-solving and data processing. ML emphasizes data collection, preprocessing, and model training, relying heavily on feature engineering and optimization techniques to improve performance. In contrast, ES and Rb focus on defining explicit rules and knowledge representation. Especially, ES incorporates reasoning mechanisms such as forward or backward chaining, while Rb systems rely on straightforward application of predefined logic. FL differs by introducing fuzzification and defuzzification steps to handle uncertainty, relying on fuzzy rules and membership functions. NLP requires specialized text

Table 1 | Advantages, disadvantages, and applications of different AI techniques in concrete research areas

AI	Advantages	Disadvantages	Applications
ML ⁹	Automation of repetitive tasks Faster and more accurate decision-making Ability to handle large volumes of data Potential for discovering new insights	High computer cost Inadequate training data Data quality Algorithmic biases	Concrete mix design Prediction of fresh, hardened, and durable properties of concrete Automation inspection Development of new materials
ES ^{294,295}	High accuracy, Quick and efficient Enhanced decision-making	Limited flexibility Lack of common sense High development costs Time-consuming maintenance Incapable of explaining logic	Concrete mix design Prediction of hardened and durable properties of concrete Automation inspection Development of new materials
FL ^{296,297}	High precision in decision-making Flexible problem-solving High efficiency	Computational intensity Human subjectivity Incompatibility Interpretability Complex rule set-up Lack of learning capability	Concrete mix design Prediction of fresh, hardened, and durable properties of concrete Automation inspection Development of new materials
NLP ^{298,299}	Enhanced communication Automation of repetitive tasks Improved data analysis Improved decision-making	Ambiguity in language Context understanding Bias in algorithms Lack of generalization	Concrete mix design Automation inspection Development of new materials
Rb ³⁰⁰	Increased efficiency and productivity Improved quality and consistency Enhanced safety Ability to perform repetitive tasks	High initial costs Technical complexity and maintenance Limited flexibility Resistance to change	Automation inspection Development of new materials
CV ³⁰¹	Enhanced security and surveillance Real-time data processing Reduction in labor-intensive tasks Enhanced robotics capabilities High efficiency and accuracy	High development and implementation costs Complexity of implementation Limited generalization Dependence on large datasets High computational requirements Inaccuracy in complex or unstructured environments Overfitting to training data	Prediction of hardened and durable properties of concrete Automation inspection Development of new materials

Table 2 | Comparisons between different ML methods

ML methods	Description	Advantages	Disadvantages	Applications
DL ³	A subset of ML using multi-layered neural networks to model complex patterns and relationships	Excellent for high-dimensional and non-linear data Identifies subtle patterns automatically	Requires large, high-quality datasets High computational cost Limited interpretability	Predicting multivariable properties, such as CS and durability in complex systems, such as UHPC or 3DPC
GA ³⁰²	Optimization algorithms inspired by natural selection that evolve solutions to complex problems	Effectively handles non-linear optimization problems No need for gradient information	Computationally intensive for large search spaces May converge to local optima	Optimizing concrete mix designs, balancing conflicting factors like cost, environmental impact, and mechanical properties
ANN ³⁰³	A family of ML models that mimic biological neurons to model complex, non-linear relationships	Flexible and powerful for non-linear relationships Works well for multi-variable systems	Risk of overfitting if not tuned properly Requires significant computational resources	Predicting compressive, tensile, and flexural strength, as well as shrinkage, creep, and hydration behavior
RL ³⁰⁴	A type of ML where an agent learns optimal actions in an environment through trial and error, guided by rewards	Handles time-dependent or sequential decisions Can adapt to real-time data	Needs a well-defined reward structure Computationally expensive and complex to implement	Optimizing curing conditions, adaptive control of 3D-printing parameters, or real-time optimization of mixing and delivery processes
IoT ³⁰⁵	A network of interconnected devices that collect and exchange real-time data	Enables real-time data collection and decision-making Facilitates predictive maintenance and monitoring	Requires infrastructure investment May face data security or connectivity challenges	Monitoring curing temperature, humidity, and shrinkage Structural health monitoring of bridges and buildings to ensure long-term durability
DM ^{306,307}	The process of extracting patterns and knowledge from large datasets using statistical and computational techniques	Identifies patterns in large datasets Useful for understanding long-term trends	Limited predictive power without integration with advanced ML models Requires high-quality preprocessing	Analyzing historical performance data for mix designs Identifying long-term durability trends and failure patterns in concrete structures
RF ⁷¹	An ensemble learning technique using multiple decision trees to improve prediction accuracy	Robust to overfitting Provides feature importance for interpretability	Computationally expensive for large datasets May not perform well for extrapolation outside the training range	Predicting mechanical and durability properties (e.g., CS, chloride penetration). Assessing the importance of different mix variables for property optimization.

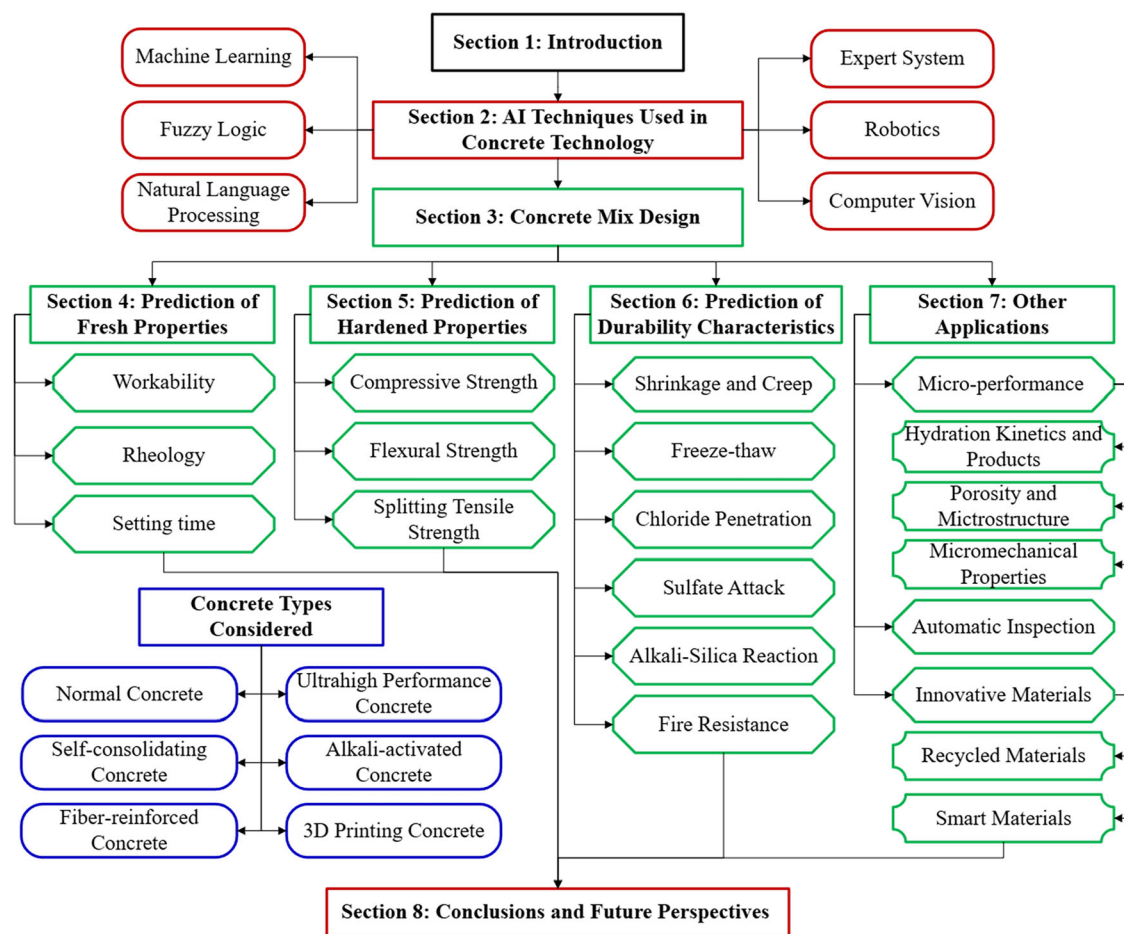


Fig. 2 | Schematic diagram of research methodology.

preprocessing (e.g., tokenization and lemmatization) and feature extraction, often followed by the application of advanced models like transformers to interpret language patterns. CV focuses on preprocessing visual data, extracting features using techniques like convolutional neural networks, and optimizing models for tasks such as object detection or image segmentation. Moreover, hybrid AI methods, which combine multiple individual models, are often used to enhance the accuracy and performance of the overall system. The advantages and disadvantages, as well as the applications in concrete research areas, are summarized in Table 1.

ML employs algorithms to analyze data, extract patterns, and make informed decisions or predictions based on the insights it has gained from the data. Various subsets of ML were developed and used in concrete, such as Deep Learning (DL), Genetic Algorithms (GA), Artificial Neural Network (ANN), Reinforcement Learning (RL), Internet of Things (IoT), Data Mining (DM), Random Forest (RF), etc. ML has been extensively applied across various areas of concrete research, including mix design of concrete⁴, prediction of fresh³³, hardened³⁴, and durable³⁵ properties, automated inspection³⁶, and the development of new materials³⁷, as illustrated in Table 1. It is important to note that, unlike other well-established ML models used in concrete technology, only a few recent studies³⁸ have employed RL in this field. The comparisons between different ML methods, in terms of their advantages, disadvantages, and applications in concrete field were summarized in Table 2.

From Table 2, it can be concluded that DL and ANN excel at capturing highly non-linear relationships between input features and complex concrete properties, though they require substantial computational power and large datasets. GA is particularly well-suited for optimization tasks, such as designing concrete mixes while balancing multiple objectives. RL is highly effective for adaptive, real-time applications, including optimizing curing conditions or 3D-printing parameters. Meanwhile, IoT and DM primarily

focus on data collection and trend analysis, providing actionable insights but lacking strength in direct predictions. RF offers a strong balance of robustness, accuracy, and interpretability, making it a reliable choice for multi-variable property prediction. The discussion has been added to the manuscript

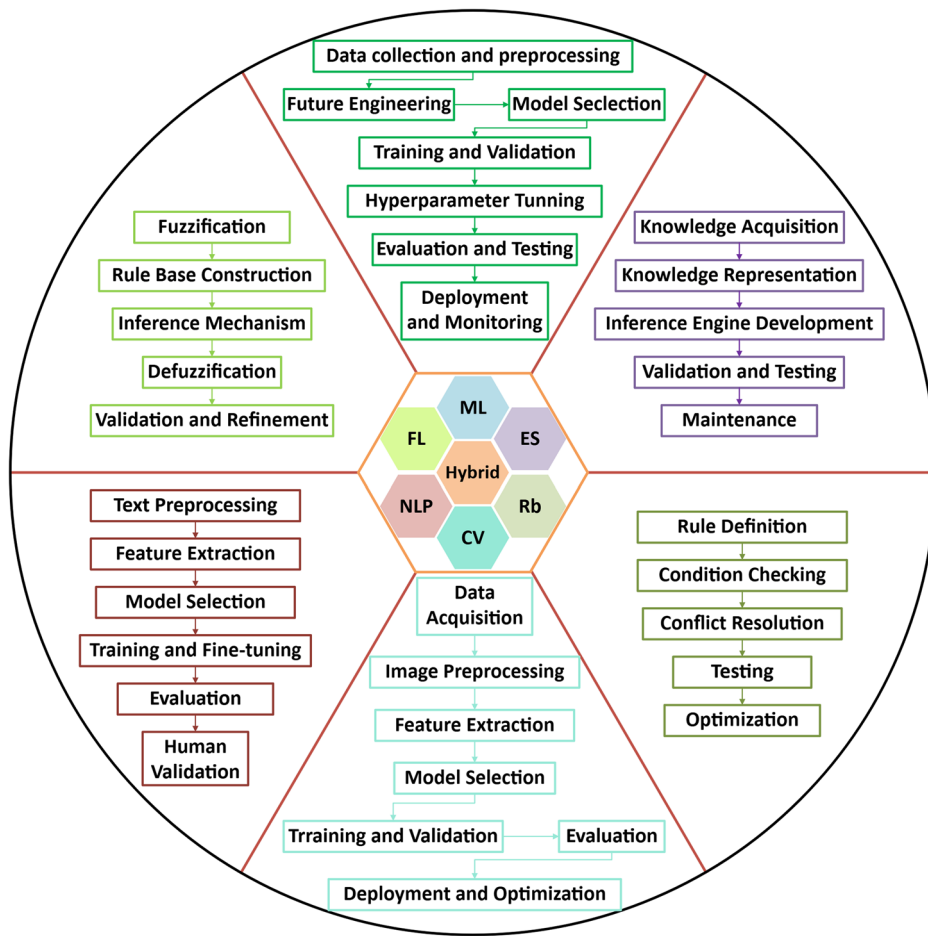
ES is designed to solve complex problems by applying reasoning to a specialized body of knowledge, typically within a narrow domain, using if-then logic to replicate human expert decision-making. ES has been applied to the research areas of mix design of concrete³⁹, predictions of hardened⁴⁰ and durable concrete properties⁴¹, automation inspection⁴², and development of new materials⁴³.

FL is a computational approach that allows for the processing of variables with multiple possible truth values, rather than just binary true or false. It is designed to solve problems that involve a spectrum of imprecise data and heuristics, enabling the derivation of a range of accurate conclusions. As an advanced AI method, FL has also been widely used in most concrete research areas, such as mix design of concrete⁴⁴, prediction of fresh⁴⁵, hardened⁴⁶, and durable⁴⁷ properties, automated inspection⁴⁸, and the development of new materials⁴⁹.

NLP is a branch of AI focused on enabling computers to interact with humans using natural language. The primary objective of NLP is to empower computers to comprehend, interpret, and respond to human language in a manner that is both meaningful and effective. It has been used in automated inspection⁵⁰ and the development of new materials⁵¹ in concrete technology. Moreover, large language models (LLMs), commonly associated with NLP, have also been applied to concrete mix design⁵²; however, their use in this area is still in the early stages of development.

Robotics involves the design, construction, operation, and use of robots that are programmable machines capable of performing tasks autonomously, semi-autonomously, or under human supervision. In concrete

Fig. 3 | An overview of AI methods and the corresponding main procedures used in concrete.



technology, robotics has been mainly popular in the 3D printing of concrete⁵³ and automated inspection or assessment⁵⁴.

CV is a branch of AI that enables computers to interpret and understand visual information from the world, such as images and videos. CV aims to replicate the intricate processes of human vision, allowing machines to perceive, analyze, and make informed decisions based on visual data. Due to its ability to analyze visual data, CV has been adapted to predict the hardened⁵⁵ and durable⁵⁶ properties of concrete, inspect concrete automatically⁵⁷, and develop new materials⁵⁸.

As shown in Table 1, certain limitations in AI methods pose challenges to their application in concrete technology. For instance, ML can handle repetitive tasks and large volumes of data automatically and provide faster and more accurate decision-making, etc. However, the high computer cost, inadequate training data with low quality, and algorithmic biases limit its application. To address the limitations of AI methods, a hybrid approach is normally adopted. For example, Topcu and Sarıdemir⁵⁹ predicted the CS of fly ash (FA)-contained concrete by combining ANN and FL. Asteris et al.⁶⁰ also accurately and efficiently predicted the CS of concrete using a hybrid ensemble of four conventional ML models, namely ANN, linear and non-linear multivariate adaptive regression splines, Gaussian process regression (GPR), and minimax probability machine regression.

Moreover, dataset quality is crucial for the performance of AI models, as it directly affects their capacity to learn, generalize, and produce accurate predictions⁶¹. However, real-world datasets are often of poor quality, containing noise, bias, outliers, or missing values, which can challenge the reliability and accuracy of ML approaches regardless of the algorithm's quality. Lyngdoh et al.⁶² effectively addressed the challenge of missing data in predicting the CS and tensile strength of concrete using ML by employing various efficient data imputation methods. These methods include removing instances with missing values, imputing using mean or median

values, applying k-Nearest Neighbors imputation, and utilizing multivariate imputation through chained equations.

Similarly, in CV, low-resolution images, inconsistent annotations, or a lack of diversity in the dataset can severely affect the ability of models to detect objects, classify images, or segment visual scenes. A cross-review framework was proposed to achieve high-quality construction material datasets for CV in the construction management domain⁶³. NLP models are equally dependent on high-quality datasets, as issues like grammatical errors, inconsistent labeling, or inadequate representation of linguistic nuances can lead to models that fail to capture the complexities of human language. In these domains, thorough preprocessing, robust data augmentation, and access to diverse, balanced datasets are crucial for achieving optimal performance.

For Rb and ES, the dataset quality primarily affects the accuracy and reliability of rules derived from data or used for validation. When rules are designed based on incomplete or erroneous data, the systems' decision-making processes can become flawed, leading to incorrect outputs. In FL, dataset quality impacts the creation of membership functions and fuzzy rules; poor-quality data can result in imprecise definitions of fuzzy sets, compromising the system's ability to handle uncertainty effectively. While these systems may not require large datasets like ML or CV, the reliability and representativeness of the data used to define rules or calibrate parameters are critical. Across all AI models, rigorous data validation, cleaning, and annotation are essential steps to ensure that the quality of the dataset supports accurate and robust model performance.

Concrete mix design

Concrete normally comprises cement, water, fa, ca, or some supplementary cementitious materials (SCMs, i.e., FA, calcined clay, limestone powders, silica fume (SF), etc.), and chemical admixtures (i.e., superplasticizer (SP), etc.). Therefore, optimizing the concrete mix design is crucial for achieving

maximum economic efficiency (i.e., minimizing cement content⁶⁴) and superior performance in construction. Computational methods for optimizing concrete mixtures offer powerful tools for designing concrete with improved properties while minimizing costs and environmental impact⁴. These techniques, ranging from classical statistical methods to advanced AI algorithms, are increasingly being applied to concrete mix designs for both conventional and sustainable concrete solutions. However, the traditional computational methods most frequently used in concrete mix design, such as response surface methodology, linear combinations, and statistical models, primarily rely on empirical relationships. While these methods are relatively simple, practical, and have served the industry well over the years, their limitations are becoming more apparent as the construction sector faces the demands of high-performance, sustainable, and cost-efficient concrete. These traditional approaches often lack precision, flexibility, and the ability to effectively incorporate modern materials or address environmental concerns. As a result, there is a growing need for more advanced computational techniques, such as ML, FL, ES, and NLP, to overcome these limitations and improve concrete mix design in the modern context. The most commonly used AI algorithms are reviewed in this section.

