

Prediction of Strength of Sustainable Concrete with Supplementary Cementitious Materials and Recycled Aggregate Using Artificial Intelligence and Machine Learning: A Review

P. Vamsi Krishna¹, Dr.P.Sundar Kumar², Dr.Jerripotu Gopal Rao³,

¹Research Scholar, Vignan University, Vadlamudi, Guntur-522213, Andhra Pradesh,

Email: vamsi4004@gmail.com

²Associate Professor, Vignan University, Vadlamudi, Guntur-522213, Andhra Pradesh.

Email: pskumarphd@gmail.com

³Professor, Vignan University, Vadlamudi, Guntur-522213, Andhra Pradesh. Email: drjg_civil@vignan.ac.in

Abstract

The construction industry's dependence on ordinary Portland cement (OPC) and natural aggregates is a major contributor to global CO₂ emissions and natural-resource depletion, motivating the increasing use of supplementary cementitious materials (SCMs) such as fly ash, ground granulated blast-furnace slag (GGBS), silica fume, and metakaolin, together with recycled aggregate (RA) derived from construction and demolition waste. However, incorporating SCMs and RA introduces significant variability and non-linearity into the strength-development behaviour of concrete, which classical mix-design equations and regression models struggle to capture reliably. Artificial intelligence (AI) and machine learning (ML) techniques — including artificial neural networks (ANN), support vector machines (SVM), decision trees, ensemble methods (Random Forest, Gradient Boosting, XGBoost, LightGBM, CatBoost, AdaBoost, Bagging), gene expression programming (GEP), and adaptive neuro-fuzzy inference systems (ANFIS) — have emerged as powerful data-driven alternatives capable of learning these complex mix-property relationships directly from experimental data. This review synthesizes 28 peer-reviewed studies published between 1998 and 2026 that apply ML/AI methods to predict the compressive strength of concrete containing SCMs, recycled aggregates, or both. The review compares model architectures, dataset characteristics, input parameters, and reported performance metrics (R^2 , RMSE, MAE), and synthesizes the influencing parameters identified through sensitivity and SHapley Additive exPlanations (SHAP) analyses across the literature. Ensemble tree-based methods, particularly Random Forest, XGBoost, and CatBoost, are found to consistently outperform single learners across both SCM- and RA-based datasets, with reported R^2 values ranging from 0.79 to 0.99. The review identifies persistent gaps — limited standardization of input features, scarcity of studies combining SCMs and RA simultaneously with interpretable AI, and a shortage of externally validated, deployment-ready models — and outlines directions for future research, including federated multi-source databases, hybrid metaheuristic-optimized models, and explainable AI for sustainable mix-design optimization.

Keywords: machine learning; artificial intelligence; supplementary cementitious materials; recycled aggregate concrete; compressive strength prediction; sustainable concrete; ensemble learning; SHAP

1. Introduction

Concrete is the most widely consumed man-made material on Earth, and ordinary Portland cement (OPC) production alone is estimated to contribute approximately 7–8% of global anthropogenic CO₂ emissions. Simultaneously, the extraction of natural sand and coarse aggregate for concrete production places mounting pressure on finite natural resources and generates substantial environmental degradation. These twin pressures have driven a rapid expansion of research into sustainable concrete, in which a portion of the OPC is replaced by supplementary cementitious materials (SCMs) — fly ash, ground granulated blast-furnace slag (GGBS), silica fume, metakaolin, and other pozzolanic or latent-hydraulic by-products — and a portion of the natural coarse or fine aggregate is replaced by recycled aggregate (RA) reclaimed from construction and demolition (C&D) waste.

While the environmental case for SCMs and RA is well established, their mechanical behaviour is considerably more complex than that of conventional OPC-natural-aggregate concrete. SCM reactivity depends on chemical composition

(CaO, SiO₂, Al₂O₃ content), particle fineness, curing regime, and replacement level, while RA properties — higher water absorption, lower density, adhered residual mortar, and greater micro-cracking — introduce additional sources of variability that are difficult to represent with closed-form empirical equations such as Abrams' law or ACI mix-design charts. Consequently, a substantial body of research over the past decade has turned to artificial intelligence (AI) and machine learning (ML) as data-driven alternatives capable of learning non-linear, high-dimensional relationships between mix constituents and resulting strength directly from experimental datasets, without requiring an explicit mechanistic model.

The seminal application of ANN to concrete strength prediction is generally credited to Yeh (1998), who demonstrated that a neural network trained on mix-proportion data could predict the compressive strength of high-performance concrete with a coefficient of determination (R^2) of approximately 0.91–0.92, substantially outperforming linear regression based only on water-to-cement ratio and age ($R^2 \approx 0.57$). Since then, the range of algorithms applied to this problem has expanded dramatically, encompassing support vector regression, decision trees, ensemble methods (bagging, boosting, and stacking), gene expression programming, adaptive neuro-fuzzy inference systems, and, more recently, deep learning and explainable-AI frameworks such as SHapley Additive exPlanations (SHAP).

Two active but largely parallel strands of this literature have focused, respectively, on ML-based strength prediction of concrete containing SCMs, and ML-based strength prediction of concrete containing recycled aggregate. A smaller but growing number of studies address the two simultaneously — most commonly in the context of self-compacting recycled aggregate concrete (SCRAC) incorporating fly ash, GGBS, or silica fume. Despite the volume of individual studies, a consolidated review that maps the algorithms, datasets, performance metrics, and identified influencing parameters across all three strands — SCM concrete, recycled aggregate concrete (RAC), and their combination — is still needed to orient new researchers and practitioners and to identify where the literature remains thin.

2. Research Significance and Objectives

This review addresses that need by systematically consolidating the ML/AI literature on strength prediction of sustainable concrete incorporating SCMs and/or recycled aggregate. The specific objectives are: (i) to summarize the material characteristics of SCMs and RA that govern strength development and that serve as model inputs; (ii) to catalogue the ML/AI algorithms applied in this domain and their comparative characteristics; (iii) to tabulate and compare the datasets, input features, and reported performance metrics of published studies for SCM concrete, RAC, and combined SCM–RA concrete; (iv) to synthesize the influencing parameters identified through sensitivity and SHAP analyses across studies; and (v) to identify research gaps and propose directions for future work, including model interpretability, dataset standardization, and deployment-oriented validation. The review is intended to support researchers designing new ML-based strength-prediction studies and practitioners evaluating which modelling approach best fits a given sustainable-concrete application.

3. Review Methodology

This review follows a structured literature-search approach. Search strings combining (“machine learning” OR “artificial intelligence” OR “deep learning”) AND (“compressive strength”) AND (“supplementary cementitious material” OR “fly ash” OR “GGBS” OR “recycled aggregate” OR “recycled concrete”) were applied to Scopus, Web of Science, ScienceDirect, MDPI, Frontiers, and IEEE Xplore, covering publications from 1998 (the seminal Yeh ANN study) through 2026. Studies were included if they (a) applied at least one supervised ML/AI algorithm to predict the compressive strength of concrete or mortar containing an SCM, a recycled aggregate, or both; (b) reported a quantitative performance metric (R^2 , RMSE, MAE, or equivalent); and (c) were published in a peer-reviewed journal or indexed conference proceedings. Purely experimental studies with no ML component, and ML studies addressing properties other than compressive strength (e.g., only durability or workability) without a strength-prediction component, were excluded. A total of 28 studies satisfied these criteria and form the evidentiary basis for Sections 6–9; foundational machine-learning methodology papers (e.g., for Random Forest, XGBoost, SVM, and SHAP) are additionally cited in Section 5 to describe the algorithms themselves.

