

Application of Machine Learning Techniques for Predicting Compressive Strength of Sustainable Concrete

Anil W. Kharche¹, Amogh. A. Malokar², Snehal S. Pawar³, Mayuri D. Patil⁴

¹Professor, Department of Civil Engineering, Padm. Dr. V. B. Kolte College of Engineering, Malkapur, Maharashtra, India

^{2,3,4}Assistant Professor, Department of Civil Engineering, Padm. Dr. V. B. Kolte College of Engineering, Malkapur, Maharashtra, India

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ABSTRACT

Self-compacting concrete (SCC) offers high workability, essential for complex and densely reinforced structures, but predicting its 28-day compressive strength typically involves time-consuming and costly laboratory tests [1]. This challenge is further complicated by the incorporation of recycled aggregates, a practice aimed at promoting sustainable construction. To address these issues, a novel hybrid model was developed, integrating a Gradient Boosting Regression Tree (GBRT) with Bayesian Optimization. This model effectively and accurately estimates the compressive strength of SCC containing recycled aggregates.

The model's performance was rigorously evaluated using standard metrics: RMSE, MAE, and R². Across five-fold cross-validation, the GBRT-Bayesian Optimization hybrid model achieved an average RMSE of 6.000, an MAE of 3.968, and an R² of 0.806, underscoring its robust predictive capabilities and suggesting its potential as a cost-effective alternative to conventional testing methods. The superiority of this hybrid approach in terms of prediction accuracy and resilience was further demonstrated through comparisons with single learner models like Support Vector Regression (SVR) and K-Nearest Neighbors (KNN), where the hybrid model outperformed them on test data.

To ensure transparency for this black-box model, the SHapley Additive exPlanations (SHAP) technique was employed to identify the most influential predictors and their trends. The resulting model provides an accurate, fast, and economical method for predicting the 28-day compressive strength of self-compacting concrete incorporating recycled aggregates. For practical application, the model has been converted into a user-friendly graphical interface, serving as a valuable decision-support tool for civil engineers and practitioners in optimizing mix designs and ensuring quality control in real-world construction projects.

Keywords:- SCC, SHAP, KNN, Concrete, RMSE etc.

1.INTRODUCTION

Traditional experimental methods for assessing concrete properties require sophisticated equipment, meticulous sample preparation, and lengthy testing periods, making them costly and time-consuming. These conventional approaches demand substantial financial resources, specialized labor, and considerable time for data collection and analysis [1]. Consequently, there is a growing interest in machine learning (ML) as a transformative solution, offering accurate prediction of concrete properties with minimal experimental data [1].

Machine learning techniques facilitate the development of intelligent models capable of predicting concrete strengths, particularly when incorporating sustainable materials such as industrial wastes. This not only optimizes material performance but also significantly reduces associated laboratory and equipment costs [2]. The application of these advanced soft computing prediction techniques holds the potential to significantly boost the adoption of waste foundry sand in sustainable concrete production, thereby fostering waste reduction and promoting environmentally conscious construction practices [3].

2.MACHINE LEARNING TECHNIQUES EMPLOYED FOR COMPRESSIVE STRENGTH PREDICTION

Various machine learning (ML) algorithms have been extensively employed for predicting the compressive strength (CS) of concrete, particularly when sustainable materials are incorporated. Random Forest (RF), Support Vector Machine (SVM), Extreme Gradient Boost (XGBoost), and K-nearest neighbors (KNN) have been widely utilized to predict the compressive strength of concrete containing sustainable materials like textile effluent sludge [4]. Hybrid ML models that integrate algorithms such as RF and SVM, and hybrid deep learning models combining convolutional neural networks (CNN) and long short-term memory networks (LSTM), have

also been developed for strength prediction [4]. Notably, ensemble-based ML techniques, including AdaBoost and boosting, have shown superior performance in predicting compressive strength compared to individual ML techniques like artificial neural networks (ANN) [5], with AdaBoost matching XGBoost's performance with an R2 of 0.98 [1].

Beyond standalone and hybrid approaches, advanced metaheuristic optimization algorithms have been leveraged to enhance ML model performance. For instance, differential evolution (DEA), human felicity algorithm (HFA), nuclear reaction optimization (NRO), and lightning search algorithm (LSA) have been used to optimize RF models for predicting the CS of alkali-activated concrete, with the NRO-RF model demonstrating the highest performance with an R2 of 0.931 [6]. Other influential techniques in this field include Decision Trees (DT), Multilayer Perceptron (MLP), Bagging Regressor (BR), Genetic Programming (GP), Evolutionary Polynomial Regression (EPR), and Multigene Expression Programming (MEP) [7], [8], [9], [10], [11], [12]. The accuracy of these predictive models varies, as illustrated in the table below, which summarizes the performance metrics of different ML techniques for compressive strength prediction.