Machine learning

Figure 4 shows the flow of using ML for concrete mix design. ML normally needs a large volume of data; therefore, dataset preparation is the first step for concrete mix design. As seen in Fig. 4, the data can be collected from lab experiments, finite element simulations, published literature, and field tests. Once sufficient data is collected, it should be normalized and split into different datasets based on relevant features before proceeding with further analysis. For example, the concrete data was normalized and split into training, validation, and test datasets⁶⁵.

Then, the appropriate ML algorithms should be selected for specific cases. There are various ML algorithms, namely Linear Regression (LR), Non-linear Regression (NLR), RF, ANN, and Support Vector Regression (SVR), etc., as shown in Fig. 4. Compared to other ML approaches, LR is a straightforward and relatively simple supervised ML algorithm with low computational costs. Therefore, LR has been widely used to linearly correlate a dependent variable with one or more independent predictors⁶⁶. However, the relationship between the variables for the concrete mix design is not always linear, which leads to inaccurate predictions with LR. NLR can be used to handle input variables that have non-linear relationships with the output variable, reaching a more accurate prediction than LR⁶⁷. By employing an LNR programming, Yeh⁶⁸ optimized a high-performance concrete mix proportion to achieve the desired workability and CS.

RF is an ensemble ML algorithm composed of multiple Decision trees (DTs). These DTs are built using randomly selected subsets of data that are generated through bootstrap aggregating⁶⁹. Compared with other ML methods, RF can avoid overfitting problems⁷⁰. Sun et al.⁷¹ have established five RF models to optimize the mix design of AAC, which meets the property requirements, namely CS, slump, static yield stress, dynamic yield stress, and plastic viscosity.

ANN is highly nonlinear and capable of capturing complex relationships between input and output variables in a system, without requiring prior knowledge of the nature of these interactions⁷². For purposes of saving cost, labor, and time and reducing the number of trials and errors, the prediction models were built based on ANN⁷² for optimizing concrete mix proportions. Five parameters, namely nominal water-cement ratio, equivalent water-cement ratio, average paste thickness, FA-binder ratio, and grain volume fraction of fa, were considered the factors that impact mix proportions. These five parameters are then non-linearly correlated to the behaviors of concrete (such as strength, slumps, etc.) with the proposed prediction models according to ANN. Yue et al.⁷³ optimized the design of high-strength concrete mix proportions to improve crack resistance with a relationship among slump, CS, tensile strength, elastic modulus, and mix proportion built using ANN.

SVR is also a powerful modeling tool developed by Cortes and Vapnik in 1995⁷⁴ and is widely used in concrete mix design due to its superior generalization capacity and computation ability⁷⁵. SVR uses kernel parameters to understand the complex correlation between the input and output data and

thereby converts nonlinear problems to linear ones^{76,77}. Huang et al.⁷⁵ used an SVR and firefly algorithm based multi-objective optimization model to efficiently find the optimum mix design of steel fiber reinforced concrete. High correlation coefficients of the uniaxial CS (0.91) and flexural strength (0.85) were yielded on the test dataset. However, it should be noted that a major weakness of SVR is its performance being highly dependent on hyperparameters, which are challenging to tune using traditional optimization methods⁷⁸.

Hyperparameters must be optimized to reach a robust performance result in non-parametric models. Therefore, multiple hyperparameter tuning methods have been developed and used in concrete mix design optimization, such as particle swarm optimization (PSO)⁷⁹, K-fold cross-validation⁶⁵, Bayesian optimization⁸⁰, and Grid/Random search⁸¹, etc. Among these hyperparameter tuning approaches, the Grid search method can be only applied to solve some simple problems with few parameters due to its computation complexity⁸². On the contrary, nature-inspired optimization methods, such as PSO, can be used for more complex problems with more accurate and reliable results⁸³.

Various error metrics were applied to evaluate the abilities of ML methods for concrete mix design, including coefficient of determination (R^2), mean absolute error (MAE), mean absolute percentage error (MAPE), root mean squared error (RMSE), mean squared error (MSE), correlation coefficient (R), scatter index (SI), symmetric mean absolute percentage error (SMAPE), etc. R^2 defines the proportion of variance in the dependent variable that is explained by the independent variables. R represents the strength and direction of a linear relationship between the actual and predicted values. SI refers to the normalized prediction accuracy, which can be used for datasets having wide-range variable values. Compared to other metrics, MAE is less sensitive to outliers as it assigns equal weight to all errors. MAPE measures the relative error, indicating the magnitude of errors in relation to the actual values. RMSE weights larger errors more significantly than smaller ones it can, therefore, assess prediction accuracy more effectively. MSE measures the average of the squared differences between the actual values and the predicted ones by the models. SMAPE measures the percentage difference between the actual and predicted values, which provides a more balanced view compared to the traditional measures such as MAPE. These metrics are defined below^{84,85}:

$$R^2 = 1 - \frac{\sum_i (y_{E,i} - y_{P,i})^2}{\sum_i (y_{E,i} - \bar{y})^2} \quad (1)$$

$$MAE = \frac{1}{n} \sum_i |y_{E,i} - y_{P,i}| \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_i (y_{E,i} - y_{P,i})^2} \quad (3)$$

$$MAPE = \frac{100}{n} \sum_i \left| \frac{y_{E,i} - y_{P,i}}{y_{E,i}} \right| \quad (4)$$

$$MSE = \frac{1}{n} \sum_i (y_{E,i} - y_{P,i})^2 \quad (5)$$

$$R = \frac{n \sum_i y_{P,i} y_{E,i} - (\sum_i y_{P,i})(\sum_i y_{E,i})}{\sqrt{n(\sum_i y_{P,i}^2) - (\sum_i y_{P,i})^2} \sqrt{n(\sum_i y_{E,i}^2) - (\sum_i y_{E,i})^2}} \quad (6)$$

$$SI = \frac{RMSE}{\bar{y}} \quad (7)$$

$$SMAPE = \frac{1}{n} \sum_i \frac{|y_{E,i} - y_{P,i}|}{\frac{|y_{E,i} + y_{P,i}|}{2}} \times 100 \quad (8)$$

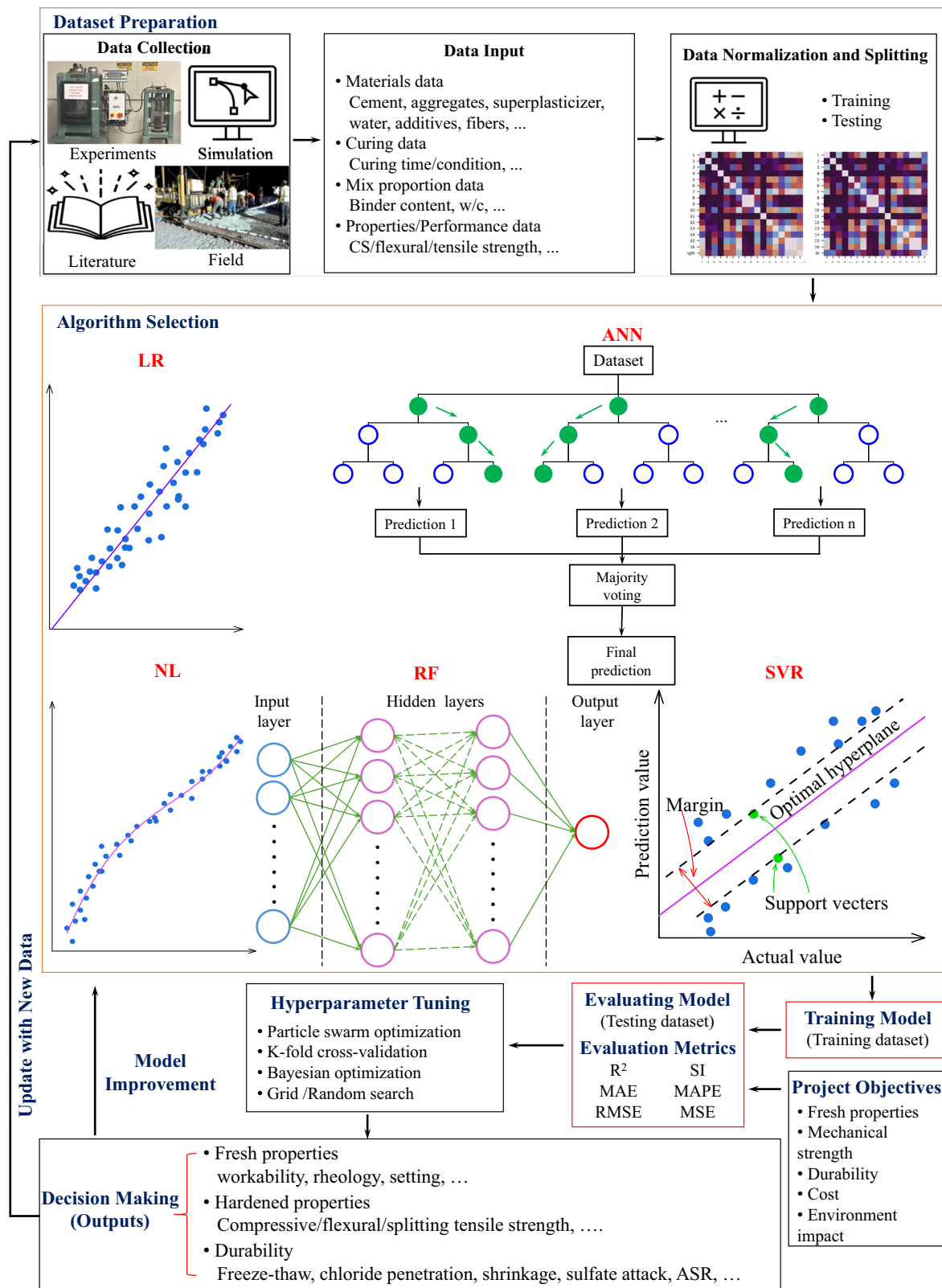


Fig. 4 | Chart flow of ML used in concrete mix design.

where $y_{E,i}$ and $y_{P,i}$ are the experimental and predicted values, respectively, of the i th data sample, n is the number of data points, and $\bar{y}$ is the average value in the database.

Multiple objectives are typically pursued simultaneously during concrete construction⁸⁶. Therefore, to achieve the optimal tradeoff among the

multiple objectives of concrete performance, durability, economic cost, and climate impact, corresponding models were applied in ML for concrete mix design optimization, effectively linking the multiple input design parameters with the desired output objectives⁶⁵. Sustainable concretes can be optimally designed to account for factors such as the sustainability index, CS, cost,

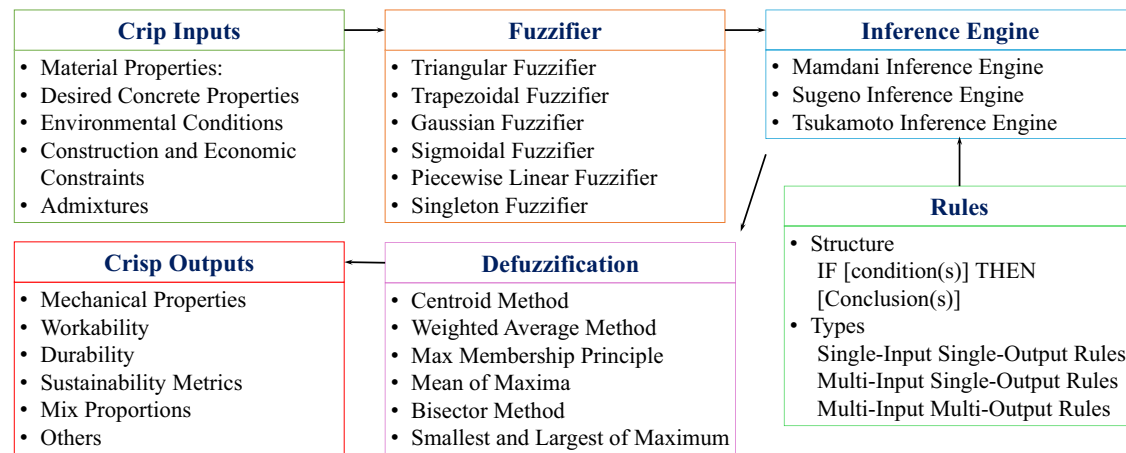


Fig. 5 | FL architecture.

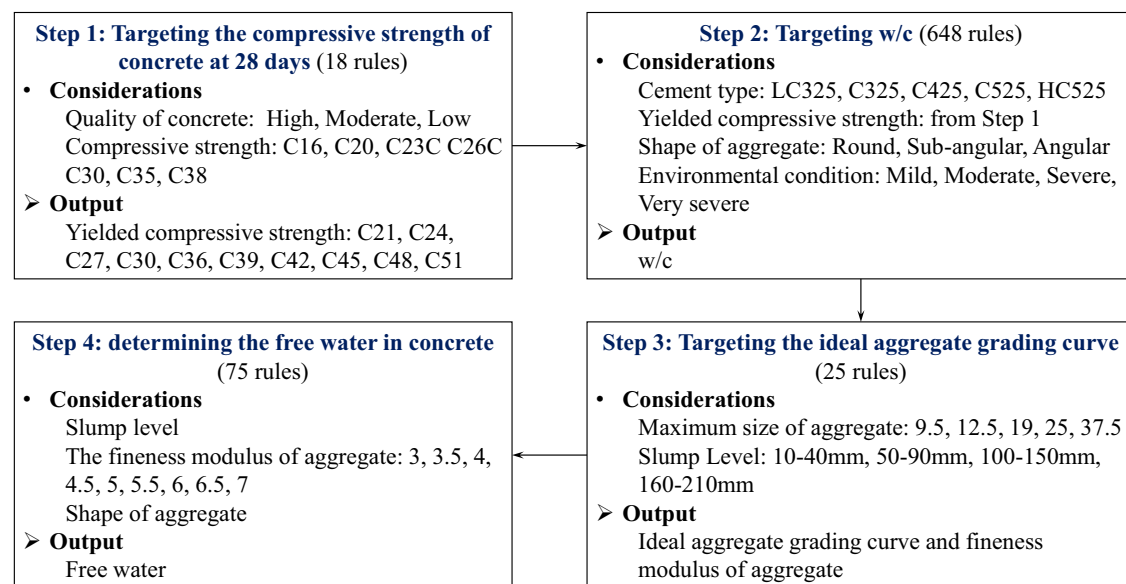


Fig. 6 | A schematic representation of a fuzzy system for concrete mix design with four sub-fuzzy systems (Note: C_n in Step 1 represents an approximate specific CS of n MPa at the age of 28 days, for example, C16 means the 28-day CS of approximately

16 MPa. In Step 2, C325, C425, and C525 mean the concrete has CSs of standard cement mortar of 325, 425, and 525 kg/cm² at the age of 28 days, respectively. LC325 and HC325 have CS below and above 325 kg/cm², respectively).

environmental impacts, embodied CO₂, energy consumption, and resource consumption⁸⁷.

Fuzzy logic

FL can also effectively manage the linguistic and probabilistic aspects of concrete mix proportioning, making it a suitable technique for developing feasible concrete mix designs⁸⁸. Figure 5 presents the FL architecture, which consists of four main parts, namely rules, fuzzifier, inference engine, and defuzzification⁸⁹. Rules refer to all the rules and If-then conditions to control the decision-making system, which can be divided into three types: Single-Input Single-Output Rules, Multi-Input Single-Output Rules, and Multi-Input Multi-Output Rules. Fuzzification converts the inputs into the fuzzy set for further processing. There are multiple fuzzifiers available, including triangular, trapezoidal, Gaussian, sigmoidal, piecewise linear, and singleton Fuzzifiers. The Inference Engine determines the degree of match between the fuzzified inputs and the rules. Three main Inference Engines can be selected based on the specific targets of the modeling: Mamdani, Sugeno, and Tsukamoto. The last step of defuzzification converts the fuzzy set back into a crisp value as output. For concrete mix design specifically, the outputs

can be the mechanical properties (i.e., CS, flexural and tensile strength), workability (i.e., slump value and flowability), durability (i.e., freeze-thaw, chloride penetration, sulfate attack, ASR, fire resistance, shrinkage and creep), sustainability metrics (i.e., cement content and carbon footprint), and optimal mix design, etc.

Figure 6, created based on ref. 88, shows a schematic representation of using a fuzzy system for concrete mix design. Four sub-fuzzy systems were designed to optimize the concrete mix proportions, in terms of target CS, water-to-cement (w/c) ratio, ideal grading curve, and fineness modulus of aggregate, and free water. For example, in the target CS sub-fuzzy system, concrete quality and CS were considered the inputs, and with 18 rules included, the target CS of the concrete can be reached as output. Then, the cement type, shape of aggregate, environmental condition, and the target CS were used as the inputs for the w/c ratio sub-fuzzy system for reaching a target w/c ratio with 648 rules in total followed. Subsequently, the maximum size of aggregate and slump level of concrete were then used as inputs for the ideal aggregate grading curve sub-fuzzy system. The ideal aggregate grading curve and fineness modulus of aggregate were achieved with 25 rules. Eventually, the free water sub-fuzzy system was proposed to determine the

target free water in concrete mix design. It should be noted that the free water in concrete means the excess water beyond what is needed from the chemical reaction between the water and cement and is typically added to improve the workability of the concrete mixture. By utilizing this FL system, the maximum aggregate packing density and reduced cement content can be achieved, leading to a concrete design with a lower environmental impact compared to traditional methods.

Natural language processing/Large language models

Traditionally, NLP has been used in construction primarily for reviewing specifications during the early phases of a project, as it helps practitioners automatically analyze construction documents^{90,91}. Recently, Völker et al.⁵² have sought to demonstrate the effectiveness of using LLMs, typical of NLP, by adopting a knowledge-driven design (KDD) approach in the design of AACs. The novel KDD approach outperforms traditional data-driven design, which struggles to manage the dynamic and complex nature of concrete systems, particularly AACs. In contrast, KDD operates largely independently of traditional training data by incorporating fuzzy domain knowledge and lab feedback expressed in natural language. Therefore, it can simplify complex AI processes. Chat models (GPT-3.5-Turbo and GPT-4.0-Turbo) were used in the study⁵² to explore the optimal formulations of ACCs with the inputs of FA, ground granulated blast-furnace slag (GGBFS), FA/GGBFS ratio, w/c, and curing methods (i.e., ambient and heat curing). It concluded that the chat-based design approach, enhanced by contextual information and post-training strategies like verifier models, outperformed traditional methods. Moreover, it found that GPT-3.5-Turbo surpassed GPT-4-Turbo at a lower cost, highlighting the effectiveness of AI-driven design optimization without reliance on initial training data. However, this study focused solely on a specific AAC design, highlighting the need for further research to extend the application of LLMs to other types of concrete. Improving the quality of context could be a valuable strategy for enhancing future explanations provided by LLMs.

