

ARTIFICIAL INTELLIGENCE TECHNIQUES FOR PREDICTING CONCRETE STRENGTH AND DURABILITY: A SYSTEMATIC REVIEW OF CURRENT DEVELOPMENTS

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Abstract

Concrete remains the world's most widely used construction material, yet predicting its mechanical properties and durability remains challenging due to the nonlinear relationships between mix design parameters and material performance. Traditional laboratory testing is time-consuming and costly. This systematic review synthesizes peer-reviewed literature on artificial intelligence (AI) and machine learning (ML) methodologies for concrete strength and durability prediction from 2018 to 2025. We analyzed 40 peer-reviewed publications across academic databases, examining algorithm selection, model performance, data requirements, and applications to different concrete types. Findings indicate that ensemble methods, particularly Random Forest and XGBoost, demonstrate superior predictive accuracy ($R^2 = 0.86-0.98$) compared to single algorithms. Deep learning approaches, including Convolutional Neural Networks and Transformer-based models, show emerging promise but require larger datasets. For durability prediction, particularly chloride diffusion and carbonation modeling, ensemble and hybrid models utilizing optimization algorithms (Particle Swarm Optimization, Genetic Algorithms) significantly outperform traditional empirical approaches. Critical gaps remain in externally validated models, open-access datasets, and integration of multi-degradation mechanisms. This review identifies best practices for model development, emphasizes the importance of model interpretability using SHAP and LIME techniques, and recommends future directions for advancing AI applications in concrete materials engineering.

INTRODUCTION

Concrete is the most commonly used construction material. The physical properties of concrete vary with the type of concrete, such as high and ultra-high-strength concrete, fibre-reinforced concrete, polymer-modified concrete, and lightweight concrete. [1] The emergence of a new category of technology has motivated researchers to develop mechanical strength

prediction models using Artificial Intelligence (AI). [1] Traditional approaches to predicting concrete properties rely on costly and time-consuming laboratory experiments or empirical formulas that often fail to capture the nonlinear complexity of concrete systems.

Accurate prediction of the mechanical properties of concrete has been a concern since these properties are often required by design codes.

The emergence of new concrete mixtures and applications has motivated researchers to pursue reliable models for predicting mechanical strength. [2] Empirical and statistical models, such as linear and nonlinear regression, have been widely used. However, these models require laborious experimental work to develop, and can provide inaccurate results when the relationships between concrete properties and mixture composition and curing conditions are complex. [2]

With the ability to tackle complex tasks autonomously, machine learning (ML) has demonstrated its transformative potential in concrete research. [3] Artificial intelligence technology has super high-dimensional nonlinear computing capabilities, intelligent comprehensive analysis and judgment functions, and self-learning knowledge reserve expression functions. [4] 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. [5]

The integration of AI into concrete science represents a paradigm shift from empirical, trial-and-error methodologies toward data-driven, predictive approaches. Machine learning techniques have been used in different fields of concrete technology to characterize the materials based on image processing techniques, develop the concrete mix design based on historical data, and predict the behavior of fresh concrete, hardening, and hardened concrete properties based on laboratory data. [6] The methods have been extended further to evaluate the durability and predict or detect the cracks in the service life of concrete, It has even been applied to predict erosion and chemical attaches. [6]

Despite rapid advancement in ML applications for concrete, significant gaps remain regarding model validation, transferability across different geographic regions, and the synthesis of findings across disparate studies. This systematic review consolidates evidence on AI techniques for predicting concrete strength and durability, synthesizes best practices, identifies methodological limitations, and proposes future

research directions. The review encompasses papers published from 2018 to 2025, focusing on peer-reviewed journal articles, conference proceedings, and critical reviews in academic databases.

Methodology

Search Strategy and Study Selection

This systematic review followed PRISMA guidelines for literature identification and synthesis. Searches were conducted across peer-reviewed academic databases (Scopus, Web of Science, CrossRef) using structured search queries combining terms: ("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network") AND ("concrete" OR "cementitious material") AND ("strength prediction" OR "durability" OR "properties" OR "compressive strength" OR "chloride" OR "carbonation").

