

Comparative Assessment of Regression-Based Machine Learning Models for Predicting the Compressive Strength of Fibre-Reinforced Concrete

Nour H. Almarahlleh^{1,*}

¹ Department of Civil Engineering, Tafila Technical University, Tafila, Jordan.

* Corresponding author: nour@ttu.edu.jo

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ABSTRACT

Concrete industry has widely incorporated fibres in mixes due to their potential to improve concrete mechanical properties, enhance the toughness and durability of concrete reinforced members, and their ability to control crack widths in reinforced concrete members. Metallic and non-metallic fibres have been used in concrete mixes in various civil engineering applications; however, metallic fibres have shown to be more susceptible to harsh environmental conditions including corrosion. Moreover, they present higher environmental impact compared to non-metallic fibres. Recent research has considered the fibre reinforced concrete with non-metallic fibres due to the shortfalls associated to metallic fibres. Currently existing research on concrete compressive strength has largely focused on experimental investigations into the effects of fibre type, fibre volume fraction (percentage), ratio (fibre length to diameter), and ratio of water to cement. However, limited studies explored the employment of machine learning (ML) to analyze and predict the compressive strength of concrete considering the influence of these parameters. Therefore, this study employs 262 datasets from experimental research on fibre-reinforced concrete and develops an ML-based analysis framework. Eight different regression algorithms were incorporated and evaluated, including linear models, Ridge regression, support vector regression (SVR), k-nearest neighbours (K-NN), CART, random forest, gradient boosting, and Extra Trees. Results of ML indicate that the Extra Trees model achieved the strongest random holdout performance, with $R^2 = 0.984$, RMSE = 4.79 MPa, and MAE = 3.37 MPa. Five-fold cross-validation confirmed high internal predictive ability, with mean $R^2 = 0.966$. However, grouped validation by source produced a lower mean R^2 of 0.193, showing that random splits may overestimate external performance.

Keywords: Fibres; compressive strength; machine learning; linear models; regression; k-nearest neighbours; CART; random forest; gradient boosting; Extra Trees.

1 Introduction

In construction, concrete has been considered as the most used material. Therefore, the enhancement of its behaviour has become essential. Fibres such as steel are utilized in concrete to improve the mechanical behaviour and cracking performance under various loading ACI 544 [1]. Several researchers [2,3] have incorporated various types of fibres in concrete mixes and evaluated their behaviour, findings revealed that fibre reinforced concrete (FRC) showed higher compressive and tensile strength, crack resistance, toughness and the deflection. Initially, previous studies [4–7] examined the performance of FRC and evaluated the influence of different fibres on the mechanical behaviour of concrete. For instance, [6] incorporated polypropylene and glass fibres in different mixes and examined the tensile and the compressive strength of FRC, results were compares to reference samples and showed significant improvement of 13% in compressive strength and 50% in the tensile strength.

Further, [4] compared the compressive strength of both metallic and non-metallic (glass) fibres, authors reported that glass fibres with volume fraction of 5% reduced the compressive strength compared to steel fibres effect. Wu et al. [7] studied the impact of fibre's shape and their content on concrete compressive strength, specimens with higher aspect ratio exhibited noticeable improvements in the compressive strength. Furthermore, the influence of varying water to cement ratio (w/c) was investigated

to assess its influence on the compressive strength [8,9]. Results indicated that the values of both splitting tensile and compressive strengths are lower in concrete mixtures having high water-to-cement ratio, this is due to the increased porosity which results in weaker interfacial bonding, and the greater formation of microcracks.

The accurate prediction of material properties is critical in structural engineering because it allows the reliable estimation of the material properties, especially for advanced materials like fibre reinforced concrete (FRC). The complex composition of FRC, which includes cement, water content, fibre type and dosage, supplementary cementitious materials etc., makes prediction of the mechanical behaviour of FRC, particularly compressive and tensile strengths, challenging. The effect of these constituents is both individually and mutually, and leads to highly non-linear and interdependent material behaviour, which makes accurate modelling and performance prediction difficult.

For these, Machine Learning (ML) techniques have been utilized in civil engineering applications and materials science to evaluate and predict concrete properties. These methods are common and are employed in many applications, particularly in the prediction of the compressive strength of various concrete mixes. In the previous article [10], they used a back propagation neural network with the quantity of some constituents such as sand, coarse aggregate, cement, steel fibres, fly ash and crushed stone as input variables. This model allowed the assessment of compressive strength of SFRC with fly ash content.

