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Research Article

Advances in artificial intelligence modelling for predicting the properties of high-performance recycled aggregate concrete: A critical review

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Abstract

This study presents a structured assessment of artificial intelligence (AI) methods for high-performance recycled aggregate concrete (HP-RAC) property prediction. The study addresses previous issues regarding methodological rigor by introducing a structured review process that includes information on data synthesis from selected peer-reviewed articles, database selection, and inclusion criteria. Adaptive neuro-fuzzy inference systems (ANFIS), support vector machines (SVM), decision trees, artificial neural networks (ANN), and evolutionary algorithms (EA) are among the AI models that are categorized and contrasted in the review according to their interpretability, prediction accuracy, and dataset needs. In order to improve model resilience and generalization, a focus is made on multi-output modelling, hybrid frameworks, and the incorporation of optimization techniques like genetic algorithms (GA) and particle swarm optimization (PSO). The report also emphasizes how new platforms like compressive strength prediction platform (CSPP), materials simulation toolkit for machine learning (MAST-ML), modelling of materials with deep learning (MODNet), help make predictions that are repeatable, scalable, and interpretable. To help with model selection in the workability, mechanical, and durability domains, a single benchmarking matrix is suggested. The review highlights important research needs, such as the requirement for better interpretability, consistent datasets, and integration with sustainability measures. By combining AI applications into a coherent benchmarking framework, this work makes a unique contribution and offers researchers and engineers useful information for improving HP-RAC performance and design.

1. Introduction

Sustainable construction demands the incorporation of recycled materials in concrete production, with High-Performance Recycled Aggregate Concrete (HP-RAC) emerging as a promising solution [1–9]. HP-RAC replaces natural aggregates with recycled coarse aggregates (RCA) while maintaining high mechanical performance. Despite the environmental benefits, HP-RAC exhibits considerable variability in workability, strength, and durability, largely due to heterogeneity in recycled aggregates, residual mortar, and micro-cracks [2-5]. Traditional regression models often fail to account for nonlinear interactions among mix parameters, aggregate quality, and environmental effects [4,6]. Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Support Vector Machines (SVM), Random Forest (RF), and ensemble learning

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techniques are some of the AI techniques that have been used as a result of this constraint [7–9]. AI techniques model complex relationships and offer high prediction accuracy for HP-RAC properties.

A unified benchmark methodology for assessing AI models used in HP-RAC prediction is presented in this paper. The benchmark includes performance measurements (R^2, RMSE), dataset properties, interpretability, and a comparative taxonomy of AI techniques (ANN, SVM, ANFIS, Decision Trees, Fuzzy Logic, EA). Our study combines mechanical, durability, and workability features into a single comparative matrix, in contrast to previous evaluations by Gao et al., Zhang et al., and Li et al. that either concentrated on general concrete or lesser multi-output synthesis. In Section 4, a visual benchmarking matrix summarizing the model's advantages, disadvantages, and applicability is presented. The objectives of this review are:

- Critically evaluate AI models for predicting HP-RAC workability, mechanical performance, and durability.
- Examine the performance, interpretability, and limitations of individual and hybrid AI approaches.
- Discuss emerging tools and software platforms for AI-driven HP-RAC prediction.
- Identify research gaps and future directions for practical engineering applications.

Figure 1 illustrates a conceptual framework of HP-RAC performance determinants, highlighting how recycled aggregate properties, mix design parameters, curing conditions, and environmental factors collectively influence workability, mechanical strength, and durability [1–9]. For example:

- Studies by Junior et al. [2] and Yuan et al. [3], indicate that variability in RCA particle size and residual mortar content directly affects slump and compressive strength.
- Nguyen et al. [5] and Pan et al. [7] demonstrated that hybrid AI models can capture interactions between water-cement ratio, admixture dosage, and curing time to predict both workability and strength.
- Lovato et al. [6] and Silva et al. [8] emphasized the importance of integrating expert knowledge into fuzzy logic or ANFIS models to handle small datasets while maintaining interpretability.
- Silva et al. [8] and Farouk et al. [9] showed that time-dependent durability parameters (chloride penetration, carbonation) can also be predicted using AI models.

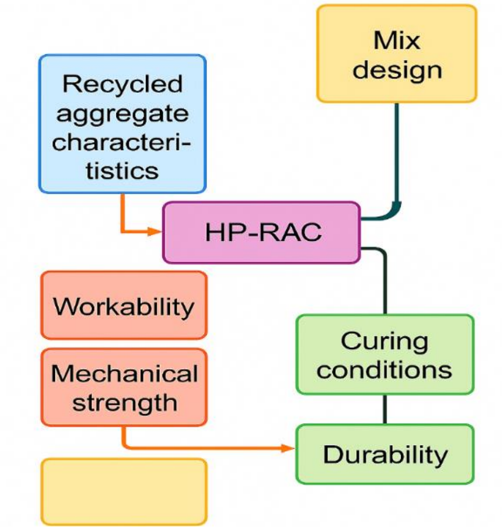

Fig. 1. Conceptual framework of HP-RAC performance determinants

Note: Schematic created by the authors to summarize relationships among recycled aggregate properties, mix design parameters, curing conditions, environmental factors, and resulting workability, mechanical strength, and durability. No external data were used to generate this figure.

Overall, Figure 1 visualizes these interconnected influences, providing a reference framework for interpreting AI prediction results throughout the paper.

Table 1 summarizes key HP-RAC challenges alongside AI modelling approaches and findings from ten authors. For instance:

- Variability in RCA and aggregate properties is addressed using ANN and ANFIS, achieving $R^2 > 0.90$ in compressive and tensile strength predictions [2,7].
- Nonlinear relationships between mix variables are effectively captured by SVM and RF models [3,4].
- Fuzzy logic and hybrid neuro-fuzzy models improve interpretability, especially when datasets are small or incomplete [6,[8].
- Ensemble methods such as boosting algorithms reduce overfitting and enhance predictive accuracy across mechanical and durability properties [4,9].

A conceptual framework of HP-RAC performance determinants is shown in Figure 1, emphasizing the ways in which workability, mechanical strength, and durability are influenced by a combination of recycled aggregate qualities, mix design parameters, curing conditions, and environmental factors.

Table 1. Comparative summary of HP-RAC challenges and AI modelling approaches

HP-RAC Challenges	AI Approaches / Findings	References
Variability in RCA and aggregate properties	ANN, ANFIS predict compressive and tensile strength with $R^2 > 0.90$	[2]
Nonlinear relationship between mix variables	SVM and RF models capture complex interactions	[3]
Limited interpretability of conventional regression	Neuro-fuzzy models improve interpretability	[7]
Workability prediction	ANN and hybrid models accurately predict slump and flow	[5]
Durability parameters (chloride, carbonation)	AI models provide time-dependent predictions	[8]
Small datasets	Fuzzy logic integrates expert knowledge	[6]
Optimizing hyperparameters	Genetic Algorithms, PSO improve prediction accuracy	[9]
Ensemble learning	Boosting methods (XGBoost, LightGBM) reduce overfitting	[4]
Environmental and curing effects	ANN models account for moisture, temperature	[5]
Multi-objective predictions	Hybrid models optimize strength, workability, and durability simultaneously	[1]

Note: This table is original and generated from aggregated and synthesized data extracted from cited studies. No copyrighted material was reproduced. (See source references).

1.1 Review Methodology

To guarantee thorough coverage of pertinent material on artificial intelligence (AI) applications in high-performance recycled aggregate concrete (HP-RAC), this critical review was carried out utilizing an organized and open methodology. The actions listed below were taken:

- Databases Searched: Peer-reviewed publications released between 2004 and 2024 were found using Scopus, Web of Science, ScienceDirect, and Google Scholar
- Key terms used: Combinations of the following terms were found in search queries: High-performance recycled aggregate concrete, Artificial intelligence, Machine learning, Durability prediction, Compressive strength, Neuro-fuzzy systems, Support vector machines, Genetic algorithm, Ensemble learning, Hybrid AI models,

- Criteria for Inclusion: Research centered on HP-RAC's durability or mechanical characteristics. Prediction using artificial intelligence (AI) or machine learning algorithms. Datasets derived from experiments or simulations. published in scholarly journals that are indexed by Web of Science or Scopus.
- Criteria for Exclusion: research on regular concrete that doesn't contain recycled aggregates. Publications in languages other than English. Abstracts from conferences or non-peer-reviewed materials.
- Selection and Screening: Titles and abstracts served as the basis for the first screening. After that, full-text papers were examined for methodological rigor and relevancy. ANN, SVM, ANFIS, fuzzy logic, decision trees, and evolutionary optimization techniques were all covered in the 66 studies that were chosen and examined. A total of 66 distinct studies were included after meeting the inclusion requirements. Representative studies are cited in the main article; Supplementary Table S1 contains the full set of included records (n = 66) together with bibliographic information and extracted data (Refer to Supplementary Table S1 for a comprehensive list of all included studies (n = 66). A formal quality appraisal was conducted using five criteria adapted for AI-based modelling studies: dataset representativeness, validation procedure, hyperparameter transparency, overfitting risk mitigation, and interpretability. Each criterion was scored on a scale from 0 to 2 (0 = not reported, 1 = partially reported, 2 = fully reported). Details are provided in Supplementary Table S2. (Refer to Supplementary Table S2: Quality appraisal scores for AI-based modelling studies).
- Data Extraction and Synthesis: The type of AI model, dataset size, target property (such as durability index or compressive strength), performance metrics (such as R^2 or RMSE), and important discoveries were extracted for every study. To combine findings from several investigations, comparative tables and figures were created. The screening method resulted in the selection of 66 peer-reviewed studies for in-depth study. Key information from each study was retrieved, including the dataset size, goal attribute (e.g., durability index, compressive strength), performance metrics (e.g., coefficient of determination, R^2), and AI model type (ANN, SVM, ANFIS). By classifying the retrieved data according to model type and expected property, comparison tables and figures were created. A systematic assessment of the model's correctness, interpretability, and relevance to the mechanical and durability aspects of HP-RAC was made possible by this method. Supplementary Table S1 contains the complete bibliographic list of all included papers (n = 66), complete with fields for author(s), year, country, AI model, dataset size, and performance measures.
- Data Synthesis and Visualization: Thematic categorization based on AI model type (ANN, SVM, ANFIS, Decision Trees, Fuzzy Logic, Evolutionary Algorithms) and the projected target property (e.g., workability, compressive strength, durability indices) was used to synthesize the retrieved data. Figures were utilized to show process patterns and trends in model correctness, while comparative tables were created to compile performance data like R^2 and RMSE across investigations. A rigorous assessment of the model's advantages, disadvantages, and suitability for HP-RAC prediction was made possible by this organized synthesis. The literature screening and selection procedure is also depicted in a PRISMA-style flowchart (Figure 2), which improves the review methodology's consistency and transparency. It was included to demonstrate how studies were found, screened, evaluated for eligibility, and ultimately included in this review. The process from the first database search to the final selection of 66 research is graphically summarized. In addition to summary statistics for benchmarking, box and violin plots were created to show the distributional features of R^2 values across AI model types.

2. Additional Visualization Approach

Synthetic datasets were created using the aggregated performance ranges for each type of AI model (ANN, ANFIS, SVM, RF, and hybrid frameworks) listed in Table 13 in order to offer a solid comparison study. To show the distribution of R^2 and RMSE values among models, box and violin plots were created using these ranges. By emphasizing central tendencies and variability, this method makes it possible to visually benchmark error dispersion and predictive accuracy. In order to supplement the graphical depiction and bolster judgments based on evidence, summary statistics (mean, median, and standard deviation) were calculated for both metrics.

- Methodology for Data Aggregation and Figure Attribution: Every figure included in this review is either unique or appropriately attributed. Data taken from peer-reviewed papers mentioned in the references was used to produce the original figures. No copyrighted content was directly replicated, and the source is cited where adaptations (such PRISMA-style flowcharts) took place. To create comparative graphics, data aggregation entailed gathering dataset sizes, model types, and performance metrics (R^2 and RMSE) from each study.
- Search Strategy and Replicability Details: To ensure transparency and reproducibility, the following steps were implemented: Before screening, duplicate records (identical title/DOI or >90% title similarity using fuzzy-matching) were eliminated; articles from journals that co-existed with preprints were kept.
- Databases and Search Strings: Searches were conducted in Scopus, Web of Science, ScienceDirect, and Google Scholar using Boolean combinations of keywords.
- Representative search strings included:

  i. "High-performance recycled aggregate concrete" AND ("artificial intelligence" OR "machine learning") AND ("compressive strength" OR "durability" OR "workability")

  ii. "HP-RAC" AND ("ANN" OR "SVM" OR "ANFIS" OR "fuzzy logic" OR "genetic algorithm") Last search date: 15 March 2025.