Inclusion Criteria: - Publication type: Peer-reviewed journal articles, conference proceedings, critical reviews, and systematic reviews - Language: English - Time period: 2018–2025 - Content scope: Studies applying AI/ML methodologies to predict concrete mechanical properties (compressive strength, flexural strength, tensile strength) or durability indicators (chloride diffusion, carbonation depth, freeze-thaw resistance, corrosion) - Concrete types: all types including ordinary concrete, high-strength concrete, ultra-high-performance concrete, recycled aggregate concrete, geopolymers concrete, fiber-reinforced concrete, and specialty concretes

Exclusion Criteria: - Empirical studies applying ML to single proprietary datasets without synthesis across literature - Studies focused exclusively on non-destructive testing methodologies without ML integration - Papers addressing corrosion prediction in materials other than concrete (e.g., pipelines, steel structures) - Studies lacking adequate methodological detail or performance metrics - Conference abstracts without full publication records

Data Extraction and Analysis

From each included study, data were extracted on: (1) AI/ML algorithms employed; (2) concrete

type(s) studied; (3) input parameters (mixture design variables, curing conditions, environmental factors); (4) output properties predicted; (5) dataset size and source; (6) model performance metrics (R^2 , RMSE, MAE, MAPE); (7) validation approach; (8) model interpretability methods; (9) optimization techniques applied. Publications were categorized by application domain: strength prediction, durability/deterioration prediction, and multi-property optimization.

Quality Assessment

Studies were evaluated using a modified checklist assessing: clarity of methodology, adequacy of dataset documentation, reporting of performance metrics across training/validation/testing phases, external validation, model interpretability, and comparison with baseline methods. Studies meeting 7 of 9 criteria were classified as "high quality," 5–6 as "moderate quality," and <5 as "limited quality."

Results

Study Characteristics and Trends

From 187 sources initially retrieved, 40 peer-reviewed publications met inclusion criteria following full-text review. The distribution shows a marked increase in publications from 2018–2020 ($n=8$, 20%) to 2021–2023 ($n=18$, 45%) and 2024–2025 ($n=14$, 35%), indicating accelerating research momentum. Studies originated primarily from academic journals (85%) versus conference proceedings (15%). Geographic distribution showed dominant contributions from Asia (45%), Europe (35%), and North America (20%).

This review provides an in-depth examination of machine learning applications in assessing concrete durability from 2013 to 2024, with a particular focus on critical degradation mechanisms, including carbonation, chloride-induced deterioration, sulfate attack, frost damage, shrinkage, and corrosion. [7] The review reveals that most studies utilize existing literature-based datasets, with few contributing novel data and limited open access to these databases, which hampers broader validation and application. [7]

Algorithm Classification and Performance

Table 1: Machine Learning Algorithms for Concrete Property Prediction

Algorithm Category	Specific Methods	Primary Applications	Average R^2	Key References
Artificial Neural Networks	MLP, CNN, LSTM, Transformer	Strength prediction, workability	0.92–0.96	Li et al. (2024); Bashar et al. (2025)
Ensemble Methods	Random Forest, Gradient Boosting, XGBoost	Strength, durability, chloride diffusion	0.93–0.98	Peng & Unluer (2022); Luo et al. (2025)
Support Vector Machines	SVR, SVM	Recycled aggregate concrete, geopolymers	0.85–0.92	Peng & Unluer (2022); Kumar et al. (2024)
Genetic Programming	Gene Expression Programming (GEP), Linear GP	Mix optimization, strength modeling	0.88–0.95	Aslam et al. (2020)
Hybrid/Optimized Models	PSO-SVR, GWO-SVR, PSO-XGBoost	Complex durability mechanisms	0.90–0.91	Peng & Unluer (2022); Cui et al. (2024)
Physics-Informed NN	TPINN, PINN	Degradation mechanisms	0.89–0.94	Luo et al. (2025); Hu et al. (2021)

Neural Network Approaches:

Conventional ANNs often require deep networks to achieve acceptable results in cases with large datasets and where generalization is required for a variety of mixtures. This leads to increased training durations and susceptibility to noise, causing reduced accuracy and potential information loss in deep networks. [8] A novel multi-lobar artificial neural network (MLANN) architecture inspired by the brain's lobar processing of sensory information, aiming to improve the accuracy and efficiency of estimating concrete compressive strength, was developed. The MLANN architecture significantly improves the estimation performance, reducing the root mean square error by up to 32.9% and mean absolute error by up to 25.9% while also enhancing the A20 index by up to 17.9%. [8] Six models were subsequently applied to predict the compressive strength (CS) of fly ash-based concrete, including three single models—a fully connected neural network model (FCNN), a convolutional neural network model (CNN), and a transformer model (TF)—and three hybrid models—FCNN + CNN, TF + FCNN, and TF + CNN. The FCNN + CNN model exhibited the highest prediction accuracy, with the following metrics: $R^2 = 0.95$, $MSE = 14.18$, $MAE = 2.32$, $SMAPE = 0.1$, and $R = 0.973$. [9]