Table 1 summarizes the inclusion and exclusion criteria applied during screening.

Criterion	Included	Excluded
Material scope	Concrete/mortar with SCM and/or recycled aggregate	Conventional OPC-natural-aggregate concrete only
Modelling approach	Supervised ML/AI (ANN, SVM, tree-based, GEP, ANFIS, deep learning)	Purely empirical/regression-only studies with no ML component
Outcome variable	Compressive strength prediction (primary or secondary outcome)	Studies addressing only workability, durability, or fresh-state properties
Reporting	Quantitative R^2 , RMSE, or MAE reported	No quantitative performance metric reported
Source type	Peer-reviewed journal or indexed conference proceedings	Theses, preprints without peer review, non-indexed sources

Table 1. Inclusion and exclusion criteria applied in the review.

4. Sustainable Concrete Constituents: SCMs and Recycled Aggregate

4.1 Supplementary Cementitious Materials

SCMs are broadly classified as pozzolanic (fly ash, silica fume, metakaolin, rice husk ash) or latent-hydraulic (GGBS), depending on whether they react primarily with the calcium hydroxide liberated during cement hydration or possess intrinsic (if slow) hydraulic reactivity of their own. Fly ash, a by-product of coal combustion, has slow early-age reactivity but contributes to long-term strength gain, improved workability, and reduced heat of hydration. GGBS, a by-product of pig-iron smelting, reduces the heat of hydration and can improve long-term strength and durability when properly activated. Silica fume, an ultrafine by-product of silicon/ferrosilicon production, is highly pozzolanic and can substantially increase early strength at low replacement levels but increases water demand. Because the compressive-strength contribution of an SCM depends jointly on its chemical-oxide composition (CaO , SiO_2 , Al_2O_3 , Fe_2O_3), fineness, replacement percentage, and curing age, purely empirical mix-design equations calibrated on OPC concrete generalize poorly to SCM-blended systems — a key motivation for the ML-based approaches reviewed in Section 6.

4.2 Recycled Aggregates

Recycled aggregate, most commonly recycled concrete aggregate (RCA) obtained by crushing waste concrete from demolished structures, differs from natural aggregate primarily through the residual mortar adhered to the original aggregate particles. This adhered mortar increases water absorption (often 3–8% versus <1% for natural aggregate), reduces particle density, increases porosity, and introduces additional interfacial transition zones, all of which tend to reduce compressive strength relative to an equivalent natural-aggregate mix at full replacement — reported reductions range from roughly 10% to 30% depending on replacement ratio, parent-concrete strength, and pre-treatment. Key parameters governing RAC strength that recur as ML model inputs across the literature include the RCA replacement ratio, parent-concrete strength, water absorption and bulk density of both natural and recycled aggregate, the effective water-to-cement ratio, and aggregate-to-cement ratio. Because these parameters interact non-linearly — for example, the strength penalty of RCA is more pronounced at higher parent w/c ratios and largely negligible at low replacement levels — RAC strength prediction is a second natural application domain for ML/AI, reviewed in Section 7.

5. Machine Learning and AI Techniques for Strength Prediction

Figure 1 summarizes the generic workflow followed by nearly all ML-based concrete strength-prediction studies reviewed in this paper: data collection (typically compiled from multiple published experimental datasets or, less commonly, an in-house testing programme), pre-processing, feature selection, train–test splitting with cross-validation, model development, hyperparameter optimization, validation, and — in an increasing share of recent studies — model interpretation via SHAP or partial-dependence analysis.

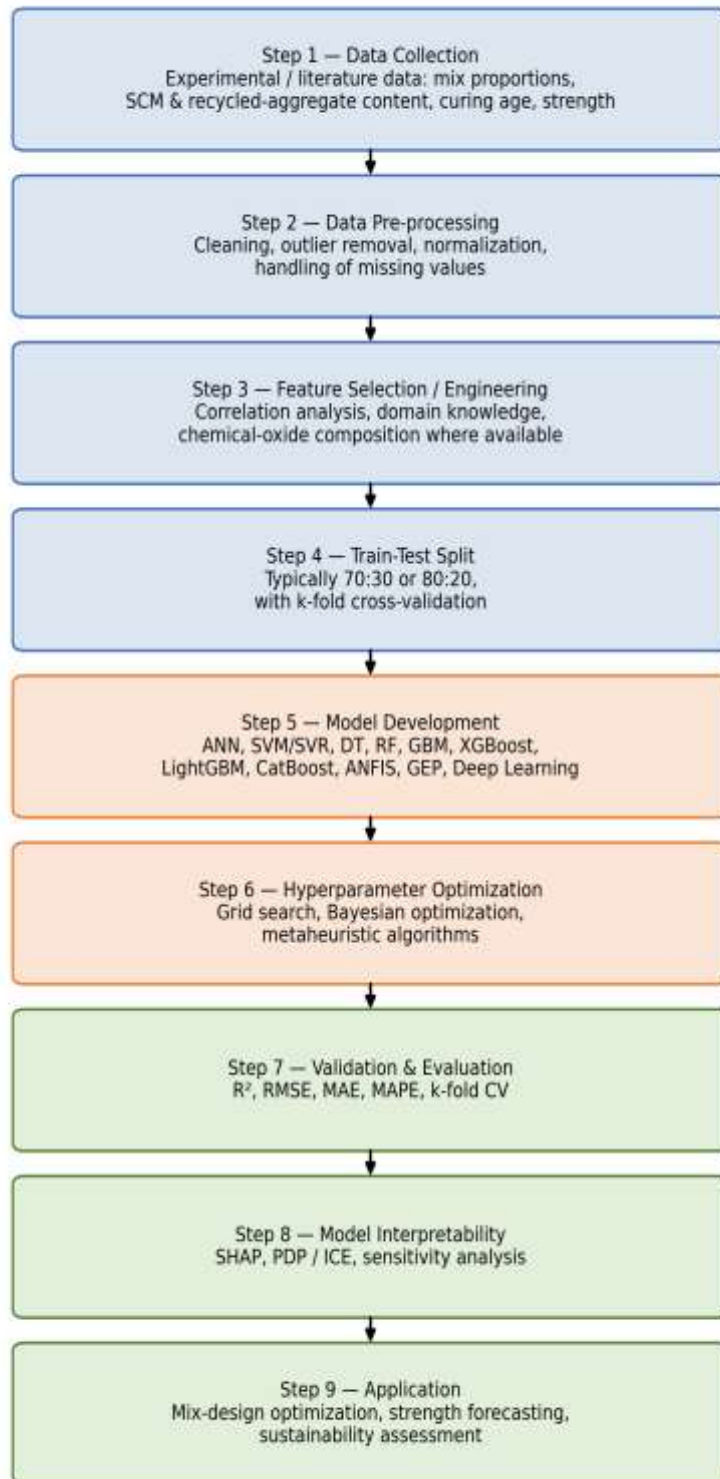


Figure 1. Generic ML workflow for concrete strength prediction, synthesized from the reviewed literature.