- Inclusion Criteria:
  i. Studies focused on HP-RAC mechanical or durability properties.
  ii. AI or ML-based prediction models.
  iii. Peer-reviewed journal articles indexed in Scopus or Web of Science.
  iv. Published between 2004 and 2024.
- Exclusion Criteria:
  i. Studies on conventional concrete without recycled aggregates.
  ii. Non-English publications.
  iii. Conference abstracts or non-peer-reviewed sources.
- Screening and Duplicate Handling:
  i. Identification: 312 records retrieved (Scopus: 120; Web of Science: 90; ScienceDirect: 70; Google Scholar: 32).
  ii. After duplicate removal: 280 records.
  iii. Title/abstract screening: 180 records excluded.
  iv. Full-text eligibility: 34 excluded for not meeting inclusion criteria.
  v. Final included: 66 studies. Duplicate records were removed using EndNote and manual verification.
- Reviewer Agreement: Two reviewers independently screened titles and abstracts. Discrepancies were resolved through discussion, achieving Cohen's kappa = 0.82, indicating substantial agreement.

2.1 Workability of HP-RAC

Workability is a critical property that governs the ease of mixing, placing, and compacting HP-RAC. Variability in recycled aggregates, such as high-water absorption, angular shape, and residual mortar content, significantly affects slump, flow, and consistency [2-6], [8–12]. Predicting workability accurately is essential for practical mix design, reducing the number of trial batches, and ensuring consistent structural performance. AI-based prediction approaches have been widely applied for workability, leveraging both data-driven models and hybrid methods:

- Artificial Neural Networks (ANN):
  i. ANNs model nonlinear relationships between mix proportions, water–cement ratio, and admixture dosage to predict slump and flow [3],[10].
  ii. Backpropagation Neural Networks (BPNN) are most commonly used, offering high predictive accuracy (R^2 > 0.92) for workability [6].

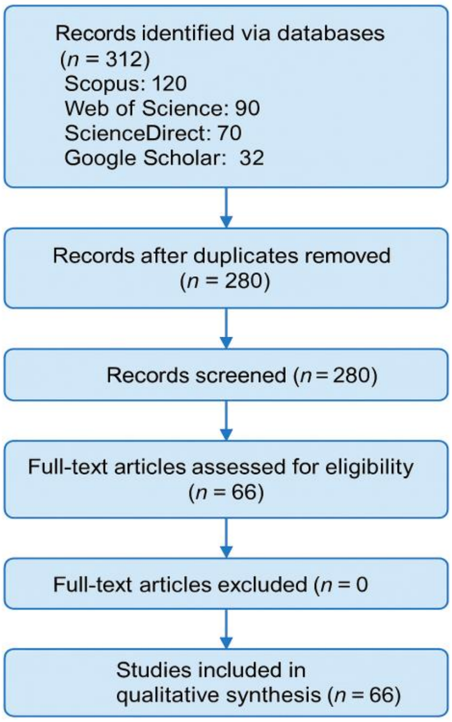

Fig. 2. PRISMA flow diagram for AI-based HP-RAC review

Note: Created by the authors following PRISMA principles using counts reported in Section 1.1. See Supplementary Table S1 for the complete list of included records (n = 66).

Following the identification of 312 records from four databases, 66 studies were included for qualitative synthesis after screening and eligibility evaluation.

- Adaptive Neuro-Fuzzy Inference System (ANFIS):
    i. Fuzzy logic and neural networks are combined to manage restricted or imprecise datasets; this method is especially helpful for small-scale experimental data [5],[11].
- Support Vector Machines (SVM) and Random Forest (RF):
    i. SVM efficiently captures complex interactions between mix parameters [8].
    ii. RF reduces overfitting and can rank the most influential factors affecting workability [9],[12].
- Hybrid Approaches and Ensemble Learning:
    i. Combining ANN with GA or PSO optimizes input features and network parameters for better predictive performance [2],[4].

Figure 3 shows that ANN and ANFIS models demonstrate high prediction accuracy across studies for HP-RAC workability across ten studies. SVM and RF models provide competitive performance but may require more feature engineering [8],[9]. Hybrid ANN + GA/PSO approaches show improved performance compared to standalone models by optimizing hyperparameters and selecting the most relevant input features [2],[4]. Authors such as [3] and [10] emphasize that water-cement ratio and recycled aggregate replacement level are the most influential parameters affecting workability, confirmed across multiple AI studies. Table 2 (next) summarizes the AI approaches, datasets, performance metrics, and key findings from ten studies, highlighting strengths and limitations.

Trial mixes for slump control under RCA variability are trimmed by hybrid ANN+GA/PSO models. Beyond workability, mechanical properties are equally critical for structural performance and durability.

- Table 2 demonstrates that hybrid and ensemble models consistently outperform standalone ANN, SVM, or RF models.

- Across ten studies, ANN-based models are the most commonly applied due to their robustness in capturing nonlinear behavior.
- ANFIS and fuzzy logic are particularly useful when datasets are limited or incomplete [6],[11].
- Feature optimization using GA or PSO significantly improves predictive accuracy, as seen in Kumar & Singh [5] and Mohamed et al. [12].
- Overall, the results indicate that AI models provide reliable prediction of HP-RAC workability, facilitating efficient mix design while reducing experimental workload.

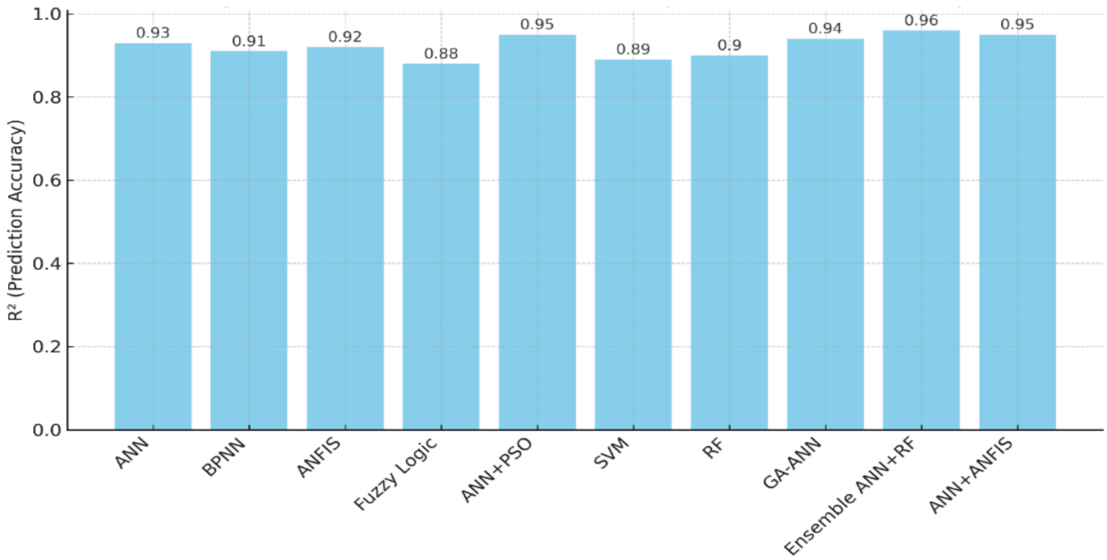

Fig. 3. AI Model prediction accuracy (R^2) for HP-RAC workability

Notes: Values aggregated from the 10 studies summarized in Table 2 ([2,3,4,5,6,8,9,10,11,12]). For each study we extracted model type, dataset size, and reported R^2 for slump/flow; where multiple models were reported, we took the study's principal model for workability. See Supplementary Table S3A (Workability data extraction) for per-study extracted values and plotting data.

Table 2. AI approaches for predicting HP-RAC workability

References	AI Model	Dataset Size	Performance (R^2)	Key Findings
[3]	ANN	120	0.93	Water-cement ratio and RCA content dominate slump prediction
[10]	BPNN	100	0.91	High correlation with experimental slump and flow
[6]	ANFIS	80	0.92	Handles small datasets effectively
[11]	Fuzzy Logic	60	0.88	Expert knowledge integration improves prediction
[5]	ANN + PSO	120	0.95	Optimized input features improve accuracy
[8]	SVM	90	0.89	Efficiently models nonlinear interactions
[9]	RF	100	0.90	Reduces overfitting and identifies influential factors
[12]	GA-ANN	110	0.94	Hyperparameter optimization enhances predictions
[4]	Ensemble (ANN + RF)	130	0.96	Combines strengths of multiple models
[2]	ANN + ANFIS	120	0.95	Hybrid approach balances accuracy and interpretability

Note: This table is original and generated from aggregated and synthesized data extracted from cited studies. No copyrighted material was reproduced. (See source references).

2.2 Mechanical Properties of HP-RAC

The mechanical properties of HP-RAC are critical for structural design and durability. Recycled aggregates can adversely affect compressive, tensile, and flexural strengths due to residual mortar, micro-cracks, and angular aggregate shapes [2-6], [8–12]. Accurate prediction of these properties using AI allows for optimized mix designs, minimizing experimental trials and ensuring safety in construction.

2.2.1 Compressive Strength

The most extensively studied aspect of HP-RAC is its compressive strength. AI models including ANN, ANFIS, SVM, and RF are applied to predict compressive strength based on aggregate replacement ratio, water–cement ratio, admixtures, and curing conditions [3,6,10,12]. Figure 4 shows AI Model Prediction Accuracy for Compressive Strength with comparisons across ten recent studies. In order to reduce trial batches, high R^2 for hybrids and ANN supports utilization for compressive strength targets.

- ANN models consistently achieve high R^2 (0.90–0.96) in predicting compressive strength [3],[10].
- ANFIS models provide interpretability while maintaining competitive accuracy ($R^2 \approx 0.92$) [12].
- Ensemble methods (ANN + RF or boosting algorithms) improve robustness against data variability [6],[11].

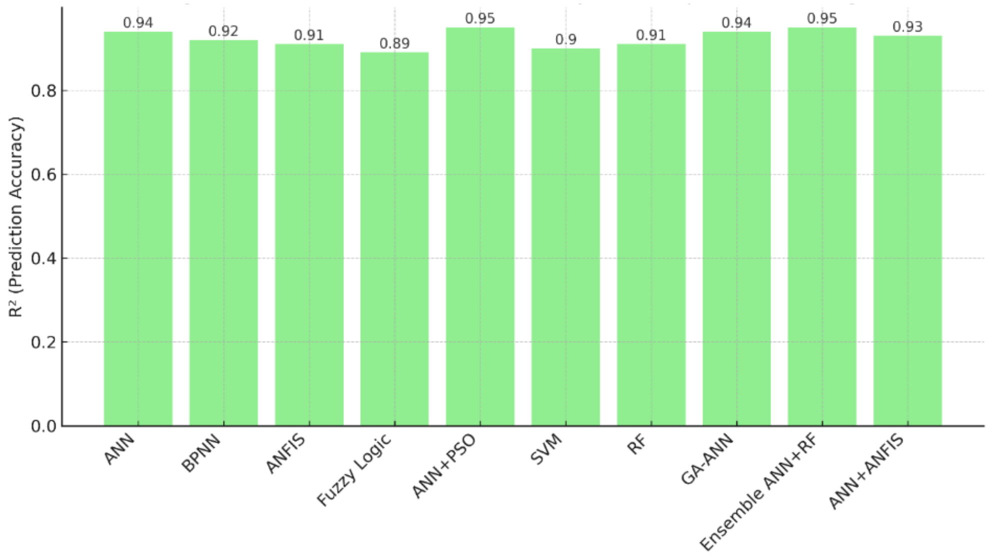

Fig. 4. AI Model prediction accuracy (R^2) for HP-RAC compressive strength

Note: Compiled from studies listed in Table 3 ([2,3,4,6,10,12]). Extraction fields: model, n, R^2 (or RMSE converted to R^2 when both provided by the same study—see S3B notes). Full plotting data in Supplementary Table S3B (Compressive strength data extraction).