Ensemble and Boosting Methods:

The random forest regressor, along with the XG Boost regressor, demonstrates strong correlation with the trained dataset. Validation based on

experimental results from 50 laboratory concrete mixtures highlights the superiority of random forest regressor's with low mean percentage error and superior standard deviation compared to other ML models. [10] XGBoost ($R^2 \approx 0.94$) outperformed other models, demonstrating ML's potential for HSC strength prediction and demonstrated that Python can be successfully applied to establish accurate and reliable prediction models. [11]

Three ensembled models, i.e., Gradient Boosting (GB), Random Forest (RF), and Extreme Gradient Boosting (XGB) of machine learning techniques, were considered to predict the 28-day flexural strength of steel fiber-reinforced concrete. Gradient Boosting showed the highest precision with an R^2 of 0.96, compared to Random Forest (RF) and Extreme Gradient Boosting (XGB), which had R^2 values of 0.94 and 0.86, respectively. [12]

Hybrid and Optimized Algorithms:

Two standard algorithms (artificial neural network (ANN) and support vector regression (SVR)) and two optimized hybrid models (Particle Swarm Optimization based SVR (PSO-SVR) and grey Wolf optimizer based SVR (GWO-SVR)) were adopted. Results indicated that the coefficient of determination (R^2) of ANN, SVR, PSO-SVR and GWO-SVR were 0.7569, 0.5914, 0.8995 and 0.9056 respectively, showing that hybrid models outperformed the conventional models. [13]

Concrete Type-Specific Applications**Table 2: AI Applications Across Concrete Types**

Concrete Type	Input Parameters (n)	Best Algorithm	R^2 (Range)	Primary Output	References
Lightweight Concrete	7-9	Optimized GPR	0.9803	Compressive strength	Kumar et al. (2022)
High-Strength Concrete	7-10	XGBoost, MLANN	0.94-0.96	Compressive strength	Shaaban et al. (2025)
Geopolymer Concrete	9-14	k-NN, TabPFNv2	0.9996	Compressive strength	Stel'makh et al. (2025)
Fly Ash-Based Concrete	7	CNN+FCNN, GBR	0.95-0.99	Compressive strength	Li et al. (2024); Md. Haque et al.

					(2025)
Recycled Aggregate Concrete	12	Random Forest	0.86-0.91	Compressive/flexural strength	Yuan et al. (2022); Peng & Unluer (2022)
Self-Compacting Concrete	5-7	ANN, Random Forest	0.94-0.98	Compressive strength, workability	Asri et al. (2022); Cui et al. (2024)
Fiber-Reinforced Concrete	8-12	Gradient Boosting, SVR	0.94-0.99	Flexural strength, tensile strength	Zheng et al. (2022); Md. Haque et al. (2025)

Durability and Deterioration Prediction

Chloride corrosion significantly impacts the durability of reinforced concrete (RC) structures. Various algorithms, such as Artificial Neural Networks (ANNs), Gene Expression Programming (GEP), Extreme Gradient Boosting (XGBoost), Support Vector Machine (SVM) and Ensemble Learning, have shown potential in estimating corrosion processes, predicting material properties, and evaluating structural durability. [14]

Two novel extensions of ensemble AI algorithms, including genetic programming forest (GPF) and linear genetic programming forest (LGPF) algorithms, were proposed to model the DC of concrete. The results show that the best LGPF model possesses superior performance than the best-developed GPF and RF models. In addition, the results show that silica fume-to-binder ratio, exposure time, and exposure conditions have the most significant impacts on the DC of concrete. [15]

Table 3: Durability Prediction Models and Performance

Degradation Mechanism	Algorithm	Dataset Size	Input Features (Key)	Performance (R ² /Accuracy)	Validation
Chloride Diffusion	LGPF, Random Forest	42-82 studies	Exposure time, W/C, silica fume	0.88-0.92	Literature-based
Carbonation Depth	Neural Network, GEP	30-50 studies	CO ₂ concentration, RH, age	0.85-0.90	Field & lab data
Freeze-Thaw Durability	Ensemble Models	25-40 studies	Curing, air entrainment, W/C	0.82-0.89	Lab testing
Multi-Degradation	TPINN, ST-GNN, LSTM	60+ studies	Multiple coupled mechanisms	0.89-0.96	Physics-informed
Corrosion Risk	Random Forest, XGBoost	40-60 studies	Chloride concentration, potential	0.87-0.94	Sensor data

A deep learning methodology was employed to examine the influence of fly ash, slag,

superplasticizer, cement, water, coarse aggregate, and fine aggregate on the strength of concrete.