In the previous study [11], concrete mechanical properties were represented as functions of input factors such as water, cement, coarse aggregate, fine aggregate and superplasticizer and developed an extreme learning machine (ELM) model predicting the compressive strength of concrete. The results indicated that the model predict the compressive strength of high-strength concrete (HSC) with good accuracy. Moreover, [12] built a predictive model of compressive strength based on 131 data samples taken from literature using adaptive neuro-fuzzy inference system (ANFIS) and artificial neural networks (ANN). The study results showed that water-to-cement ratio has a large effect on the strength prediction. The results obtained by ANFIS model showed $R^2 = 0.974$, indicating the efficiency and high accuracy of the model in predicting the tensile strength of materials in engineering applications.

Although a lot of research has been conducted in predicting of concrete mechanical properties, it is still difficult to estimate the properties of fibre-reinforced concrete (FRC) because of the interaction between its constituents. There is still little research in the current literature related to the use of ML techniques for predicting the compressive strength of FRC mixes. It is mainly due to the limited experimental data and the complicated interdependence between the material parameters. Several researchers [13–16] developed ML models to examine influence of different constituents on the compressive strength of FRC, these factors include mixing water, cement, types of fibres, superplasticizer content, additives such as fly ash and silica fume, and the contents of aggregate, and the compressive strength.

Further, [14] proposed the ML models for predicting Basalt Fibre Reinforced Concrete (BFRC) compressive strength. Four different machine learning models, Support Vector Machine (SVV), Random Forest (RF), Backpropagation Neural Network (BPNN), and Extreme Gradient Boosting (XGB), were optimized and researchers predicted the compressive strength of BFRC using these models, which were interpreted using SHAP (Shapley Additive Explanations). A database of 309 samples of compressive strength obtained from published studies was built up and supported by eight experimental sets. SHAP interaction plots were created to understand the impact of each input feature on the model output and find the best range of basalt fibre properties. The results indicated that the XGB model presented the highest R^2 value of 0.9431, the lowest root mean squared error RMSE equals to 3.2325 and the lowest MAE of 2.3355.

To create prediction models for the compressive strength of steel fibre recycled aggregate concrete (SFR-RAC), Zhang et al. [16] combined four ML models, which were Support Vector Machine (SVM), Backpropagation Artificial Neural Network (BP-ANN), Gradient Boosted Adaptive Boosting (AdaBoost), and GBRT. A database of 465 experimental compressive strength values of various mix proportions was used. Bayesian optimization methods were used to train and optimize the models. It

was found that AdaBoost and GBRT showed good predictive ability, the difference in the values of predicted and experimental strength was within 20%.

Likewise, an optimized model using XG-Boost algorithm was designed by [17] to predict the strength of fibre reinforced coral aggregate concrete. A -total of 834 experimental datasets were compiled from 15 literature sources. The hyper parameters of the XG-Boost model were optimized by the following algorithms: The Hunger Games Search (HGS), Sooty Tern Optimization Algorithm and Whale Optimization Algorithm, leading to the development of better XG-Boost models to predict the compressive strength of fibre reinforced recycled aggregate concrete. The model performance was assessed in terms of comparison between predicted and observed values, and analysis of residual distribution through the standard performance measures.

For sensitivity analysis, several works [18-20] have been done on the effect of the input parameters on the compressive strength of concrete. Besides, [19] applied a random forest algorithm for deriving the most important inputs to the concrete compressive strength. The parameters considered in their study were: Age, w/c ratio, coarse and fine aggregate contents, fly ash, blast furnace slag. The experimental results showed that w/c ratio and age had the greatest influence on the model as compared to the other variables. Similarly, [20] performed an importance analysis using CART on a set of 328 concrete mixtures. Their results indicated that the age of the concrete was the most important factor affecting the compressive strength, followed by stone powder percentage in the concrete.

More recently, [18] performed sensitivity analysis to evaluate the influence of concrete constituents as input parameters (i.e., recycled plastic aggregate, cement content and the amount of superplasticizer) on the compressive strength of self-consolidating concrete. The results showed that these parameters play an important role in modelling the mechanical properties of concrete.

The review of the available research on concrete compressive strength reveals that previous studies developed and performed different models for predicting the conventional concrete compressive strength including algorithms of artificial neural networks, linear regression, and support vector regression. However, available studies focused on steel fibre reinforced concrete (SFRC), particularly in assessing the performance of boosting and tree-based ML algorithms for compressive strength prediction. Therefore, this study aims at developing machine learning models for predicting the compressive strength of different types of fibre reinforced concrete. Also, examining the combined influence of fibre characteristics on strength behaviour. This approach aims to support efficient mix design and reduce the need for extensive experimental testing of concrete compressive strength.