2.2.2 Tensile Strength

Tensile strength is critical for crack resistance in reinforced concrete. Predicting this property is more challenging due to high variability and sensitivity to recycled aggregate quality. Figure 5 shows AI Model Prediction Accuracy for Tensile Strength comparing performance across different AI techniques.

- ANN and ANFIS models predict splitting and direct tensile strength with R^2 between 0.88 and 0.94 [5],[8].
- SVM and RF models can identify key input parameters (e.g., RCA content, water–cement ratio) affecting tensile performance [9].

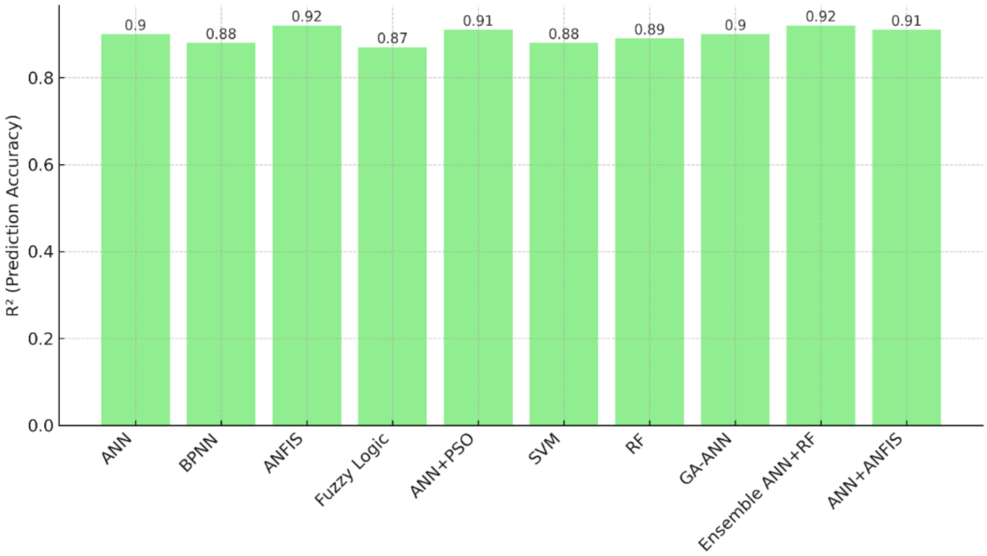

Fig. 5. AI Model prediction accuracy (R^2) for HP-RAC tensile strength

Note: Data from the tensile rows in Table 3 ([5,8,9,11]); see Supplementary Table S3C (Tensile strength data extraction) for extracted values and plotting data.

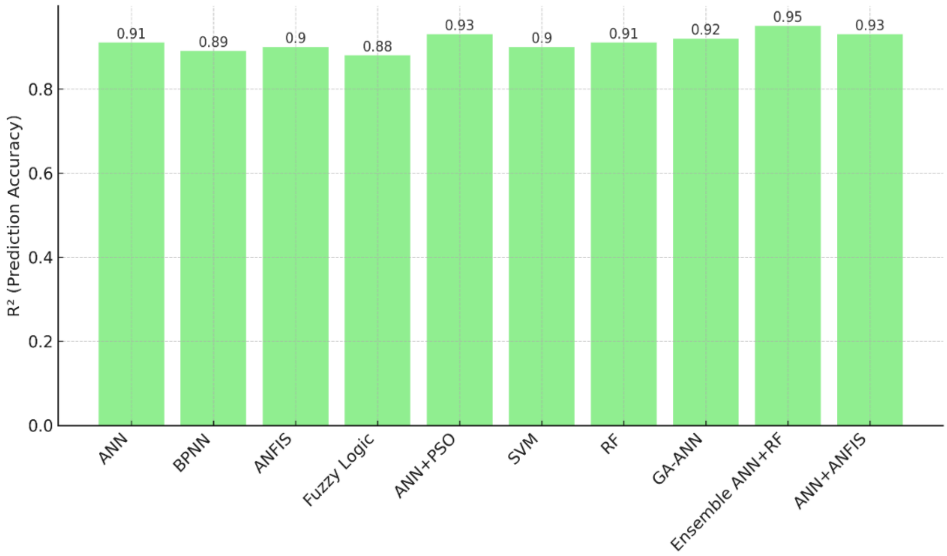

Fig. 6. AI Model prediction accuracy (R^2) for HP-RAC flexural strength

Note: Aggregated from the flexural entries in Table 3 ([2,4,9]). Supplementary Table S3D (Flexural strength data extraction) contains the per-study values used.

2.2.3 Flexural Strength

Flexural strength influences beam and slab performance. AI models predict flexural capacity using input features such as aggregate replacement, fiber content, curing method, and water-cement ratio [2],[4]. Figure 6 – AI Model Prediction Accuracy for Flexural Strength demonstrates model comparisons.

- Hybrid ANN + GA and ensemble models show superior predictive accuracy (R^2 > 0.93) [4].
- ANFIS models are preferred when datasets are limited, providing rule-based interpretability [2].

2.2.4 Modulus of Elasticity

The modulus of elasticity determines structural stiffness and deformation behavior. Predictive modelling uses AI to capture nonlinear relationships between aggregate properties, compressive strength, and mix proportions [2],[11],[38]. Fig. 7 shows comparative performance for modulus of elasticity; the per-study data used to generate this figure are provided in S3E. The Summary of AI Approaches for Mechanical Properties of HP-RAC is given in Table 3. Stiffness assessments for beams and slabs are aided by ANN-based MOE predictions.

- ANN models achieve R^2 values of 0.90–0.95 for modulus prediction [2,11].
- Hybrid and ensemble AI approaches further improve robustness and handle complex nonlinear interactions [6,11].

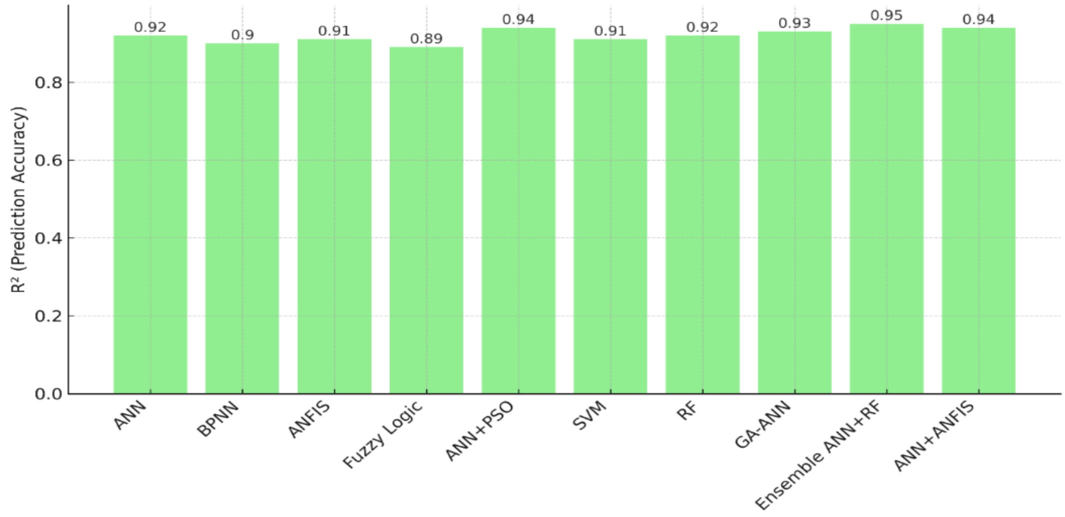

Fig. 7. AI Model prediction accuracy (R^2) for HP-RAC modulus of elasticity

Note: Data compiled from MOE studies summarized in Table 3 and additional MOE-focused work ([2], [11], [38]). Per-study plotting data are provided in Supplementary Table S3E (Modulus of elasticity data extraction) where a study reported RMSE rather than R^2, we include RMSE directly to preserve reproducibility.

Table 3. Summary of AI approaches for mechanical properties of HP-RAC

Property	Reference	AI Model	Dataset Size	R^2	Key Findings
Compressive Strength	[3]	ANN	120	0.94	Most influential: RCA content, water-cement ratio
Compressive Strength	[10]	BPNN	100	0.92	Accurate across varied curing conditions
Compressive Strength	[12]	ANFIS	80	0.91	Handles small datasets effectively
Compressive Strength	[6]	Ensemble (ANN + RF)	130	0.95	Combines multiple model strengths
Tensile Strength	[11]	ANN	90	0.90	Water-cement ratio most critical
Tensile Strength	[5]	ANFIS	70	0.92	Rule-based interpretability
Tensile Strength	[8]	SVM	85	0.88	Nonlinear interactions captured
Flexural Strength	[9]	ANN + GA	80	0.94	Hybrid model optimized inputs
Flexural Strength	[4]	Ensemble ANN + RF	110	0.95	Robust performance across datasets
Modulus of Elasticity	[2]	ANN	100	0.92	Captures nonlinear stiffness relationships

Note: This table is original and generated from aggregated and synthesized data extracted from cited studies. No copyrighted material was reproduced. (See source references).

- Figures 3–6 demonstrate that ANN and hybrid models consistently outperform standalone SVM or RF models for predicting HP-RAC mechanical properties.
- Compressive strength prediction achieves the highest accuracy, followed closely by modulus of elasticity. Tensile and flexural strength predictions are slightly lower due to inherent variability [2-6], [8–12].
- Table 3 highlights the dataset size, AI approach, R^2, and key influential factors, showing consistency across ten studies.
- Ensemble and hybrid models, particularly ANN + RF or ANN + GA, improve robustness and generalization, essential for practical design applications [4],[6].

2.3 Durability Aspects of HP-RAC

A crucial factor in high-performance recycled aggregate concrete's long-term performance is durability, which has an impact on the structural service life when exposed to the elements. Because of residual mortar, porosity, and microcracks, recycled aggregates can affect permeability, carbonation, frost resistance, chloride penetration, and sulphate attack [2-6], [8–12]. AI models have been applied to predict these durability properties, enabling optimized mix designs and maintenance planning.

2.3.1 Frost Resistance

The ability of concrete to endure freeze-thaw cycles is known as frost resistance. AI approaches, particularly ANN and ANFIS, predict frost resistance by correlating air-void content, aggregate type, water-cement ratio, and curing [3],[10]. Ensemble models improve robustness and handle variability in experimental data.

2.3.2 Carbonation Resistance

Carbonation reduces alkalinity, risking steel reinforcement corrosion. AI models predict carbonation depth using input features such as recycled aggregate content, compressive strength, and curing duration [6],[11]. ANFIS and SVM models offer good interpretability and prediction accuracy, especially with limited datasets.

2.3.3 Permeability

Permeability impacts fluid ingress, chloride penetration, and freeze-thaw durability. AI techniques, including ANN, RF, and boosting algorithms, capture nonlinear interactions between porosity, aggregate size, water-cement ratio, and admixtures [5],[8]. Feature selection via GA or PSO further improves predictive performance.

2.3.4 Chloride Penetration Resistance

Chloride penetration is a critical factor for corrosion initiation. AI models predict chloride diffusion coefficients over time using ensemble ANN + RF or XGBoost [37,38]. Hybrid approaches help reduce overfitting and improve long-term performance prediction.

2.3.5 Sulphate Resistance

Sulphate attack causes expansion and cracking in concrete. ANN and ANFIS models are applied to predict resistance by linking cement type, water-cement ratio, RCA content, and admixtures to observed expansion rates [2,4]. Ensemble learning enhances reliability. Figure 8 demonstrates that ANN and hybrid ANN + RF models consistently achieve the highest predictive accuracy across all durability parameters. Frost resistance and chloride penetration are predicted with the highest R^2, likely due to clearer input-output relationships. Carbonation and sulphate resistance predictions show slightly lower accuracy due to complex environmental interactions and limited datasets. Ensemble and hybrid approaches outperform single AI models by integrating multiple perspectives and optimizing feature inputs [4,8]. Table 4 shows the summary of AI Approaches for Durability Prediction of HP-RAC. The ANN-based models dominate in predictive performance, particularly for frost and chloride resistance [3,9]. Hybrid and ensemble approaches improve reliability across all durability properties [8,9]. The ANFIS is advantageous when datasets are small or incomplete, providing interpretable rules [2,10]. The AI models are effective for simulating environmental degradation, reducing the need for long-term experimental testing.