The algorithms applied in this domain fall broadly into individual learners, ensemble learners, and hybrid/metaheuristic-optimized models, as summarized in Figure 2.

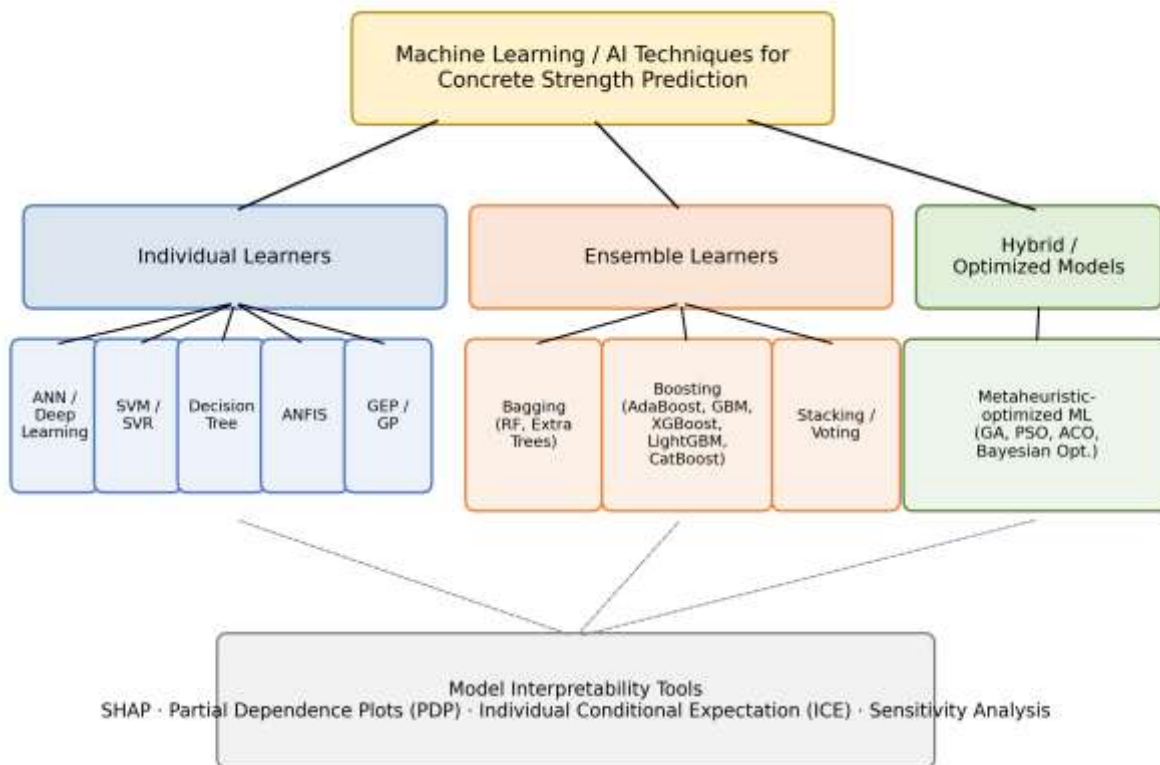


Figure 2. Taxonomy of ML/AI algorithms applied to concrete strength prediction in the reviewed literature.

Artificial neural networks (ANN), inspired by the trained-by-backpropagation architecture of Rumelhart, Hinton, and Williams (1986), remain the most historically established individual learner for this problem, following Yeh's (1998) demonstration on high-performance concrete. Support vector regression (SVR), based on the support-vector formulation of Cortes and Vapnik (1995), constructs a maximum-margin regression function and performs well on smaller, noisier datasets. Decision trees provide an interpretable, rule-based individual learner but are prone to overfitting when used alone. Adaptive neuro-fuzzy inference systems (ANFIS) combine fuzzy-rule interpretability with neural-network learning and have been applied where input–output relationships are expected to follow expert-interpretable rules. Gene expression programming (GEP), an evolutionary technique descended from genetic programming (Koza, 1992), evolves explicit mathematical expressions relating inputs to strength, offering a transparent closed-form alternative to black-box learners.

Ensemble learners aggregate multiple weak learners to reduce variance (bagging: Random Forest, Extra Trees) or sequentially correct residual error (boosting: AdaBoost, Gradient Boosting Machine, XGBoost (Chen and Guestrin, 2016), LightGBM (Ke et al., 2017), CatBoost), and consistently outperform individual learners across the studies reviewed here (see Sections 6–9). Random Forest, introduced by Breiman (2001), builds many de-correlated decision trees on bootstrap-resampled data and averages their predictions, offering strong resistance to overfitting with minimal tuning. Boosting algorithms such as AdaBoost (Freund and Schapire, 1997) and its gradient-boosting descendants iteratively fit new learners to the residual errors of the ensemble built so far, generally achieving the highest reported accuracy in the reviewed literature (Section 9) at the cost of greater hyperparameter-tuning sensitivity. Stacking and voting ensembles combine heterogeneous base learners (e.g., XGBoost, Extra Trees, Decision Tree, and Linear Regression) through a meta-learner, and have achieved the highest reported R^2 values in the RAC literature reviewed in Section 7.

A growing share of recent studies additionally apply SHapley Additive exPlanations (SHAP; Lundberg and Lee, 2017), partial dependence plots (PDP), and individual conditional expectation (ICE) curves to render otherwise opaque ensemble models interpretable, identifying which input parameters most strongly and in which direction influence

predicted strength — a capability of particular importance for mix-design optimization and is discussed further in Section 10. Table 2 summarizes the principal characteristics of the algorithm families most frequently encountered in the reviewed literature.

Algorithm family	Operating principle	Typical strength	Typical limitation
ANN	Layered network of weighted, non-linearly activated neurons trained by backpropagation	Captures complex non-linearities; well established	Prone to overfitting on small datasets; limited interpretability
SVM / SVR	Maximum-margin regression using kernel-transformed feature space	Performs well with small, noisy datasets	Sensitive to kernel/hyperparameter choice; scales poorly to very large datasets
Decision Tree	Recursive binary splitting of feature space to minimize prediction error	Highly interpretable rule structure	High variance; prone to overfitting when used alone
Random Forest / Extra Trees (Bagging)	Averages predictions of many trees trained on bootstrap-resampled data/features	Robust, low-variance, minimal tuning required	Larger model size; less interpretable than a single tree
AdaBoost / Gradient Boosting / XGBoost / LightGBM / CatBoost (Boosting)	Sequentially fits learners to residual errors of the ensemble built so far	Highest reported accuracy in most reviewed comparisons	Greater hyperparameter sensitivity; higher risk of overfitting without careful tuning
ANFIS	Fuzzy if-then rules tuned via neural-network learning	Rule-level interpretability	Rule-base complexity grows quickly with input count
GEP / Genetic Programming	Evolutionary search over symbolic expression trees	Produces an explicit, transportable mathematical equation	Generally lower accuracy than tuned ensemble methods

Table 2. Principal ML/AI algorithm families applied to concrete strength prediction.