This research employed a dataset of 262 values of concrete compressive strength collected from available research conducted on FRC. Eight machine learning algorithms were used to develop prediction model of concrete compressive strength. These algorithms include linear models, Ridge regression, support vector regression, k-nearest neighbours, CART, random forest, gradient boosting, and Extra Trees. In the first stage, the collected dataset was pre-processed using the clustering technique i.e., K-means++ to address the imbalances during the data partitioning to enhance prediction reliability. Subsequently, the best-performing model was subjected to importance analysis to evaluate the contribution of individual variables, followed by an investigation of the interaction effects among different fibre properties. Finally, key findings and conclusions were drawn.

2 Data Description and Methodology

This research compiled 262 observations of the compressive strength of FRC, from 35 published experimental studies [21-56]. Then, eight machine ML algorithms were developed to build predictive models of the compressive strength. Predictive models are linear models, Ridge regression, k-nearest neighbours, Support vector regression, CART, random forest, gradient boosting and Extra Trees. In the present study, the independent variables reported in the experimental studies gathered from the literature that affect the compressive strength FRC are (w/c) ratio, fibre type through the modulus of elasticity (E), fibre percentage (volume fraction (%)), and fibre aspect ratio (l/d). Concrete compressive strength

(f'_c) is chosen as the dependent variable used in this study. More details about those parameters are available in [57].

2.1 Research Methodology

The research methodology adopted this study is presented in Fig. 1. The methodology involved the development of a machine learning for predicting FRC compressive strength. A database of published experimental studies (35 studies) was first compiled and then cleaned to include only complete studies with the required input variables: w/c, fibre modulus of elasticity, fibre percentage, and fibre aspect ratio. The dataset was then split into training and testing subsets, and a 5-fold cross validation method was used during the model development. The machine learning algorithms tested were linear models, Ridge regression, Support vector regression (SVR), k-nearest neighbours (K-NN), CART, random forest, gradient boosting and Extra Trees. The coefficient of determination (R^2), mean absolute error (MAE) root mean square error (RMSE) and mean absolute percentage error (MAPE) were considered to evaluate the performance of each model. Lastly, the feature importance (sensitivity) analysis was done to understand how each input variable is in relation to the predicted residual strength.

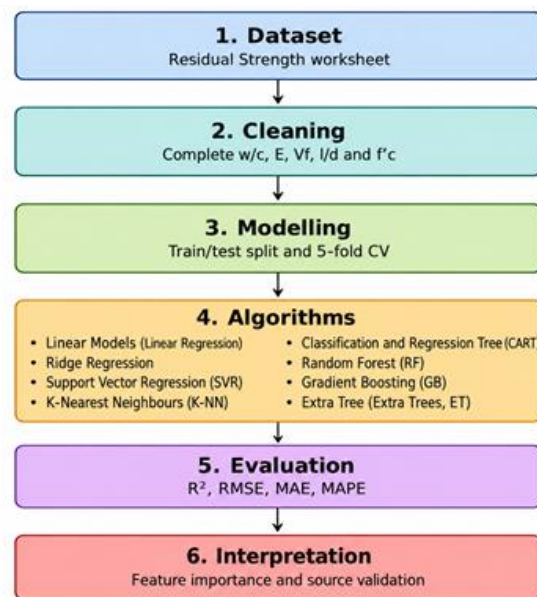


Fig. 1. Research methodology for predicting compressive strength in FRC.

2.2 Data Statistical Description

The descriptive statistics of the independent inputs influencing the FRC compressive strength obtained from 262 observations are presented in Table 1.

Table 1: Descriptive statistics of the final complete-case modelling dataset.

Variable	Min	Q1	Mean	Median	Q3	Max	SD
w/c	0.160	0.250	0.391	0.45	0.490	0.600	0.138
E (GPa)	0.000	69.00	132.089	110.0	200.00	750.00	116.346
Percentage %	0.000	0.50	0.976	1.00	1.500	4.50	0.808
Aspect ratio	0.000	52.50	293.309	80.00	300.00	3125.00	499.386
f'_c (MPa)	3.500	40.33	68.232	55.00	87.097	182.20	42.033