Table 1: Performance metrics of different ML techniques for compressive strength prediction.

Model / Technique	R ² Value (Compressive Strength)	MAE (MPa)	RMSE (MPa)	Reference
LSTM (standalone)	0.90	N/A	N/A	[4]
Hybrid CNN-LSTM	0.89	N/A	N/A	[4]
Boosting	0.96	1.69	2.04	[5]
AdaBoost	0.93	N/A	N/A	[5]
AdaBoost	0.98	0.124 * (for Fsp)	N/A	[1]
XGBoost	0.98	N/A	N/A	[1]
NRO-RF	0.931	N/A	N/A	[6]
TSA-RF	0.918	N/A	N/A	[6]
RF	0.96	N/A	N/A	[9]
DT-Gradient Boosting	0.98	N/A	N/A	[10]
ANN	0.981	2.13	2.86	[8]

**Note: MAE for AdaBoost (0.124 MPa) was reported for splitting tensile strength (Fsp) prediction, not compressive strength.*

3.APPLICATIONS IN SUSTAINABLE CONCRETE TYPES AND MATERIALS

Machine learning (ML) models are extensively applied to predict the compressive strength (CS) of various sustainable concrete types, including those incorporating basalt fibers [1] and textile effluent sludge [4]. This approach offers a practical, cost-effective, and less time-consuming alternative to traditional experimental methods for evaluating mechanical properties. Concrete utilizing sustainable materials like waste foundry sand (WFS) has also benefited from ML, with models such as SVR-GWO demonstrating high accuracy in CS prediction for waste foundry sand concrete (WFSC) [3]. Furthermore, research has explored fly-ash-based concrete, with the Random Forest (RF) model proving highly exact in investigating the CS of concrete containing fly ash [9]. Other sustainable materials investigated include metakaolin [12], waste glass aggregates [13], and bagasse ash concrete [7].

ML techniques have also been employed to research self-compacting geopolymer concrete (SCGPC) and high-strength geopolymer concrete (HSGPC) with varying alkali concentrations. For SCGPC, KNN and SVM models have shown excellent accuracy in predicting compressive strength [2]. Similarly, the compressive strength of HSGPC, influenced by alkali molarity, has been effectively modeled using artificial neural networks (ANN), with ANNs providing reliable predictions and demonstrating the significant impact of the curing regime on final strength [8]. Additionally, ML techniques address the challenges of incorporating recycled aggregates into self-compacting concrete, where the inferior properties of recycled aggregates can impact mechanical properties. Studies have successfully used ML to evaluate optimal performance and predict compressive strength for self-compacting concrete with recycled aggregates [14] and recycled coarse aggregate concrete (RCAC) [10].

The application of ML techniques aids in identifying the optimal content of input variables in concrete mixes, thereby guiding informed decision-making for material optimization and sustainable construction practices. For instance, sensitivity analysis using methods like Hoffman and Gardeners as well as SHAP technique have been instrumental in identifying key drivers of strength in fiber-reinforced concrete [1] and waste glass aggregate

concrete [13]. This highlights the critical role of optimal water content in achieving desirable strength and workability, promoting circular economy initiatives in construction, and reducing reliance on conventional trial-and-error methods.

Table 2: Sustainable Concrete Types and Materials

Sustainable Concrete Type	Sustainable Material	Reference
Basalt fiber-reinforced concrete	Basalt fibers	1
Basalt fiber-reinforced concrete	Basalt fibers	15
Concrete utilizing TES	Textile effluent sludge (TES)	4
Waste foundry sand concrete (WFSC)	Waste foundry sand (WFS)	3
Fly-ash-based concrete	Fly ash (FA)	9
Basalt fiber-reinforced concrete mixed with fly ash	Fly ash (FA)	1
Self-compacting geopolymer concrete (SCGPC)	Ground granulated blast furnace slag (GGBS), Fly ash (FA), NaOH, Na ₂ SiO ₃	2
Concrete with MK	Metakaolin (MK)	12
Waste glass aggregate concrete	Waste glass aggregates	13
Sustainable bagasse ash concrete (BAC)	Sugarcane bagasse ash (BA)	7
High-strength geopolymer concrete (HSGPC)	Alkali molarity (NaOH, NaSi), FA, CAg	8
Self-compacting concrete with recycled aggregates	Recycled aggregates	14
Recycled coarse aggregate concrete (RCAC)	Recycled coarse aggregate	10