6. Machine Learning-Based Strength Prediction of Concrete with SCMs

Yeh's (1998) foundational study, using 1,030 mix records now widely known as the UCI concrete compressive-strength dataset, established that an ANN incorporating cement, fly ash, GGBS, water, superplasticizer, coarse and fine aggregate, and age as inputs could predict compressive strength with $R^2 \approx 0.91$ – 0.92 , versus $R^2 \approx 0.57$ for regression based on water-to-cement ratio and age alone. This dataset has since become a de facto benchmark, reused (often augmented with additional SCM types) in a large share of subsequent studies, including several reviewed in this section.

Ahmad et al. (2021), using the same 1,030-record dataset, compared bagging, AdaBoost, GEP, and decision-tree models for predicting the compressive strength of fly-ash- and GGBS-blended concrete. The bagging ensemble achieved the highest accuracy ($R^2 = 0.92$, RMSE = 4.54 MPa), followed by AdaBoost ($R^2 = 0.82$), GEP ($R^2 = 0.81$), and decision tree ($R^2 = 0.79$); k-fold cross-validation confirmed the bagging model's superior and more stable performance across folds. Sensitivity analysis identified curing age, cement content, and superplasticizer dosage as the most influential parameters, consistent with the underlying chemistry of delayed pozzolanic/latent-hydraulic reaction in fly ash and slag.

Aslam and Shahab (2024) extended this comparison substantially, evaluating eleven ML techniques — GEP, ANN, Random Forest, SVM, ANFIS, optimized Gaussian process regression, Gradient Boosting, XGBoost, AdaBoost, K-nearest neighbours, and bagging — on a dataset spanning five SCM types (fly ash, GGBS, silica fume, lime powder, and calcined clay), using grid-search cross-validation for hyperparameter tuning. Consistent with the pattern observed elsewhere in this review, ensemble tree-based methods outperformed individual learners, and the study explicitly

recommended ensemble methods for practical blended-cement-concrete strength forecasting given the heterogeneity of SCM combinations. Sathiparan (2026) took a complementary, chemistry-first approach, using ANN, K-nearest neighbours, SVR, and XGBoost to relate the oxide composition of SCMs (rather than only their mass replacement ratio) to cement-mortar compressive strength, finding that silica-rich SCMs (e.g., silica fume) significantly enhanced strength while calcium-oxide content governed early-age strength development — a finding that reinforces the value of chemical-composition features alongside mix-proportion features as ML inputs.

Table 3 summarizes the key characteristics of these and related SCM-focused studies.

Study	SCM(s)	Dataset (n)	Algorithm(s)	Best R ²	Key finding
Yeh (1998)	Fly ash, GGBS, silica fume	1,030	ANN vs. regression	≈ 0.91–0.92	ANN far exceeds regression using only w/c and age (R ² ≈ 0.57)
Ahmad et al. (2021)	Fly ash, GGBS	1,030	Bagging, AdaBoost, GEP, DT	0.92 (Bagging)	Ensemble (bagging) > individual learners; age, cement, superplasticizer most influential
Aslam & Shahab (2024)	Fly ash, GGBS, silica fume, lime powder, calcined clay	Multi-source (11 SCM combinations)	GEP, ANN, RF, SVM, ANFIS, OGPR, GB, XGB, AdaBoost, KNN, Bagging	Ensemble best (exact value study-specific)	Ensemble tree-based methods recommended for blended-cement CS prediction
Sathiparan (2026)	Multiple SCMs (oxide-composition based)	Cement-mortar dataset	ANN, KNN, SVR, XGBoost	Not directly comparable (oxide-based features)	Silica-rich SCMs raise CS; CaO content governs early strength

Table 3. Selected studies on ML-based compressive-strength prediction of SCM-blended concrete.

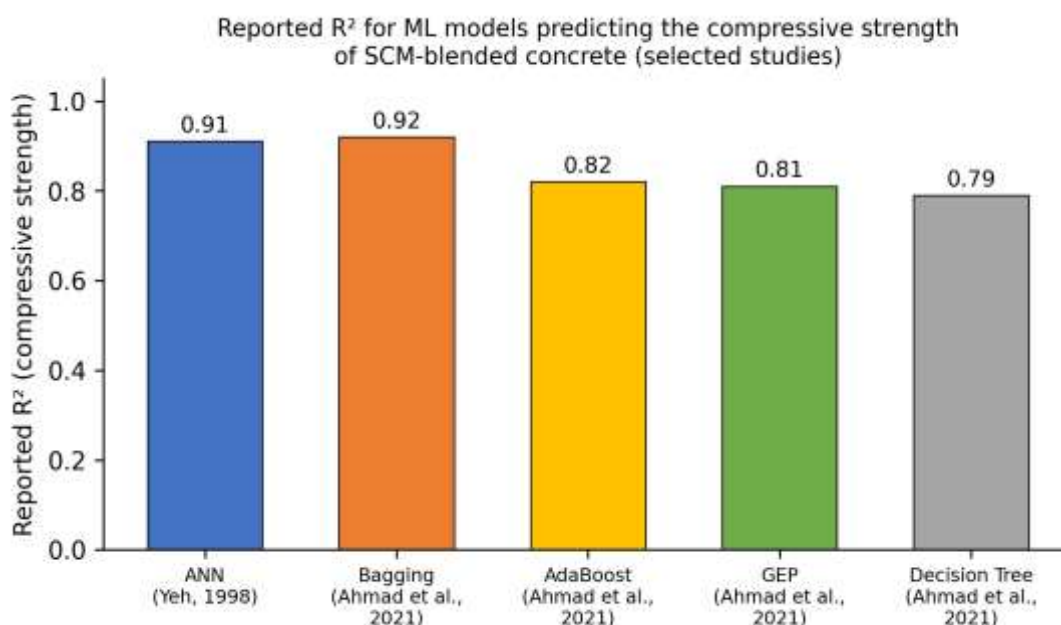


Figure 3. Reported R² for individual and ensemble ML models on the widely used 1,030-record SCM concrete dataset (Yeh, 1998; Ahmad et al., 2021).

7. Machine Learning-Based Strength Prediction of Recycled Aggregate Concrete

Yuan et al. (2022) applied ensemble Random Forest and Gradient Boosting models to a 12-input-feature RAC dataset covering recycled-aggregate replacement ratio, parent-concrete strength, bulk density and water absorption of both natural and recycled aggregate, aggregate-cement ratio, and effective water-cement ratio. Random Forest outperformed Gradient Boosting for both compressive strength ($R^2 = 0.91$ vs. 0.87) and flexural strength ($R^2 = 0.86$ vs. 0.79), with correspondingly lower MAE (4.19 MPa vs. 4.78 MPa for compressive strength). Phoeuk and Kwon (2023), using a larger multinational RAC dataset, compared four boosting/bagging ensembles — CatBoost, LightGBM, Random Forest, and XGBoost — and found CatBoost achieved the best blind-evaluation performance ($R^2 = 0.938$, MAE = 2.64 MPa, RMSE = 3.89 MPa), outperforming even conventional SVM and ANN baselines cited in that study.