The w/c varied between 0.16 and 0.60, with a mean of 0.391 and a standard deviation of 0.138, as shown in Fig. 2, which is a reasonable range of variability. The fibre modulus of elasticity was also found to have a wide range from 0 to 750 GPa with a mean of 132.1 GPa, which was due to the presence of fibre types in the mix with different mechanical properties. The fibre volume fraction ranged from 0 to 4.5%

with a mean of 0.98% and a median of 1.0%. The aspect ratio was also seen to have a wide range from 0 to 3125, with a mean of 293.3 and a relatively high standard deviation of 499.4 showing that there was considerable variation in fibre geometry. Concrete compressive strength (f'_c) values ranged from 3.5 to 182.2 MPa, with the average value of 68.2 MPa and the standard deviation (SD) of 42.0 MPa. The wide ranges of the input variables as well as compressive strength reflect the variety of the data set collected and help to build strong ML models that can capture the different and complex relationships between the material parameters and concrete performance.

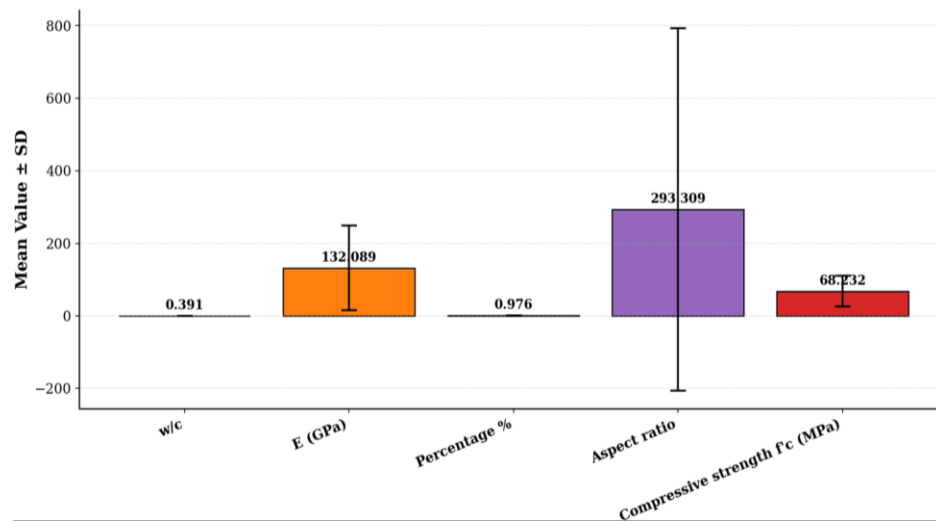


Fig. 2. Mean value and standard deviation of the independent variables and concrete compressive strength.

The compressive strength distribution is presented in Fig. 3. The distribution is non-uniform, with most of the observations occurring between 20 and 80 MPa, which is the range of strength typically observed in traditional reinforced concrete structures. This is attributed to the fact that concrete with the strength of normal strength concrete, is the most widely utilised material in construction, and hence has been investigated more in experimental studies.

The second cluster of observations is found at around 140–190 MPa, corresponding to high strength fibre reinforced concrete mixtures. Normally, these concretes are developed for certain purposes, including the building of bridges, mega structures, and other large-scale ventures that demand higher mechanical properties. Therefore, fewer experimental studies have been carried out for these mixtures and less often observed in the high-strength range. One source of bimodal distribution of the compressive strength may be that the dataset includes both conventional and high-strength concrete mixes.

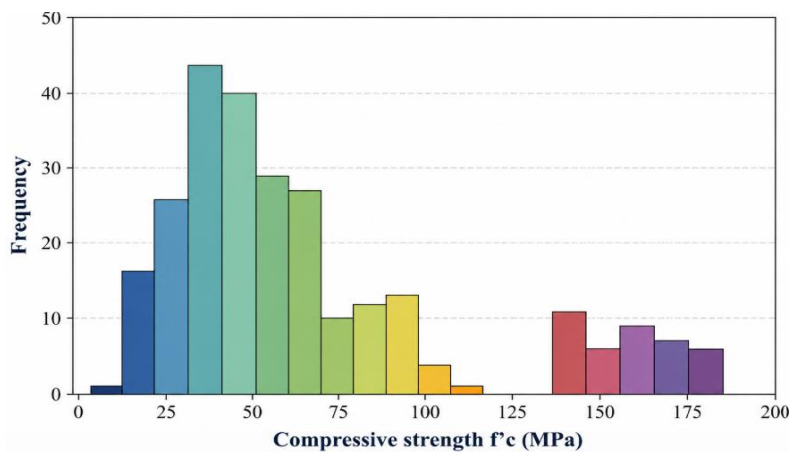


Fig. 3. Distribution of compressive strength in the final modelling dataset.