4.KEY FACTORS AND INFLUENCING PARAMETERS

The accurate prediction of compressive strength in sustainable concrete relies heavily on understanding the influence of various input parameters and material properties. A critical factor identified across multiple studies is the age of the concrete, which significantly impacts the compressive strength, particularly in mixtures containing waste foundry sand [3] and high-strength geopolymer concrete where the curing regime plays a major role [8]. For specialized concretes like alkali-activated concrete, specific chemical ratios are paramount; higher SiO/NaO ratios, along with increased sodium hydroxide (NaOH) and blast furnace slag ratio (BFSR), positively contribute to compressive strength. Conversely, an excess of water, aggregate content, and precursor content can have detrimental effects on its strength [6].

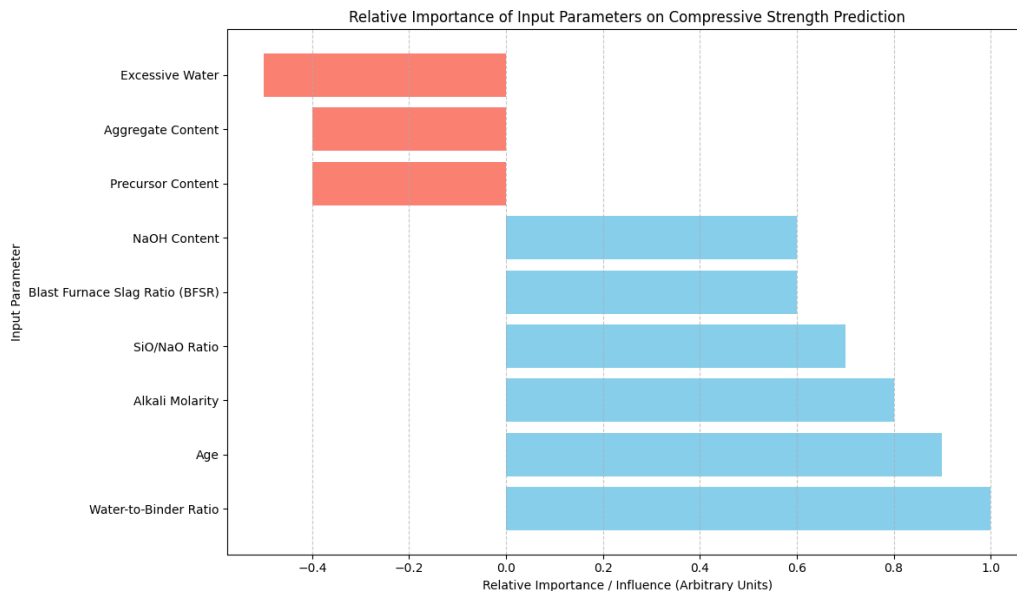


Fig: importance of several key input parameters on compressive strength prediction

Alkali molarity, or concentration, is another key influencing factor, playing a significant role in the geopolymerization process and directly affecting the resulting compressive strength of high-strength geopolymer concrete [8]. Furthermore, in waste glass aggregate concrete, the water-to-binder ratio has been identified as the most influential factor dictating its mechanical properties [13]. To systematically identify these crucial parameters, researchers employ sensitivity analysis techniques such as SHapley Additive exPlanation (SHAP) and the Hoffman and Gardeners method. These methods are instrumental in determining which input

parameters exert the most significant influence on the prediction process for various sustainable concrete types [1], [3], [10], [13].

The relative importance of several key input parameters on compressive strength prediction, as highlighted by these sensitivity analyses, is illustrated in the chart below.

5.CONCLUSION

Machine learning (ML) models offer accurate, fast, and economical alternatives to traditional laboratory testing for predicting the compressive strength of sustainable concrete, particularly for complex mixtures like self-compacting concrete with recycled aggregates or recycled coarse aggregate concrete. The integration of ML with sustainable materials such as waste foundry sand and waste glass aggregates promotes resource efficiency and significantly reduces the environmental impact within the construction industry. These models aid in optimizing mix designs and ensuring quality control by identifying the most influential input parameters through sensitivity analyses like SHAP.

For future research, there is a clear need to improve the interpretability of ML models, develop more consistent and comprehensive datasets, and integrate sustainability measures to enhance model resilience and generalization in predicting the properties of high-performance recycled aggregate concrete. Furthermore, the development of user-friendly graphical interfaces for predicting compressive strength will empower civil engineers and practitioners. These interfaces can reduce reliance on physical testing and promote efficient, data-driven decision-making in the development of sustainable concrete, as demonstrated for alkali-activated concrete and self-compacting concrete with recycled aggregates.

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