Alternative Machine Learning Tools for Calculating the Tensile Strength of Self-Compacting Concretes with Recycled Aggregates

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***Abstract*—This research focused on comparing various predictive software tools to assess the tensile strength of concrete made with recycled aggregates. To achieve this, we gathered published experimental data to evaluate different machine-learning models. We examined their effectiveness in predicting tensile strength and analyzed the material contributions to self-compacting concrete design through sensitivity analysis. The results demonstrated satisfactory accuracy in property predictions, with the XGBoost method emerging as the most effective predictive model at 28 days. Ultimately, this study highlighted the advantages of incorporating recycled aggregates and machine learning in both the preparation and assessment of tensile strength. These findings have important implications for sustainable construction practices and minimizing environmental impact in the construction sector.**

***Keywords*— Machine-learning, Concrete, Tensile strength, SCC, Recycling, Materials**

I. INTRODUCTION

The fast and steady development at the level of infrastructure in many countries has led to the widespread use of concrete as a construction material [1]–[3], which in turn has required that the technologies used in this sector are constantly changing as part of the efforts for continuous improvement and innovation. Consequently, various types of concrete have recently been developed, with self-compacting concrete (SCC) standing out due to its high potential for application. Simultaneously, there has been growing interest in incorporating recycled aggregates (RA) in its production [4]–[8]. The aforementioned recycled aggregates are derived from construction and demolition waste (CDW) and are used as substitutes for conventional aggregates [9]–[11].

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Their use aims not only to reduce costs but also to mitigate the environmental impacts caused by their accumulation of solid waste [12]. This approach demonstrates that economic development can be aligned with sustainability and environmental protection [|13].

SCC is one of the most widely used materials in construction due to its mechanical properties, with compressive strength (fck) being the most prominent. Additionally, there is no need to use external energy to make this concreted cure (no mechanical vibration) and its high fluidity is a key characteristic that distinguishes this type of concrete, enhancing its versatility and ease of application [14], [15]. It is an efficient concrete, very durable and guarantees uniformity. However, SCC's complex composition, which includes cement (Cmt), water (W), mineral admixtures (MA), fine aggregate (FA), coarse aggregate (CA), and a water reducer (superplasticizer) (SP), necessitates a meticulous mix design process to achieve optimal performance. This means that the behavior of related mechanical properties such as tensile strength (fst), fck, flexural strength and modulus of rupture, among others, need to be known [14]. Therefore, artificial intelligence techniques have been employed for their estimation, such as machine learning (ML), due to their simplicity, reliability, and capacity to learn from experimental data allow for highly accurate predictions [2], [11].

Currently ML methods have been used to model and predict the mechanical properties of SCC [16]–[20]. ML, has proven effective because it processes large amounts of data and predicts the mechanical properties of SCC with good accuracy, reducing experimental testing and analysis times [3], [11], [16].

This paper aims to compare four machine learning (ML) methods—namely, Extreme Gradient Boosting (XGBoost), Gradient Boosting (GB), Cat Boosting (CB), and Extra Trees Regressor (ETR)—to estimate the fst of SCC with RA after 28 days. Additionally, the study examines the influence of each input variable on the fst prediction through sensitivity analysis. This research represents a significant contribution to the understanding of the application of artificial intelligence and ML in generating fast and reliable results.

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II. METHODS

A. *Database for ML*

The sample used in this research consists of 381 different concretes incorporating (RA), sourced from various studies published in academic journals. Table I shows the information needed.