The Pearson correlation matrix was conducted to explore the correlations between significant predictors and determine their relationship to compressive strength (f'_c) as shown in Fig. 4. The correlation coefficient (r) ranges from -1 to $+1$; the negative values reveal that the inverse relationship, while the positive ones show that there is a direct one.

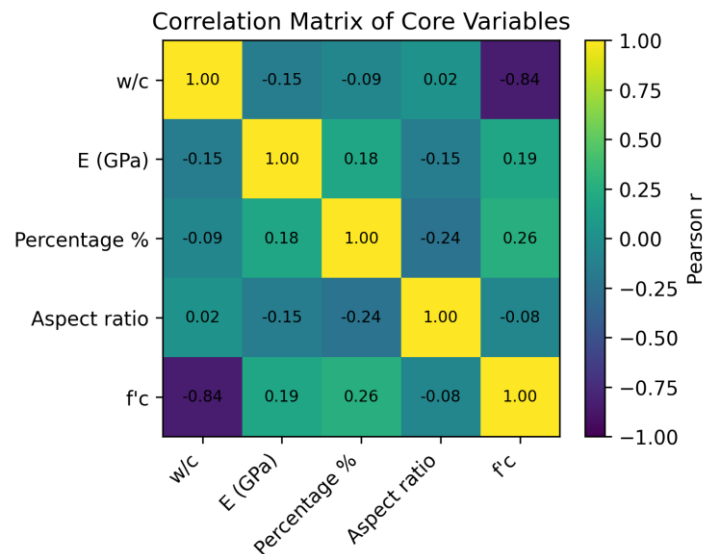


Fig. 4. Pearson correlation matrix of the core predictors and compressive strength.

The Pearson correlation matrix shows that w/c ratio ($r = -0.84$) has a strong negative relationship with compressive strength (f'_c), which indicates that this ratio is the major factor influencing the strength of the material. The percentage composition and elastic modulus, on the other hand, showed weak positive correlations with the compressive strength, indicating a relatively small effect. The value of the aspect ratio has an insignificant relationship ($r = -0.08$). In addition, the overall low correlation values between the independent variables indicated that there is very minimal multi-collinearity that is beneficial for good regression and machine learning modelling. Previous studies [57,58] have reported correlations of over ± 0.7 as being a strong relationship between the two variables and values over ± 0.9 as showing a very high or near perfect correlation.

3 Machine Learning Models

After the review process, eight models: linear models, Ridge regression, the support vector regression, the k-nearest neighbours, CART, random forest, gradient boosting, and Extra Trees were employed to predict the compressive strength of FRC. These models are briefly described in Table 2.

Table 2: Summary of ML Algorithms used in this study

Algorithm	Definition
Linear Models	Models that assume a linear relationship among variables as input and the target, expressed as a weighted sum.
Ridge Regression	A linear regression technique that incorporates L2 regularization in addition to the loss function to prevent overfitting and handle multi-collinearity.
SVR	A regression method that fits a function within a specified error margin while maximizing generalization.
k-NN	A non-parametric algorithm that predicts values based on k nearest samples in the feature space.

CART	A decision tree algorithm that recursively splits data into subsets to perform regression or classification.
Random Forest	Decision trees built on random data subsets, with predictions aggregated to improve accuracy.
Gradient Boosting	An ensemble technique that sequentially creates models to minimize prediction errors of prior models.
Extra Trees	An ensemble method that introduces randomness in feature selection and split points to enhance generalization.

3.1 Performance of ML

The performance of the ML models was evaluated and assessed using a holdout test set to ensure an unbiased assessment of predictive capability on unseen data. In this stage, four statistical metrics were utilized to quantitatively evaluate each model performance. These metrics include the Coefficient of Determination (R^2), Mean Absolute Error (MAE), Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE), as presented in Table 3. Results obtained from the holdout test reveal that ensemble tree models outperform the linear and distance-based baseline models. It was observed that the Extra Trees model achieved the best performance, with $R^2 = 0.984$, RMSE = 4.79 MPa, MAE = 3.37 MPa, and MAPE = 6.37%. Also, Gradient Boosting and Random Forest models demonstrated strong performance, indicating that nonlinear relationships are predominant in the response surface.

Table 3: Holdout test performance of the compared machine-learning models.

