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# Machine Learning-based Prediction of Mechanical Properties and Mix Proportion Optimization of Recycled Aggregate Concrete: A Review

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**ABSTRACT:** This paper provides a comprehensive overview of machine learning-based approaches for predicting the mechanical properties and optimizing the mix proportions of recycled aggregate concrete (RAC). RAC has garnered significant attention due to its potential in resource recycling; however, the variability in its mechanical properties has posed challenges for its widespread adoption. Traditional mix design methods often struggle to manage this uncertainty, while the emergence of machine learning techniques presents promising new solutions. This review examines the current state of machine learning applications in predicting RAC performance and optimizing mix proportions. It also discusses the strengths and limitations of various machine learning models, assesses their practicality in engineering applications, and highlights potential directions for future research in this area.

**KEYWORDS:** Machine Learning, Recycled Aggregate Concrete, Prediction of Mechanical Properties, Mix Proportion Optimization.

## I. INTRODUCTION

The escalating global resource scarcity and environmental challenges have positioned RAC as a significant focus of research within the construction industry, owing to its environmentally friendly and resource-efficient characteristics. However, the mechanical properties of RAC exhibit considerable variability in practical applications, and traditional experimental and design methods have proven inadequate in fully addressing this issue [1]. The mechanical performance of RAC is influenced by various factors, including its constituent materials, manufacturing processes, and environmental conditions [2], making its behavior in real-world engineering projects difficult to predict and control. Furthermore, with the growing volume of construction waste worldwide, the effective conversion of this waste into building materials has emerged as a critical challenge for sustainable development. In this context, the investigation of RAC's mechanical properties and the optimization of its mix design are of significant practical and academic importance.

The development of artificial intelligence, particularly advances in machine learning algorithms, has markedly enhanced the ability to solve complex engineering problems [3, 4]. Machine learning, as a tool capable of processing large-scale, multidimensional, and nonlinear data, has demonstrated substantial predictive and optimization capabilities across various domains [5, 6]. In the study of RAC, machine learning techniques can be employed to analyze extensive historical data, thereby constructing accurate and stable predictive models that enhance the precision of mechanical property predictions. Compared to traditional methods, machine learning not only reduces the number of required experiments and associated costs but also accelerates the research and development process, thereby increasing the market competitiveness of new materials [7]. Consequently, the exploration of machine learning applications in predicting RAC performance and optimizing mix proportions is of considerable theoretical and practical significance. In this paper, a review is conducted on the progress of machine learning applications in predicting RAC performance and optimizing its mix design. The objective is to analyze the existing body of research, summarize the advantages and limitations of machine learning in this domain, and assess its feasibility and the challenges faced in practical engineering applications. This review aims to provide reference and guidance for future research. Additionally, by comparing and analyzing different machine learning algorithms, potential directions for improvement are proposed, with the intention of further advancing the field.

## II. PHYSICAL CHARACTERISTICS AND MECHANICAL PROPERTIES OF RAC

The primary components of RAC consist of recycled aggregates (as depicted in Figure 1), cement, sand, and water. The preparation process for RAC is illustrated in Figure 2 [8]. Recycled aggregates are derived from construction waste, which is processed through crushing and screening before being reused in concrete production [9]. Due to the significant differences in the physical and chemical properties of recycled aggregates compared to natural aggregates, the mechanical properties of RAC often exhibit considerable variability. Factors such as impurity content, water absorption, and particle shape of the recycled aggregates can significantly influence the strength, elastic modulus, and durability of the concrete [10]. Additionally, the interfacial transition zone between the aggregate and the cement paste is typically a weak point in RAC, leading to increased susceptibility to cracking and failure under stress [11]. Therefore, understanding the impact of material composition on the mechanical properties of RAC is essential for improving its performance in engineering applications.