Li et al. (2025) focused specifically on precast recycled aggregate concrete, comparing decision tree, Random Forest, gradient boosting decision tree, and XGBoost, with tree-structured ensembles again dominating single-tree performance after grid-search hyperparameter tuning and five-fold cross-validation. Fei et al. (2023), working with recycled powder (rather than coarse aggregate) mortar, compared XGBoost, Random Forest, LightGBM, and AdaBoost on 204 experimental records, with XGBoost achieving the highest accuracy (training $R^2 = 0.950$; test $R^2 = 0.842$) and identifying — via SHAP analysis — the mass replacement rate of recycled powder as the single most influential parameter, followed by particle size, powder type, and water-binder ratio. Pan et al. (2024) proposed a stacking ensemble (XGBoost, Extra Trees, Decision Tree, and Linear Regression combined through a SHAP-informed meta-learner) trained on a combination of 63 in-house recycled-concrete specimens and the 1,030-record UCI dataset, achieving the highest reported accuracy among the RAC studies surveyed here ($R^2 = 0.987$, RMSE = 1.97 MPa), illustrating the benefit of supplementing limited in-house RAC data with the larger, well-characterized conventional-concrete dataset.

Other studies in this stream, including Zhang et al. (2023, ML combined with Bayesian hyperparameter optimization), Abduljaleel et al. (2024, an eight-algorithm comparison spanning SVM, ANN, XGBoost, decision tree, Random Forest, Gradient Boosting, CatBoost, and AdaBoost), and Ebid et al. (2024, multiple AI predictive models for RAC), reinforce the same overall pattern: tree-based ensembles, and boosting methods in particular, consistently rank among the top performers, while reported R^2 values across the RAC literature span a comparatively wide 0.79–0.99, reflecting differences in dataset size, feature richness, and RAC-specific pre-treatment (e.g., carbonation, washing) captured — or not — as model inputs. Table 4 and Figure 4 summarize these comparisons.

Study	RA type	Dataset (n)	Algorithm(s)	Best R^2	Key finding
Yuan et al. (2022)	Coarse RCA	Literature-compiled, 12 features	Random Forest, Gradient Boosting	0.91 (RF, compressive)	RF outperforms GB for both compressive and flexural strength
Phoeuk & Kwon (2023)	Coarse RCA (multinational)	Multinational dataset	CatBoost, LightGBM, RF, XGBoost	0.938 (CatBoost)	CatBoost best; outperforms conventional SVM/ANN baselines
Li et al. (2025)	Precast RCA	Literature-compiled	DT, RF, GBDT, XGBoost	Ensemble best (tree-based)	Tree ensembles dominate single-tree DT after tuning
Fei et al. (2023)	Recycled powder	204	XGBoost, RF, LightGBM, AdaBoost	0.950 train / 0.842 test (XGBoost)	SHAP: RP replacement rate is dominant influencing factor
Pan et al. (2024)	Coarse RCA + UCI dataset	63 (in-house) + 1,030 (UCI)	Stacking ensemble (XGBoost, Extra Trees, DT, Linear Regression)	0.987	Combining in-house RAC data with UCI dataset boosts accuracy

Table 4. Selected studies on ML-based compressive-strength prediction of recycled-aggregate concrete/mortar.

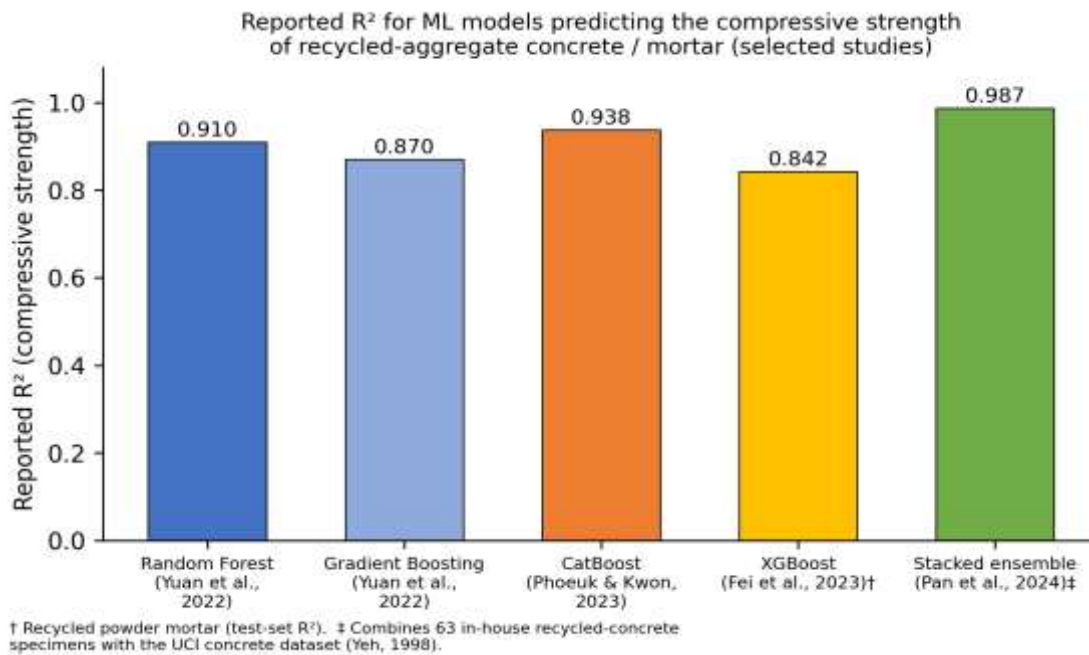


Figure 4. Reported R^2 for ML models predicting the compressive strength of recycled-aggregate concrete/mortar across selected studies.

8. Machine Learning-Based Strength Prediction of Concrete Combining SCMs and Recycled Aggregate

Concrete that simultaneously incorporates SCMs and recycled aggregate offers the greatest potential sustainability benefit but is the least studied combination in the ML literature, most commonly appearing in the context of self-compacting recycled aggregate concrete (SCRAC), where cementitious mineral admixtures are needed to compensate for the higher water demand and altered rheology introduced by RA. Jagadesh et al. (2024) compiled 602 SCRAC mix records and compared ANN configurations using two normalization schemes and three transfer functions, finding the best-performing configuration achieved $R^2 \approx 0.7\text{--}0.8$ at optimal ($k = 7$) cross-validation, using cementitious content, water, natural and recycled coarse aggregate content, and chemical/mineral admixture dosage as inputs. In a related study, Jagadesh et al. (2023) used mix-ratio-based ML models to assess SCRAC compressive strength, reinforcing the feasibility of ML approaches for this material class. Palencia Coto et al. (2022) applied ensemble ML models to predict the compressive strength of self-compacting concrete with recycled aggregates, an early contribution establishing the ensemble-learning approach for this specific concrete class.

More recent work has combined SCMs, recycled aggregate, and increasingly sophisticated ensemble methods within a single study. Singh, Kapoor, and Singh (2025) developed and compared six ML models — multilayer perceptron, gradient-boosting regression, bagging regression, extreme-gradient-boosting regression, K-nearest-neighbours regression, and support-vector regression — for both the compressive strength and fresh-state properties of self-compacting recycled-aggregate concrete, additionally applying multi-objective Pareto optimization to balance strength against workability, illustrating a trend toward multi-objective, sustainability-aware ML frameworks rather than strength prediction in isolation. Khan et al. (2026) similarly developed a data-driven ensemble-learning framework for compressive-strength estimation of sustainable self-compacting concrete incorporating recycled aggregates. Collectively, these studies indicate that the combined SCM–RA modelling problem is tractable with the same algorithm families used for SCM-only or RA-only concrete, but that reported accuracies (R^2 typically in the 0.70–0.90 range for ANN-based studies, though higher for tuned ensemble methods) tend to be somewhat lower than for the larger, more standardized single-variable datasets reviewed in Sections 6 and 7 — most plausibly because combined SCM–RA datasets remain comparatively small and are assembled from more heterogeneous source studies with inconsistent reporting of RA pre-treatment and SCM chemical composition.