Model	R^2	RMSE (MPa)	MAE (MPa)	MAPE (%)
Extra Trees	0.984	4.786	3.367	6.367
Random Forest	0.967	6.873	4.892	9.527
Gradient Boosting	0.963	7.315	5.772	11.536
CART	0.957	7.906	5.425	9.649
KNN	0.922	10.611	7.543	15.403
SVR-RBF	0.911	11.344	8.479	16.034
Ridge Regression	0.710	20.433	15.601	26.472
Linear Regression	0.709	20.452	15.646	26.651

Fig. 5 presents the performance of the ML models considered in this study by using R^2 , RMSE, MAE, and MAPE. It was found that the Extra Trees algorithm achieved the highest overall performance. In terms of other ensemble-based models, i.e., Random Forest and Gradient Boosting, models also demonstrated good performance, with R^2 values above 0.96 and low values of error metrics. Whereas the CART model exhibited slightly lower performance with accuracy R^2 of 0.957. In contrast, k-NN and SVR-RBF demonstrated moderate results identified by the increased prediction errors. However, Linear Regression and Ridge Regression, resulted in lower R^2 values (approximately 0.71) and substantially higher values of the statistical metrics. This indicates the limited capacity to model the complex and nonlinear relationships in the dataset.

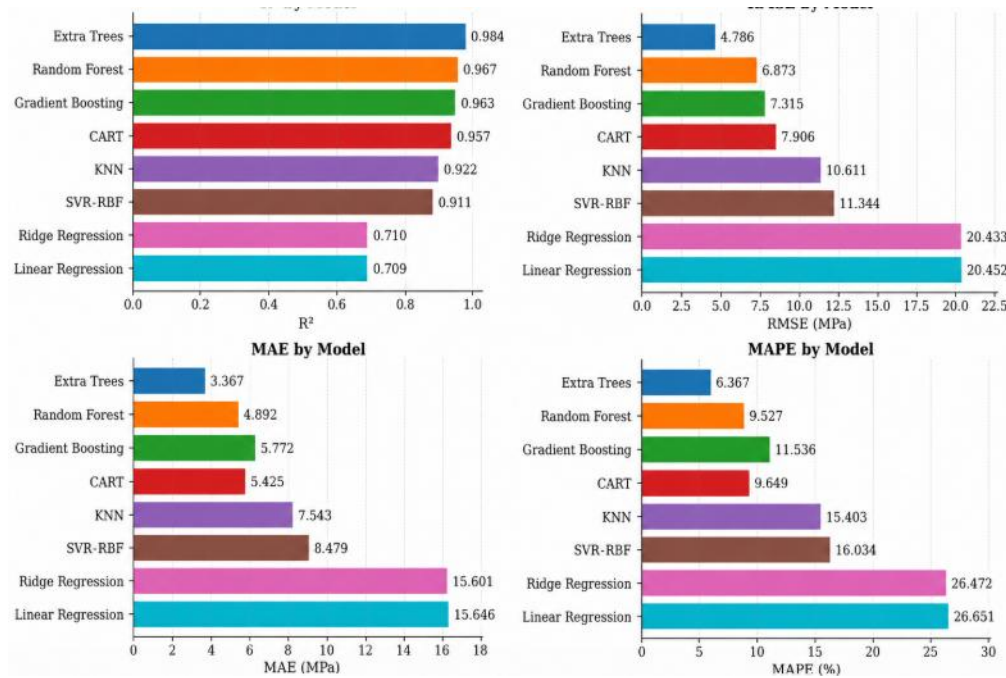


Fig. 5 Comparison of the tested regression models on the holdout test set.

4 Results, Analysis and Discussions

To predict the compressive strength, Extra Trees ML model was performed. Results of predicted versus experimentally obtained values are presented in Fig. 6. It is noticed that the values of the predicted and measured compressive strength are closely aligned along the 45° reference line. This behaviour reveals the strong agreement between the predicted and experimental compressive strength values, highlighting the high accuracy of the predictive model on the holdout test set.

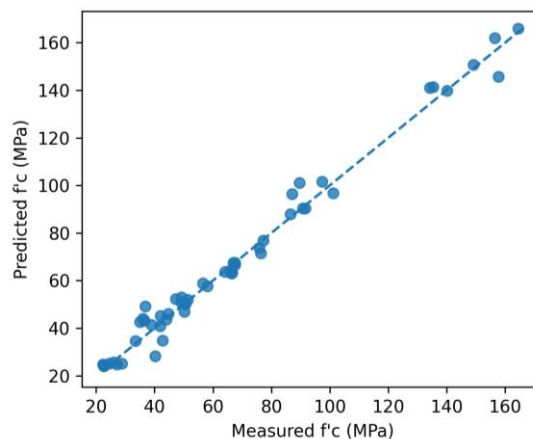


Fig. 6. Predicted versus measured compressive strength for Extra Trees.