Prediction of fresh properties of concrete

Fresh properties of concrete refer to the characteristics of concrete in its plastic or freshly mixed state before it hardens. These properties are crucial because they influence the workability, ease of placement, and overall quality of the finished concrete. Fresh properties of concrete, such as workability⁹², rheology³³, and setting time⁹³, etc., have been successfully predicted using various AI-driven methods.

Workability

Workability refers to the ease with which concrete can be mixed, placed, compacted, and finished without segregation or bleeding. It is a key property of fresh concrete, influencing the handling and final quality of the structure. Multiple methods have been proposed and used to evaluate the workability of fresh concrete, such as slump flow⁹⁴, flow table test⁹⁵, T₅₀⁹⁶, J-Ring⁹⁷, L-box⁹⁸, funnel test⁹⁹, Kelly ball test¹⁰⁰, etc. Although these methods provide simple and convenient indicators of concrete workability, they are typically performed before the placement of concrete. If the results show that the concrete is not up to standard, this can lead to material waste and necessitate adjustments to the concrete mix design. Therefore, various AI-driven models have been developed to predict the workability of concrete before or during the mixing process, allowing for adjustments before the concrete is poured.

A DL model incorporating a convolutional neural network (CNN), a recurrent neural network (RNN), and a long short-term memory (LSTM) network was proposed by Yang et al.¹⁰¹ to automatically estimate slump value and slump flow value, using image data captured in a mixing station. Other AI-driven methods were also used to predict the concrete workability. For instance, a total of 1719 self-consolidating concrete mixtures from over 100 published studies in the last decade were collected and then the slump flow and V-funnel values were predicted using the extreme gradient boosting (XGB) ML algorithm¹⁰², and it concluded that the XGB technique is highly capable of learning the relationship between the mix design and

workability properties with high accuracy. The Least Squares-Support Vector Regression (LS-SVR) was also employed to model the nonlinear relationship between the mix design and slump values of concrete¹⁰³. The precise prediction of LS-SVR was confirmed by the low average MAPE values (< 3%) obtained from the cross-validation process.

Moreover, open datasets based on historical and experimental data play a critical role in establishing benchmarks for the prediction process. There are a few available data sets that can be used to analyze and establish benchmarks, for example, the comprehensive concrete slump and strength dataset on Kaggle¹⁰⁴ and UCI Machine Learning Repository¹⁰⁵ etc.

Rheology

In addition to workability, rheology has also been an essential tool for defining the fresh-state properties of concrete, particularly for SCC, 3D-printed concretes, and UHPC^{106,107}. Rheology is a field of physics that examines how matter deforms and flows, focusing on the relationships between stress, strain rate, and time¹⁰⁸. Despite the lack of standardized methods for measuring concrete rheology, shear yield stress (τ_0) and plastic viscosity (μ) are generally recognized as key parameters^{109,110}. Other parameters, including thixotropy¹¹¹, structural build-up¹¹², shear-thinning and thickening¹¹³, flow resistance¹¹⁴, and torque viscosity¹¹⁵, have also been investigated as rheological properties of concrete.

Several models, such as Bingham's model¹¹⁶, Herschel-Bulkley¹¹⁷, and Modified Bingham model¹¹⁸, have been used to characterize the rheology of concrete. However, due to the complexity of heterogeneous concrete, various factors, including cement type, aggregate properties, water-to-binder (w/b) ratio, particle size, water content, and chemical additives, can impact its rheology, leading to potential inaccuracies in modeling¹⁰⁶. Therefore, many researchers have successfully developed various AI-driven models, such as decision tree¹⁵, ANN¹¹⁹, hybrid PSO-LSSVR model¹²⁰, etc., to enhance the accuracy, reliability, and efficiency of concrete rheology predictions.

As shown in Fig. 7, Nazar et al.³³ developed a new mathematical model for predicting rheology parameters, i.e., τ_0 and μ , of concrete using an ML algorithm gene expression programming (GEP) (Fig. 7a). Initially, the static-length chromosomes are generated by all individuals. Then, the expression trees with an evaluation of fitness were proposed to represent these chromosomes. After the best-fit individuals were chosen, the best solution was acquired based on the iteration of fitness. Eventually, genetic functions are staged to obtain the final mathematical expression with the best performance. Figure 7b exhibited the comparison between the tested and predicted results based on the GEP model. The accuracy of predicting both τ_0 and μ is validated by the R² values exceeding 0.97. Moreover, the low absolute errors between the experimental and predicted results for τ_0 and μ (see Fig. 7c), with average errors of 5.30 and 2.34 and maximum errors below 10 and 5, respectively, further validate the accuracy of the developed GEP model.

Setting time

The setting of cement refers to the process through which cement transitions from a liquid or semi-liquid state to a solid or hardened state after being mixed with water¹²¹. This process involves two stages: initial and final settings. The setting time is also an essential indicator for ensuring the overall quality of concrete. The setting time of cement can directly impact the workability, hardened properties, and constructability of concrete. To allow adequate time for mixing, transporting, and constructing with concrete, the cement's setting time should be both reasonable and consistent. It was reported that the setting of concrete can be influenced by various factors, such as clinker compositions¹²², admixtures¹²³, temperature¹²⁴, humidity¹²⁵, cement fineness¹²⁶, w/c ratio¹²⁷, etc. Given the importance and the complex factors influencing setting time, a precise estimation method based on external standards is essential for effective quality control of concrete.

Except for the traditional methods for measuring the setting time of cement, such as the Vicat needle test, penetration resistance, Gillmore needles, etc.,¹²⁸ several alternative and indirect estimation methods have also

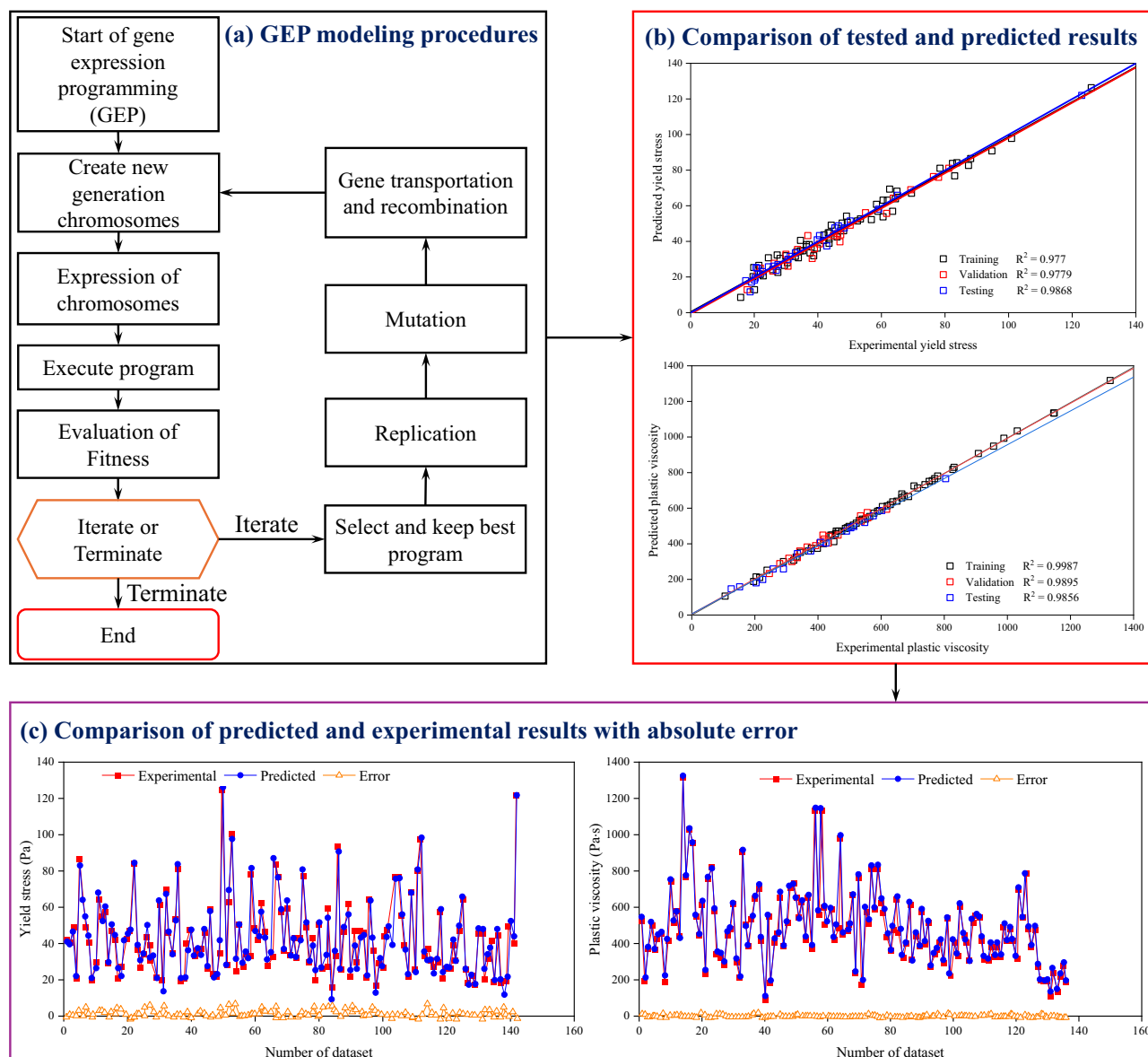


Fig. 7 | An ML algorithm gene expression programming (GEP) model to predict the concrete rheology. a GEP modeling procedures, **b** comparison of tested and predicted results, **c** comparison of predicted and experimental results with absolute error.

been proposed. For example, semi-adiabatic calorimetry¹²⁹, isothermal calorimetry¹³⁰, ultrasonic pulse velocity testing¹³¹, and electrical resistivity¹³². However, direct measurement methods can be subjective and vary between operators, while indirect estimation methods often involve complex data interpretation¹³³. These limitations can impact the accuracy and reliability of both approaches.

Several AI-driven models have also been adapted to study the setting time of cement recently, which are summarized in Table 3. By considering the compositions of cement, Oley et al.⁹³ successfully predicted the setting behavior of cement using various ML models. Compared with LR and k-nearest neighbor regressor (KNN), the DT ensemble models, especially the Extra tree (Extra) estimator, showed higher accuracy in estimating the setting behavior of cement, with the R^2 , RMSE, and MAPE values of 0.547, 25.5 mm, and 14.7%, respectively. The NNs¹³⁴, back-propagation neural network (BPNN)¹³⁵, and ANN¹³⁶ were also used to predict both the initial and final setting time of different cement/concrete, such as SSC, hydroxyapatite cement, and regular cement paste, respectively. As an alternative approach to deep NNs, a broad learning system was proposed by Guo et al.¹³⁷ to enable the rapid and accurate prediction of the setting time of

cement with features that contain clinker composition and physical properties. The ultrasonic wave characteristics, such as P-wave energy, velocity, main frequency, and amplitude at the main frequency, along with S-wave energy, velocity, main frequency, and amplitude at the main frequency, were used as inputs for data-driven models to predict the initial setting time of cement¹³⁸. It was concluded that this approach outperforms traditional detection techniques (such as isothermal calorimetry, P-wave, and S-wave methods) in both accuracy and timeliness.

Other than ML methods, FL was also adopted in predicting the setting behavior of cement. For example, Gulbandilar and Kocak¹³⁹ successfully predicted the effects of FA and SF on the setting time of cement using FL with R^2 values up to 0.96. Then, the accuracy of FL in predicting the setting time of cement was again confirmed with R^2 values higher than 0.93 by considering the influence of GGBFS and waste tire rubber powder¹⁴⁰.

Discussion on the reliability of the models

As outlined in Section “AI techniques used in concrete technology”, various metrics can be used to evaluate the prediction accuracy and reliability of AI-driven models. Among these, the R^2 value is the most employed, while others

Table 3 | Examples of AI-driven models used in studying the setting time of cement

Inputs	AI models	Metrics	Main Findings
(1) ⁹³ Compositions of cement (SiO ₂ , Al ₂ O ₃ , Fe ₂ O ₃ , CaO, C ₃ S, C ₂ S, C ₃ A, C ₄ AF, Free CaO, MgO, SO ₃ , Na ₂ O, K ₂ O, loss on ignition, Blaine fineness)	LR, Gradient trees, KNN, Bagging tree, Random tree, Extra tree, Boosted tree	RMSE, MAPE, R^2	Ensembles of DTs consistently produced the lowest errors among the algorithms. The Extra tree showed the highest R^2 value of 0.547, and the lowest RMSE and MAPE of 25.5 mm and 14.7%, respectively.
(2) ¹³⁴ Water, cement, FA, metakaolin, ground granulated GGBFS, SF, fa, ca, SP	NNs	Correlation coefficient (R), MSE	The models developed by using NN have a high prediction capacity for both initial and final setting times of SCCs, with R values higher than 0.9991 and MSE values lower than 0.1503.
(3) ¹³⁵ Concentration of NaH ₂ PO ₄ · 2H ₂ O, liquid/powder ratio	BPNN	MSE, average error	The MSE value fell below 0.001. The average errors were lower than 4.8% using the 3-output NN.
(4) ¹³⁶ Composition of cement (CaO, Al ₂ O ₃ , Fe ₂ O ₃ , SiO ₂), w/c, cement content and fineness, temperature, slag, FA, SF, cementitious materials' fineness	ANN	R , MSE	High R values above 0.949 were yielded in all cases. The best prediction performance was obtained with five hidden neurons. Higher prediction performances were observed from Levenberg-Marquardt than Scaled conjugate gradient, with an R -value of 0.9986.
(5) ¹³⁷ Clinker compositions and physical properties	Broad learning system	MAPE, MSE, RMSE, R , R^2	The R^2 values up to 0.994 and low MAS, MAPE, MSE, and RMSE values confirmed satisfactory prediction results.
(6) ¹³⁸ Ultrasonic features: P-wave energy, velocity, main frequency, and amplitude at the main frequency; S-wave energy, velocity, main frequency, and amplitude at the main frequency	KNN, LR, RF, Support vector machines (SVM), Gradient Boosting (GB), DT, XGB	SHapley Additive explanation (SHAP)	Higher accuracy and timeliness than traditional detection techniques (isothermal calorimetry, P-wave, and S-wave methods).
(7) ¹³⁹ Cement, FA, SF	FL	R^2	The R^2 values for the predictions of initial and final setting time are 0.96 and 0.92, respectively.
(8) ¹⁴⁰ Cement, GGBFS, waste tire rubber powder	FL	R^2	The R^2 values for the predictions of initial and final setting time are 0.93 and 0.95, respectively

Table 4 | R^2 values of representative AI models for predicting fresh properties of concrete

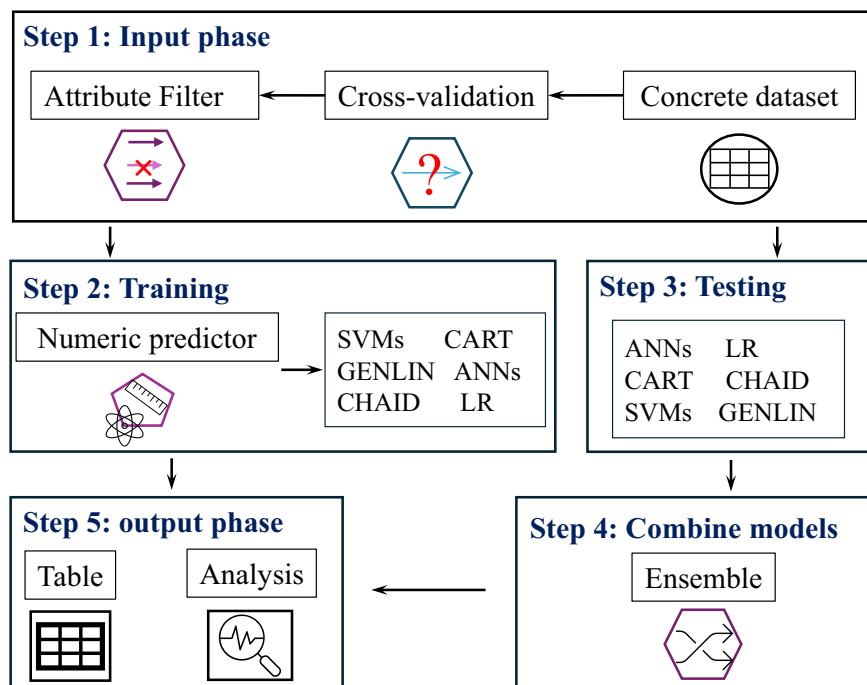
AI model	R^2	R^2	
		Workability (slump)	Rheology
			τ_0 μ
XGB	0.98 ¹⁰² , 0.9392 ³⁰⁸ , 0.814 ¹⁴² , 0.7833 ¹⁴³		0.980 ³⁰⁹ , 0.94 ³¹⁰ , 0.87 ³¹¹
RF	0.97 ³¹² , 0.9317 ³⁰⁸ , 0.897 ⁹² , 0.8278 ¹⁴³ , 0.787 ¹⁴²		0.98 ³¹² , 0.964 ³¹³ , 0.95 ³¹⁰
LS-SVR	0.97 ¹⁰³		0.990 ³¹⁴
Bagging	0.9415 ¹⁴³		0.953 ¹⁵
GEP	0.916 ³¹⁵ , 0.86 ³¹⁶		0.979 ³³
ANN	0.91 ^{103,317} , 0.82 ³¹⁸ , 0.818 ³¹⁵		0.962 ³¹⁹ , 0.895 ³¹³
AdaBoost	0.8900 ¹⁴³		-
MLP	0.82 ¹⁰³		0.84 ³¹⁰
KNN	0.731 ¹⁴²		-
DT	0.715 ¹⁴² , 0.2455 ¹⁴³		0.9329 ¹⁵
SVR	0.592 ¹⁴²		0.71 ³¹⁰
Ridge	0.2972 ¹⁴³		-
LR	0.222 ¹⁴²		0.79 ³¹⁰

might be equally or more relevant depending on the specific cases. Therefore, only the R^2 values of various representative AI models used to predict the fresh properties of concrete are discussed here to assess the reliability of these models. As summarized in Table 4, it is evident that XGB and RF are the most frequently used AI models for predicting concrete fresh properties, and generally achieve the highest R^2 values among all the models. According to Smith¹⁴¹, an R^2 value greater than 0.8 can be considered indicative of a strong correlation between the predicted and measured data. Therefore, in addition to XGB and RF, other AI models such as LS-SVR, Bagging, GEP, ANN, AdaBoost, and multi-layer perceptron (MLP) also achieved R^2 values greater than 0.8 when predicting the workability and rheology of concrete,

indicating acceptable prediction accuracy. Moreover, the DT showed R^2 values exceeding 0.89 in predicting the rheology of concrete, specifically in terms of τ_0 and μ ¹⁵. However, DT yielded low R^2 values (0.715¹⁴² and 0.2455¹⁴³) in predicting the workability of concrete. SVR and LR exhibited unsatisfactory R^2 values when predicting the workability and τ_0 of concrete, although their performance was notably better for predicting μ .