Table 5 summarizes the combined SCM–RA studies identified in this review.

Study	Materials	Dataset (n)	Algorithm(s)	Reported accuracy	Key finding
Palencia Coto et al. (2022)	SCC + recycled aggregate	Literature-compiled	Ensemble ML models	Not directly comparable	Early demonstration of ensemble ML for SCC with RA
Jagadesh et al. (2023)	SCRAC (mix-ratio based)	Literature-compiled	ML (mix-ratio approach)	Not directly comparable	ML feasible for SCRAC strength assessment from mix ratios
Jagadesh et al. (2024)	SCRAC (cementitious + RA + admixtures)	602	ANN (6 configurations)	$R^2 \approx 0.7\text{--}0.8$	Best at normalization technique 2, TANSIG transfer function, $k = 7$
Singh, Kapoor & Singh (2025)	SCRAC	Literature-compiled	MLP, GBR, Bagging, XGBoost, KNN, SVR	Ensemble best (study-specific)	Multi-objective Pareto optimization balances strength vs. workability
Khan et al. (2026)	Sustainable SCC + RA	Literature-compiled	Ensemble learning framework	Not directly comparable	Data-driven ensemble framework for sustainable SCC with RA

Table 5. Selected studies on ML-based compressive-strength prediction of concrete combining SCMs and recycled aggregate.

9. Comparative Performance Analysis

Synthesizing the algorithm choices across the 17 individual studies discussed in Sections 6–8 that name specific algorithms (Figure 5), XGBoost is the most frequently applied algorithm (used in 8 of the 17 studies), followed by Random Forest (6), ANN and Gradient Boosting (5 each), and SVM/SVR and Decision Tree (4 each). This pattern mirrors the broader ML literature: boosting and bagging ensembles have become the de facto default choice for tabular, structured-data regression problems such as concrete mix-property prediction, owing to their strong out-of-the-box accuracy, relative robustness to feature scaling, and manageable computational cost compared to deep neural architectures.

Comparing Figures 3 and 4, reported R^2 values are, on average, slightly higher and less variable for SCM-concrete studies (0.79–0.92 across the four models compared on the common 1,030-record dataset) than for RAC studies (0.842–0.987 across five studies using different, non-standardized datasets). This is a somewhat counter-intuitive finding given that RA introduces additional physical variability (adhered mortar, water absorption) beyond SCM chemistry; the wider RAC range more likely reflects the absence of a single standardized benchmark dataset analogous to the UCI/Yeh dataset for OPC and SCM concrete, together with the tendency of the highest-performing RAC studies (e.g., Pan et al., 2024) to supplement small in-house datasets with this same larger conventional-concrete dataset. This observation itself constitutes one of the research gaps discussed in Section 11: the RAC literature would benefit from a common, standardized benchmark dataset analogous to Yeh's (1998) 1,030-record dataset for SCM concrete.

10. Key Influencing Parameters and Feature Importance

Figure 6 synthesizes the categories of input parameters used across the reviewed studies, spanning the binder system, the aggregate system, mix water and admixtures, curing conditions, chemical composition (where reported), and physical/mechanical properties of the recycled aggregate.

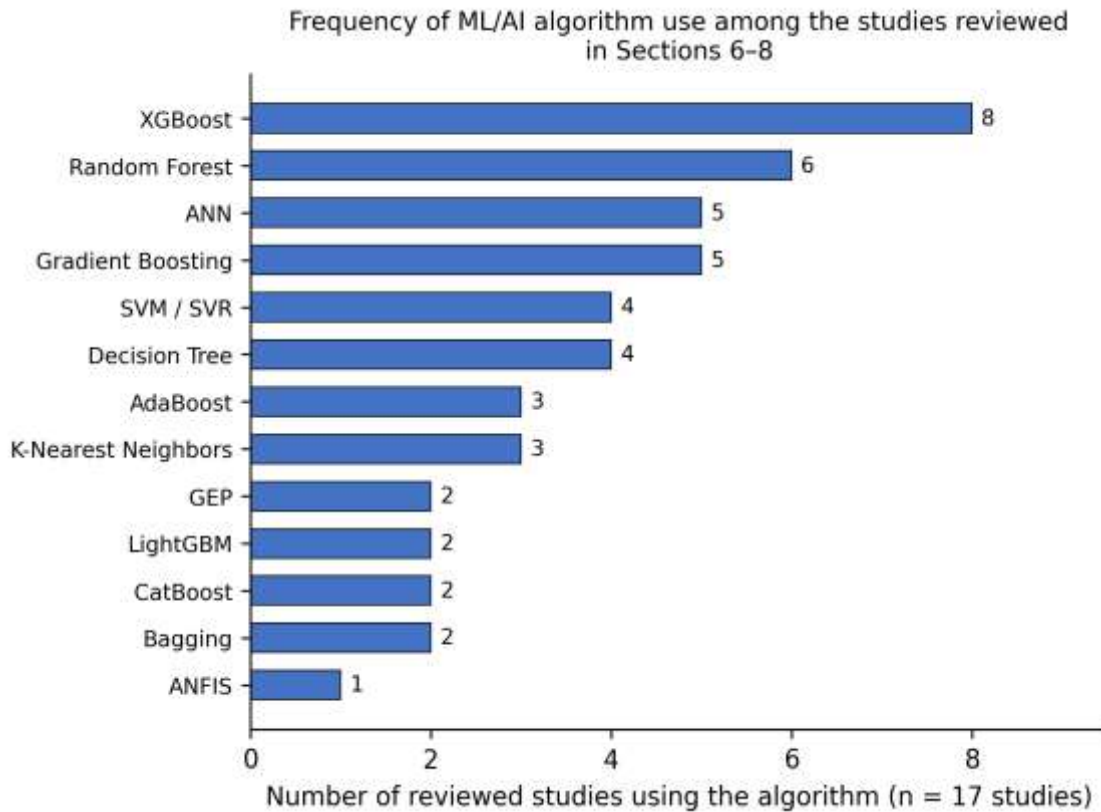


Figure 5. Frequency of ML/AI algorithm use among the 17 individual studies reviewed in Sections 6–8 that report specific algorithm names.