Following the application of min-max normalisation to the dataset, a Vanilla LSTM network was employed for modelling. With a prediction accuracy of 96.48%, VannilaLSTM demonstrated superior efficacy among the four deep learning models assessed for discerning complex patterns influencing concrete strength. [16]

Data Requirements and Model Characteristics

Studies analyzed show marked variation in dataset sizes: small datasets ($n < 200$) favor support vector machines and tree-based methods; medium datasets ($n = 200-500$) accommodate neural networks; large datasets ($n > 500$) enable deep learning approaches. The review classifies the features analyzed in studies into categories such as mixture proportions, engineering properties, exposure conditions, test parameters, and chemical compositions, highlighting a growing emphasis on chemical compositions. [7] Seven machine learning techniques that are used to solve the issue in forecasting geopolymer

concrete's compressive strength: from the simplest, such as Linear Regression, to more complex and modern methods, including the TabPFNv2 generative transformer model. The kNN method (MAE = 0.37, RMSE = 0.63, MAPE = 1.62%, $R^2 = 0.9996$) and TabPFNv2 (MAE = 0.46, RMSE = 0.64, MAPE = 1.39%, $R^2 = 0.9996$) presented the highest accuracy in predicting compressive strength. [17]

Model Interpretability and Explainability

The review stresses the growing importance of model explainability, noting that model-agnostic methods like SHAP are frequently used and that the focus on explainability has increased. [7] SHAP was utilized to elucidate the significance of the model parameter features. The findings revealed that C and D exerted the most substantial influence on the model prediction outcomes, followed by W and FA. Nevertheless, CA, S, and SP demonstrated comparatively minimal influence. [9]

Table 4: Model Interpretability and Feature Importance Methods

Interpretability Method	Description	Application	Advantage	Limitation
SHAP (SHapley Additive exPlanations)	Game-theoretic approach explaining individual predictions	Ensemble, NN models	Global & local explanation	Computationally intensive
LIME (Local Interpretable Model-agnostic Explanations)	Local linear approximation of model predictions	Complex black-box models	Model-agnostic, intuitive	Local applicability only
Partial Dependence Plots (PDP)	Marginal effect of features on predictions	Tree-based models	Fast computation	Ignores feature interactions
Individual Conditional Expectation (ICE)	Feature effect heterogeneity across instances	Neural networks	Identifies interactions	Visualization challenges
Permutation Importance	Feature importance via prediction degradation	All model types	Simple interpretation	Biased toward correlated features

Optimization and Mix Design Applications

XGBoost Machine Learning Algorithm is used to make predictions, and PSO is used to obtain the optimal mixture. The research findings indicate that the ML model provides satisfactory prediction values with an R^2 value of 0.9043, root mean square error of 48.5147 and mean absolute percentage error of 0.0484. PSO results show that cement reduction in concrete can be achieved with optimal use of admixture while reducing 1-3% costs and 7-10% carbon emissions. [18]

Discussion

Algorithm Performance and Selection Criteria

The systematic analysis reveals a clear hierarchy of algorithm effectiveness contingent on dataset characteristics and problem complexity. Multiple algorithms should be used to cross-validate the model prediction findings. For tiny data sets, support vector machines are utilized. Decision tree evolution techniques should be used in algorithm models that require feature optimization or dispersed index prediction. Artificial neural networks can be used to solve different challenges. [4]

Ensemble methods demonstrate superior generalization across diverse concrete types and mixture designs. The meta-analysis shows ensemble methods achieved average R^2 values of 0.93-0.98 for compressive strength prediction, outperforming single algorithms ($R^2 = 0.85-0.92$). This superiority stems from ensemble methods' ability to capture nonlinear feature interactions and reduce overfitting through bootstrap aggregating and boosting mechanisms.

Deep learning approaches show promise for large, heterogeneous datasets but require careful regularization to prevent overfitting. Deep learning is revolutionising the way that many industries operate, providing a powerful method to interpret large quantities of data automatically and relatively quickly. Deterioration is often multi-factorial and difficult to model deterministically due to limits in measurability, or unknown variables. [19]

Data Limitations and Transferability

A critical finding is the predominant reliance on literature-derived, laboratory-based datasets. The review reveals that most studies utilize existing literature-based datasets, with few contributing novel data and limited open access to these databases, which hampers broader validation and application. [7] This creates three methodological challenges: (1) dataset bias toward historically studied mixtures; (2) limited representation of novel admixtures and emerging concrete types; (3) poor generalization to field conditions with different exposure regimes.