There is limited data available on the prediction accuracy of AI models for estimating the setting time of cement. For example, Oley et al.⁹³ have found quite low R^2 values in using LR, KNN, and DTs in predicting both the initial ($R^2 \leq 0.547$) and final ($R^2 \leq 0.513$) setting time of cement. The low accuracy of these ML approaches in predicting the setting time of cement

Fig. 8 | Flow chart of the ensemble modeling for predicting concrete CS¹⁴⁸.



may be attributed to factors such as the lack of suitable and sufficient data, variable environmental conditions, diverse curing practices, and the inherent variability of construction operations. In another study¹³⁵, the average errors in predicting the initial and final setting times were 5.7% and 17.7%, respectively, when mechanical strength, initial setting time, and final setting time were treated as individual outputs for three separate BPNNs. More interestingly, when these three parameters were predicted simultaneously by a single BPNN, the average errors for the initial and final setting times decreased to 4.1% and 4.8%, respectively. High R^2 values of 0.989 and 0.994 were observed when the Broad Learning System was employed to predict the initial and final setting times of cement, respectively¹³⁷.

Prediction of hardened properties of concrete Compressive strength

CS is one of the most crucial and commonly used metrics of concrete's quality and performance, directly reflecting its ability to withstand axial loads without failure and influencing all aspects of the design, construction, and maintenance of concrete structures⁷. The CS of concrete is mainly influenced by the water-cement ratio, as well as other variations, such as cement type, cement content, aggregate type, mineral and chemical admixtures, curing conditions, etc.^{144,145}. Traditionally, achieving the target CS of concrete involves labor-intensive methods using multiple "trial batches". Given the heterogeneous and complex nature of concrete, a mathematical model that accurately and effectively predicts CS based on the mentioned factors would be valuable in both the scientific and industrial fields of concrete technology. Consequently, the use of AI-driven models to predict the CS of concrete has emerged as a prominent and extensively studied topic in concrete technology. For example, Elshaarawy et al.¹⁴⁶ considered eight input parameters, including cement, GGBFS, cs, fa, FA, water, SP, and curing days, with CS as the output for ML prediction. It was concluded that Categorical boosting (CatBoost) model was the most accurate with the highest R^2 of 0.966 and lowest RMSE of 3.06 MPa. Moreover, a user-friendly Graphical User Interface (GUI) was developed to improve cost efficiency and optimize resource management for designers. Similarly, Shafighfard et al.¹⁴⁷ provided and validated a GUI through experimental tests to predict the CS, cost, and carbon emission of high-performance alkali-activated concrete.

By evaluating the performance of the ML models, such as ANNs, classification and regression trees (CART), Chi-squared automatic interaction detector (CHAID), LR, generalized linear model (GENLIN), and SVM, Chou and Pham¹⁴⁸ combined the best-performing models into an ensemble model, and mathematically expressed as below:

$$g_{en}(\cdot) = \sum_{j=1}^N c_j * g(\cdot) \quad (9)$$

where, $g_{en}(\cdot)$ is the ensemble-based function, $g(\cdot)$ is the individual estimated function for each specified algorithm, c_j represents the linear combination coefficients, which are derived from the average values of various weights. It should be noted that the dot in the bracket indicates that the function can operate on any input without specifying a specific value at that point.

It was concluded that the prediction results obtained from this ensemble model are more accurate and reliable than those generated by conventional models or experts¹⁴⁹. The ensemble model consists of five steps, and the flow chart is illustrated in Fig. 8. Step 1 is the input phase of the dataset based on the cross-validation algorithm. Step 2 is the training of data using the numerical predictor node. Then, the nugget node was used to validate testing data in Step 3. Step 4 combined the models with the ensemble node. In the last output step, the analytical results are assessed through table and analysis nodes. By applying the ensemble model, this study successfully predicted the CS of concrete with average correlation coefficients higher than 93.3%.

Other AI-driven models have also been employed to predict the CS of concrete. For instance, Feng et al.¹⁵⁰ utilized the adaptive boosting (AdaBoost) algorithm based on 1030 data sets, with concrete mixture components such as ca, fa, cement, water, additives, and curing time, as inputs, and CS as output. The model's accuracy was validated using R^2 , MSE, MAE, and MAPE values, which were 0.94, 1.93 MPa, 1.43 MPa, and 4.3%, respectively, surpassing the performance of ANN and SVM. Wu et al.¹⁵¹ effectively applied a MLP to predict the permeability and CS of pervious concrete with high accuracy, achieved R^2 values of 0.97 and 0.98, respectively. The accuracy and efficiency of the hybrid ensemble ML models higher than single conventional ML models were also demonstrated elsewhere¹⁵². A DL method, combined with an ANN, was

employed to predict the CS of concrete using an expansive experimental database of nearly 1100 data points¹⁵³. The approach demonstrated high accuracy, achieving R^2 values greater than 0.85 in both regression and classification tasks.

Data collected from refs. 146,150,151,154–176, Fig. 9 summarized the R^2 values obtained for predicting the CS of concrete using various AI models from different studies. Although the concrete type, mix proportions, database, and input parameters differ among these studies, the figure can still provide a comparative overview of the prediction accuracy achieved by the various models. As expected, LR showed the lowest accuracy, with an average R^2 value of 0.55. This is due to its assumption of linear relationships, its inability to capture complex interactions between variables, and its lack of flexibility in modeling the non-linear and multifaceted behavior of concrete. The higher average R^2 value of 0.76 was obtained by NLR, but it remains below 0.80. XGB, RF, GEP, ANN, GB, and SVM presented the average R^2 values higher than 0.80, which may be considered acceptable accuracy in predicting the CS of concrete. It should be noted that the ensembled AI models achieved the highest average R^2 value (0.93) with low scatter, indicating their robustness as the most reliable AI technique.

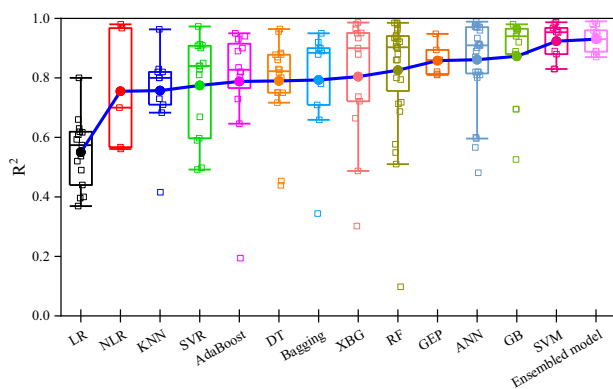


Fig. 9 | R^2 values of different AI models in predicting the CS of concrete.

Flexural strength

Flexural strength is also a critical factor in the design of concrete structures, as it affects flexural cracking, deflection behavior, brittleness, and shear strength¹⁷⁷. Normally, concrete flexural strength is somewhat proportional to its CS, both strengths are dependent on multiple variables as concrete is a nonhomogeneous material. Currently, research has been conducted to predict the flexural strength of concrete with various models, and the selected publications focused on different types of concrete, namely normal concrete, SFRC, 3DPC, and UHPC, which are representatively listed in Table 5.

As shown in Table 5, the inputs vary for different types of cement. Cement, water, ca, fa, SCMs, the w/c or w/b ratio, and, in some cases, SPs, are typically considered inputs for normal concrete. The AI models, such as RT, KNN, MLP, NN, SVR, RF, GB, XGB, ANN, GPR, M5P, LR, XGB, GEP, and ANN, have been reported in predicting the flexural strength of normal concrete^{178–181}. Among these methods, it was concluded that GP and SVM¹⁷⁸, MLP¹⁷⁹, XGB¹⁸⁰, and ANN¹⁸¹ demonstrated excellent predictive performance in each case. In particular, Li et al.¹⁸⁰ recommended XGB to predict the flexural strength of concrete with SCMs.

In addition to the input parameters used for normal concrete mentioned above, parameters related to the steel fibers, such as volume fraction, length, diameter, and aspect ratio etc., should be included in predicting the flexural strength of SFRC^{182,183}. For 3DPC, the addition of VMA, fiber data, and load direction, especially, should be considered^{184,185}. Ali et al.¹⁸⁴ concluded that SVM can fit the flexural strength data of 3DPC to the regression model better than DT, GPR, and XGB, with the highest R^2 value of 0.8936. In contrast, Uddin et al.¹⁸⁵ found an R^2 value of 0.94 in predicting the flexural strength of 3DPC using XGB, which outperforms FR, SVM, light gradient boosting machine (LightGBM), CatBoost, and natural gradient boosting (NGBoost).

More input parameters should be included in predicting the flexural strength of UHPC, due to its compositional complexity. For example, Qian et al.¹⁸⁶ successfully predicted the flexural strength of UHPC by considering a bunch of inputs, such as cement, aggregates, FA, slag, SF, limestone powder, quartz powder, SP, water, polystyrene fiber, steel fiber, polystyrene fiber length and diameter, steel fiber length and diameter, and curing age. It was found that the ensemble ML algorithm, namely GB, reached the highest

Table 5 | Examples of AI-driven models used in predicting the flexural strength of concrete

	Concrete	Inputs	AI model	Metrics
(1) ¹⁷⁸	Normal concrete	Free water, cement, fa, ca, SCMs	RT, KNN, MLP, NN, SVR, RF, GB, XGB	MAPE, MAE
(2) ¹⁷⁹		Slump, waste foundry sand, w/c, aggregates, cement, curing age, and water	ANN, SVR, GPR, M5P	RMSE, R^2 , MAE
(3) ¹⁸⁰		w/b, cement content, SF, FA, slag, aggregates, curing age	LR, RF, XGB	MSE, R^2 , MAE, RMSE
(4) ¹⁸¹		Cement, metakaolin, w/b, aggregates, SP, and curing age	GEP, ANN, M5P, RF	R^2 , RMSE, Relative squared error (RSE), MAE, Discrepancy ratio, Performance index
(5) ¹⁸²	SFRC	w/c, sand-to-aggregate ratio, ca size, SP, SF, volume fraction of the hooked steel fiber, and fiber aspect ratio	LR, Ridge regression, Lasso regression, KNN, DT, RF, AdaBoost, GBR, XGB, SVR, MLP	MSE, MAE, MAPE
(6) ¹⁸³		w/c, sand, aggregate, SP, SF, FA, steel fiber volume, length, and diameter	GB, RF, XGB	R^2
(7) ¹⁸⁴	3DPC	Water, cement, SF, FA, nano clay, Viscosity Modifying Agent (VMA), ca, and fiber	DT, SVR, GPR, XGB,	MSE, R^2 , MAE, RMSE
(8) ¹⁸⁵		Cement, c/b, ground slag, SF, SP, length, diameter, and aspect ratio of fiber, fiber volume fraction, fiber type, curing age, load direction, hydroxypropyl methylcellulose	RF, SVM, XGB, LightGBM, CatBoost, NGBoost	MAE, MSE, RMSE, MAPE, SMAPE
(9) ¹²	UHPC	Cement, SF, limestone powder, river sand, w/c	GA-based ANN	R^2 , Relative percent deviation, RSME
(10) ¹⁸⁶		Cement, aggregates, FA, slag, SF, limestone powder, quartz powder, SP, water, polystyrene fiber, steel fiber, polystyrene fiber length and diameter, steel fiber length and diameter, curing age	SVR, MLP, GB	R^2 , MAPE, RMSE, MAE
(11) ¹⁸⁷		Cement, slag, sand, water, SF, FA, nanosilica, limestone powder, ca, quartz powder, SP, curing age, aspect ratio of steel fibers	Bagging, GB, DT-AdaBoost, XGB	R^2 , MAE, RMSE

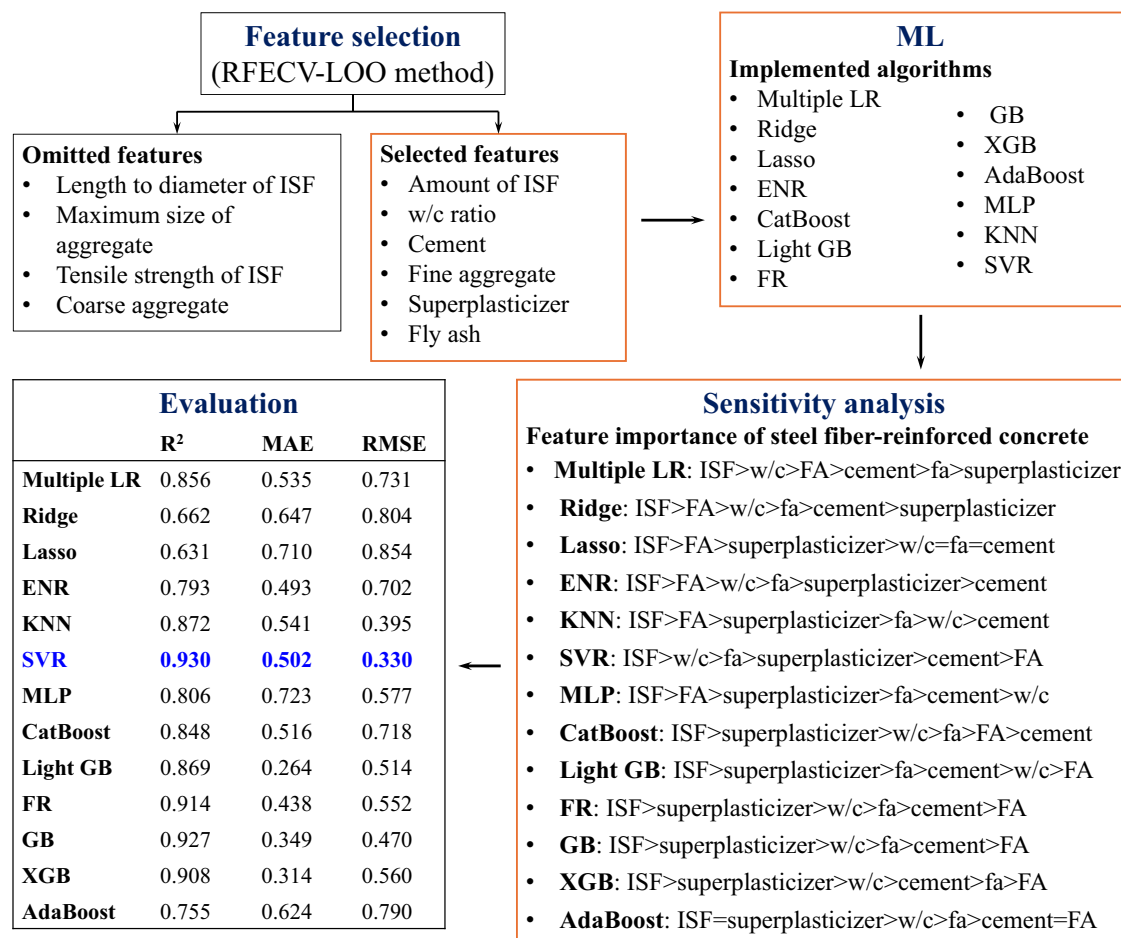


Fig. 10 | A representative example of predicting the splitting tensile strength of concrete using ML algorithms.

accuracy of R^2 value than that of individual models (such as SVM and MLP). However, In another study by Wang et al.,¹⁸⁷ the Bagging model showed the highest R^2 value of 0.95, which is higher than that of using GB ($R^2 = 0.93$), DT-AdaBoost ($R^2 = 0.93$), and XGB ($R^2 = 0.85$). It also concluded that the steel fiber plays the most important role in UHPC flexural strength prediction, with the highest feature importance of 0.26. Moreover, the GA-ANN model demonstrated excellent performance in predicting UHPC flexural strength, achieving R^2 values exceeding 0.95¹².

Splitting tensile strength

The splitting tensile strength has a significant impact on the initiation of cracking in concrete, as concrete is inherently weak in tension¹⁸⁸. Therefore, the splitting tensile strength is a crucial mechanical property of concrete and plays a significant role in structural design considerations¹⁸⁹. Due to the inhomogeneity of concrete, its splitting tensile strength directly or indirectly depends on various parameters¹⁹⁰, including w/c, aggregate properties, curing conditions, cement type and content, admixtures, the addition of SCMs and fibers, etc. To effectively estimate the splitting tensile strength for concrete design, AI-driven models have been developed, emerging as a prominent and strong contender in the field.

As one of the most widely used AI techniques, ML models, both individual (i.e., ANN¹⁹¹, DT¹⁹², SVM¹⁹³) and ensemble^{194,195} approaches, have been proposed to predict the splitting tensile strength of concrete. It should be noted that the ensemble ML approach normally outperforms many standalone ones, in terms of accuracy and prediction performance^{194,196,197}. Figure 10 exhibited a representative example of predicting the splitting tensile strength of steel fiber-reinforced concrete that contains ISF using ensemble ML techniques¹⁹⁸. The most significant features were selected by Recursive feature elimination with cross-validation and leave-one-out

method, including ISF, cement, w/c, FA, SP, and fa as input parameters. In contrast, the least important features, such as length to the diameter of ISF, the maximum size of aggregate, the tensile strength of ISF, and ca, were eliminated from the prediction. The ML techniques used in that study include multiple LR, Ridge regression, Lasso regression, elastic net regression, KNN, SVR, CatBoost, lightGBM, RF, GB, extreme GB, AdaBoost, and MLP. The sensitivity analysis revealed that ISF content was the most influential factor affecting the splitting tensile strength of concrete, whereas FA had a minimal impact. Eight metrics, namely R^2 , MSE, RMSE, MAE, MAPE, Mean bias error (MBE), t -statistic test (T_{stat}), and SI, were used to comprehensively evaluate and compare the ML models. It was concluded that SVR showed the most superior performance to other ML algorithms ($R^2 = 0.930$, RMSE = 0.330, MAE = 0.502). Then GB was ranked in the second position ($R^2 = 0.927$, RMSE = 0.470, MAE = 0.349), while the weakest performance was yielded by Lasso ($R^2 = 0.631$, RMSE = 0.854, MAE = 0.71).