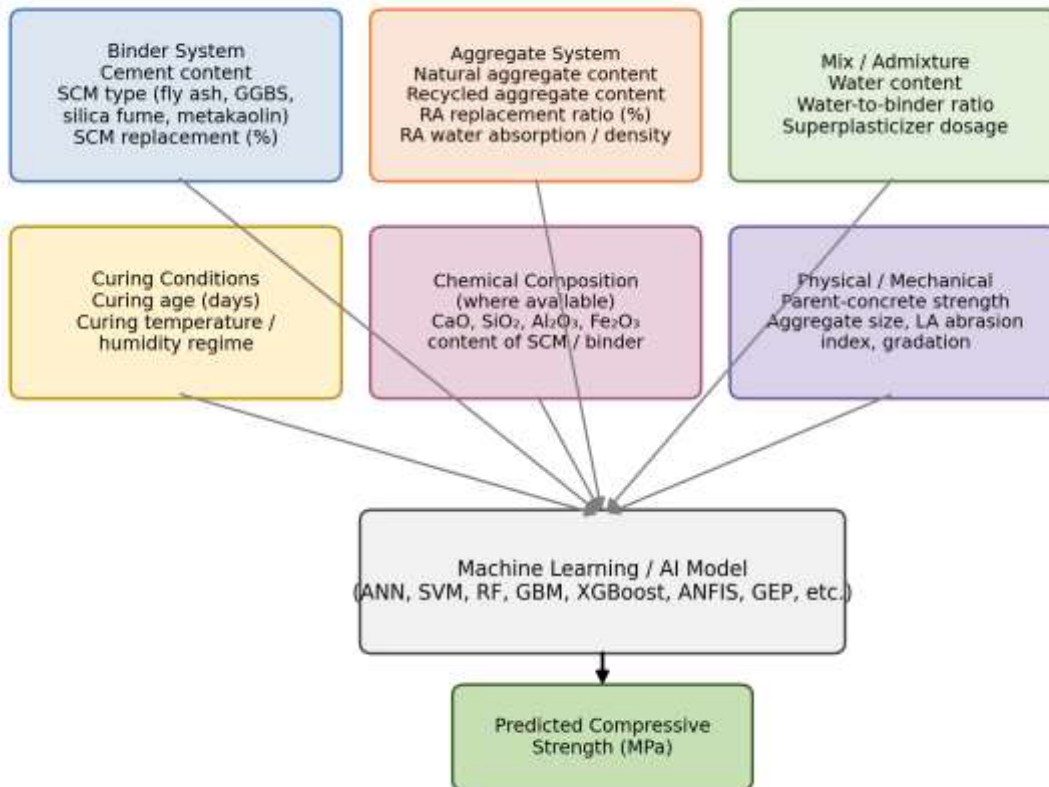


Figure 6. Synthesis of input-parameter categories used by ML models for sustainable-concrete strength prediction across the reviewed literature.

Sensitivity and SHAP analyses across the reviewed studies converge on several recurring findings. First, curing age is consistently identified as one of the most influential parameters for both SCM and RAC strength prediction (e.g., contributing 27.8% in the sensitivity analysis of Ahmad et al., 2021), reflecting the well-established time-dependent nature of pozzolanic and latent-hydraulic reactions. Second, cement/binder content and water-to-binder ratio rank consistently among the top three or four influencing parameters across nearly all reviewed studies, consistent with classical Abrams'-law strength-governing behaviour persisting even in blended, recycled-aggregate systems. Third, for RA-containing concrete, the RCA replacement ratio and RCA water absorption are repeatedly identified as dominant RA-specific parameters (e.g., Fei et al., 2023, identified recycled-powder replacement rate as the single most important feature via SHAP). Fourth, for SCM-containing concrete, chemical-oxide composition — particularly SiO₂ and CaO content — has emerged in more recent studies (e.g., Sathiparan, 2026) as a more physically meaningful and transferable feature than SCM mass-replacement percentage alone, since the latter conflates materials of very different reactivity under a single numerical value.

These convergent findings carry a practical implication for future model development: a well-specified sustainable-concrete strength-prediction model should, where data permit, include curing age, binder content and type, water-to-binder ratio, RA replacement ratio and its physical properties (absorption, density), and — where available — the chemical-oxide composition of any SCM used, rather than relying on mass-replacement percentages or mix-design labels alone.

11. Research Gaps and Challenges

Despite the substantial and rapidly growing volume of literature reviewed here, several gaps persist. First, the SCM-concrete and RAC-concrete literatures remain comparatively siloed: only five of the 28 reviewed studies address SCMs and recycled aggregate simultaneously (Section 8), despite this combination offering the largest cumulative sustainability benefit. Second, unlike the standardized 1,030-record UCI/Yeh dataset that anchors much of the SCM-concrete literature, no equivalent standardized benchmark dataset exists for RAC or combined SCM-RA concrete, making cross-study comparison of reported R² values difficult and likely contributing to the wider performance range

observed in Section 9. Third, relatively few studies (Fei et al., 2023; Pan et al., 2024, among those reviewed here) apply model-interpretability tools such as SHAP; the majority still report only aggregate accuracy metrics without explaining which parameters drive individual predictions, limiting practical adoption by mix-design engineers who require actionable, physically interpretable guidance rather than a black-box strength estimate. Fourth, external validation — testing a model trained on literature-compiled data against an independent, prospectively collected experimental dataset from a different laboratory or region — remains rare; most reported R^2 values reflect internal train–test splits or k-fold cross-validation on a single compiled dataset rather than genuine out-of-distribution generalization. Fifth, comparatively few studies incorporate the chemical-oxide composition of SCMs as model inputs despite evidence (Section 10) that this improves physical interpretability and cross-material transferability relative to mass-replacement-percentage inputs alone. Finally, deployment-oriented outputs — web-based or spreadsheet mix-design tools that practising engineers can use directly — remain uncommon in the academic literature reviewed, representing a translation gap between research-stage models and field-usable tools.

12. Future Research Directions

Building on the gaps identified above, five directions appear especially promising. First, the development and public release of a standardized, multi-source RAC and combined SCM–RA benchmark dataset, analogous to the UCI/Yeh dataset, would substantially improve cross-study comparability and accelerate methodological progress, particularly if it captured chemical-oxide composition, RA pre-treatment method, and parent-concrete provenance alongside conventional mix-proportion variables. Second, wider adoption of SHAP, partial-dependence, and individual-conditional-expectation analyses alongside every reported ensemble model would improve practical interpretability and trust among practising engineers. Third, hybrid and metaheuristic-optimized models — combining ensemble learners with genetic algorithms, particle swarm optimization, ant colony optimization, or Bayesian optimization for hyperparameter tuning — merit continued development, as several of the highest-accuracy studies reviewed here (Pan et al., 2024; Zhang et al., 2023) already point in this direction. Fourth, multi-objective frameworks that jointly optimize compressive strength alongside sustainability metrics (embodied carbon, cost) and fresh-state workability, as demonstrated for SCRAC by Singh, Kapoor, and Singh (2025), should be extended to the broader SCM and RAC literature, since strength alone is an incomplete design objective for sustainable concrete. Fifth, prospective external validation studies — in which a model trained on literature-compiled data is tested against newly cast, independently tested specimens — are needed to establish genuine field-readiness before ML-based strength prediction can be confidently incorporated into design codes or practice guidelines.