TABLE I. DIFFERENT DATA USED IN THE STUDY

No	Reference	mixture	% data	No	Reference	mixture	% data
1	Ali and Al-Tersawy [21]	18	4.73	22	Nieto et al. [22]	22	5.78
2	Aslani et al. [23]	15	3.94	23	Nili et al. [24]	10	2.63
3	Babalola et al. [25]	14	3.68	24	Pan et al. [26]	6	1.57
4	Bahrami et al. [27]	10	2.63	25	Revathi et al. [28]	5	1.31
5	Behera et al. [29]	6	1.57	26	Revilla-Cuesta et al. [30]	5	1.31
6	Chakkamalayath et al. [31]	6	1.57	27	Sadeghi-Nik et al. [32]	12	3.15
7	Duan et al. [33]	10	2.63	28	Señas et al. [34]	6	1.57
8	Fiol et al. [35]	12	2.33	29	Sharifi et al. [36]	6	1.57
9	Gesoglu et al. [37]	24	6.3	30	Sherif and Ali [38]	15	3.94
10	Grdic et al. [39]	3	0.79	31	Silva et al. [40]	5	1.31
11	Güneyisi et al. [41]	5	1.31	32	Singh et al. [42]	12	3.15
12	Guo et al. [43]	11	2.89	33	Sun et al. [44]	10	2.63
13	Katar et al. [45]	4	1.05	34	Surendar et al. [46]	7	1.84
14	Khodair et al., 2017 [47]	20	5.25	35	Tang et al. [48]	5	1.31
15	Kou & Poon [49]	13	3.41	36	Thomas et al. [50]	4	1.05
16	Krishna et al. [51]	5	1.31	37	Tuyan et al. [52]	12	3.15
17	Kumar et al. [53]	4	1.05	38	Uygunoğlu et al. [54]	8	2.10
18	Long et al. [55]	4	1.05	39	Wang et al. [56]	5	1.31
19	Mahakavi and Chithra [57]	25	6.56	40	Yu et al. [58]	3	0.79
20	Manziz [59]	4	1.05	41	Zhou et al. [60]	6	1.57
21	Martínez-García et al. [61]	4	1.05		Total	381	100

B. *Variables for the sensitivity test*

For the sensitivity analysis, the input variables included Cmt, MA, W, FA, CA, and SP, while the output variable was fst. These variables were employed to model the fst of SCC with RA utilizing ML techniques. Table II shows the minimum, maximum, mean, standard deviation, skewness and kurtosis values. In addition, Fig. 1 presents the frequency distribution along with the normal curve for each input variable, allowing for an examination of the behavior of each variable.

TABLE II. MINIMUM, MAXIMUM, MEAN, STANDARD DEVIATION, ASYMMETRY AND KURTOSIS OF THE INPUT AND OUTPUT VARIABLES.

Parameters	Cmt (kg/m3)	MA (kg/m3)	W (kg/m3)	FA (kg/m3)	CA (kg/m3)	SP (kg/m3)	Fst (MPa)
Min	78.00	0.00	45.50	532.20	328.00	0.00	0.96
Max	550.00	515.00	246.00	1200.00	1170.00	16.00	7.20
Mean	368.73	138.26	167.29	844.71	796.05	5.07	3.52
SD	98.38	94.94	31.01	130.52	154.06	3.12	1.00
As	-0.849	0.396	-0.365	0.593	-0.292	0.852	0.896
K	0.252	-0.280	1.696	0.728	1.173	1.047	1.477

Caption: Min = minimum value, Max= máximum value, SD= standard deviation, As= asymmetry , K= kurtosis

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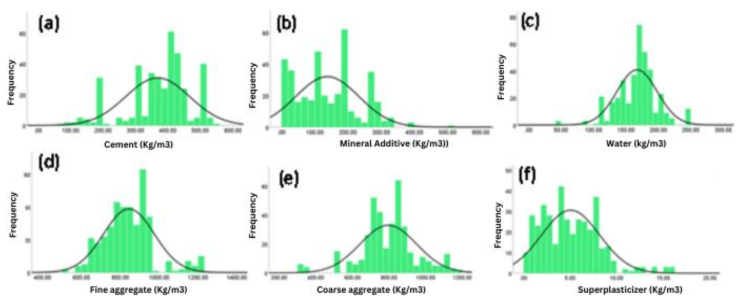

Fig. 1.Frequency distribution with Normal curve of the input variables: (a) Cmt; (b) MA ; (c) W; (d) FA; (e) CA; (f) SP

The MaxAbs Scaler software was employed to normalize both the input and output variables utilized in modeling the fst. Equation 1, where x represents a data point, was applied to determine the maximum value of each characteristic.

$$x_{scaled} = \frac{x}{\max(|x|)} \tag{1}$$

C. Data Visualization

The correlations among the input characteristics (independent variables) were analyzed to identify potential dependencies between the various attributes, thereby aiding in the optimization of the predictive models [62] and maximizing prediction accuracy. To achieve this, a Pearson correlation matrix (heat map) was generated for the independent variables (Input). The analysis revealed that no correlation among the characteristics exceeded 0.80 (Fig. 2), indicating the absence of multicollinearity [16], [63].