The FZ model was also utilized and validated to predict the splitting tensile strength of lightweight concrete containing scoria aggregate and FA when exposed to high temperatures of up to 800 °C⁴⁶. A small error of 6.48% was found comparing the experimental and predicted results. The high potential of using FL for predicting the 3, 7, 14, 28, 56, and 90 days splitting tensile strengths of recycled aggregate concretes containing SF was also confirmed by Topçu and Saridemir⁹⁹. It was found that the RMSE, R^2 , and MAPE values from the training were 0.2020, 99.77%, and 4.2165%, respectively, while for the testing, these values were 0.2955, 99.52%, and 5.7306%, respectively. Moreover, Bui et al.⁴⁰ developed an ES based on an ANN and a modified Firefly algorithm. Its efficiency and accuracy in predicting the splitting tensile strength of UHPC were confirmed by achieving a high R^2 value of 0.95.

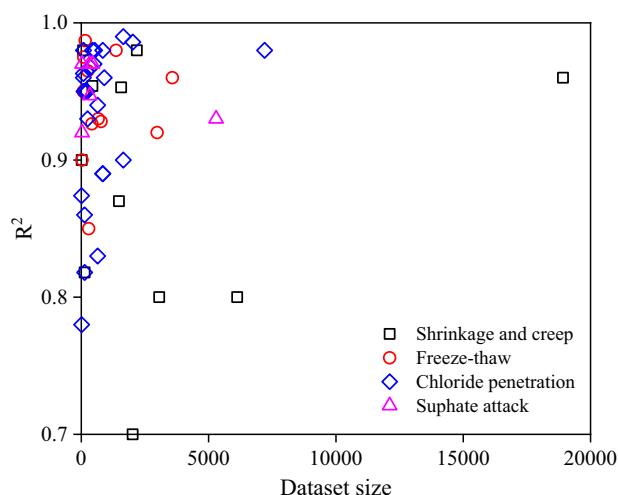


Fig. 11 | Dataset- R^2 value curves for different research topics.

Prediction of durability characteristics of concrete

Durability is a key concern throughout the service life of concrete structures, as issues can lead to deterioration, reduced lifespan, and increased maintenance costs. Designers often enhance durability by optimizing mix proportions; however, traditional optimization through long-term testing is costly and time-consuming. Recently, several AI models have emerged as a cost-effective and efficient alternative for predicting concrete's long-term performance.

The typical approach for predicting concrete durability using AI models involves first identifying the input and output parameters and then applying various ML algorithms. The model parameters are obtained through the training process. The created models are then tested using validation data. RMSE, MAPE, and R^2 are mostly used metrics to evaluate prediction accuracy. The sensitivity analysis is conducted to find out the importance of different inputs. Especially, SHAP method has been widely adopted for the result and sensitivity²⁰⁰ through which the contribution of each factor can be concluded. While most of the research focused on a single durability topic (shrinkage, chloride concentration, sulfate attack, etc.), in severe environments, concretes can face couple environmental damage, for predicting concrete behavior under these, Beskopylny et al.²⁰¹ predicted compressive evolution under different environmental damage, regarding the number of freezing-thawing cycles, chloride content, sulfate content, and the number of moistening-drying cycles as prediction inputs.

Various metrics are adopted for verifying the prediction accuracy. Such as R^2 , MAE, and RMSE, of which R^2 is the most widely used indicator for interpreting prediction accuracy. Prediction accuracy is dependent on multiple factors. Especially, it was widely accepted that the prediction accuracy is correlated to the dataset size. Figure 11 shows the relationships between the dataset size and R^2 values in different research topics, including shrinkage and creep, freeze-thaw, chloride penetration, and sulfate attack. It should be noted that each data point corresponds to the result from one reference. Therefore, a total of 56 references were used to generate this figure.

It can be seen from Fig. 11 that most datasets contain fewer than 2000 data points, whereas the high prediction accuracy was reached with the R^2 values higher than 0.8. Moreover, it is interesting that the prediction accuracy is not positively correlated to the dataset size. For instance, in some studies shown in Fig. 11, R^2 values as high as 0.98 were achieved, even with dataset sizes smaller than 100. In contrast, lower R^2 values are observed in some cases where the dataset sizes exceed 3000 or even reach up to 5000. This might be because the large datasets are normally compiled from different studies, resulting in variations in raw materials and testing conditions. Therefore, errors are inevitable due to the inherent variability of raw data from different sources. Moreover, the selection of the inputs and outputs

may also impact on the prediction accuracy. It is expected that a higher accuracy of prediction results may be reached when the deeper connections between the inputs and outputs are selected.

Shrinkage and creep

Shrinkage and creep are widely investigated durability topics using AI techniques. A variety of AI techniques have been applied; the summary of existing research works is in Table 6. It can be seen from Table 6 that the most adopted methods are RF, XGB, and KNN. For different parameters, different AI models show the best accuracy. Indicated the importance of training special models for problems. However, for most trained models, the R^2 is around 0.9, which suggests high prediction accuracy. The research area can be divided into three parts. The first is a prediction based on the mixing proportions. Includes w/c ratio, aggregate-cement ratio, SF content, FA content, slag content, and so on. The second one is a prediction based on environmental factors such as curing conditions, loading age, and loading level. Also, some researchers predicted long-term creep based on short-term shrinkage performance. Some prediction methods can help improve the accuracy. Taffese et al.²⁰² used the sum of cement and pozzolan content to calculate the w/c ratio and obtained a better accurate result. Liang et al.²⁰³ processed data through Bayesian Optimization and cross-validation, and obtained EML models with higher accuracy. Hilloulouin²⁰⁴ confirmed that the ensemble ML models have better prediction accuracy. Data number and quality would be another important issue in model accuracy²⁰⁵. From their research, specimens exhibit significant fluctuations due to the influence of environmental temperature and humidity, w/b, and aggregate-to-cement ratio (a/c)²⁰⁶. There are different targets in the research, some used typical machine learning algorithms to predict long-term concrete behavior, for different inputs and output conditions, different AI models are trained and verified, so the best AI model parameters can be determined, the most appropriate model for specific problems can be determined. In other research, the optimized models were developed based on existing models and problems, then comparisons were made to prove better accuracy for developed models.

Freeze-thaw

Many freeze-thaw predictions targeted the effect of different additions of concrete in the improved free-thaw resistant ability (Table 7). Gao et al.²⁰⁷ and Huang et al.²⁰⁸ reported improved frost-resist ability with rubber added. The ML approach provided accurate predictions along with recommendations for optimal rubber content. Except for rubber, different additions are put in concrete for certain purposes, and their effects on freeze-thawing resistance are predicted. Cemalgil et al.²⁰⁹ predicted the abrasion loss for concretes modified by SF and steel fiber. Most of the database set is a couple hundred capacity, but Huang et al.²⁰⁸ built a model with more than 3500 databases, the model obtained high accuracy, with more than 95% of the predictions distributed within the $\pm 20\%$ confidence interval. Li et al.²¹⁰ generated a large dataset containing 8096 data points, with an ML-guided design, and proposed a microencapsulated phase change material incorporated concrete for free-thaw mitigation. Except for dataset size, the selection of ML technique can also highly affect the prediction accuracy. Li et al.²¹¹ adopted four different learning methods to predict Free-thawing performance and found that while gradient Boosting and Extreme Gradient Boosting models demonstrate relatively higher prediction accuracy, the XGB model exhibits stronger generalization ability. Among various ML models selected, support SVR²¹¹ and XGB¹⁵² are the most commonly used techniques. The explainable ML also attracts many interests. Sun et al.²¹² proposed an explainable ML model named the Generalized Additive Model with interaction networks and reached similar prediction accuracy as other ANN models. Chen et al.²¹³ confirmed key factors after screening are the water-binder ratio, cement content, ca content, fa content, high-efficiency water-reducing agent, and FA content. Qiao et al.²¹⁴ also developed an Interpretable ML model for dune sand and fiber-reinforced concrete, and XGB reached the best result. Taheri and Sobanjo²¹⁵ developed an ensemble ML approach for asphaltic concrete, take consideration traffic load.

Table 6 | Summary of ML in Shrinkage and creep prediction

	Inputs	AI models	Indicators	Metrics	Main findings
(1) ²⁰⁶	<u>Material</u> : Cement content and type, w/c, a/c <u>Project</u> : RH, temperature, age <u>Properties</u> : Creep, volume-surface ratio, CS	<u>Prediction</u> : Integrating Gated Recurrent Units and Self-Attention mechanism	Creep/shrinkage, CS	R , R^2 , MAE, RMSE	The training results of the Gated Recurrent Units and Self-Attention model indicate good performance and considerable generalization capability.
(2) ²⁰²	<u>Material</u> : Cement content, pozzolan content, w/b, cement and pozzolan type <u>Project</u> : Exposure condition	<u>Prediction</u> : Bagging, RF, AdaBoost, GB, XGB, CatBoost, LightGBM	Concrete aging factor	MAE, MSE, RMSE, R^2	LightGBM algorithm outperforms all models with a remarkable MAE of 0.110, MSE of 0.018, RMSE of 0.133, and R^2 of 0.818.
(3) ²⁰⁵	<u>Material</u> : w/c, a/c, cement and aggregate type <u>Project</u> : RH, temperature, exposures <u>Properties</u> : Mechanic	<u>Prediction model</u> : CNN <u>Characterize</u> : K-means clustering	creep and shrinkage	RMSE, MAE, NMAE	The presented models require a large amount of data to achieve good performance
(4) ²⁰⁰	<u>Material</u> : w/b, a/c Recycled ca (RCA) and its replacement ratio FA, SF <u>Project</u> : Temperature <u>Properties</u> : Strain	<u>Prediction</u> : BPNN, SVM, RF, XGB, GPR, KNN, LR, LSM <u>Characterize</u> : SHAP	Strain	RMSE, R^2 , MAE, u, Composite performance index (CPI), MD, MD max	XGB model has the highest Prediction accuracy. (2) Key influencing factors of RAC drying shrinkage were identified as the drying age, elastic modulus, w/b ratio, aggregate-to-cement ratio, replacement ratio of RCA, and FA content.
(5) ²⁰³	<u>Project</u> : Loading time <u>Properties</u> : CS, age	<u>Prediction</u> : RF XGB, LGBM <u>Characterize</u> : SHAP	Creep	R^2 , RMSE, MAE	Compared with XGB and RF, LGBM can achieve higher accuracy in a significantly shorter calculation time on the NU database.
(6) ³²⁰	<u>Material</u> : w/c, w/b, a/c, Cement content, SF, FA, filler, SP <u>Project</u> : Temperature <u>Properties</u> : CS	<u>Prediction</u> : SVM, ANN, GB <u>Characterize</u> : SHAP	Shrinkage, swelling	R^2 , RMSE, MAE	(1) XGB model exhibited the highest accuracy among these model (2) ML models can accurately predict autogenous shrinkage, and their hyperparameters can be optimized through grid search.
(7) ³²¹	<u>Properties</u> : Degree of hydration, Unhydrated cement particle ratio, porosity	<u>Prediction</u> : Deep CNN (DCNN)	Shape estimate	R^2	(1) DCNNs can correctly capture the local importance of different microstructural phases. (2) DCNN allows therefore Prediction of the creep modulus based on microstructural input.
(8) ³²²	<u>Properties</u> : Total shrinkage	<u>Prediction</u> : PSO-expectation maximization (EM)	CS	R^2 R , RMSE	(1) The growth rate for pozzolanic concrete is greater than the ACI time function. (2) Concrete containing slag shows a more gradual slope compared to the other two pozzolans.
(9) ³²³	<u>Properties</u> : short-term creep	<u>Prediction</u> : IA method	creep coefficient values	R^2	(1) The results obtained after applying the proposed AI method significantly reduced the error in long-term Prediction. (2) AI method is sensitive to the number and accuracy of the short-term measurements.
(10) ³²⁴	<u>Material</u> : FA <u>Project</u> : Loading ages	<u>Prediction</u> : B4 model	Creep coefficient	R^2	(1) Recommended content of FA is not more than 40%, the water-cement ratio w/b is not more than 0.55, and the stress level is not more than 0.4. (2) The content of fly ash has a great positive influence on creep recovery deformation.
(11) ³²⁵	<u>Project</u> : Load duration and applied load level, curing age	<u>Prediction</u> : ANN	Time-dependent strain	R^2	Creep and hysteretic recovery strain with the load duration and applied load level due to its viscoelastic property and the internal micro-damage accumulation.
(12) ³²⁶	<u>Material</u> : w/c, w/b, a/c, cement, Filler, SP, super absorbent polymer <u>Project</u> : Age <u>Properties</u> : Shrinkage, Swelling	<u>Prediction</u> : KNN, RF, GB, XGB <u>Characterize</u> : Monte Carlo simulation	Shrinkage Swelling	MCS, R^2 , RMSE, MAE	The creep and hysteretic recovery strain of SSCAC increased with the load duration and applied load level due to its viscoelastic property and the internal micro-damage accumulation, while decreased with the curing ages owing to the cement hydration.

Chloride penetration

Chloride ions can penetrate concrete and cause corrosion of reinforcing steel, thus reducing the durability of structures. Therefore, it is critical to estimate the chloride penetration behavior of concrete for different mixing proportions. Table 8a-c summarize the ML techniques used for the prediction of chloride penetration in concrete with various methods. They are categorized into three groups based on the testing conditions: (a) total electric charge passed through the concrete, (b) the rate of chloride migration under an electric field, and (c) chloride transport without the

application of an electric field. The model input used for chloride ingress can be classified into three types: (1) mixing proportion inputs, such as w/c ratio, content of different admixtures (slag, FA, SF, limestone and calcined clay); (2) environmental inputs, such as relative humidity, temperature and exposure condition; (3) concrete property inputs, such as chloride ion diffusion coefficient (CIDC) and results of RCP test (RCPT), this is the result of given inputs, thus can be used to adjust parameters of ML model.

Zheng and Cai²¹⁶ adopted XGB, backpropagation algorithm (BP), SVR, and BP algorithm optimized by Bayesian formula to predict CIDC of

Table 7 | Summary of ML in freeze-thaw prediction

	Inputs	AI models	Indicators	Metrics	Main findings
(1) ²¹¹	<u>Material</u> : Porosity, w/c, FA, slag, sand, CA, RCA, SP, air-entraining agent (AEA), mineral admixtures, water, cement <u>Project</u> : F-T cycles	<u>Prediction</u> : SVM, RF, GB, XGB	Mass loss rate	MAE, MAPE, MSE, RMSE, R^2	GB and XGB are the most accurate methods, XGB exhibiting stronger generalization ability
(2) ²¹³	<u>Material</u> : Cement, SP, FA, CA, w/c, s/a. particle size distribution, mud content, elongated particle content <u>Properties</u> : Water absorption capacity	<u>Prediction</u> : RF model and NSGA-II	Chloride ion migration coefficient and dynamic elastic modulus	R^2 , RMSE	Filtered RF Prediction model has high precision, R^2 of the frost resistance and impermeability is higher than 0.95, RMSE is less than 0.1
(3) ²⁷²	<u>Material</u> : Cement, water, sand, ca, rubber	<u>Prediction</u> : RG, ANN, SVR, RF, XGB, Stacking	RDEM and MLR	RMSE, MAE, R^2	XGB ensemble has the best Prediction performance
(4) ²⁰⁸	<u>Material</u> : w/c, cement, Additive, FA, CA, Rubber, <u>Properties</u> : Relative dynamic modulus of elasticity, F-T cycle	<u>Prediction</u> : ANN, SVR, Extreme learning machine (ELM)	Relative dynamic modulus of elasticity, F-T cycle	R^2 , RMSE, MAE	An improved mixed sparrow search algorithm was used to optimize these three models and gain better results
(5) ³²⁷	<u>Material</u> : AEA, water, and RCA <u>Properties</u> : durability factor value	<u>Prediction</u> : AN, GPR, multivariate adaptive regression spline	Durability factor value	RMSE, MAPE, R^2	The ANN model showed the highest Prediction accuracy
(6) ²⁰⁹	<u>Material</u> : Cement, crushed stone aggregate, SP, SF, steel fiber content <u>Project</u> : F-T cycle, days	<u>Prediction</u> : PSO, gray Wolf optimizer (GWO), Generalized ELM (GRELM), GRELM-PSO, GRELM-GWO	Abrasion resistance AL and F-T	RMSE, R^2	GRELM-PSO-GWO provided more accurate results in all sets from 74% to 91% by extending input parameters
(7) ²¹²	<u>Material</u> : Cement, GGBFS, FA, water, AEA, SP, fine aggregate, ca. <u>Project</u> : curing period (time) <u>Properties</u> : F-T cycles, CS, dynamic elasticity modulus, mass loss	<u>Prediction</u> : generalized extreme learning machine, XGB, EBM	CS, dynamic elasticity modulus, and mass loss rate	RMSE, MAE, R^2	The superior accuracy of the generalized extreme learning machine model when compared to other ML models like EBM and XGB
(8) ²¹⁵	<u>Material</u> : Pavement structure and construction, <u>Project</u> : construction quality, climate, traffic, in-service	<u>Prediction</u> : RF, Extremely RT, XGB <u>Characterize</u> : SHAP	Path crack Prediction	R^2	(1) XGB is the most effective among the evaluated models
(9) ²¹⁴	<u>Material</u> : Water, cement, RS, Dune sand, ca, fiber, Admixture <u>Project</u> : F-T cycles <u>Properties</u> : damage indicator	<u>Prediction</u> : KNN, ANN, SVR, DT, RF, XGB, CatBoost, LGBM	Damage indicator	R^2 , RMSE	Ensemble learning models generally outperform classical learning models. XGB was verified to have optimal performance, with an R^2 of 0.965 and RMSE of 0.019 on the test set
(10) ³²⁸	<u>Material</u> : Cement, sand, ca, SP, FA, w/b	<u>Prediction</u> : RF, NSGA-II	Relative dynamic elastic modulus	RMSE, R^2 , MAPE	(1) RF-NSGA-II can effectively predict concrete durability and optimize the mix ratio. (2) The developed RF model has an excellent regression learning ability
(11) ³²⁹	<u>Material</u> : w/c, AEA <u>Project</u> : F-T cycle, temperature <u>Properties</u> : CS	<u>Prediction</u> : ANN, RF, SVM <u>Characterize</u> : SHAP	Deteriorated CS	R^2 , MAE, RMSE	The ANN model demonstrated the highest Prediction accuracy than the RF and SVM models.

machine-made sand. The Bayesian BP model can achieve the best prediction while the SVR is the poorest the CIDC trend with different parameters varies. Kumar et al.²¹⁷ confirmed that FA and SF have a positive effect on the chloride penetration resistance. RAC is a hot topic in aggregate replacement to better exploit its potential, Xie et al.²¹⁸ built RACbase and collected experimental data of resistance to chloride ion attack, carbonation, sulfate attack, and freeze-thaw. Taffese and Espinosa-Leal²¹⁹ explained chloride migrating by concluding key effective factors using different ML methods. Hosseinzadeh et al.²²⁰ presented a reliable and efficient prediction model for non-steady-state migration coefficients, using water, cement, slag, FA, SF, fa, ca, SP, fresh density, CS, CS test age, and migration test age as input variables. The results showed that XGT and SVR could accurately predict the chloride migration coefficients, achieving R^2 values exceeding 0.90.