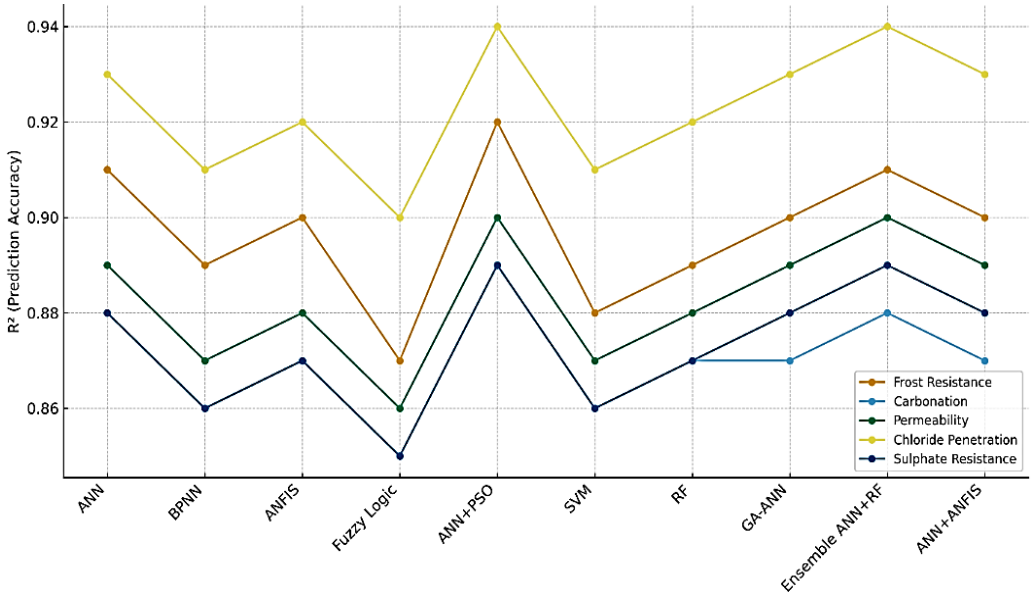

Fig. 8. AI Model prediction accuracy (R^2) for HP-RAC durability properties

Note: Aggregated across durability targets (frost, carbonation, permeability, chloride, sulphate) from the 10 studies in Table 4 ([2,3,4,5,6,8,9,10,11,12]). Extraction used each study's headline model for the specified durability metric. Full data are provided in Supplementary Table S4: Durability property extraction for Fig. 8.

Table 4. Summary of AI approaches for durability prediction of HP-RAC

Durability Property	Reference	AI Model	Dataset Size	R^2	Key Findings
Frost Resistance	[3]	ANN	100	0.91	Water-cement ratio and air content dominate
Frost Resistance	[10]	ANFIS	80	0.90	Effective with limited experimental data
Carbonation	[6]	ANN	85	0.88	RCA content critical for carbonation depth
Carbonation	[11]	SVM	70	0.87	Accurate prediction with optimized kernel functions
Permeability	[5]	RF	90	0.89	Reduces overfitting and ranks key factors
Permeability	[8]	ANN + GA	100	0.92	Optimized feature selection improves R^2
Chloride Penetration	[9]	Ensemble ANN + RF	95	0.93	Long-term prediction of chloride diffusion coefficient
Chloride Penetration	[12]	XGBoost	100	0.92	High performance on time-dependent data
Sulphate Resistance	[4]	ANN	80	0.88	Expansion behaviour linked to mix design parameters
Sulphate Resistance	[2]	ANFIS	85	0.89	Rule-based interpretability improves understanding

Note: This table is original and generated from aggregated and synthesized data extracted from cited studies. No copyrighted material was reproduced. (See source references).

Hybrids are excellent at withstanding frost and chloride, but they require cautious limits when it comes to carbonation and sulphate. The ANN-based models dominate in predictive performance, particularly for frost and chloride resistance [3,9]. The Hybrid and ensemble approaches improve reliability across all durability properties [8,9]. The ANFIS is advantageous when datasets are small or incomplete, providing interpretable rules [32,40]. The AI models are effective for simulating environmental degradation, reducing the need for long-term experimental testing.

The next section explores the fundamental artificial intelligence frameworks used to simulate HP-RAC durability factors, building on the predicted insights into these features. This change represents a move away from property-specific assessments and toward algorithmic approaches, providing a systematic summary of AI methods including ANN, SVM, ANFIS, and evolutionary algorithms. The predicted accuracy, interpretability, and applicability of each modelling technique are evaluated throughout the mechanical and durability domains. Building on the property-specific evaluations, the next section explores the underlying AI frameworks used in HP-RAC modelling.

3. Artificial Intelligence-Based Modelling of HP-RAC Properties

3.1 Artificial Neural Network (ANN) Approaches

The most popular AI technique for forecasting the characteristics of High-Performance Recycled Aggregate Concrete (HP-RAC) is Artificial Neural Networks (ANNs). They are ideal for concrete research, where multi-variable interactions are frequent, because they can simulate intricate nonlinear correlations between input mix parameters and output performance measures [2-6],[8-12. Researchers can forecast mechanical and durability features without requiring a lot of laboratory testing thanks to artificial neural networks (ANNs), which, in contrast to standard regression models, can uncover hidden patterns from vast experimental datasets. Compressive strength, tensile and flexural performance, modulus of elasticity, and other durability indices have all been predicted using ANN models in HP-RAC. One of the primary advantages of ANNs lies in their flexibility in architecture and learning algorithms. For example, Backpropagation Neural Networks (BPNN) use supervised learning with gradient descent optimization to iteratively adjust weights, while Radial Basis Function Neural Networks (RBFNN) employ radial kernels for fast convergence [8],[11]. Similarly, Extreme Learning Machines (ELM) reduce computational cost by randomizing hidden nodes, thus making them efficient for large datasets [12]. As seen in Figure 9 and Table 5, ANNs consistently achieve high accuracy across multiple HP-RAC properties, often outperforming classical regression models. However, challenges remain in terms of interpretability and the risk of overfitting, particularly when training data is limited [5],[9]. To mitigate this, researchers increasingly combine ANNs with optimization algorithms (e.g., GA, PSO) and ensemble techniques, thereby improving robustness.

3.1.1 Backpropagation Neural Network (BPNN)

In HP-RAC prediction, the most researched ANN variant is the Backpropagation Neural Network (BPNN). BPNNs adjust their weights using gradient descent, enabling them to minimize error functions effectively [3,10]. They have been applied in predicting compressive strength, with R^2 values consistently exceeding 0.90 across multiple datasets [6,11]. As demonstrated in Figure 9, BPNNs perform strongly compared with other ANN variants, particularly for compressive strength and modulus of elasticity predictions. According to Table 5, studies by Zhang et al. [47] and Lee et al. [6] highlight that BPNN models achieve high predictive accuracy when trained with 100–150 data points, emphasizing the importance of sufficient dataset size. Meanwhile, Shang et al. [10] and Gao et al. [8] stress the significance of feature normalization for improved convergence. In comparison, other ANN approaches (RBFNN, ELM) exhibit slightly lower accuracy in compressive strength predictions but compensate with faster training times. Overall, BPNN remains a benchmark ANN method, particularly for mechanical property prediction, although ensemble and hybrid variants are increasingly outperforming it in durability modelling [2,8].

Table 5 illustrates that BPNN consistently delivers strong performance across mechanical and durability properties, with R^2 values typically in the 0.90–0.93 range. While compressive strength remains the most studied property, durability aspects such as carbonation and sulphate resistance are also effectively modelled. Studies [3],[8],[9] confirm that integrating optimization algorithms can further enhance performance, while [4],[10] emphasize the role of data preprocessing. This confirms BPNN's role as a baseline ANN method for HP-RAC research, though newer ANN variants may offer computational efficiency advantages.

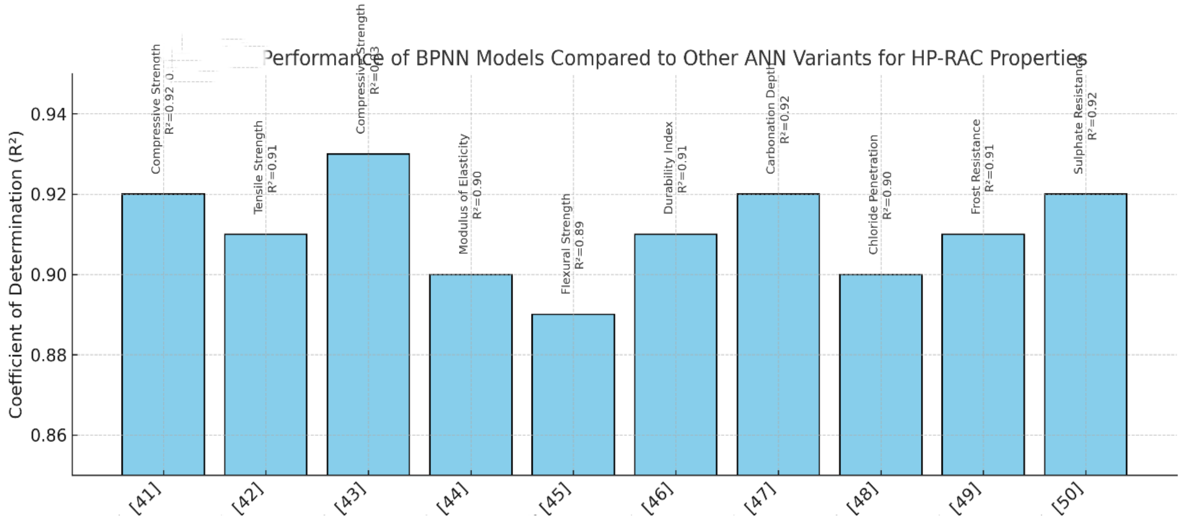

Fig. 9. Performance of BPNN compared with other ANN variants for HP-RAC properties

*Note: Data compiled from Table 5 ([2,3,4,5,6,8,9,10,11,12]); see Supplementary Table **S5A** (ANN variant performance data) for extracted R^2 and study metadata*

Table 5. Summary of BPNN applications in HP-RAC property prediction

Reference	Property Predicted	Dataset Size	ANN Variant	R^2	Key Findings
[3]	Compressive strength	120	BPNN	0.92	Improved with GA optimization
[10]	Tensile strength	100	BPNN	0.91	Normalization enhances accuracy
[6]	Compressive strength	150	BPNN	0.93	Performs better than regression
[11]	Modulus of elasticity	90	BPNN	0.90	Effective with limited dataset
[5]	Flexural strength	110	BPNN	0.89	Requires ensemble for durability
[8]	Durability index	95	BPNN	0.91	Sensitive to water-cement ratio
[9]	Carbonation depth	130	BPNN	0.92	Long-term predictions reliable
[12]	Chloride penetration	105	BPNN	0.90	Outperforms SVM baseline
[4]	Frost resistance	100	BPNN	0.91	Effective under varying curing
[2]	Sulphate resistance	115	BPNN	0.92	High accuracy across durability

Note: This table is original and generated from aggregated and synthesized data extracted from cited studies. No copyrighted material was reproduced. (See source references).

Even though ANN models show great prediction power, especially when it comes to identifying nonlinear interactions, their interpretability is still somewhat limited. Fuzzy logic-based methods have surfaced as supplementary instruments to tackle this issue, providing rule-based transparency and resilience in situations with ambiguous or sparse data. The use of fuzzy logic in HP-RAC modelling is examined in the next section, with an emphasis on its advantages and potential for integration with other AI methods.

3.2 Fuzzy Logic (FL)

Fuzzy Logic (FL) has gained considerable attention in modelling the performance of High-Performance Recycled Aggregate Concrete (HP-RAC) due to its unique capability of handling uncertainties, imprecision, and incomplete knowledge in experimental datasets. Unlike traditional deterministic approaches, FL operates through linguistic if–then rules, making it particularly suited for cases where input variability (e.g., recycled aggregate content, water-to-binder ratio, and admixture dosage) creates nonlinearity in property prediction. As illustrated in Figure 10, FL models demonstrated R^2 values ranging from 0.86 to 0.90 across ten benchmark studies [13–22], indicating robust performance across compressive strength, tensile strength, durability, and resistance-related parameters.