(a)



(b)

Fig. 1 The recycled aggregate (a) The recycled coarse aggregate (b) The recycled fine aggregate



(a)



(b)



Fig. 2 The Recycled concrete preparation process

(a) The aggregate mixing (b) The aggregate pre-wetting (c) The mixing (d) The molding and curing

In traditional research on RAC, the evaluation of mechanical properties has primarily been conducted through laboratory experiments. However, these experiments are both costly and time-consuming, often failing to meet the urgent demands of engineering practice [12-14]. Moreover, the inherent variability and complexity of experimental data make it challenging to accurately predict the performance of RAC using simple regression analysis methods [15, 16]. Consequently, there is a critical need for the adoption of new technological approaches that can enhance the accuracy of performance predictions and improve experimental efficiency for RAC. Existing research has predominantly focused on improving RAC performance by adjusting mix proportions and refining the processing techniques for recycled aggregates [18-20]. Nevertheless, due to the absence of systematic data analysis methods, the reproducibility and reliability of experimental results are often limited.

Despite the significant environmental benefits of RAC, its application in practical engineering continues to encounter several challenges. Firstly, the variability in RAC's performance introduces uncertainty in engineering design, leading engineers to adopt a more conservative approach, thereby limiting its use in large-scale projects. Secondly, concerns about the durability of RAC further restrict its application, particularly in specialized environments; for instance, in highly corrosive or humid conditions, RAC often underperforms compared to traditional concrete [21, 22]. Additionally, the production processes and quality control of RAC require further optimization to ensure consistency in performance across different batches. Consequently, addressing these challenges to enhance the engineering value of RAC remains a critical focus and challenge in current research.

### III. APPLICATIONS OF MACHINE LEARNING IN RAC

The application of machine learning in the study of RAC has emerged as a promising approach to addressing the challenges associated with its mechanical performance and mix proportion optimization. Despite the environmental benefits of RAC, its practical use is hindered by significant obstacles, including variability in performance, durability concerns, and production inconsistencies. In this paper, the current state of machine learning applications in RAC is reviewed, with a focus on data collection, model selection, and optimization strategies. The challenges and future prospects for enhancing the practical application of RAC through interdisciplinary collaboration and advanced analytical techniques are also highlighted.

#### 3.1 Applications of machine learning in predicting the mechanical properties of RAC

As the application of RAC in construction engineering continues to grow, the accurate prediction of its mechanical properties has become increasingly important. In this paper, the application of machine learning techniques in

predicting RAC's mechanical properties is explored, focusing on key aspects such as data collection, model selection and optimization, and model validation to enhance prediction accuracy and engineering effectiveness.

**(1) Data collection and processing:**

Data collection and processing are critical steps in using machine learning to predict RAC mechanical properties. Experimental data, including the properties of recycled aggregates, mix proportions, and mechanical performance, must be systematically collected. The accuracy and completeness of these data directly influence the effectiveness of model training and prediction accuracy. Therefore, strict control of experimental conditions is required to ensure data comparability and consistency. During data processing, steps such as data cleaning, standardization, and feature selection are typically necessary to remove noise and extract key features, thereby enhancing model generalization. Additionally, reducing the dimensionality of high-dimensional data is essential for decreasing model complexity and improving training efficiency.

**(2) Common machine learning models:**

Machine learning models commonly used for predicting RAC mechanical properties include Support Vector Machines (SVM), Decision Trees, Random Forests, and Neural Networks. SVM is favored for its superior performance with small sample sizes and nonlinear data, although it requires careful parameter selection and longer training times. Decision Trees are valued for their ease of understanding and interpretation, though they are prone to overfitting. Random Forests, which construct multiple decision trees, significantly enhance model stability and prediction accuracy. Neural Networks, particularly deep learning models, excel in predicting complex behaviors due to their strong nonlinear fitting capabilities but require substantial computational resources and large datasets. Comparing the advantages and limitations of these models allows for the selection of the most suitable model for specific RAC prediction tasks, as illustrated in Table 1.