Sulfate attack

Sulfate attack on concrete involves two main processes: (1) a physical process, which entails the transportation of sulfate ions through the

porous media (cement paste), and (2) a chemical reaction between the sulfate ions and the hydration products. As summarized in Table 9, the prediction of concrete sulfate attack resistance is largely focused on the concrete with different supplementary cementitious materials (SCMs) or additives. Hilloulin et al.²⁰⁴ investigated the effect of different SCM proportions in sulfate attack resist ability improvement, different SCMs, such as FA, slag, pozzolan, limestone, SF, and calcined clay, were regarded as inputs in the model construction. A range of 7 different models is applied, and the appropriate and inappropriate models are determined. Bamshad et al.²²¹ worked on recycled aggregate concrete, by using different recycled aggregate parameters and a well-designed induced sulfuric acid attack experiment the benefits of recycled aggregate in resisting acid rain are reported, and also well reflected by ML models. Yu et al.²²² considers coupled factors in affecting sulfuric ion transportation by applying the ML method to analyze critical factors. Sun et al.²²³ developed software with a GUI based on GWO-SVR to help assist in predicting concrete behavior under sulfate attack. Tran²²⁴ investigated the effects of different SCM (SF,

Table 8 | (a) Summary of ML used for prediction of rapid chloride penetration (total electric charges passed through concrete); (b) Summary of ML used for prediction of chloride migration coefficient (rate of chloride migration under an electric field). (c); Summary of ML used for prediction of chloride diffusion coefficient (no electric field)

a			
	Inputs	AI models	Main findings
(1) ²¹⁷	<u>Material</u> : Cement, FA, SF, CA, water, sand <u>Property inputs</u> RCPT	<u>Prediction</u> : Teaching–learning-based optimization, AC, IC	(1) ANN-Teaching–learning-based optimization model is the optimal hybrid ANN model for predicting RCPT values in SCC (2) The use of FA and SF enhances the resistance of a material to chloride penetration, especially at elevated temperatures
(2) ³³⁰	<u>Material</u> : FA, GGBFS, SF, lime powder <u>Property inputs</u> Slump, CS, RCPT	<u>Prediction</u> : non-linear multi-layered ML regression model	(1) Parameters with more data present result in slightly better performance (2) It is always recommended to increase the input database in order to enhance the reliability and statistical accuracy of the Predictions.
(3) ³³¹	<u>Material</u> : Mixing, w/b, cement, slag, FA, SF, and lime, AEA, SP	<u>Prediction</u> : Naïve bayes, KNN, DT, SVM, RF	Just taking the influential features into account does not improve prediction performance,
b			
(1) ²¹⁹	<u>Material</u> : Cement types, water, w/b, aggregates, super absorbent polymer <u>Property inputs</u> Slump, spread, air, density, mechanical, migration	<u>Prediction</u> : XGB	Concrete mix components are also important in predicting the chloride migration coefficient with reasonable accuracy.
(2) ³³²	<u>Material</u> : w/b, cement type, FA, Lime Filler, mineral admixture, SF, ca, super absorbent polymer, AEA <u>Project</u> : Age <u>Property inputs</u> CS, slump, spread, density, air Content	<u>Prediction</u> : SVM, ANN, KNN <u>Characterize</u> : Relief analysis	(1) SVM model outperformed with a higher coefficient of determination (R^2) score of 0.90, whereas ANN and KNN yielded R^2 scores of 0.88 and 0.83. (2) SVM, KNN, ANN accurately predicted the behaviors (3) W/b and cement type are the prominent input factors affecting the target variable.
(3) ³³³	<u>Material</u> : Materials composition <u>Project</u> : Curing and exposure conditions. <u>Property inputs</u>	<u>Prediction</u> : BP-ANN, SVR, GP, XGB, RF, PSO	(1) XGB outperformed others, achieving an R^2 value of 0.9382 and an MSE of 3.016 (2) PSO-XGB demonstrated the best efficiency. 3. Parameters related to external conditions are more effective.
(4) ³³⁴	<u>Material</u> : Cement, SP, W, w/c,sand, CA, rubber size, content. <u>Property inputs</u> Chloride permeability coefficient	<u>Prediction</u> : ELM, RF, Elman NN <u>Characterize</u> : Mixed whale optimization algorithm.	(1) MWOA is effective with the optimized Elman NN, RF, and ELMAN models improving the Prediction accuracy by 54.4%, 629%, and 36.4% compared with the initial model.
(5) ³³⁵	<u>Material</u> : Cement, GGBFS, FA, Passed charge w/b FA.	<u>Prediction</u> : Linear, lasso, and ridge <u>Characterize</u> :	(1) Passed charge analysis considering long-term age shows a significant variability decrease of passed charge by W/B ratio with increasing age and added admixtures. (2) ML model regression shows high correlation.
(6) ³³⁶	<u>Material</u> : Sand, FA, w/b, pre-wet water-to-total water ratio basalt fiber. <u>Project</u> : Age, Temperature, RH. <u>Property inputs</u> Cl distribution.	<u>Prediction</u> : GA-SVR, visualization of CAC-CC. <u>Characterize</u> : SHAP	(1) GA-SVR model provides best predictions. (2) GA-SVR model also exhibits smaller mean and standard deviation in the residual distribution. 3.W/b and the prewetted water to total water ratio are the two most critical features.
(7) ²²⁴	<u>Material</u> : C ₂ A content, w/b, cement, FA, GGBFS, SF, Aggregate, W <u>Property inputs</u> Surface Cl diffusion.	<u>Prediction</u> : SVM, ELM, KNN, LGB, XGB, RF, GB, AdaBoost <u>Characterize</u> : SHAP	(1) GB model has highest performance in prediction of chloride diffusion coefficient. (2) Water, aggregate, and W/B are the increased factors which induce to increase the chloride diffusion coefficient
(9) ³³⁷	<u>Material</u> : W/b, ca, SP, FA, SF, AEA <u>Project</u> : Cement age	<u>Prediction</u> : RFR, ANN, SVR, HEM-IV, HEM-ANN <u>Characterize</u> : SHAP	(1) Ensemble models outperform single models, combined random forest and ANN model showing the highest accuracy. (2) SHAP reveals that w/c is the most effective factors.
(10) ³³⁸	<u>Material</u> : C ₃ A, w/b, cement, FA, GGBFS, Aggregate, water <u>Property inputs</u> Specific surface	<u>Prediction</u> : Adaptive neuro-fuzzy inference system (ANFIS), ANN, SVM, ELM <u>Characterize</u> : Taylor diagram and Boxplot	(1) Water/binder ratio is the most relevant parameter. (2) Cement, aggregate, and water content appeared to be the most relevant parameters with a MI value greater the SVM models with R^2 values of 0.959 and 0.958 in the training and testing stage.
(11) ³³⁹	<u>Material</u> : W/b, w/c, basalt and poly fiber. <u>Project</u> : Environmental, age <u>Property inputs</u> Depth, age	<u>Prediction</u> : PSO-SVR <u>Characterize</u> : SHAP	(1) The PSO-SVR model exhibits significant accuracy and generalization ability. (2) Depth and age were the most critical influencing factors. The decrease in age, water-cement ratio, and water-binder ratio, the addition of basalt fibers and polypropylene fibers, and the increase in depth are negative.
(12) ³⁴⁰	<u>Material</u> : Cement, FA, GGBFS, SF, SP, water, sand, ca <u>Project</u> : Exposure, temperature, Chloride content	<u>Prediction</u> : LR, GPR, SVM, MLP-ANN, and RF models, ensemble weighted voting-based model	(1) The ensemble ML model produces higher accuracy of prediction compared to all standalone ML models tested in this study.

Table 8 (continued) | (a) Summary of ML used for prediction of rapid chloride penetration (total electric charges passed through concrete); (b) Summary of ML used for prediction of chloride migration coefficient (rate of chloride migration under an electric field). (c); Summary of ML used for prediction of chloride diffusion coefficient (no electric field)

b			
	<u>Property inputs</u> Surface chloride concentration		(2) Adoption of more diverse datasets and consideration of more factors in conventional models can improve their prediction.
(13) ³⁴¹	<u>Project</u> : Exposure time	<u>Prediction</u> : 1D-CNN <u>Characterize</u> : Multivariate nonlinear model	1D-CNN model has good prediction accuracy in predicting the chloride concentrations in the stable diffusion zone.
c			
(1) ²²²	<u>Material</u> : w/c, ca, and its volume fraction <u>Project</u> : Temperature, RH, exposures <u>Property inputs</u> Cl diffusion, surface distribution	<u>Prediction</u> : BPNN, DT, RF, LR, RR, KNN	(1) W/C and V are the most significant factors. (2) Volume fraction of ca has a hindering effect on the diffusion of chloride ions in concrete structures.
(2) ³⁴²	<u>Material</u> : Cement, FA, GFS, SF, SP, sand, ca, w/b <u>Project</u> : Exposure, temperature, Chloride <u>Property inputs</u> Cl concentration.	<u>Prediction</u> : GEP, DT, ANN <u>Characterize</u> : K-fold cross-validation	GEP obtained the highest value of the linear correlation coefficient.
(3) ³⁴³	<u>Material</u> : SF, slag, FA <u>Project</u> : Depth, T, seawater sulfate <u>Property inputs</u> Concentration.	<u>Prediction</u> : CART, SVR, XGB <u>Characterize</u> : K-Fold, SHAP	(1) The addition of mineral admixtures can improve its resistance to Cl corrosion. (2) XGB models were in good agreement with the measured values. (3) Depth is the most effective factor.
(4) ³⁴⁴	<u>Material</u> : Cement, FA, ca, sand, w/c <u>Project</u> : age, soaking time <u>Property inputs</u> sampling depth	<u>Prediction</u> : RF, GBR, DT	(1) RF model shows 30–40% FA content is preferred. (2) Replacing part of cement with fly ash in the mixture of concrete below this threshold of fly ash because it changes the phase structure and pore structure.
(5) ³⁴⁰	<u>Material</u> : Cement, FA, GGBFS, SF, SP, water, sand, ca <u>Project</u> : Exposure, temperature, chloride content <u>Property inputs</u> Surface chloride concentration	<u>Prediction</u> : LR, GPR, SVM, MLP-ANN and RF models, ensemble weighted voting-based model	(1) Ensemble ML model produces higher accuracy of prediction compared to all standalone ML models tested in this study. (2) Adoption of more diverse datasets and consideration of more factors in conventional models can improve their prediction.
(6) ³⁴¹	<u>Project</u> : Exposure time	<u>Prediction</u> : 1D-CNN <u>Characterize</u> : Multivariate nonlinear model	1D-CNN model has good prediction accuracy in predicting the chloride concentrations in the stable diffusion zone.

GGBFS, and FA in the sulfate attack resist. The influence of all input variables is quantified.

Alkali-silica reaction

ASR is one of the major concerns in concrete durability since it can cause cracks and deformations²²⁵. Although many experiments^{226,227} have been conducted, there are few databases built for ASR study, and the research for ASR using ML methods is limited, highlighting the need for further investigation.

Yang et al.²²⁸ built the first database of ASR expansion data, comprising around 1900 sets of data from the literature. The relationship between ASR expansion and four experimental factors, including reactivity, temperature and relative humidity, specimen geometry, and time-dependent behavior, was then deeply analyzed using ANN models. By combining chemo-mechanical and kinetics-based approaches, ANN was applied to develop a time- and temperature-dependent model of ASR²²⁹. This model concluded that the aggregate size and connected porosity have a coupled effect on the ASR-induced expansion. Hariri-Ardebili²³⁰ applied XGB to establish a predictive model for ASR expansion, achieving a high validation accuracy of 90%. The model was based on a comprehensive database containing 2000 samples of ASR expansion data. SHAP was then used to evaluate the relative importance of factors influencing predictions. The analysis concluded that higher silica content, elevated alkali levels, and longer reaction times were strongly correlated with increased ASR expansion, while larger aggregate sizes and higher w/c ratios were associated with reduced expansion. Zhang et al.²³¹ adopted hybrid ensemble methods, and suggested

higher prediction performance than individual models, with *R* and RMSE values of 97.2% and 0.066 mm, respectively. Similarly, Yang et al.²³² performed the PSO-XGB model for ASR expansion and got the result with excellent stability. From the research, the most effective factors of ASR expansion are alkali content, aggregate particle size, and silica content, contributing to up to 35% of the variation in ASR expansion.

Figure 12 depicts a representative flowchart illustrating the application of a heterogeneous ensemble ML network, integrating CNN and RF models, for assessing ASR damage in concrete²³³. The ASR experiment was conducted on a concrete block specimen with the dimensions of 305 mm × 305 mm × 1120 mm, incorporating reactive coarse aggregate and NaOH. Acoustic emission sensors were used to monitor the resulting ASR damage in the concrete. The acoustic emission waveforms were then transformed into continuous wavelet transform images. A feature-based dataset was generated by extracting parametric features from the AE waveforms. The heterogeneous ensemble ML network composed of CNN and RF was employed to classify the acoustic emission data into different ASR phases with high accuracy (93%), which can be used to evaluate the ASR damage on concrete structures in the field.

Fire resistance

Building fires have become a growing concern due to the increasing density of residential populations and the rapid expansion of high-rise developments. As the most widely used construction material, concrete is generally more fire-resistant than others such as steel, wood, and bamboo. However, the fire resistance of concrete can vary depending on its composition, design,

reinforcement, and the conditions of loading and fire exposure²³⁴. Given the complexity of concrete and the variability of temperature distributions under fire conditions, the thermal and mechanical properties of concrete exhibit highly nonlinear behavior, making the accurate prediction of its fire resistance particularly challenging²³⁵. Therefore, AI-driven models have been increasingly employed to develop practical and accurate methods for predicting the fire resistance of concrete.

Zhao et al.²³⁶ evaluated the fire resistance of concrete-filled steel tubular columns using an XGB model, with the corresponding flowchart presented in Fig. 13. A total of 172 samples were collected and 9 features were selected for the modeling: cross-sectional area, tube thickness, column length, tube yield strength, concrete cylinder strength, load ratio, eccentricity ratio, section type, and temperature curve type. 23 samples were identified as noise using the code formulas and ABQUS-based numerical simulation. By deliberately excluding the noisy data, the remaining dataset was split into training/validation (80%) and testing (20%). The balancing composite motion optimization was then used to set the hyperparameters of the XGB model based on the training and validation datasets. Subsequently, SHAP, feature importance, partial dependence plots, and Surrogates were used to interpret the modeling results. Based on the modeling results, it was concluded that the cross-section area and load ratio were the most influential factors in predicting the fire resistance of concrete-filled steel tubular columns. Moreover, the feature importance on the prediction followed the rank of cross-section area, load ratio, tube thickness, yield strength of the tube, cylinder strength of the concrete, column length, and eccentricity ratio.

Similarly, by considering 7 inputs (including concrete grade, heating time, section factor, thickness of concrete cover to the steel section, perimeter of cross-section, steel area ratio, and thickness of concrete cover to the rebars), Li et al.²³⁵ demonstrated that ANN achieved higher accuracy ($R^2 = 0.999$) compared to analytical equations (0.953) in predicting the fire resistance of concrete-encased steel composite columns. The outputs represented the equivalent temperatures of steel section, concrete section, and steel rebars. Naser and Kodur²³⁷ successfully developed an ensemble ML approach comprising RF, XGB, and DL to assess the fire resistance and fire-induced spalling of both normal-strength and high-strength RC columns. The results indicated that concrete cover thickness, compressive strength, and geometric size of the column were the most important factors influencing the spalling phenomenon. In a recent study²³⁸, the ensemble learning approaches, such as LR, KNN, DT, GB, RF, CatBoost, LightGBM, and XGB, were used to predict the fire-induced spalling depth of concrete tunnel lining. It was concluded that XGB exhibited the best performance among all the models, showing the highest R^2 value of 0.815 and the lowest RMSE and MAE values of 7.243 and 4.38, respectively. Moreover, the amount of polypropylene fiber is the most critical factor influencing the fire resistance of concrete tunnel linings. The compressive strength of the fiber-reinforced concrete subjected to elevated temperatures up to 900 °C was also successfully predicted by Chen et al.²³⁹ using a convolution-based DL approach. The DL approach was developed by modifying the architecture of CNN to allow the integration of an arbitrary number of input features.

Other applications

In addition to predicting the macro-performance of concrete, such as fresh properties, mechanical properties, and durability, AI has been applied to various other aspects of concrete technology. This Section summarizes the application of AI techniques in areas such as micro-performance prediction, automated inspection, and the development of new concrete materials, such as recycled and smart materials.