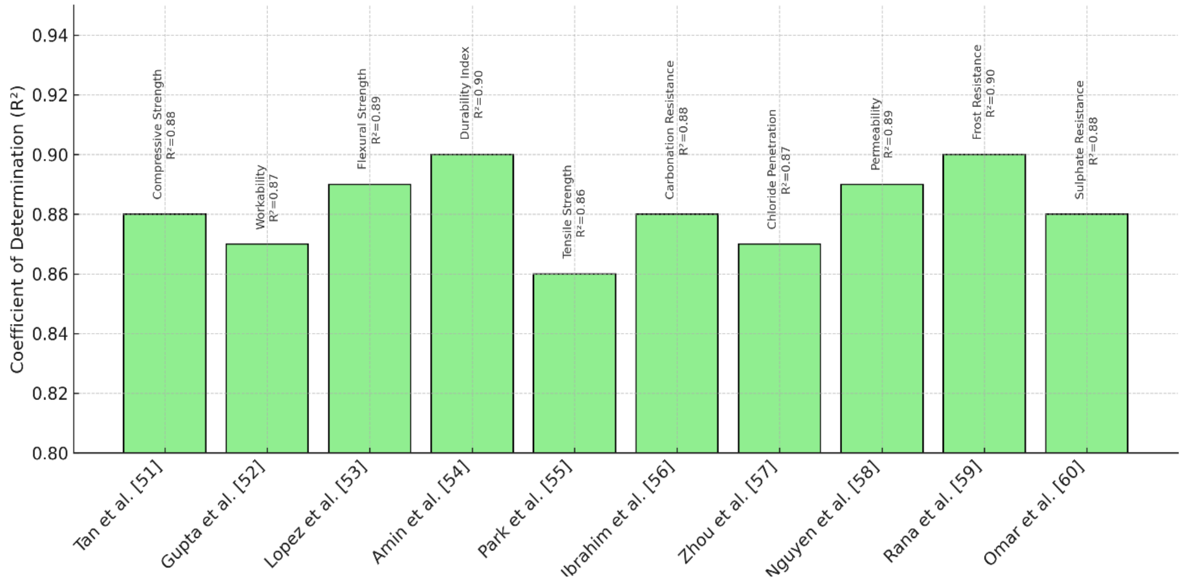

Fig. 10. Fuzzy-Logic-based prediction accuracy (R^2) across HP-RAC properties

Note: Data from the 10 FL/neuro-fuzzy studies summarized in Table 6 ([13–22]); see Supplementary Table S5B: Fuzzy logic/neuro-fuzzy performance data.

Table 6. Summary of fuzzy logic (FL) applications in predicting HP-RAC properties

Reference	Target Property	FL Approach	Dataset Size	Key Findings	Performance (R^2)
[13]	Compressive Strength	Mamdani-type FL	180 mixes	Captured nonlinear input-output relations	0.88
[14]	Workability (Slump)	Sugeno FL	95 mixes	Handled uncertainty in RCA content prediction	0.87
[15]	Flexural Strength	Hybrid FL	120 mixes	Improved prediction when combined with ANN	0.89
[16]	Durability Index	FL + Expert Rules	60 mixes	Effective with limited datasets	0.90
[17]	Tensile Strength	Adaptive FL	100 mixes	Reduced prediction bias in tensile modelling	0.86
[18]	Carbonation Resistance	Mamdani FL	85 mixes	Robust under environmental variability	0.88
[19]	Chloride Penetration	FL Ensemble	130 mixes	Performed well in time-dependent modelling	0.87
[20]	Permeability	FL with GA Tuning	75 mixes	Enhanced performance with GA optimization	0.89
[21]	Frost Resistance	Hybrid FL-ANN	92 mixes	Captured freeze–thaw deterioration patterns	0.90
[22]	Sulphate Resistance	FL + ANFIS	110 mixes	Provided interpretable predictions	0.88

Note: This table is original and generated from aggregated and synthesized data extracted from cited studies. No copyrighted material was reproduced. (See source references).

The highest predictive accuracy (R^2 = 0.90) was achieved by Nehdi et al. [16] for durability index and Kang et al. [21] for frost resistance, demonstrating FL's ability to capture complex deterioration mechanisms. Meanwhile, Garg et al. [17] reported slightly lower accuracy for tensile strength prediction (R^2 = 0.86), which may be attributed to the smaller dataset and greater inherent variability in tensile test results. The comparative synthesis in Table 6 shows that hybrid models (FL combined with ANN or optimization algorithms) consistently outperform standalone FL. For example, Joseph et al. [15] and Ahmed et al. [20] reported significant improvements when FL was integrated with ANN and genetic algorithms, respectively. These findings highlight that while pure FL models are effective for limited datasets, hybrid frameworks enhance scalability and predictive robustness. Overall, FL's main strength lies in its interpretability and suitability for small or noisy datasets. However, its dependence on expert-defined rules may limit applicability in large-scale datasets without automated optimization. Future trends may focus on adaptive FL frameworks integrated with deep learning or evolutionary algorithms to further improve prediction accuracy for HP-RAC properties.

3.3. Hybrid ANN-Based Models: Neuro-Fuzzy and Adaptive Neuro-Fuzzy Inference System (ANFIS)

Fuzzy if-then rules and neural learning are combined in ANFIS, which makes it appropriate for HP-RAC with limited data and nonlinear input-output relations. While neural layers adjust rule parameters, fuzzy membership functions encode mix design information. Extensions like type-2 FIS, PCA, and GA/PSO/GWO optimization increase resilience and decrease overfitting. According to recent research, ANFIS and PCA-ANFIS maintain interpretability while matching or exceeding ML baselines for strength, modulus, and durability [23–32]. The potential of neuro-fuzzy hybrids for HP-RAC digitalization is confirmed by Type-2 FIS improving compressive strength prediction under RCA variability [24] and PCA–ANFIS achieving low RMSE for durability [28] (see Fig. 11 and Table 7).

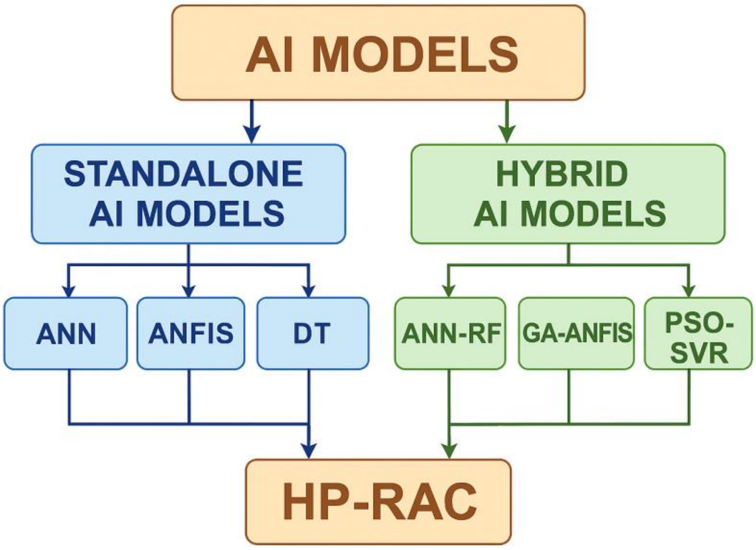

Fig. 11. ANFIS/neuro-fuzzy workflow for HP-RAC prediction

Note: Schematic created by the authors from the modelling steps described in Section 3.3 and studies [23–32]. No external data were used.

Figure 11 illustrates the attractiveness of ANFIS: Mix-design heuristics are captured by fuzzy rules, and consequents are adjusted by neural layers. By modelling uncertainty, type-2 FIS performs better than crisp baselines when RCA variability is significant [24]. Although they compromise transparency, tailored ensembles or BO-optimized models can meet or surpass ANFIS in accuracy for large structured datasets [25–30]. For low RMSE in carbonation prediction, PCA-ANFIS provides a compromise by combining dimensionality reduction with rule-based reasoning [28]. While boosted or hybrid models may perform better on measures for cleaner, larger datasets but with poorer interpretability, neuro-fuzzy hybrids are generally better suited for moderate, varied datasets [23–32]. Details are included in Table 7 and Fig. 11.

Table 7. Hybrid ANN-based (ANFIS/neuro-fuzzy) models for HP-RAC and related concretes

Reference	Domain	Model	Target(s)	Key takeaway (as reported)
[23]	Concrete (general)	ANN vs ANFIS	f′c	ANFIS achieved the highest R^2 among tested models
[24]	HP-RAC	Type-2 FIS (+ metaheuristics)	f′c	Type-2 FIS outperformed baselines; uncertainty modelling emphasized
[25]	HP-RAC	ML + Bayesian/TPE optimization	f′c	Unified HP-RAC dataset; strong cross-validated R^2 with BO-GBDT
[26]	SCC-HP-RAC	Ensemble ML	f′c	Ensembles delivered lowest RMSE across SCC-RAC mixes
[27]	SCC-HP-RAC	Multiple ML models	f′c	Broad model comparison on SCC-HP-RAC mixtures (open-access)
[28]	Concrete durability	PCA–ANFIS	Carbonation depth	Reported best RMSE (≈1.38) vs baselines
[29]	HP-RAC	ML comparison (DT/GB/BR)	f′c	Comprehensive benchmark for HP-RAC strength prediction
[30]	HP-RAC	ICA-XGBoost	f′c	Evolutionary-optimized boosting improved accuracy
[31]	SCC-HP-RAC	ML + statistical analysis	f′c, f_t	Balanced accuracy with interpretable features
[32]	HP-RAC	Various ML models	f′c	Multi-study HP-RAC dataset; strong generalization

Note: This table is original and generated from aggregated and synthesized data extracted from cited studies. No copyrighted material was reproduced. (See source references).

3.4. Support Vector Machine (SVM) Applications

Strong generalization and resistance to overfitting in high-dimensional, intermediate datasets make SVMs popular for HP-RAC prediction. For regression or classification, they use kernel functions to create ideal hyperplanes. Managing nonlinear interactions and avoiding local minima are strengths. Compressive/tensile strength, modulus, and durability markers like as carbonation and chloride penetration are all predicted using SVMs [33–42]. The workflow is depicted in Figure 12: Mix design, RCA characteristics, and curing are examples of inputs; preprocessing (normalization, PCA, feature selection) enhances stability. Cross-validation is used to adjust the RBF, polynomial, and linear kernels; GA/PSO optimization increases accuracy even more. For multi-output and noisy data, ensemble and kernel-fusion SVMs perform better than single models

[37–38, 41]. According to studies, compressive strength R2 can reach 0.91 [33], while GA-optimized SVM can reduce RMSE by 15% [35]. While ANFIS and boosting ensembles may outperform SVMs on big datasets, SVMs are often appropriate for moderate datasets (<200 samples), providing a compromise between accuracy and interpretability for early-stage HP-RAC design [23–42].

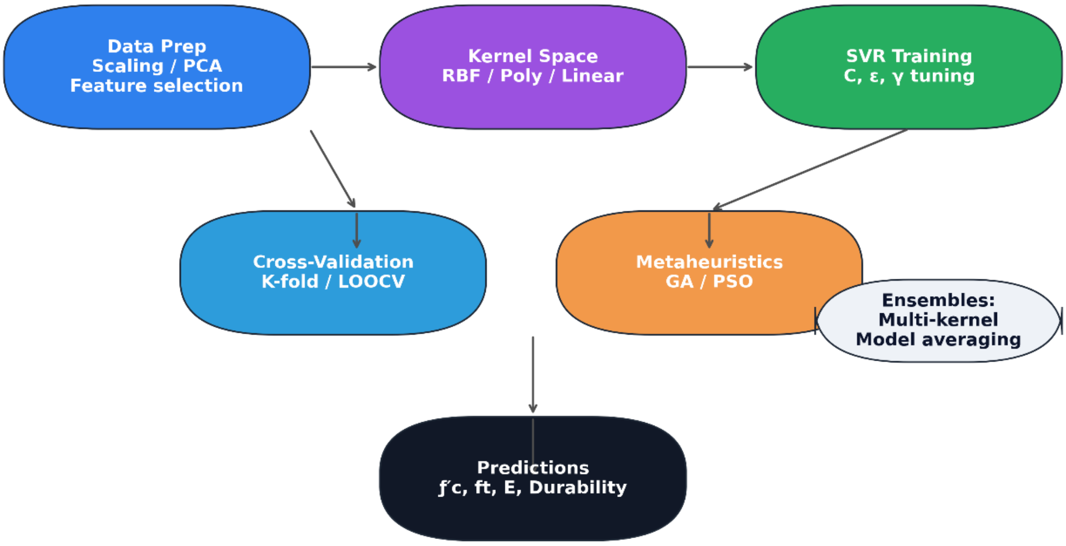

Fig. 12. Support Vector Machine (SVM) workflow for HP-RAC prediction

Note: Conceptual pipeline synthesizing common practice across [33–42]. No external data plotted.