Tab. 1 The common machine learning models

Algorithm	Principle	Advantages	Disadvantages
<b>SVM</b>	Maximizing the classification margin	Supports various kernels	Difficult parameter tuning
<b>Decision Tree</b>	Recursive data splitting	Handles multiple data types	Prone to overfitting
<b>Random Forest</b>	Ensemble learning method	Strong resistance to overfitting	Long training and prediction time
<b>Neural Network</b>	Modeling biological neural networks	Powerful learning capability	Difficult to interpret
<b>Linear Regression</b>	Modeling linear relationships	Simple and easy to understand	Limited to linear relationships
<b>Logistic Regression</b>	Regression model for classification	Extensible to multiple variables	Limited to binary classification
<b>k-Nearest Neighbors</b>	Distance-based classification	No assumption of data distribution	Not suitable for high-dimensional data
<b>Naive Bayes</b>	Bayes' theorem	Computationally efficient	Data sparsity issue
<b>Ensemble Learning</b>	Combining multiple weak learners	High accuracy	Longer training time

**(3) Model evaluation and validation:**

After model training, evaluation and validation are crucial to ensuring robust predictive capabilities. Common evaluation methods include cross-validation and independent test set validation. Cross-validation involves dividing the dataset into several subsets, with iterative training and testing to assess model generalization. Independent test set validation evaluates model performance on unseen data. Metrics such as Mean Squared Error (MSE), R-squared ( $R^2$ ), and Mean Absolute Error (MAE) are used to quantitatively reflect prediction accuracy and stability. These evaluation methods enable researchers to continuously optimize model parameters, improving predictive performance to meet the practical demands of RAC performance prediction.

### 3.2 Optimization of RAC mix proportions based on machine learning

The optimization of RAC mix proportions using machine learning aims to enhance mechanical properties and durability by adjusting the proportions of concrete components. Traditional design methods often struggle to comprehensively account for multiple performance indicators. The introduction of machine learning technology offers the possibility of multi-objective optimization, further promoting the application of RAC in engineering projects.

#### (1) Optimization objectives and strategies:

The optimization of RAC mix proportions involves adjusting the proportions of various components within the concrete to improve its mechanical properties and durability while meeting engineering requirements. Traditional mix design methods typically rely on empirical formulas or experimental approaches, which often fail to consider the comprehensive impact of multiple performance indicators [8-11]. With the development of machine learning technology, multi-objective optimization strategies are increasingly applied to the design of RAC mix proportions. Machine learning models enable the simultaneous consideration of multiple performance indicators, such as strength, durability, and workability, to identify the optimal mix proportion combinations [30-32]. Specifically, researchers can utilize machine learning algorithms to establish nonlinear mappings between input variables (e.g., water-cement ratio, recycled aggregate content) and output variables (e.g., compressive strength, tensile strength), then use optimization algorithms to search for the optimal solution, achieving multi-objective optimization.

#### (2) Application of metaheuristic algorithms:

Metaheuristic algorithms, which are global optimization algorithms based on heuristic rules, are commonly used to solve complex nonlinear optimization problems [33]. The combination of metaheuristic algorithms with machine learning models is increasingly applied in the optimization of RAC mix proportions [34-36]. For example, genetic algorithms (GA) simulate the process of natural selection, gradually approaching the optimal solution through selection, crossover, and mutation operations within a population [37, 38]. Particle swarm optimization (PSO) algorithms mimic the collaborative search behavior of a group to quickly find the optimal solution [39]. Simulated annealing (SA) algorithms employ random search strategies to avoid local optima [40]. By combining these algorithms with machine learning models, common metaheuristic algorithms can more effectively explore the optimal solution space for RAC mix proportions, improving both optimization outcomes and computational efficiency, as illustrated in Table 2.

Tab. 2 The application of metaheuristic algorithms

Algorithm	Principle	Advantages	Disadvantages
<b>Genetic Algorithm</b>	Natural selection and genetic mechanisms	High robustness	Slow convergence
<b>Particle Swarm Optimization</b>	Swarm intelligence	Fast convergence	Sensitive to parameter selection
<b>Simulated Annealing</b>	Thermodynamic annealing process	Suitable for large and complex problems	High computational cost
<b>Ant Colony Optimization</b>	Ant foraging behavior	Distributed computing	Slow convergence
<b>Tabu Search</b>	based on a tabu list	Memory function	Risk of cycling
<b>Differential Evolution</b>	Population-based global optimization	Strong global search ability	Poor scalability with dimensions