It can be noticed that compressive strength values distribute with low dispersion when compressive strength values range between 40 MPa and 120 MPa which reveals that predicted values are accurate for normal concrete. With high compressive strength values higher than 130 MPa, scattered values were observed, however, a good level of accuracy was noticed.

Further, the clustering of the values of compressive strength around the diagonal line indicates that the prediction errors are low complying with high value of R^2 and low error metrics obtained from the Extra Trees model. It can be concluded that the nonlinear relationship between the input parameters and the target (compressive strength) can be captured by the model. It is observed from the figure that the Extra

Trees model offers reliable predictions of compressive strength, especially within the normal compressive strength concrete.

In addition, the residuals distribution with respect to the predicted compressive strength was studied and is presented in Fig. 7. The residual plot for the Extra Trees model indicates that the prediction errors appear to be generally well distributed around the zero line which suggests that the model does not show any significant bias and produces balanced predictions without consistent over or under predicting. It was observed that residual values range between -10 to 10 MPa, which indicates a good accuracy. Further, random distribution was observed in the residuals compared to the predicted compressive strength. It is worth mentioning that outliers associated to large deviations were observed in high values of compressive strength (130MPa) and therefore, accuracy of predicted value reduced.

Also, the residuals are more clustered at low compressive strength, which indicates more stable predictions at that range. The observed pattern of the residuals supports the robustness of the model developed by Extra Trees.

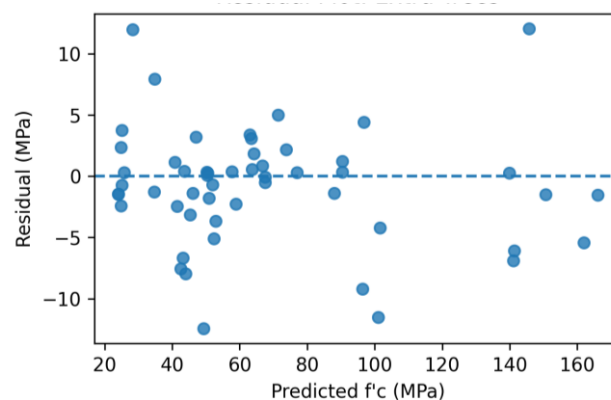


Fig. 7. Residual distribution against predicted compressive strength for Extra Trees.

4.1 Cross-Validation and Source-Aware Validation

This study performed Five-fold shuffled cross-validation to assess the internal robustness of the considered models and their ability to generate new data from several sources with source-aware validation. Previous study [59] performed on predicting concrete compressive strength stated that Cross-validation demonstrated reliable estimation of the model's ability to generalize the unseen data. Five-fold shuffled cross-validation resulted in the same general pattern. The results shown in Table 4 indicate that Extra Trees showed the highest mean cross-validated R^2 of 0.966 ± 0.021 , followed by Random Forest and then Gradient Boosting.

Table 4: Five-fold shuffled cross-validation performance.

Model	Mean R^2	SD R^2	RMSE (MPa)	MAE (MPa)
Extra Trees	0.966	0.021	7.432	4.709
Random Forest	0.963	0.020	7.826	5.175
Gradient Boosting	0.961	0.014	8.083	6.142
CART	0.936	0.029	10.404	7.690
KNN	0.877	0.060	14.263	9.383
SVR-RBF	0.832	0.063	16.973	11.905
Ridge Regression	0.730	0.020	21.759	17.332
Linear Regression	0.730	0.020	21.761	17.354

Fig. 8 demonstrates the comparison of the performance of each evaluated model, results show high discrepancy in different metrics. Ensemble-based methods including Extra Trees, Random Forest, and Gradient Boosting exhibited the highest R^2 values of 0.966, 0.963, and 0.961, respectively with the

lowest values of RMSE and MAE, this revealed the high accuracy of predictive models. Extra Trees model outperformed the other models with low variability identified by a standard deviation of 0.021.

While the non-ensemble methods, i.e., k-NN and SVR-RBF, exhibited moderate performance, with lower R^2 values of 0.877 and 0.832, respectively, and higher prediction errors. Linear and Ridge regression models showed weak performance associated to the lowest R^2 of 0.73 and the highest RMSE and MAE values. This indicates their limited ability to capture the nonlinear relationships between the input parameters (concrete constituents) and the compressive strength as a target. Further, the higher standard deviation observed for k-NN and SVR-RBF indicates less consistent performance across folds. Comparison results indicate the reliability and robustness of ensemble learning models in compressive strength prediction.