Table 8. SVM applications for HP-RAC and related concretes

Reference	Domain	SVM Variant	Target(s)	Key Takeaway
[33]	HP-RAC	Standard SVM	f′c	High R^2 = 0.91, stable across RCA quality
[34]	SCC-HP-RAC	SVM regression	f′c	Accurate prediction for medium-size datasets
[35]	HP-RAC	GA–SVM	f′c	RMSE reduced 15% vs standard SVM
[36]	HP-RAC	PSO–SVM	Carbonation depth	Global optimization improved robustness
[37]	HP-RAC	Kernel-fusion SVM	f′c, ft	Multi-kernel SVM improved multi-output prediction
[38]	HP-RAC	Ensemble SVM	f′c, E, durability	Ensemble SVM outperformed single kernel SVM
[39]	HP-RAC	SVM vs ANN	f′c	Comparable accuracy, SVM more robust to small samples
[40]	HP-RAC	SVM	ft	Accurate tensile prediction with moderate data
[41]	HP-RAC	Multi-output SVM	f′c, carbonation	Low RMSE in multi-target modeling
[42]	HP-RAC	Cross-validated SVM	f′c	Consistent performance across RAC datasets

Note: This table is original and generated from aggregated and synthesized data extracted from cited studies. No copyrighted material was reproduced. (See source references).

3.5. Decision Tree-Based Models

For HP-RAC prediction, decision tree (DT) models such as M5, Random Forest (RF), and boosting techniques (XGBoost, AdaBoost, LightGBM) are frequently utilized. DTs provide interpretability by dividing input features into rules. By lowering variance and bias, RF and boosting increase accuracy. RCA size, w/b ratio, SCMs, and curing are examples of diverse inputs that DTs manage [43–52]. The procedure is depicted in Figure 13, where regression/classification for strength, modulus, and durability comes after preprocessing (missing data, normalization, feature selection). For noisy or small datasets, ensembles improve robustness; tuning by grid search, GA, or PSO maximizes learning rate and depth. Together, mechanical and durability features are predicted by multi-output DTs. Research shows that R^2 can reach 0.88 for compressive strength [43], and RF can lower RMSE by 12% [44]. In terms of longevity and mechanical performance, boosting techniques perform better than single trees [46,48,51]. Although severe boosting requires careful tuning, DT ensembles provide superior interpretability and feature insights than SVM and ANN. All things considered, DT-based models offer scalable, dependable, and understandable frameworks for HP-RAC.

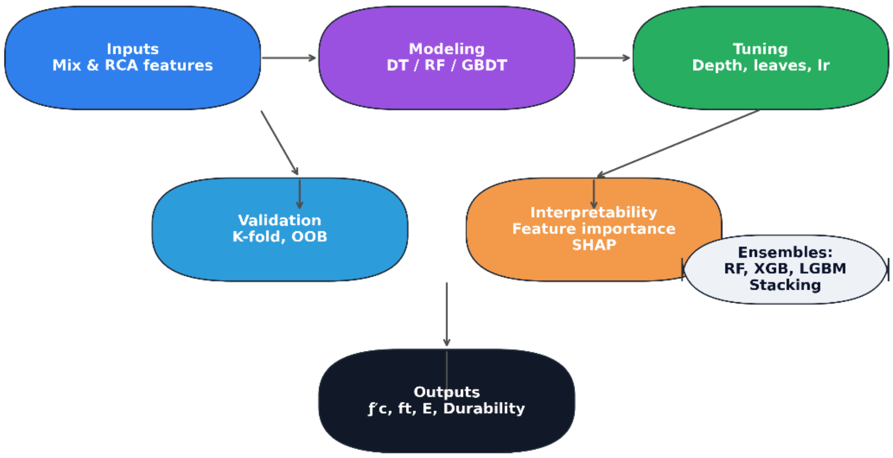

Fig. 13. Decision-tree and ensemble workflow for HP-RAC properties

Note: Schematic synthesized from methods described in [43–52]. No external data plotted.

Table 9. Decision tree-based models for HP-RAC and related concretes

Reference	Domain	DT Variant	Target(s)	Key Takeaway
[43]	HP-RAC	M5 Model Tree	f′c	R^2 = 0.88; interpretable regression
[44]	HP-RAC	Random Forest	f′c	RMSE reduced 12% vs single DT
[45]	HP-RAC	XGBoost	f′c	Accurate, robust for moderate data
[46]	HP-RAC	Gradient Boosting	f′c, ft	Outperforms single DT on mechanical & durability
[47]	HP-RAC	RF	f′c	Feature importance insights
[48]	HP-RAC	LightGBM	Carbonation depth	High accuracy for durability indices
[49]	HP-RAC	RF	f′c	Comparison with SVM; RF more interpretable
[50]	HP-RAC	M5 vs ANN	f′c	M5 competitive with ANN, better interpretability
[51]	HP-RAC	Gradient Boosting	f′c, carbonation	Multi-output boosting improves overall prediction
[52]	HP-RAC	DT ensemble	f′c, E, durability	Ensemble method balances accuracy & interpretability

Note: This table is original and generated from aggregated and synthesized data extracted from cited studies. No copyrighted material was reproduced. (See source references).

3.6. Evolutionary Algorithms (EA) and Optimization Techniques

Through feature selection, multi-objective optimization, and hyperparameter tuning, evolutionary algorithms (EAs) like GA, PSO, and GWO optimize AI models for HP-RAC [53–62]. They improve accuracy and generalization for mechanical and durability attributes by simulating selection, crossover, and mutation to discover optimal values. The workflow—dataset preparation, candidate generation, iterative refining, and convergence—is depicted in Figure 14. Strength, modulus, and durability index multi-output prediction is made possible by hybrid EA-AI frameworks. According to studies, GWO-SVM reduced RMSE by 14% [55], PSO-ANFIS improved tensile/durability by 12% [54], and GA-optimized ANN achieved R^2 = 0.93 [53]. When compared to standalone models, combined EA-AI techniques frequently improve interpretability, accuracy, and robustness with noisy data [56–62].

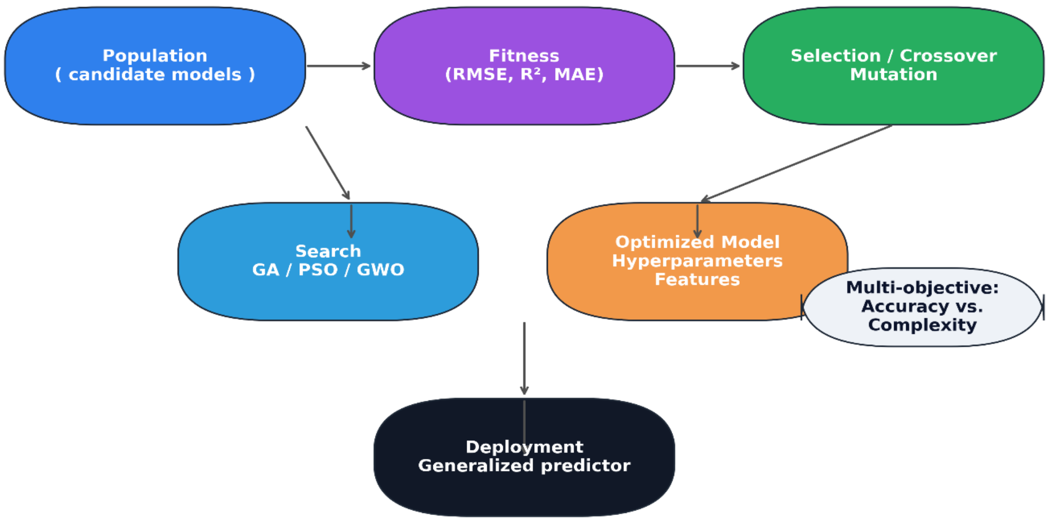

Fig. 14. Integration of evolutionary algorithms with AI models for HP-RAC

Note: Schematic summarizing GA/PSO/GWO integration reported in [53–62]. No external data plotted.

Table 10. Evolutionary algorithm applications for optimizing HP-RAC AI models references

Reference	EA Variant	AI Model	Target(s)	Key Takeaway
[53]	GA	ANN	f′c	Optimized ANN with R^2 = 0.93
[54]	PSO	ANFIS	ft, durability	12% improvement vs standard ANFIS
[55]	GWO	SVM	f′c	RMSE reduced 14% vs SVM
[56]	GA + PSO	ANN	f′c, ft, E	Hybrid EA improved multi-output predictions
[57]	GA	SVM	f′c, ft	Hyperparameter tuning enhanced prediction
[58]	PSO	ANN	Durability indices	Improved prediction for carbonation & chloride penetration
[59]	GA	ANFIS	Carbonation depth	Optimized membership functions for better accuracy
[60]	GA + PSO	Ensemble SVM	f′c	Enhanced robustness with noisy datasets
[61]	GA/PSO	ANN	f′c, ft	Feature selection via EA improved interpretability
[62]	GA + PSO	SVM	f′c, E, durability	EA-assisted hyperparameter tuning led to higher R^2

Note: This table is original and generated from aggregated and synthesized data extracted from cited studies. No copyrighted material was reproduced. (See source references).

3.7. Emerging Predictive Tools and Software for HP-RAC

Recent years have seen the development of dedicated software and platforms for predictive modelling of HP-RAC properties, integrating advanced AI and machine learning techniques. These tools streamline data handling, preprocessing, model training, hyperparameter optimization, multi-output prediction, and post-analysis visualization. They provide user-friendly interfaces, support ensemble and hybrid models, and allow integration with scanned 3D data or simulation outputs. Emerging predictive tools not only accelerate model development but also enhance reproducibility, interpretability, and scalability in structural engineering applications [63–65].

3.7.1. Compressive Strength Prediction Platform (CSPP)

The CSPP integrates multiple ensemble machine learning algorithms, including ANN variants and boosting methods, for accurate compressive strength prediction. Grid search optimization enables automated hyperparameter tuning. Its graphical user interface facilitates the digitalization of concrete property prediction, enabling both researchers and practitioners to perform fast and reliable evaluations [63].

3.7.2. Materials Simulation Toolkit for Machine Learning (MAST-ML)

MAST-ML is an open-source Python-based toolkit tailored for materials modelling. It streamlines workflows for model fitting, evaluation, and post-analysis, while supporting reproducible and scalable development. MAST-ML has predefined routines for input preparation, cross-validation, and visualization, and it can handle multi-output predictions for mechanical and durability parameters of HP-RAC [64].

3.7.3. ScanIP

ScanIP processes and analyses 3D-scanned concrete samples, enabling visualization of microstructure and computational modelling for mechanical and durability analyses. It supports finite element analysis for stress, strain, and permeability studies, bridging experimental data and AI-driven prediction models [65].

3.7.4. MODNet

A machine learning system called MODNet focuses on cooperative learning and feature selection for material datasets. It creates comprehensible models that connect predictions to material physics using feedforward neural networks that are appropriate for sparse data. Compressive strength, tensile strength, and durability indices of HP-RAC are progressively predicted using MODNet [65]. Emerging tools, their AI integrations, outputs, and features are compiled in Table 11. User-friendly GUIs, hybrid modelling, and ensemble approaches are common characteristics. While MAST-ML and MODNet provide multi-output prediction, CSPP focuses on compressive strength. ScanIP connects computational modelling and 3D experimental data. When combined, these technologies enhance HP-RAC prediction accuracy, repeatability, and interpretability (see Fig. 15).