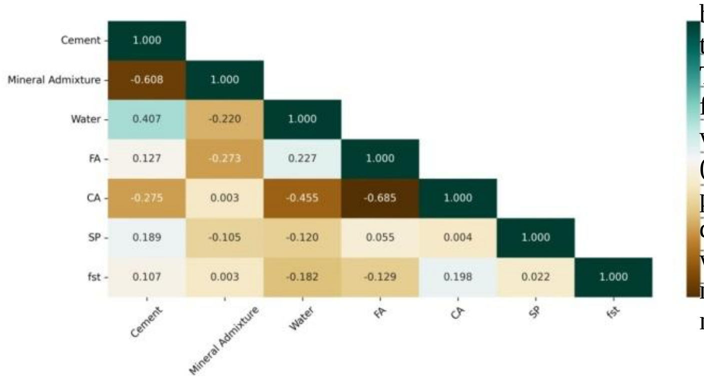

Fig. 2. Heat map for Pearson correlations.

D. ML tools used

ML methods are becoming more common as the computing power used to evaluate the performance of materials in the construction industry increases [64], [65]. In this study, four methods were selected for fst prediction based on their widespread use in related studies: XGBoost, GB, CB, and ETR. These methods were chosen attended on the following characteristics.

1. GB

Machine learning tool designed in 2001, which is a supervised method that combines numerous base learners or simple learning models as a weighted sum to reduce bias and variance and reweight data that were misclassified, gradually improving the performance of the method [66]. It is used for regression and classification problems [67], [68].

2. ETR

Machine learning model proposed in 2005, is usable in regression and classification problems [69]. It employs a set of random decision trees to predict numerical values and differs from other regression methods because it uses a random feature and cutoff point selection process to build the trees [69]–[71] which makes it faster and less prone to overfitting [69].

3. CB

This model uses binary decision trees as the basis for prediction [72]. The CB uses two key algorithms for processing: (1) the permutation algorithm which is used to evaluate the importance of categorical features and works by randomly permuting the values of a feature and observing how it affects the model performance. This algorithm uses the one_hot_max_size (OHMS) technique and, (2) the feature coding algorithm used to convert categorical variables into numerical values. These two algorithms work together to handle categorical features in CB and improve CB performance efficiently.

4. XGBoost

The scalable ensemble machine learning method for tree boosting utilizes a more regularized formulation of the technique to mitigate overfitting and enhance performance. This method incorporates two self-compatible regularization functions, namely column shrinkage and under sampling, which contribute to its [73]. Compared to Gradient Boosting (GB), it demonstrates reduced processing time and improved prediction capabilities, particularly when handling large datasets, allowing it to function as an advanced GB method with parallel distributed processing. Marani and Nehdi [74] note that this approach employs a loss function to assess the model's goodness of fit.

E. Model validation

1. Division of the data set

For the purpose of modeling the fst, the data were randomly partitioned into three distinct stacks: training, validation, and test. The training dataset consisted of 267 mixtures (70%), the validation dataset included 57 mixtures (15%), and the test dataset also contained 57 mixtures (15%). Table 3 provides the range and description of the input and output variables for each of the three datasets.

TABLE III. MINIMUM, MAXIMUM, MEAN, STANDARD DEVIATION, ASYMMETRY AND KURTOSIS OF THE INPUT AND OUTPUT VARIABLES, FOR EACH DATA SET

Data set	Parameters	Cmt	MA	W	FA	CA	SP	fst
	Unit	kg/m3	kg/m3	kg/m3	kg/m3	kg/m3	kg/m3	MPa
Training	Min	94.00	0.00	45.50	581.00	328.00	0.00	1.40
	Max	520.00	390.00	246.00	1200.00	1170.00	16.00	7.10
	Mean	371.83	135.10	168.03	846.72	790.32	4.83	3.51
	SD	93.32	92.02	31.63	129.38	154.51	2.91	0.99
	As	-0.91	0.30	-0.20	0.695	-0.53	0.62	0.91
	K	0.52	-0.68	1.60	0.79	1.35	0.53	0.15
Validation	Min	78.00	0.00	45.50	532.50	335.00	0.00	0.96
	Max	520.00	515.00	246.00	1200.00	1170.00	16.00	6.40
	Mean	375.55	143.57	167.53	851.13	789.75	5.86	3.45
	SD	95.29	107.03	32.34	142.14	151.80	3.40	0.13
	As	-1.01	0.92	-1.13	0.25	0.01	1.07	0.76
	K	1.50	1.32	3.21	.17	1.06	1.50	0.32
Test	Min	111.00	0.00	104.30	532.20	530.00	0.00	1.45
	Max	550.00	320.00	203.40	1200.00	1150.00	16.00	7.20
	Mean	347.36	147.79	163.56	828.85	829.21	5.41	3.61
	SD	121.12	69.60	26.69	127.79	152.64	3.62	1.06
	As	-0.43	0.05	-0.57	0.53	0.57	1.07	0.96
	K	-1.02	-1.14	-0.40	1.55	-0.02	0.89	1.70