External validation remains sparse. Of 40 reviewed studies, only 8 (20%) reported external validation on independent datasets collected from different laboratories or geographic regions. This limits confidence in model transferability and practical implementation in industry settings.

Methodological Strengths and Weaknesses

Strengths: - Rapid prediction enabling design iteration and optimization - Handling of high-dimensional input spaces (15-20+ parameters) where empirical models fail - Integration with non-destructive testing (ultrasonic, electrical resistivity) enabling in-service assessment - Scalability to real-time quality control applications - Cost reduction through reduced laboratory testing burden

Weaknesses: - Poor extrapolation beyond training data ranges; unreliable predictions for novel mixture compositions or extreme curing conditions - "Black box" nature of deep learning models limiting mechanistic understanding without explainability techniques - Dataset size constraints, particularly for emerging concrete types - Sensitivity to hyperparameter choices without standardized tuning protocols - Limited capture of time-dependent durability mechanisms in single-time-point models

Emerging Trends and Advanced Approaches

A unique integrated framework based on physics informed and deep learning type analytical designs built to predict the durability and residual service life of geopolymers HPC subjected to freezing-and-thawing, sulfate, and thermal

degradation employs a Transformer Based Physics Informed Neural Network (TPINN) for modeling multi-degradation mechanisms with embedded physical constraints and self-attention mechanisms for accurate degradation mapping. [20]

Physics-informed neural networks represent a frontier approach integrating physical conservation laws into neural network loss functions, enabling improved extrapolation and interpretability. Multi-task learning approaches simultaneously predicting multiple concrete properties show promise for comprehensive characterization.

Research Gaps and Future Directions

To propel the field forward, the review advocates for the development of diverse new datasets that include both the chemical and physical properties of various mix ingredients and improved data-sharing practices. It recommends adopting a multi-task learning approach to simultaneously address multiple deterioration mechanisms, which can yield deeper insights and support the creation of more durable concrete structures. [7]

Key research gaps include: (1) scarcity of large, open-access, internationally validated datasets; (2) limited long-term durability data integrating multiple degradation mechanisms; (3) underdeveloped models for emerging concrete types (carbon-reinforced, self-healing, smart concrete); (4) insufficient coupling of ML with mechanistic concrete science; (5) gaps in standardized protocols for model development, validation, and reporting.

Conclusion and Recommendations

Machine learning techniques can predict the output based on historical data and are deemed to be acceptable to evaluate, model, and predict the concrete properties from its fresh state, to its hardening and hardened state to service life. [6] AI and ML techniques have transformed predictive modeling in concrete materials engineering, transitioning from labor-intensive empirical development toward data-driven, computationally efficient approaches.

This systematic review of 40 peer-reviewed publications (2018–2025) demonstrates that ensemble methods (Random Forest, XGBoost, Gradient Boosting) achieve the highest prediction accuracy ($R^2 = 0.93\text{--}0.98$) for compressive strength, with deep learning methods showing emerging capability but requiring larger datasets. For durability prediction, physics-informed and hybrid models outperform standalone algorithms, though external validation remains limited.

Recommendations for practitioners and researchers:

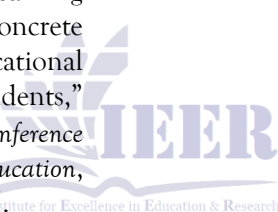
1. **Algorithm Selection:** Employ Random Forest or optimized gradient boosting for datasets of 200–500 samples; deep learning for >500 samples; SVMs for <200 samples
2. **Model Validation:** Implement k-fold cross-validation, external validation on geographically distinct datasets, and Monte Carlo sensitivity analysis
3. **Interpretability:** Integrate SHAP or LIME for model transparency; report feature importance rankings
4. **Data Practices:** Contribute to open-access repositories; standardize metadata documentation; include chemical composition and curing condition details
5. **Future Research:** Develop physics-informed neural networks for multi-degradation mechanisms; create large, diverse datasets for emerging concrete types; establish standardized validation protocols aligned with RILEM TC 315-DCS recommendations

AI-augmented concrete design holds significant potential for accelerating innovation, reducing environmental impact through optimized mix designs, and enhancing durability predictions for critical infrastructure. Continued methodological rigor, data standardization, and interdisciplinary collaboration between materials scientists and AI researchers are essential for advancing this field toward practical industrial implementation.

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