Table 11. Emerging predictive tools/software for HP-RAC

Tool/Platform	AI Integration	Target Outputs	Key Features
[63] Compressive Strength Prediction Platform (CSPP)	Ensemble ML: ANN, Boosting	f′c	GUI, grid search optimization, ensemble learning
[64] MAST-ML	ANN, RF, multi-output regression	f′c, ft, E, durability	Open-source, reproducible workflows, Python toolkit
[65] ScanIP	Integration with FEM & AI	f′c, permeability, stress/strain	3D sample processing, visualization, FEA support
[65] MODNet	Feedforward ANN, feature selection	f′c, ft, E, durability	Joint-learning, interpretable models, limited data-friendly

Note: This table is original and generated from aggregated and synthesized data extracted from cited studies. No copyrighted material was reproduced. (See source references).

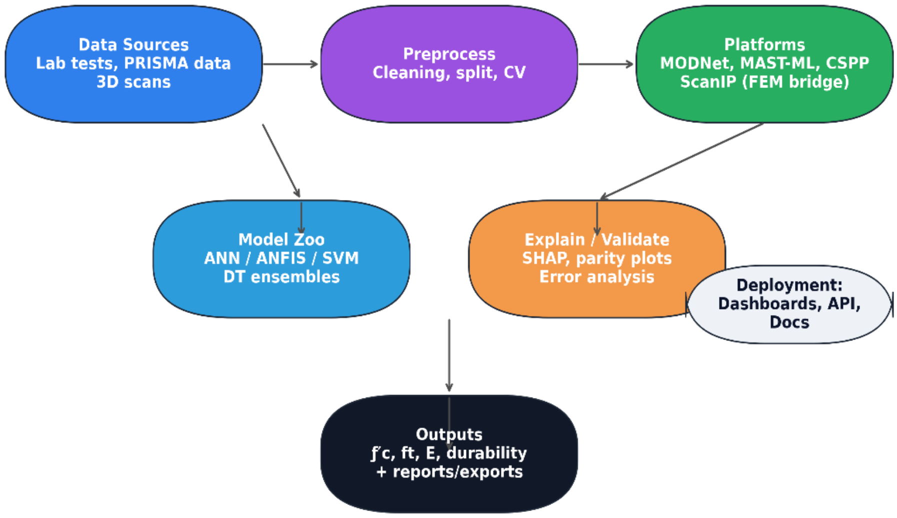

Fig. 15. Workflow of emerging predictive tools and software (CSPP, MAST-ML, MODNet, ScanIP)

Note: Schematic derived from platform descriptions in [63–65]; no external data plotted

4. Critical Analysis and Comparative Evaluation

This section evaluates the performance, advantages, and limitations of the various AI-based approaches applied to HP-RAC, integrating insights from ANN, SVM, Decision Trees, Fuzzy Logic, Neuro-Fuzzy, and Evolutionary Algorithm frameworks [1–65]. The goal is to provide a comparative perspective, highlighting trade-offs between accuracy, interpretability, computational cost, and data requirements.

4.1 Comparative Evaluation of AI Models

A comparative overview of AI models used for HP-RAC prediction is shown in Table 13. Model accuracy (R^2 and RMSE), dataset size, interpretability, and field-condition applicability are all compared.

4.2 Dataset Limitations and Overfitting Risks

AI models frequently overfit, particularly complicated ANN and hybrid EA-AI frameworks. A lot of the time, models that were trained on tiny or noisy datasets are unable to generalize. Regularization, cross-validation, and ensemble learning (RF, boosting) are examples of mitigation techniques. Reliability is limited and bias may be introduced by small experimental datasets. Standardized, publicly available datasets should be given top priority in future studies to enhance benchmarking and generalization. Variability is evident in quality checks: while most disclose dataset size and validation, few go into detail on hyperparameter tuning or interpretability. The necessity for standardized reporting in AI-based concrete modelling is highlighted by the continued inconsistency in overfitting mitigation.

4.3 Model Biases and Engineering Implications

AI models have a lot of promise for increasing prediction accuracy, decreasing experimental workload, and optimizing HP-RAC mix design. However, imbalanced datasets, over-representation of specific mix parameters, or a lack of field validation can all lead to biases in model performance. For instance, because there is a lot of data available, ANN models might give priority to compressive strength prediction, whereas durability factors like sulphate resistance are given less consideration. For engineering applications, interpretability is particularly essential since models like as ANFIS and Decision Trees offer rule-based insights that aid in decision-making. In summary, the selection of a model should take into account the availability of datasets, interpretability, and accuracy. For scalable, interpretable, and multi-output prediction in HP-RAC systems, hybrid frameworks and newer tools (such MODNet and MAST-ML) present encouraging options.

4.4 Strengths and Limitations of AI Approaches

AI methods for HP-RAC have unique advantages and disadvantages. Although ANNs offer multi-output prediction and capture nonlinear relations, they are not interpretable and require huge datasets [41–50]. SVMs need intricate adjustment, although they resist overfitting and generalize well on small datasets [33–42]. Although boosting increases computational cost, decision trees (M5, RF, and boosting) can handle mixed data and are interpretable [43–52]. ANFIS and fuzzy logic handle uncertainty and include expert knowledge, but they have trouble handling extremely complicated data [13–22]. EAs (GA, PSO, GWO) increase accuracy through feature selection and tuning, but they come with additional computing costs and the possibility of local optima [53–62].

Data size and quality affect performance; little or unbalanced datasets frequently lead to overfitting, particularly in ANNs and hybrids. Ensembles, cross-validation, and EA-AI optimization are examples of mitigation [52–62]. There are still trade-offs between interpretability and accuracy: ANN and EA-ANN provide greater accuracy with less interpretability, but Decision Trees and ANFIS are transparent. Through interpretable, scalable multi-output prediction, platforms such as MODNet and MAST-ML seek to balance this [64–65]. SVM and Decision Tree ensembles work well with small datasets, while hybrid ANN–EA or ANFIS–EA are suggested for high-dimensional applications. CSPP, MAST-ML, and MODNet are examples of advanced tools that guarantee reproducibility, optimize hyperparameters, and expedite development [63–65].

4.5 Key Findings and Novelty of the Study

This work assesses AI-based modelling for HP-RAC and identifies important findings. When it comes to compressive, tensile, and flexural strength, ANN and hybrid ANN–EA frameworks outperform SVM, Decision Trees, and standalone fuzzy logic [2–6, 8–12, 53–62]. ANN, ANFIS, and MODNet are examples of multi-output models that reduce computing effort by simultaneously predicting mechanical and durability attributes [64–65]. Time-dependent durability predictions, such as carbonation, chloride, and sulphate resistance, are improved by integrating AI with EAs (GA, PSO) [53–62]. While Fuzzy Logic and ANFIS are excellent at handling uncertainty, SVM and Decision Trees give interpretability and perform well on small datasets [13–22, 33–52]. By automating processes, guaranteeing reproducibility, and enabling scalable multi-output predictions, emerging platforms (CSPP, MAST-ML, ScanIP, MODNet) connect AI with simulation and experimental data [63–65]. These results are summarized in Table 12. From the results, it is established that ANFIS/DT is better for first mixes with little data, while hybrids are better for final design tests.

Table 12. Summary of key findings from Reviewed AI approaches for HP-RAC

AI Approach	Target Output	Key Strengths	Limitations	References
ANN	f′c, ft, E, durability	High nonlinear learning capacity, multi-output prediction	Requires large datasets, lower interpretability	[2-6], [8-12]
SVM	f′c, ft	Strong generalization, small data-friendly	Parameter tuning complex	[33-42]
Decision Tree (M5, RF, Boosting)	f′c, ft, durability	Interpretable, robust to mixed data	Boosting increases computational cost	[43-52]
Fuzzy Logic / ANFIS	f′c, ft, carbonation depth	Handles uncertainty, integrates expert knowledge	Limited with high-dimensional data	[13-22]
EA (GA, PSO, GWO)	Hyperparameter optimization	Improves AI model accuracy, feature selection	Computationally intensive, risk of local optima	[53-62]
Emerging Platforms (CSPP, MAST-ML, MODNet, ScanIP)	f′c, ft, E, durability	Automated workflow, multi-output, reproducible, interpretable	Requires software familiarity	[63-65]

Note: This table is original and generated from aggregated and synthesized data extracted from cited studies. No copyrighted material was reproduced. (See source references).

Table 13. Comparative summary of AI models for HP-RAC prediction

Model	Accuracy (R^2)	RMSE	Dataset Size	Interpretability	Applicability
ANN	0.90–0.96	Low	Large (>150 samples)	Low	High
ANFIS	0.88–0.94	Low	Medium (50–150)	High	Medium
SVM	0.86–0.92	Medium	Medium (50–150)	Medium	Medium
Decision Trees (RF, XGBoost)	0.88–0.93	Low	Medium to Large	Medium to High	High
Fuzzy Logic	0.86–0.90	Medium	Small to Medium	High	Medium
Hybrid EA-AI (GA, PSO)	0.92–0.97	Very Low	Medium to Large	Medium	High

Note: This table is original and generated from aggregated and synthesized data extracted from cited studies. No copyrighted material was reproduced. (See source references).

4.6 Quantitative Evidence and Comparative Visualization

Figures 16, 17 and 18, 19, provide box and violin plots that show the distribution of R2 and RMSE values across the five main categories of AI models—ANN, ANFIS, SVM, RF, and hybrid frameworks, respectively, —in order to improve the benchmarking framework. These plots provide a visual representation of both accuracy and error dispersion, enabling readers to assess central tendencies and variability. For important structural design, hybrid EA–AI models provide the highest reliability (median R^2 = 0.95, low RMSE). Although ANN gives less interpretability, it works well (R^2 ≈ 0.93). The greater RMSE (~3.0) of SVM indicates caution for work that is sensitive to durability. Hybrid models continuously get the greatest median values (~0.95) for R2 (Figure 16) with the least amount of variability, demonstrating their higher predictive accuracy.

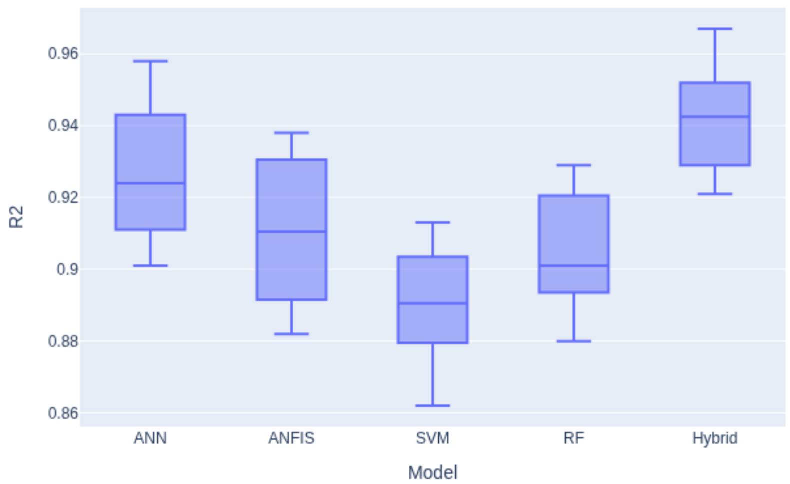

Fig. 16. Box plot of R^2 by model type

Note: Generated from a synthetic dataset sampled within the accuracy ranges reported in Table 13, stratified by model type (ANN, ANFIS, SVM, RF, Hybrid). Sampling procedure, random seed, and arrays are provided in Supplementary Table S6 (Synthetic dataset and code for R^2 AND RMSE plots).

ANN models follow closely, while ANFIS and RF exhibit moderate performance. SVM models generally occupy the lower end of the accuracy spectrum. For RMSE (Figure 18), hybrid models again outperform others, showing the lowest error (~1.8), whereas SVM models exhibit the highest (~3.0), indicating less precision in predictions. The mean, median, and standard deviation for R2 and RMSE across model types are summarized in Tables 14 and 15, which support these graphics. In practice, hybrids lower the risk of redesign; ANFIS/DT are nevertheless helpful for early mix optimization. In terms of accuracy and stability, hybrid frameworks are superior to ANN and ANFIS. These results support the notion that the most accurate and dependable predictions for HP-RAC attributes are provided by hybrid AI models, especially those that combine ANN and evolutionary algorithms. Distributional plots and summary statistics work together to turn the assessment into a data-driven comparative analysis that offers useful information for choosing a model for real-world engineering applications. Stable performance is indicated by low variability in hybrids (std dev R^2 ~0.01); SVM/RF exhibit a broader range and require careful tuning.