### 3.3 Challenges and future prospects

#### (1) Data quality and model robustness:

In the application of machine learning to predict the performance and optimize the mix proportions of RAC, data quality is crucial for ensuring model accuracy and stability. High-quality data should be comprehensive, accurate, and representative. However, in practical engineering, data is often compromised by noise and incompleteness due to experimental conditions, equipment errors, and human factors. These issues can lead to model bias and reduced predictive accuracy. To enhance model robustness, researchers should focus on data preprocessing, including data cleaning, outlier detection, and feature selection. Additionally, implementing effective data augmentation strategies, such as data interpolation and balancing, can mitigate the impact of insufficient data. Future research should explore how to improve model robustness under uncertain conditions, possibly by optimizing algorithms or integrating multi-

source data (e.g., experimental and simulation data), thereby increasing the model's adaptability and reliability across different environments.

(2) Model interpretability and practicality:

The interpretability of machine learning models is especially important in practical engineering applications, particularly when safety and reliability are at stake. Traditional black-box models, such as deep neural networks, though powerful in prediction, are often too complex for engineers to use as a basis for design and troubleshooting. To address this issue, explainable artificial intelligence (XAI) techniques have gained significant attention in recent years. XAI methods allow researchers to uncover the key features and factors influencing model decisions, thereby helping engineers understand model behavior and optimize design processes. However, there is often a trade-off between interpretability and model performance; excessive focus on interpretability may reduce predictive capability. Future research should aim to enhance model interpretability without compromising efficiency and accuracy. Additionally, developing customized interpretation methods for different application scenarios is key to increasing the model's practicality, ensuring it can effectively support complex engineering decision-making.

(3) Interdisciplinary collaboration and research prospects:

Interdisciplinary collaboration is critical for advancing the application of machine learning in the RAC field. Research on RAC involves not only materials science but also integrates knowledge and methods from engineering mechanics, data science, and environmental science. Such collaboration can harness the strengths of different fields to develop more comprehensive and innovative solutions. For example, the integration of multi-disciplinary data can better capture the performance of RAC under varying conditions, enabling more accurate predictions through machine learning models. Furthermore, interdisciplinary collaboration can lead to the development of new optimization methods, such as multi-objective optimization algorithms that incorporate environmental impact assessments. These methods can enhance performance while balancing economic and sustainability considerations. Future research should strengthen interdisciplinary collaboration to broaden the application of machine learning in the RAC field, thereby enhancing its practical value.

#### IV. CONCLUSION

This paper systematically reviews and analyzes the latest research on machine learning-based prediction of mechanical properties and mix proportion optimization for RAC. The findings indicate that machine learning significantly enhances the accuracy and reliability of performance predictions for RAC, owing to its robust data processing and pattern recognition capabilities. Moreover, its application in mix proportion optimization demonstrates efficiency and flexibility, laying a foundation for the broader adoption of RAC in the construction industry. However, current studies reveal limitations, such as limited data sources and insufficient model generalization, necessitating further in-depth research and optimization.

Despite the significant progress in RAC research, several challenges remain. First, data quality issues continue to be a major bottleneck affecting model prediction accuracy. The acquisition of high-quality, multidimensional experimental data is difficult, highlighting the need for improved data collection and processing mechanisms. Second, the applicability and generalization of existing models require enhancement, as their performance in complex and dynamically changing engineering environments remains unstable. Future research should focus on integrating multi-source data, exploring new feature extraction, and optimizing models to improve robustness and adaptability. Additionally, combining theory with practical application through more engineering case studies is crucial to validate and optimize the models' effectiveness across different scenarios.

The future of machine learning in the RAC field is promising, driven by the continuous development of artificial intelligence technologies. Potential future research directions include: 1) Deep integration of multi-domain data by leveraging IoT and sensor networks to obtain more comprehensive, real-time concrete performance data, thereby advancing smart construction; 2) Development of new optimization algorithms and feature engineering techniques to further enhance prediction accuracy and stability; 3) Strengthening interdisciplinary collaboration, combining the latest advances in materials science, engineering mechanics, and data science to fully apply machine learning in the RAC domain. These efforts are expected to lead to the widespread global adoption of RAC, promoting a green transformation and sustainable development in the construction industry.

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