Micro-performance prediction

Evaluating and predicting the micro-performance of concrete is essential for enhancing its strength, durability, and sustainability. By understanding the material's microstructure, including hydration kinetics and products, porosity, and the interfacial transition zone (ITZ), engineers or researchers can optimize concrete mix designs for improved performance and extended service life.

Cement hydration kinetics and products evolution. Cook et al.²⁴⁰ and Lapeyre et al.²⁴¹ have successfully predicted the time-dependent hydration heat evolution profiles (i.e., heat flow rate and cumulative heat release) of plain and blended ordinary Portland cement (with mineral additives: limestone, quartz, metakaolin, and SF) systems using a RF model. The deep forest model was also used to predict the hydration kinetics of FA-blended binders, achieving an R^2 value of 0.8981²⁴². The prediction accuracy further improved with the introduction of a segmentation technique, increasing the R^2 value to 0.9743. Peng and Unluer²⁴³ compared six ML algorithms in predicting the hydration and carbonation degree of carbonated reactive magnesia cement system. These algorithms include SVM, PSO-SVM, ELM, GWO-SVM, kernel extreme learning machine, and XGB. It was concluded that the GWO-SVM and XGB models outperformed all other models, achieving R^2 values of 0.9470 and 0.9663 for hydration degree predictions, and 0.9775 and 0.9727 for carbonation degree predictions, respectively. It is important to emphasize that the physicochemical characteristics of mineral additives are critical factors that must be carefully considered when predicting cement hydration kinetics.

Backscattered electron (BSE) imaging has been widely employed to visualize phase assemblages in the cement matrix, utilizing grayscale values determined by the average atomic number of the localized areas within the sample²⁴⁴. However, manually processing and identifying BSE images becomes increasingly challenging, particularly when SCMs are incorporated. Sheiati et al.²⁴⁵ proposed a DL-based BSE image segmentation to automatically quantify the phase evolution of cementitious materials and estimate the degree of hydration. Recently, Yu and Geng²⁴⁶ also demonstrated that a CNN-based supervised semantic segmentation method could effectively quantify phase assemblages in BSE images of both plain and SCM-blended cement pastes, including those containing limestone, slag, quartz, and metakaolin.

Porosity and microstructure. Porosity and microstructure are critical parameters in determining the performance and durability of concrete. The porosity of concrete affects its strength, permeability, and overall durability, while the microstructure dictates how well the concrete resists mechanical stress, chemical attack, and environmental degradation. Therefore, understanding and controlling these factors are essential in both scientific research and engineering applications, especially when designing concrete for specific performance and sustainability objectives.

Chao et al.²⁴⁷ developed a novel ML method that combines the logic development algorithm with the ensemble techniques of AdaBoost and ANN to estimate the permeability and porosity of plastic waste aggregate cement mortars. This model demonstrated superior accuracy and efficiency compared to conventional ML models, such as GA and PSO. Xu et al.²⁴⁸ reported that both RF and Bayesian optimization-CNN can accurately predict the porosity of UHPC, with the latter demonstrating superior precision, achieving an R^2 value greater than 0.95. Moreover, the GA with 1000 iterations was able also optimize the UHPC mixture, reaching a high CS of 155.21 MPa or a low porosity of 0.97%. The water distribution of UHPC containing varying porous lightweight aggregates was also successfully predicted using CNN algorithm²⁴⁹. This approach may offer deeper insight into the shrinkage associated with the presence of porous lightweight aggregates in UHPC.

In addition, Xi et al.²⁵⁰ combined the meso-scale concrete fracture model and ANN to predict the fracture properties (tensile strength and fracture energy) of ITZ in concrete. The prediction results showed good agreement with the RILEM test outcomes, demonstrating that the ANN model can effectively be used to inversely predict fracture properties of concrete ITZ. By considering w/c ratio, GGBFS, shrinkage-reducing agent, and measurement depth as inputs, Jamali et al.²⁵¹ predicted the capillary pressure, a leading cause of concrete shrinkage, using a deep neural network. This approach can provide valuable insights for optimizing mix design and implementing effective shrinkage mitigation strategies.

Table 9 | Summary of ML in sulfate attack prediction

Inputs	AI models	Indicators	Metrics	Main findings
(1) ²⁰⁴ <u>Material</u> : SCM, pozzolan, limestone, SF, calcined clay <u>Property inputs</u> Expansion	<u>Prediction</u> : LR, DT, XGB, LGBM <u>Characterize</u> : SHAP	Expansion	R^2 , RMSE, MAE	(1) XGB has the best performance with an R^2 accuracy of 0.933 and 0.788. (2) Clinker composition, mix proportion, sample geometry, and sulfate solution characteristics play an important role, with their relative contribution being 34%, 36%, 3%, and 27%, respectively.
(2) ²²¹ <u>Material</u> : Natural sand, RA, cement, <u>Project</u> : Magnetizing time	<u>Prediction</u> : DL and SVM <u>Characterize</u> : SHAP	WL	R^2	(1) MW enhances the properties, particularly CS, However, the MW is less effective than nano-silica.
(3) ²²³ <u>Material</u> : W/c, w/b, replacement of binder, slag, FA, sand, and SP <u>Project</u> : sulfate content, dry-wet cycle.	<u>Prediction</u> : SVR, GWO, PSO <u>Characterize</u> : SHAP	SC-SCRC	R , RMSE, MSE, MAE, MAPE	(1) The GWO-SVR model provides predictions that better align with the actual values. (2) The dry-wet cycle count and the water-binder ratio are the two most critical influencing factors.
(4) ³⁴⁵ <u>Material</u> : Rubber replacement, <u>Project</u> : Curing, <u>Property inputs</u> Mechanical properties	<u>Prediction</u> : linear, ridge, lasso, DT, RF, XGB, SVM <u>Characterize</u> :	CS, Tensile strength, Flexural strength	MAE, R^2 , RMSE, MAPE, RSS	(1) Rubber replacement can reduce workability and flowability, probably caused by a rise in water absorption. (2) RG and RF models obtained the best prediction.
(5) ³⁴⁶ <u>Material</u> : Short term performance	<u>Prediction</u> : PSO-LSTM Moving average, AR, Moving Average Autoregressive Model, Gray prediction model, RF, SVR, BPNN LSTM	Predicted Values of the test set	R^2 , MAE, RMSE	(1) The PSO-LSTM model is well adapted to the prediction of the deterioration data for concrete subjected to sulfate attack, with a model correlation coefficient R^2 of 0.9739. (2) PSO-LSTM can effectively capture the trend under sulfate attack.
(6) ²⁰⁴ <u>Material</u> : Cement, a/c, w/b, FA, slag, Pozzolan, limestone, MK, SF, nano SF <u>Project</u> : pH <u>Property inputs</u> Mold properties	<u>Prediction</u> : LR, DT, XGB, LGBM <u>Characterize</u> : SHAP	Expansion	R^2 , RMSE, MAE,	(1) XGB showed the best performance with an R^2 accuracy of 0.933 and 0.788 on the training and the test set, respectively. (2) Clinker composition, mix proportion, sample geometry, and sulfate solution characteristics play an important role, with their relative contribution being 34%, 36%, 3%, and 27%, respectively.

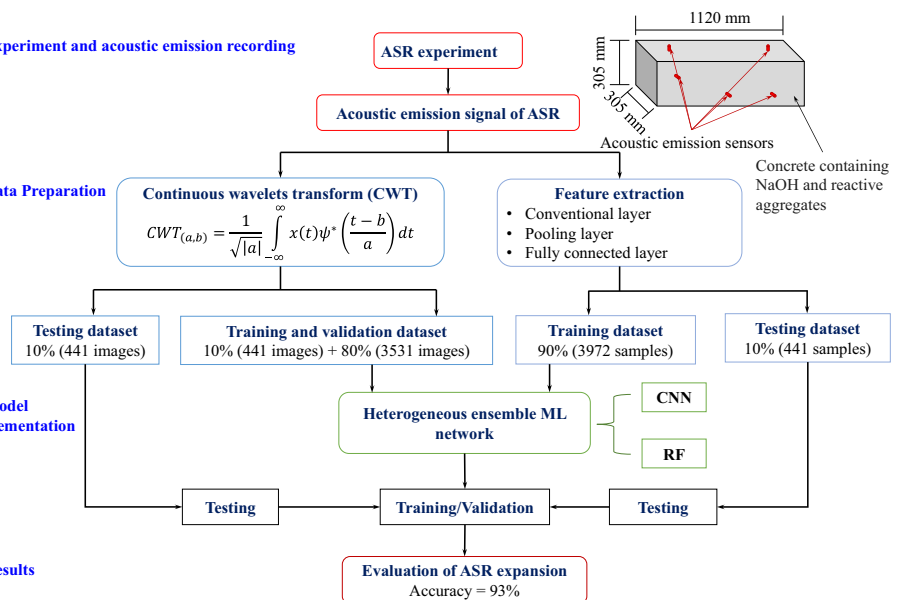
Fig. 12 | Flowchart of ASR damage evaluation using a heterogeneous ensemble ML network.

• Experiment and acoustic emission recording

• Data Preparation

• Model implementation

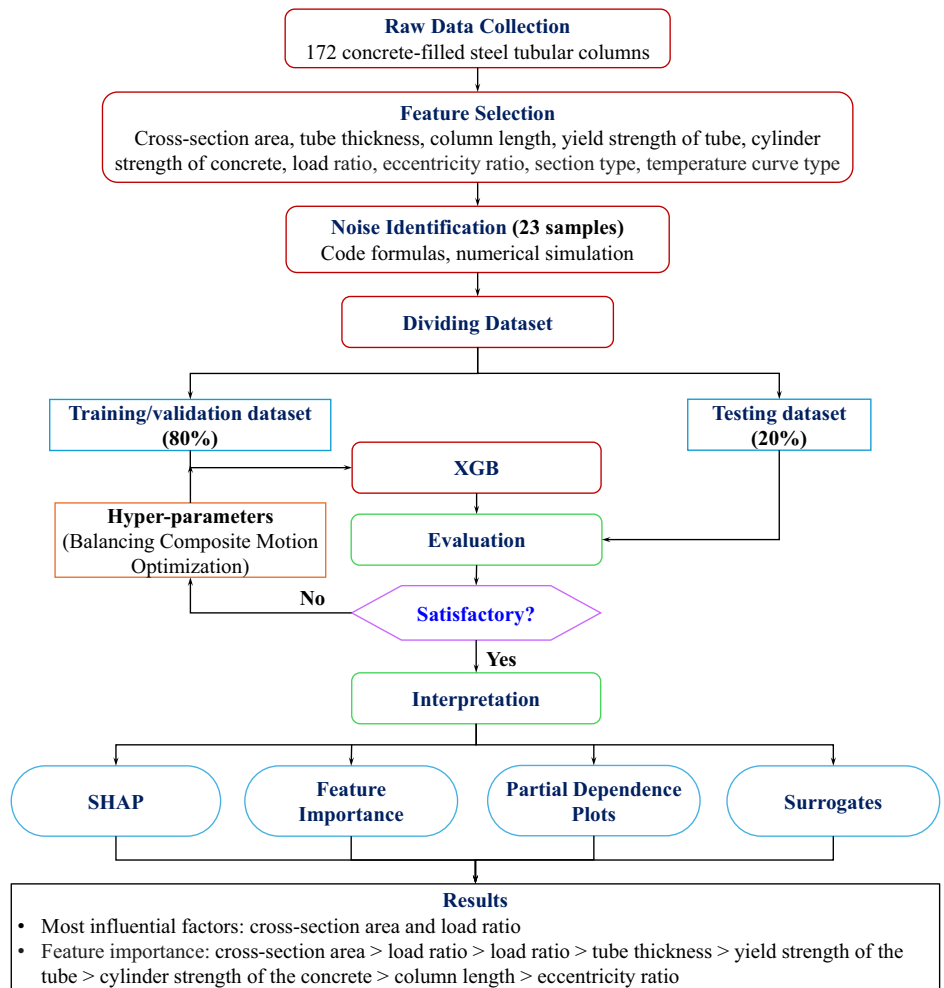
• Results



Micromechanical properties. Grid nanoindentation technology is an effective and widely used method for assessing the micromechanical properties of cementitious materials. However, conventional data processing techniques, such as the deconvolution analysis method and Gaussian Mixture Model, have limitations when applied to nanoindentation data. These methods often rely on assumptions, such as Gaussian distribution, that may not accurately represent the complex and heterogeneous nature of the data, leading to potential inaccuracies in phase identification and micromechanical property analysis. Therefore, AI

methods have recently been applied to process nanoindentation data, offering more accurate and efficient analysis by overcoming the limitations of traditional techniques. These AI-driven approaches improve phase identification and micromechanical property assessment, enhancing the reliability and precision of nanoindentation data processing. For example, Chen et al.²⁵² proposed a curve clustering analysis method to distinguish the mineral phase curves, enabling the calculation of elastic modulus/hardness distributions and mineral phases contents. Then, SVM and BPNN classifier were introduced to accurately recognize and

Fig. 13 | Flowchart of using XGB in predicting the fire resistance of concrete filled steel tubular columns.



categorize nanoindentation data, achieving accuracy level greater than 98% after being well trained. Arachchige et al.²⁵³ employed unsupervised ML techniques, including k-means clustering and Gaussian Mixture Modeling, to classify the micromechanical properties (microhardness and reduced modulus) of alkali-activated pozzolans such as calcined clay, ground bottom ashes, volcanic ashes, and fluidized bed combustion ashes. Both methods exhibited effectively analyzed statistical nanoindentation data, providing consistent results of mean, standard deviation, and weightage inherent to each cluster.

Automatic inspection

Inspection is vital for ensuring the long-term reliability, safety, and efficiency of concrete structures while minimizing risk and cost. However, due to the lack of well-designed practices, traditional methods of inspecting concrete structures, such as manual visual inspection, are labor-intensive, time-consuming, and prone to errors. To address this challenge, AI-driven automatic inspection methods have been proposed and widely adopted during the past decades, including ML²⁵⁴, Rb²⁵⁵, CV²⁵⁶, FL⁴⁸, NLP²⁵⁷, and ES²⁵⁸.

Figure 14 presents a representative flowchart that uses a CV-based statistical crack quantification algorithm for automatic inspection²⁵⁶. A three-step method was proposed in this study. In step 1, the crack areas of as-received images were automatically detected using a DL-based network. The crack pixels were extracted through an image processing algorithm, and then a crack map was generated. In Step 2, the cracks were separated into endpoints (i) and branch points (j) based on the crack map generated in Step 1. Then the cracks until no branch points were found. Subsequently, the crack length and width were calculated in Step 3. In the end, the quantification of

the resultant image is finalized as the accurate crack evaluation, which can serve as a reliable indicator for crack measurement and guide the development of an efficient maintenance plan. By following this flowchart, the average differences between the quantitative crack evaluations and actual field measurements were only 18.07% and -26.28%, respectively, in terms of crack width and length.

In addition to AI-based automated crack inspection, automatic inspection for precast concrete has also been widely implemented. For example, Ma et al.²⁵⁹ conducted a comprehensive and systematic literature review on the automatic methods used in the quality inspection of precast concrete. It was concluded that 3D laser scanners are the most used ones to inspect precast concrete slabs, beams, columns, and sleepers with millimetric accuracy, meeting standard tolerance requirements. With a suitable algorithm, automatic inspection can also be applied to connection parts, such as rebar and sleeve ports of precast concrete components, as well as to multiple components simultaneously. Kardovskyi and Moon²⁶⁰ developed an AI Quality Inspection Model by integrating Mask Region-based CNN and stereo vision to automatically detect steel rebars installed for concrete placement. However, the 1280×720 px resolution was insufficient for precise detection beyond 2 m, limiting its practical application. While AI can enhance the accuracy of concrete inspection and reduce labor requirements, further advancements in automatic inspection techniques are still needed.

Innovative materials

Recycled materials. To achieve sustainability goals, recycled materials are increasingly used in concrete, either as substitutes for cement, serving as cementitious materials, or as replacements for aggregates²⁶¹. The recycling of SCMs, such as FA, GGBFS, SF, et al., is widely employed in

concrete to replace cement, thereby reducing clinker production. The prediction of fresh and hardened properties, as well as the durability characteristics of using these SCMs were already reviewed in the above sections. Therefore, this section mainly discusses the application of AI techniques in other recycled materials, including RCA, waste rubber, waste glass, and biochar. Some representative examples of using AI techniques in investigating the recycled materials mentioned above are summarized in Table 10.

RCA is generated from construction and demolition waste. The use of RCA may help mitigate the depletion of natural aggregate and reduce the massive disposal of construction and demolition waste, leading to more sustainable concrete production²⁶². Most studies have focused on replacing natural aggregates with RCA. However, due to the variability of RCA sourced from different sites, it is challenging to control and predict the performance of RCA-added concrete^{263–265}. Research related to the use of AI techniques has been conducted in predicting various properties of RCA-added concrete, such as creep behavior²⁶⁶, CS²⁶⁷, modulus elasticity²⁶⁸, chloride penetration²⁶⁷, etc. Except for the concrete components, such as cement, SCMs, natural aggregate, and w/b, the parameters related to RCA, including the contents, water absorption capacity, and density are specially considered as inputs for the modeling of RCA-added concrete, as shown in Table 10. ANN and XGB are widely recognized as accurate models to predict the performance of RCA-added concrete, with ensemble models generally demonstrating greater efficiency and accuracy compared to individual ones.

Waste rubber from retired tires is not biodegradable, which contains hazardous materials and poses environmental concerns due to its hazardous properties²⁶⁹. Waste rubber can be used in concrete as a substitute for natural aggregates, serving a recycling purpose. Caution is required when incorporating waste rubber into concrete, as the CS may be compromised when a high proportion of waste rubber is used²⁷⁰. Deep NN was developed by Ly et al.²⁷¹ and accurately predicted the 28-day CS of rubber concrete with an R-value of 0.9874. In another study reported by Gao et al.,²⁷² the XGB ensemble model outperforms other models, including Ridge, ANN, RF, and Stacking, in predicting the frost resistance of rubber concrete.

The waste glass and biochar are also used to partially replace cement in concrete construction. Both CS and flexural strengths were successfully predicted with ML models^{273–275}. The use of these ML models accelerates advancements in concrete technology by providing rapid and cost-effective solutions for performance predictions.