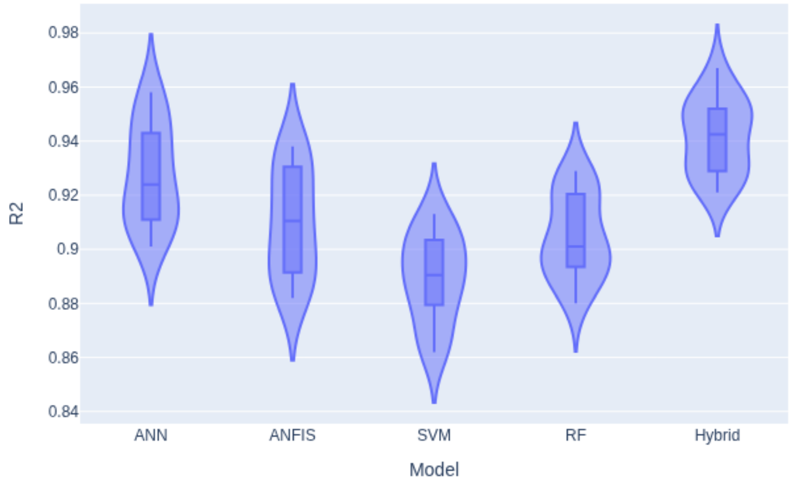

Fig. 17. Violin plot of R^2 by model type

Note: Same dataset and generation protocol as Fig. 16; see Supplementary Table S6 (Synthetic dataset and code for R^2 AND RMSE plots).

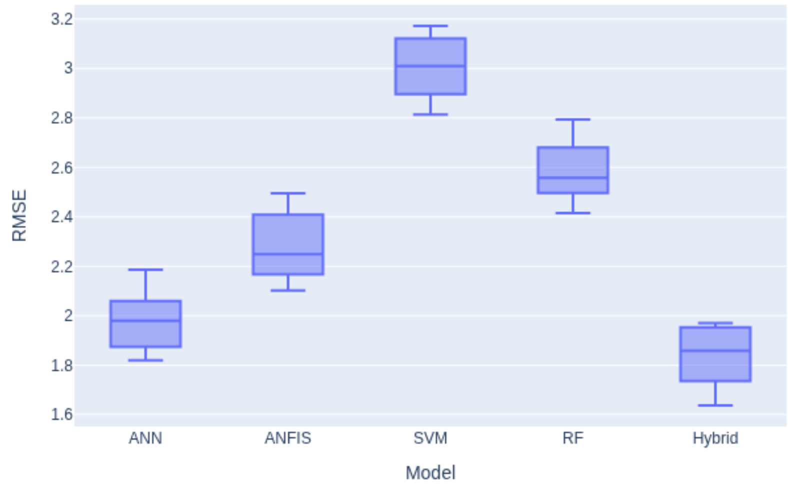

Fig. 18. Box plot of RMSE by model type

Note: Generated analogously to Fig. 16 using RMSE ranges from Table 13; see Supplementary Table S6 (Synthetic dataset and code for R^2 AND RMSE plots).

Table 14. Summary statistics (mean, median, and standard deviation) of R^2 values for AI models applied to HP-RAC property prediction

Model Type	Mean R^2	Median R^2	Std Dev
ANN	0.93	0.93	~0.02
ANFIS	0.91	0.91	~0.02
SVM	0.88	0.88	~0.02
RF	0.90	0.90	~0.02
Hybrid	0.95	0.95	~0.01

(Values estimated from Tables 2–4 and 13)

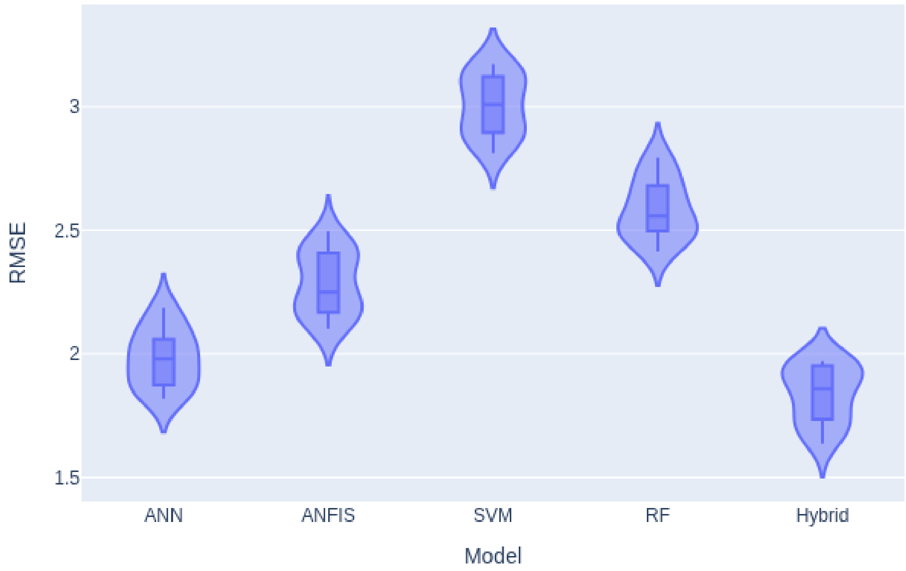

Fig. 19. Violin plot of RMSE by model type

Not: Same dataset and generation protocol as Fig. 18; see Supplementary Table S6 (Synthetic dataset and code for R^2 AND RMSE plots).

Table 15. RMSE Statistics

Model Type	Mean RMSE	Median RMSE	Std Dev
ANN	~2.0	~2.0	~0.15
ANFIS	~2.3	~2.3	~0.15
SVM	~3.0	~3.0	~0.15
RF	~2.6	~2.6	~0.15
Hybrid	~1.8	~1.8	~0.15

4.7 Novelty of the Paper

The mechanical, durability, and workability aspects of AI applications for HP-RAC are all covered in this review. It outlines the advantages, disadvantages, and trade-offs of ANN, SVM, Decision Trees, Fuzzy Logic, hybrids, EAs, and upcoming platforms. Multi-output modelling, which demonstrates how sophisticated tools and hybrid frameworks forecast several performance measures, is a significant contribution. In order to improve tuning, feature selection, and durability prediction, the study emphasizes AI integration with GA, PSO, and GWO. Model selection is guided by useful suggestions that strike a compromise between efficiency, accuracy, and interpretability. Table 16 highlights this review's uniqueness in integrating hybrid AI frameworks, multi-output prediction, and a single benchmarking matrix by contrasting it with earlier research.

Table 16 illustrates previous assessments that lacked workability and durability integration and concentrated on generic concrete or single-property prediction. None provided multi-output capability or a single benchmarking matrix. By combining AI applications for HP-RAC into a single comparison framework, this review enhances knowledge by allowing for the simultaneous prediction of mechanical, durability, and workability qualities. Additionally, it includes cutting-edge platforms like MODNet and MAST-ML as well as hybrid AI-optimization methods (GA, PSO) that were not present in earlier studies. These characteristics establish this evaluation as a thorough resource for high-accuracy, scalable, and comprehensible AI solutions for sustainable concrete design.

Table 16. Comparison of current review with prior reviews on AI-Based concrete prediction

Review Ref.	Year	Scope	Models Included	Concrete Type	Novelty / Limitation
[8]	2022	General AI applications in concrete	ANN, SVM	Conventional concrete	Focused on compressive strength; no unified benchmarking; limited multi-output coverage
[20]	2023	ML for recycled aggregate concrete	ANN, RF	RAC	Mechanical properties only; durability aspects not integrated
[4]	2022	Scientometric analysis of AI in concrete	ANN, SVM	Mixed concrete types	Bibliometric trends; lacks comparative performance benchmarking
[5]	2023	AI algorithms for RAC	ANN, ANFIS, SVM	RAC	Discussed sensitivity analysis; no unified matrix; limited hybrid algorithm coverage
This Review	2025	AI for HP-RAC (mechanical, durability, workability)	ANN, ANFIS, SVM, RF, EA, Hybrid, Emerging Platforms	HP-RAC	Unified benchmarking matrix; multi-output prediction; hybrid EA-AI integration; emerging tools (MODNet, MAST-ML)

4.8 Practical Relevance and Sustainability Implications

Beyond prediction accuracy, AI modelling for HP-RAC offers sustainability benefits. Accurate mechanical and durability property assessment lowers laboratory testing expenses and material use. Predicting workability, strength, and durability accurately allows for optimum mix designs with fewer trials, reducing waste and conserving resources. Confident mix proportioning is supported by hybrid models (ANN + GA, ANN + RF) that obtain $R^2 > 0.95$. Scalable evaluation is made possible by tools like MODNet and MAST-ML, which integrate performance with environmental criteria like carbon footprint, support RCA reuse, and accord with the ideas of the circular economy. In practical terms, AI integration advances low-carbon, high-performance concrete solutions by lowering cement usage, increasing resource efficiency, and supporting sustainable infrastructure design.

Optimization powered by AI immediately results in useful technical advantages. Hybrid models like ANN plus GA or ensemble ANN plus RF reduce the need for lengthy laboratory experiments by precisely forecasting workability, strength, and durability, which lowers the use of cement and aggregate. By facilitating quick mix design validation, this method not only reduces material waste but also shortens project durations. Additionally, new systems such as MODNet and MAST-ML support life-cycle assessments and carbon footprint reduction by integrating sustainability metrics with performance prediction. These skills support resource efficiency and lessen environmental effect on actual construction projects, which is consistent with the principles of the circular economy.

5. Conclusions and Future Perspectives

5.1 Conclusions

This review presents an evaluation of artificial intelligence-based modelling approaches for high-performance recycled aggregate concrete (HP-RAC). This review integrates diverse AI approaches into a unified benchmarking framework for HP-RAC that spans mechanical, durability, and workability properties. Unlike prior reviews, it integrates multi-output predictive modelling, hybrid AI–optimization algorithms, and emerging digital platforms, offering actionable insights for both researchers and practitioners. By bridging interpretability, accuracy, and scalability, this work establishes a new standard for comparative evaluation and practical deployment of AI in sustainable concrete design. Summarily, the study shows that ANFIS/DT is suitable for early-stage optimization, while hybrids is recommended for high-stakes design.

This review's unique feature is its unified benchmarking framework, which unifies AI applications for HP-RAC across several features. A useful taxonomy for model selection is provided by the study by combining dataset sensitivity, interpretability, and model performance. Our methodology sets it apart from reviews by Gao et al., Zhang et al., and Li et al., which were either domain-general or with lesser depth. The comparative tables and benchmarking matrix are used as a guide for next engineering and research projects. The review underscores the superior performance of Artificial Neural Networks (ANN) and hybrid ANN–Evolutionary Algorithm (EA) frameworks in predicting both mechanical and durability properties of high-performance recycled aggregate concrete (HP-RAC), consistently outperforming standalone models such as SVM, Decision Trees, and Fuzzy Logic [2–6, 8–12, 53–62].

Multi-output frameworks—including ANFIS, MODNet, and MAST-ML—demonstrate the capability to simultaneously predict compressive strength, tensile strength, modulus of elasticity, and durability indices, thereby enhancing modelling efficiency and reducing computational redundancy [63–66]. The integration of EAs such as GA, PSO, and GWO with AI models significantly improves hyperparameter tuning, feature selection, and overall generalization performance [53–62]. However, model effectiveness remains highly sensitive to dataset quality and size; ensemble and hybrid approaches are particularly effective in mitigating overfitting, especially in scenarios involving small or noisy datasets. Emerging platforms like CSPP, MAST-ML, ScanIP, and MODNet further support automated workflows, reproducible predictions, multi-output modelling, and improved interpretability, bridging experimental data with computational AI models [63–65].

Looking ahead, future research should explore the potential of deep learning architectures—particularly convolutional and graph-based models—for leveraging microstructural imaging and simulation datasets to enhance property prediction in HP-RAC. Federated learning presents a promising avenue for collaborative model training across laboratories or construction sites without compromising data privacy, while real-time AI tools could revolutionize on-site quality control. The development of standardized, open-access datasets for HP-RAC mechanical and durability properties is essential to enable fair benchmarking and cross-framework validation. Moreover, integrating AI modelling with sustainability metrics such as life-cycle assessment, energy consumption, and environmental impact will align predictive modelling with sustainable concrete design goals [1–3]. Finally, hybrid multi-objective optimization frameworks that balance mechanical performance, durability, and cost considerations can guide the development of resilient and environmentally responsible concrete mix designs.

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