F. Model evaluation

Four measures were used to evaluate the model performance: coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). These indexes evaluate the error in the predictions that the software gives for each sample in the fsk for 28-day SCC with RA in comparison to actual observations [9], [73],[75], [76].
However, the R^2 value is considered the best of these indicators for model evaluation [75], [77]. Table IV presents the R^2 values for prediction model evaluations [74], [78], [79]. It also highlights that the closer the root values of RMSE and MAE are to zero, the better the performance of the ML model in prediction [14], [18], [76]. Table V presents the R^2 results for both the overall dataset and the training and test datasets across the four models.

TABLE IV. STATISTICAL CRITERIA FOR R^2.

R^2	Yield rate	Predictive power
≥ 0.95	Excellent	Very accurate prediction
0.75 - 0.95	Very good	Good prediction
0.65 - 0.75	Satisfactory	Acceptable prediction
< 0.65	Unsatisfactory	Imprecise for prediction

TABLE V. PERFORMANCE OF XGBOOST, GB, CB AND ETR WITH DIFFERENT CHARACTERISTICS.

Characteristics		XGBoost	GB	CB	ETR
R^2	Test	0.8423	0.7709	0.7736	0.8143
	Training	0.9421	0.9292	0.9382	0.9484
	Global	0.8428	0.7717	0.7744	0.8149
RMSE	Test	0.0581	0.0700	0.0696	0.0636
	Training	0.0329	0.0365	0.0341	0.0311
	Global	0.0225	0.0270	0.0269	0.0244
MAE	Test	0.0443	0.0525	0.0516	0.0451
	Training	0.0188	0.0239	0.0217	0.0127
	Global	0.0066	0.0078	0.0077	0.0067

III. RESULTS

A. Comparison of the predictive performance of ML models.

For the analysis of the results, R^2 was selected as the primary metric to compare the performance of different ML models [75], [76], as it reflects prediction accuracy; a high value of this metric indicates a model with strong predictive capabilities. Additionally, the values of RMSE and MAE were considered (Fig. 3). Values lower than 0.05 for these metrics indicate that the ML model provides a good fit for predicting the fst of SCC with RA after 28 days [79], [80].

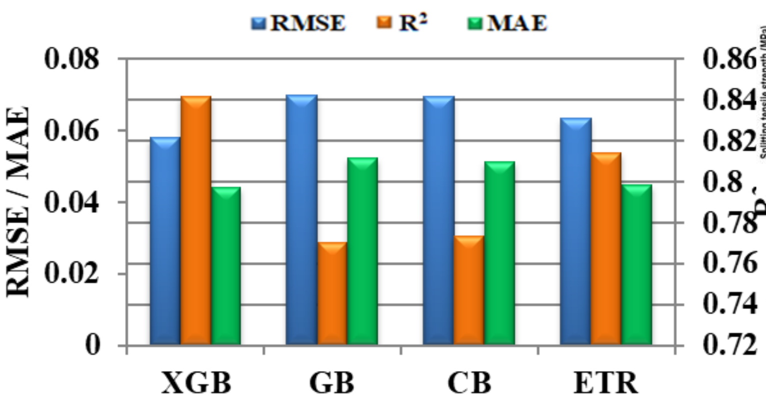

Fig. 3. R^2, RMSE, MAE and MAPE of the ML models.