Smart materials. Rapid urbanization and population growth are driving increased demand for concrete infrastructure that offers high performance, durability, and environmental sustainability. Therefore, more smart and sustainable materials are explored to either extend the service life of concrete structures or reduce the environmental impact of concrete production²⁷⁶. Recently, the development of advanced AI-driven models, including ML, FZ, Rb, and CV, has significantly facilitated the exploration of smart materials, such as those used in self-healing²⁷⁷, concrete nanotechnology²⁷⁸, and internal curing²⁷⁹.

Self-healing. Self-healing concrete is an advanced material capable of automatically repairing its own cracks through an embedded self-healing system, with or without encapsulation, introduced during casting, eliminating the need for external intervention²⁸⁰. Self-healing is widely recognized for its ability to enhance durability, reduce maintenance costs, and extend the service life of concrete infrastructures. However, the performance of self-healing in concrete depends on several independent factors, such as the survivability of healing agents during mixing and the agent releasing efficiency when cracks occur²⁸¹, etc. The inherent complexity of self-healing in concrete makes it difficult to accurately predict its healing efficiency, and laboratory measurements are often time-consuming and costly. AI techniques have emerged as an effective tool for addressing this challenging task.

Wang et al.²⁸² defined self-healing efficiency as the differences in properties, such as stress, stiffness, conductivity, and bulk, between the undamaged and damaged materials. Then the SVM, ANN, and an online ensemble learning model were used and validated to predict the self-healing efficiency using bio-hybrid self-healing material. The bacteria-based self-healing concrete was also predicted by using SVR, DT, GB, ANN, Bayesian ridge regression, and Kernel ridge regression, in terms of crack closure percentage by Zhuang et al.²⁸³ It was concluded that the integrated ML approaches showed a high potential to predict the crack closure percentage. By considering mineral admixture, percentage of mineral admixture, percentage of crystalline admixture, and type of exposure as the inputs, the accuracy of ANN in predicting the CS of self-healing concrete using crystalline admixtures was validated with high R^2 values of 0.99989, 0.99596, and 0.99923 in training, testing, and validation, respectively²⁸⁴. In a recent study, Xi et al.²⁸⁵ compared the prediction accuracy of various ML models, namely the Whale optimization algorithm (WOA), GWO, and Flower pollination algorithm (FPA), ensembled with XGB in predicting the self-healing performance of UHPC. The crack width, exposure time, and exposure conditions (tap water, salt water, geothermal water) were considered as inputs, with the crack self-healing index as the output. The highest R^2 values of 0.8853 and 0.9275 in the testing and training sets, respectively, demonstrated the most accurate predictions, achieved by the model using a combination of WOA and XGB.

Concrete nanotechnology. The use of nanomaterials, such as nano-silica, nano-clay, nano-calcium carbonate, nano-titanium dioxide, nano-graphene oxide, and carbon nanotubes, in concrete has attracted significant attention in recent years. Extensive research has demonstrated that the incorporation of these nanomaterials can effectively enhance both mechanical strength²⁸⁶ and durability of concrete²⁸⁷, as well as contribute to its sustainability²⁸⁸. AI plays a crucial role in this domain by optimizing the integration of nanomaterial²⁸⁹ and predicting the resulting properties of concrete²⁹⁰.

To improve design efficiency and lower the associated costs, Maherian et al.²⁹¹ predicted the CS of concrete modified with nano-silica and SCMs using ML algorithms, such as ANN, LR, DT, RF, SVM, KNN, and Stochastic gradient descent (SGD). A comprehensive understanding of the interactions among various factors, such as the content of cement, water, FA, GGBFS, SF, nano-silica, ca, fa, SP, and w/b, age, and the specific surface area of nano-silica, was obtained with a dataset comprising 1143 samples. Among the ML models, RF and ANN exhibited the highest accuracy in predicting the CS of nano-silica concrete, with R^2 values of 0.93 and 0.92, respectively. Moreover, it was concluded that the optimal dosage of nano silica for achieving the desired CS of concrete is approximately 10 kg/m³.

Dong et al.²⁹² developed a novel comprehensive multi-objective design optimization (MODO) method to simultaneously optimize the CS and electrical resistivity of graphene-based nanomaterials-reinforced cementitious composites (GNRCC). Four ML models, including SVR, RF, XGB, and BPNN, were employed for prediction, combined with three optimization methods, namely grid search, PSO, and Bayesian optimization. The results indicated that the Bayesian-optimized XGB outperformed other tuned estimators, achieving high R^2 values of 0.92 and 0.98 and low MAE values of 3.44 and 0.22 for predicting the CS and electrical resistivity of GBRCC, respectively. Moreover, it was also concluded that the dosage of graphene-based nanomaterials was the most influential factor affecting the CS and electrical resistivity of GNRCC, compared to other features, such as cement and sand content, physical properties of graphene-based nanomaterials, w/c, SP, ultrasonication, and curing age.

Internal curing. Only a few studies have predicted the mechanical properties of internally cured concrete using ML algorithms. For instance, Sowjanya et al.²⁷⁹ applied various ML algorithms, including DT, RF, and MLP, to predict and validate the CS, splitting-tensile, and flexural strength of concrete incorporating FA aggregate as an internal curing agent. It was found that the DT exhibited the highest performance in predicting the strength characteristics of internally cured concrete, while the MLP was the least

Fig. 14 | Flowchart of a representative CV-based statistical crack quantification algorithm for automatic inspection.

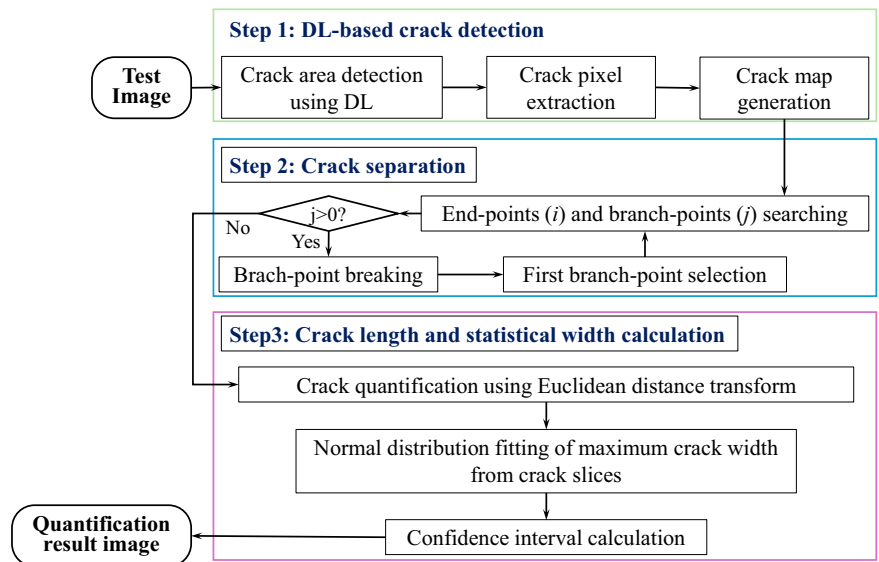


Table 10 | Examples of AI-driven models used to investigate recycled materials in concrete

No.	Materials	Inputs	AI-models	Outputs	Metrics
(1) ²⁶⁶	RCA	RCA content and water absorption capacity, w/c, natural aggregate content, loading age, relative humidity (RH), notional size, 28-day CS ratio, modulus of elasticity	Least Square-SVM, BPNN, RT, RF, XGB	Creep behavior	R^2 , MAE, RMSE, objective function (OBJ)
(2) ²⁶⁷		RCA properties (density, water absorption) Mixture proportions (water, cement, natural fa, RCA, natural ca, SP)	ANN, SVR, PSO-SVR, GWO-SVR	CS	Absolute error, error percentage, R^2 , RMSE, MAE, MAPE, standard deviation ratio, CPI
(3) ²⁶⁸		Binder type, cement, SCMs, natural ca, RCA, fa, water absorption, density, and maximum particle size of natural aggregate and RCA, water content	SVM, GPR, MLP, RF, Ensemble ML model formulated by combining RF and SVM within a weighted voting framework	28-day modulus of elasticity	R , R^2 , MAE, MAPE, RMSE, CPI
(4) ²⁶⁷		Cement, water, sand, natural ca, RCA, FA, GGBFS, water absorption, and apparent density of aggregates	ANN, GPR, SVR, CART, RF, GB	Chloride resistance	RMSE, SI, MAPE, R^2
(5) ²⁷¹	Waste Rubber	Cement, cement replacement, binder, SP, water, w/c, w/b, fa, ca, crumb rubber, chipped rubber, CS specimen type	ANN, Deep NN	CS	R^2 , MAE, RMSE, MSE
(6) ²⁷²		Content of cement, sand, and ca, rubber, rubber size, number of cycles	Ridge, SVR, ANN, RF, XGB, Stacking	Frost resistance	RMSE, MAE, R^2
(7) ²⁷³	Waste glass	cement, water, fa, WGP, SP, SF	SVM, Bagging	Flexural strength	MAE, RMSE, MAPE
(8) ²⁷⁴		w/b, slag, FA, ca, and natural fa, SP, waste glass with different sizes, concrete age	SVR, LS-SVR, ANFIS, MLP	CS	RMSE, MAE, MAPE, bias-variance (U_{95}), Nash-Sutcliffe efficiency (NSE), Confidence index (CI)
(9) ²⁷⁵	Biochar	Cement, sand, water, biochar, SP	LR, AdaBoost	CS and tensile strength	R^2 , MSE, RMSE, MAE

accurate. In another study, the ANN algorithm proved to be an accurate model for predicting the mechanical properties of concrete internally cured with Polyethylene Glycol. The R^2 values for training, testing, and validation are all higher than 0.98. Hosseinzadeh et al.²⁹³ predicted the CS degradation of concrete containing superabsorbent polymers (a material widely used for internal curing) using an ensemble learning-based prediction model. It was concluded that SVR and XGB models could accurately predict the percentage of strength reduction in concrete containing superabsorbent polymers with R^2 values of 0.90 and 0.88, respectively. However, no other AI-driven models for predicting other aspects of internal curing in concrete have been developed or made available. Therefore, further research is needed in this area, as internal curing has become widely used and extensively reported in concrete technology.

Conclusions and future perspectives

Conclusions

This study provides a comprehensive and systematic review of the application of advanced AI techniques in concrete technology, covering key areas such as mix design optimization, the prediction of fresh, hardened, and durable properties, as well as automated inspection and the investigation of new materials. The following insights and conclusions can be drawn based on the findings of this study.

- (1) Multiple AI techniques, including ML, ES, FL, NLP, Rb, and CV, have been applied in concrete technology. Among these, ML is the most widely used due to its ability to handle large volumes of complex data, make faster and more accurate decisions, and provide high accuracy in predictions and optimizations.

- (2) The process of using ML to optimize concrete mix design was summarized, highlighting that both data quality and quantity, along with the selection of appropriate algorithms, are crucial for achieving a reliable design that meets the defined objectives.
- (3) The ensemble AI models were always proven more efficient and accurate in predicting the fresh, hardened, durable properties of concrete than the single models. Especially, XGB is one of the most well-known and powerful ML algorithms for prediction tasks, due to its high accuracy, efficiency, and wide applicability. However, special attention should be given to hyperparameter tuning when the ML algorithms are used for prediction.
- (4) The AI-driven models, particularly those using ML, CV, and Rb, enhance the automation of concrete structure inspections during both degradation and precast phases. Due to their ability to handle new materials, ML models are widely used to investigate recycled and smart materials in concrete.
- (5) Although AI techniques have advanced significantly in computer science, their application in concrete technology and the broader construction industry is still developing. In parallel with the rapid advancement of AI techniques in computer science, more research efforts are needed to fully harness the benefits of AI in concrete technology. This exploration should extend beyond predictive modeling, quality control, and the optimization of material and structural properties.

Limitations

Despite its comprehensive scope, this review has certain limitations that should be acknowledged. For example, the variability, inconsistency, and poor quality in datasets used for AI applications in concrete materials may limit the generalizability and comparison of the different studies. Moreover, the challenges are associated with the black-box nature of many AI models, particularly DL, which makes it difficult to interpret their predictions or validate their reliability. As a result, there is a need for more open-access, high-quality datasets and interpretable AI models that can enhance trust and acceptance within the construction industry.

Another limitation is the underexplored integration of AI techniques into real-world engineering practice, which might be due to the complexity and variability of concrete materials and practical constraints and industry-specific barriers. Concrete properties are influenced by numerous factors, including raw material characteristics, mix proportions, curing conditions, and environmental impacts. These variables result in complex, non-linear, and highly context-specific behaviors that are challenging for AI models to generalize across diverse projects and regions. Since many AI models are developed using limited or localized datasets, their predictions often lack reliability when applied to new conditions or unfamiliar scenarios, raising concerns about their robustness and accuracy in practical applications.

In addition, AI implementation in the construction industry faces significant practical challenges. These technologies rely on high-quality, standardized data, yet the industry has been slow to adopt advanced data management practices. The deployment of AI tools also requires substantial computational resources, specialized expertise, and upfront investment, which may be prohibitive for smaller firms or projects. Furthermore, the absence of standardized guidelines, regulatory frameworks, and seamless integration with existing construction workflows further impedes the widespread use of AI in real-world engineering practices for concrete.

Future perspectives

The future of AI in concrete materials holds immense potential for improvement in several key areas: (1) the creation of high-quality, standardized, and open-access datasets to enhance model reliability; (2) the integration of interpretable and explainable AI models to increase transparency and trust; (3) the application of hybrid modeling approaches that combine AI with traditional mechanistic models for improved accuracy and insight; (4) enhancing the scalability and transferability of AI models to ensure consistent

performance across diverse projects and conditions; (5) leveraging real-time data, IoT, and digital twins in conjunction with AI to optimize and predict concrete performance over time; (6) the development of cost-effective and resource-efficient AI tools tailored for smaller-scale, real-world applications; and (7) the standardization of AI methodologies and models for practical field applications to promote widespread adoption.

AI can revolutionize material design by optimizing mix proportions for sustainability and performance, leading to the discovery of new, eco-friendly concrete formulations. It can also enhance predictive models for long-term performance, enabling data-driven maintenance through sensor monitoring and improving durability.

Furthermore, integration with smart technologies like embedded sensors and digital twins could allow real-time monitoring and simulation of structures throughout their lifecycle. AI-driven automation, particularly in 3D concrete printing and robotics, could streamline construction processes, enhancing precision and efficiency.

However, interdisciplinary collaboration between AI specialists, engineers, and material scientists will be essential to develop reliable, interpretable models, while challenges such as data availability, model transparency, and scalability must be addressed. Standardizing AI adoption in industry codes and addressing ethical concerns will further ensure the safe and effective use of AI in concrete construction, paving the way for smarter, more sustainable infrastructure.

In addition to performance prediction, AI can play a vital role in life cycle assessment, promoting more sustainable concrete practices. As AI techniques evolve, they will enhance real-time monitoring and predictive maintenance of concrete structures, thereby improving safety and reducing costs. Advancements in generative design will allow engineers to create optimized concrete mixtures tailored to specific performance criteria, leading to more resilient structures.

Moreover, the development of new materials in concrete technology stands to gain significantly from AI advancements. While internal curing techniques are widely employed in concrete, research on the application of AI-driven models in this area remains limited, indicating a promising avenue for future exploration.

Data availability

No datasets were generated or analysed during the current study.

Abbreviations

AAC	Alkali-activated concrete
AdaBoost	Adaptive boosting
AEA	Air-entraining agent
a/c	Aggregate-to-cement ratio
AI	Artificial intelligence
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial Neural Network
ASR	Alkali-silica reaction
ARIMA	Moving Average Autoregressive Model
BPNN	Back-propagation neural network
BSE	Backscattered electron
ca	Coarse aggregate
CART	Classification and regression trees
CatBoost	Categorical boosting
CHAID	Chi-squared automatic interaction detector
CI	Confidence index
CIDC	Chloride ion diffusion coefficient
CNN	Convolutional neural network
CPI	Composite performance index
CS	Compressive strength
CV	Computer Vision
DCNN	Deep Convolutional Neural Network
DL	Deep Learning
DM	Data Mining
DT	Decision tree

ELM	Extreme learning machine
EM	Expectation maximization
ES	Expert system
Extra	Extra trees
FA	Fly ash
fa	Fine aggregate
FL	Fuzzy Logic
FPA	Flower pollination algorithm
GA	Genetic Algorithms
GB	Gradient Boosting
GEP	Gene expression programming
GENLIN	Generalized linear model
GGBFS	Ground granulated blast-furnace slag
GRELm	Generalized extreme learning machine
GNRCC	Graphene-based nanomaterials-reinforced cementitious composites
GPR	Gaussian process regression
GUI	Graphical User Interface
GWO	Grey Wolf optimizer
IoT	Internet of Things
ITZ	Interfacial transition zone
KDD	Knowledge-driven design
KNN	K Nearest neighbor regressor
LightGBM	Light gradient boosting machine
LLMs	Large language models
LS-SVR	Least Squares-Support Vector Regression
LSTM	Long short-term memory
LR	Linear Regression
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MBE	Mean bias error
ML	Machine learning
MLP	Multi-Layer Perceptron
MODO	Multi-objective design optimization
MSE	Mean squared error
NGBoost	natural gradient boosting
NLP	Natural Language Processing
NLR	Non-linear regression
NSE	Nash-Sutcliffe efficiency
OBJ	Objective function
PSO	Particle swarm optimization
R	Correlation coefficient
R ²	Coefficient of determination
Rb	Robotics
RCA	Recycled coarse aggregate
RCPT	Rapid chloride penetration test
RF	Random Forest
RH	Relative humidity
SHAP	SHapley Additive exPlanation
RL	Reinforcement Learning
RMSE	Root mean squared error
RNN	Recurrent neural network
RSE	Relative squared error
SCC	Self-compacting concrete
SCMs	Supplementary cementitious materials
SF	Silica fume
SFRC	Fiber-reinforced concrete
SI	Scatter index
SMAPE	Symmetric mean absolute percentage error
SP	Superplasticizer
SVM	Support vector machines
T _{stat}	t-statistic test
U ₉₅	Bias-variance
UHPC	Ultra-high-performance concrete
VMA	Viscosity Modifying Agent

w/b	Water-to-binder
w/c	Water-to-cement
WOA	Whale optimization algorithm
XGB	Extreme gradient boosting
τ_0	Shear yield stress
μ	Plastic viscosity
3DPC	3D printing concrete

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Competing interests

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