13. Conclusions

This review has synthesized 28 studies applying machine learning and artificial intelligence techniques to predict the compressive strength of concrete incorporating supplementary cementitious materials, recycled aggregate, or both. Ensemble tree-based methods — particularly Random Forest, XGBoost, and CatBoost — consistently outperform individual learners such as single decision trees, with reported R^2 values spanning 0.79–0.92 for SCM-concrete studies built on the widely used 1,030-record benchmark dataset, and 0.842–0.987 for RAC studies built on more heterogeneous, non-standardized datasets. Curing age, binder content, water-to-binder ratio, RA replacement ratio, and — where available — SCM chemical-oxide composition emerge as the most consistently influential parameters across sensitivity and SHAP analyses. Studies addressing SCMs and recycled aggregate simultaneously remain comparatively scarce and report somewhat lower and more variable accuracy than single-variable studies, reflecting smaller, more heterogeneous datasets. Future progress in this domain will depend on the development of standardized, richly featured benchmark datasets for RAC and combined SCM–RA concrete; wider adoption of model-interpretability tools; continued development of hybrid, metaheuristic-optimized ensembles; multi-objective frameworks that jointly optimize strength and sustainability; and, critically, prospective external validation that moves ML-based strength prediction from a research demonstration toward a field-deployable design tool for sustainable concrete.

References

- Abduljaleel, Y. W., Al-Obaidi, B., Khattab, M. M., Usman, F., Syamsir, A., & Albaker, B. M. (2024). Compressive strength prediction of recycled aggregate concrete based on different machine learning algorithms. *Al-Iraqia Journal for Scientific Engineering Research*, 3(3). <https://doi.org/10.58564/IJSER.3.3.2024.221>
- Ahmad, W., Ahmad, A., Ostrowski, K. A., Aslam, F., Joyklad, P., & Zajdel, P. (2021). Application of advanced machine learning approaches to predict the compressive strength of concrete containing supplementary cementitious materials. *Materials*, 14(19), 5762. <https://doi.org/10.3390/ma14195762>
- Aslam, F., & Shahab, M. Z. (2024). Supplementary cementitious materials in blended cement concrete: Advancements in predicting compressive strength through machine learning. *Materials Today Communications*, 38, 107725. <https://doi.org/10.1016/j.mtcomm.2023.107725>
- Ben Chaabene, W., Flah, M., & Nehdi, M. L. (2020). Machine learning prediction of mechanical properties of concrete: Critical review. *Construction and Building Materials*, 260, 119889. <https://doi.org/10.1016/j.conbuildmat.2020.119889>
- Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32. <https://doi.org/10.1023/A:1010933404324>
- Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785–794). <https://doi.org/10.1145/2939672.2939785>
- Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, 20(3), 273–297. <https://doi.org/10.1007/BF00994018>
- Ebid, A. M., Ulloa, N., Onyelowe, K. C., Zuñiga Rodriguez, M. G., Andrade Valle, A. I., & Zárate Villacres, A. N. (2024). Multiple AI predictive models for compressive strength of recycled aggregate concrete. *Cogent Engineering*, 11(1). <https://doi.org/10.1080/23311916.2024.2385621>
- Fei, Z., Liang, S., Cai, Y., & Shen, Y. (2023). Ensemble machine-learning-based prediction models for the compressive strength of recycled powder mortar. *Materials*, 16(2), 583. <https://doi.org/10.3390/ma16020583>
- Freund, Y., & Schapire, R. E. (1997). A decision-theoretic generalization of on-line learning and an application to boosting. *Journal of Computer and System Sciences*, 55(1), 119–139. <https://doi.org/10.1006/jcss.1997.1504>
- Gamil, Y. (2023). Machine learning in concrete technology: A review of current researches, trends, and applications. *Frontiers in Built Environment*, 9, 1145591. <https://doi.org/10.3389/fbuil.2023.1145591>
- Jagadesh, P., de Prado-Gil, J., Silva-Monteiro, N., & Martínez-García, R. (2023). Assessing the compressive strength of self-compacting concrete with recycled aggregates from mix ratio using machine learning approach. *Journal of Materials Research and Technology*, 24, 1483–1498.
- Jagadesh, P., Khan, A. H., Priya, B. S., Asheeka, A., Zoubir, Z., Magbool, H. M., Alam, S., & Bakather, O. Y. (2024). Artificial neural network, machine learning modelling of compressive strength of recycled coarse aggregate based self-compacting concrete. *PLOS ONE*, 19(5), e0303101. <https://doi.org/10.1371/journal.pone.0303101>
- Jang, J.-S. R. (1993). ANFIS: Adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man, and Cybernetics*, 23(3), 665–685. <https://doi.org/10.1109/21.256541>
- Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q., & Liu, T.-Y. (2017). LightGBM: A highly efficient gradient boosting decision tree. *Advances in Neural Information Processing Systems*, 30, 3146–3154.
- Khan, A. Q., Rasheed, M. D., Naveed, M. H., et al. (2026). Data-driven modeling of compressive strength in sustainable self-compacting concrete incorporating recycled aggregates using ensemble learning techniques. *Data-Centric Engineering*, 7. <https://doi.org/10.1017/dce.2026.10075>
- Koza, J. R. (1992). *Genetic Programming: On the Programming of Computers by Means of Natural Selection*. MIT Press.

- Li, S., Wang, B., Gao, Y., & Yu, Y. (2025). A compressive strength prediction model for precast recycled aggregate concrete based on machine learning. *AIP Advances*, 15(7), 075133. <https://doi.org/10.1063/5.0280234>
- Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems*, 30, 4765–4774.
- Palencia Coto, M. C., Martínez García, R., De Prado Gil, J., & Silva Monteiro, N. (2022). To predict the compressive strength of self compacting concrete with recycled aggregates utilizing ensemble machine learning models. *Case Studies in Construction Materials*, 16, e01046. <https://doi.org/10.1016/j.cscm.2022.e01046>
- Pan, B., Liu, W., Zhou, P., & Wu, D. O. (2024). Predicting the compressive strength of recycled concrete using ensemble learning model. *IEEE Access*, 13, 2958–2969.
- Phoeuk, M., & Kwon, M. (2023). Accuracy prediction of compressive strength of concrete incorporating recycled aggregate using ensemble learning algorithms: Multinational dataset. *Advances in Civil Engineering*, 2023, 5076429. <https://doi.org/10.1155/2023/5076429>
- Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. *Nature*, 323, 533–536. <https://doi.org/10.1038/323533a0>
- Sathiparan, N. (2026). Machine learning models for predicting compressive strength of cement mortar: the influence of oxides in supplementary cementitious materials. *Innovative Infrastructure Solutions*, 11, 379. <https://doi.org/10.1007/s41062-026-02798-5>
- Singh, T., Kapoor, K., & Singh, S. P. (2025). Predictive modelling on the compressive strength and fresh properties of self-compacting recycled aggregate concrete using machine learning approaches. *Materiales de Construcción*, 75(358), e375. <https://doi.org/10.3989/mc.2025.382624>
- Yeh, I. C. (1998). Modeling of strength of high-performance concrete using artificial neural networks. *Cement and Concrete Research*, 28(12), 1797–1808. [https://doi.org/10.1016/S0008-8846\(98\)00165-3](https://doi.org/10.1016/S0008-8846(98)00165-3)
- Yuan, X., Tian, Y., Ahmad, W., Ahmad, A., Usanova, K. I., Mohamed, A. M., & Khallaf, R. (2022). Machine learning prediction models to evaluate the strength of recycled aggregate concrete. *Materials*, 15(8), 2823. <https://doi.org/10.3390/ma15082823>
- Zhang, X., Dai, C., Li, W., & Chen, Y. (2023). Prediction of compressive strength of recycled aggregate concrete using machine learning and Bayesian optimization methods. *Frontiers in Earth Science*, 11, 1112105. <https://doi.org/10.3389/feart.2023.1112105>