The R^2 values for the overall dataset across the four models ranged from 0.7717 to 0.8428 MPa. Values exceeding 0.75 suggest that the machine learning models possess good predictive capability based on established R^2 criteria. Similarly, the root RMSE and MAE values were close to zero, with RMSE ranging from 0.0225 to 0.0270 MPa and MAE ranging from 0.0066 to 0.0078 MPa, indicating a strong agreement between the predicted values and the actual experimental data obtained from SCC with RA. In the training dataset, the R^2 values ranged from 0.9292 to 0.9421 MPa, demonstrating that all four models are effective predictors of the fst for SCC with RA. The test dataset enabled an evaluation of the predictive performance of each method, revealing that the XGBoost model exhibited the best performance, achieving the highest R^2 value of 0.8423. This model predicts fst with a high degree of accuracy [77], [80].

B. *Comparison of ML model results.*

The curves given in Fig. 4 illustrate that the predicted values from the XGBoost, GB, CB, and ETR models exhibit a strong correlation with the experimental fst values. The blue lines represent the experimental data in each graph, while the red lines depict the predicted values. A larger discrepancy between the experimental and predicted values indicates greater errors. Consequently, the graph demonstrating the best fit is that of the XGBoost model, which accurately predicts fst more effectively than the GB, CB, and ETR models.

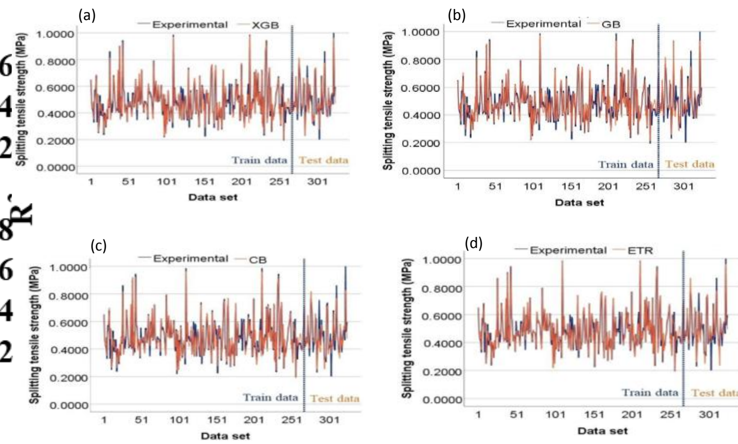

Fig. 4. Experimental and predicted tensile strength for models.

C. *Sensitivity analysis*

This analysis aids in understanding the impact of each input variable on the output variable. A higher sensitivity value indicates a greater influence of the input variables on the output variable. Shang et al. [81] emphasize that input variables significantly affect the prediction of the output variable. In this study, Cmt (30.07%), FA (22.83%), and MA (22.08%) were found to be the most influential in predicting the fst of SCC with RA (Fig. 5). In this context, Shang et al. [81] also identified Cmt as a critical factor in predicting the fst of SCC produced with RA.

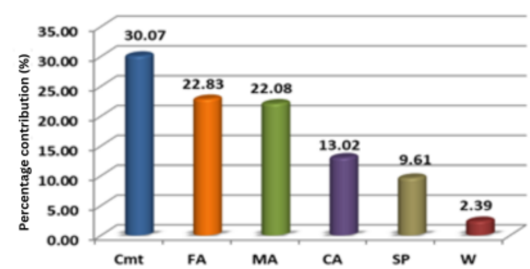

Fig. 5. Contribution of input variables to the fst in the XGBoost model.

IV. CONCLUSIONS

A database comprising 381 samples from literature published in scientific journals was employed to develop machine-learning models for XGBoost, GB, CB, and ETR. These samples were randomly partitioned into three datasets for training, validation, and testing, consisting of 267 (70%), 57 (15%), and 57 (15%) samples, respectively.

All four ML methods demonstrated satisfactory accuracy in predicting the fst of SCC with RA. The R^2 values for the training datasets were 0.9421 for XGBoost, 0.9292 for GB, 0.9382 for CB, and 0.9484 for ETR.

Among the models, XGBoost exhibited the best performance, achieving the highest R^2 value of 0.8423, along with the lowest RMSE (0.0581) and MAE (0.0443) values in the test dataset, outperforming the GB, CB, and ETR models.

The sensitivity analysis indicated that Cmt was the most significant input variable, contributing 30.07% to the prediction of SCC fst at 28 days using RA, followed by FA and MA, which each contributed over 20%. In contrast, W was the least influential parameter, contributing only 2.39% to the prediction.

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