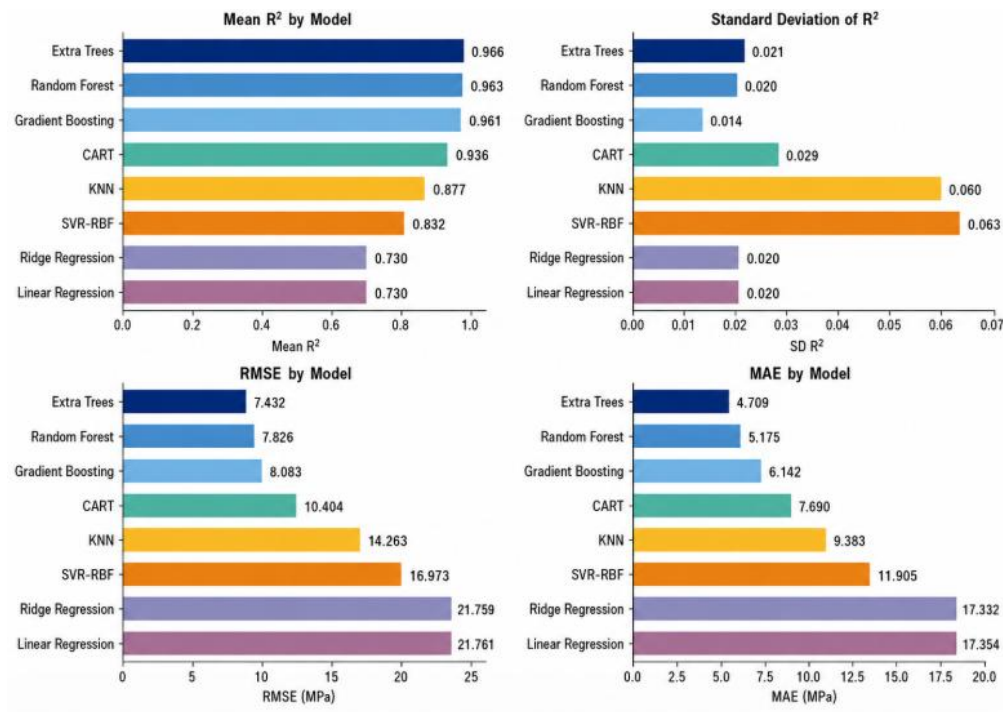


Fig. 8. Five-fold shuffled cross-validation for the ML models adopted in this study.

The validation was grouped by experimental source as presented in Table 5, results revealed that models' performance dropped substantially. The best grouped result was obtained by Extra Trees, with mean R^2 of 0.193, RMSE of 18.77 MPa, and MAE of 15.75 MPa. This gap means random-split performance should be interpreted as internal interpolation, not universal external generalization. Similarly, previous study [17] reported that XG-Boost model optimized by The Hunger Games search algorithm has shown to be the best performance with R^2 of 0.99, MAPE of 2.35, RMSE of 0.91, MAE of 0.77, and mean squared error of 0.83. Whereas the recent study [61] reported that XGBR model achieved the highest predictive performance, with 0.905 value of R^2 and an RMSE of 69.48

Table 5: Grouped validation by experimental source for the strongest models.

Model	Mean R^2	SD R^2	RMSE (MPa)	MAE (MPa)
Extra Trees	0.193	0.826	18.773	15.749
Gradient Boosting	0.154	0.796	19.230	16.429
Random Forest	0.101	0.684	20.966	17.858
CART	-0.165	0.937	23.134	19.717

4.2 Feature Importance and Sensitivity

According to the results obtained from the ML models, this study also performed a feature-importance analysis using the Extra Trees model, the model with best performance, to evaluate the influence of each parameter on fibre concrete as presented in Table 6. Result of feature-importance analysis identifies w/c ratio as the most influential predictor.

Table 6: Feature-importance results for the Extra Trees model.

Feature	Native importance	Permutation mean	Permutation SD
w/c	0.889	1.764	0.173
E (GPa)	0.049	0.049	0.008
Percentage %	0.037	0.017	0.006
Aspect ratio	0.025	0.027	0.012

In the Extra Trees model, w/c contributed up to 0.889 of native feature importance, while E, fibre percentage, and aspect ratio contributed 0.049, 0.037, and 0.025, respectively as depicted in Fig. 9. Similarly, the previous study [60] conducted on ultra-high performance FRC reported that the (w/c) ratio was the most significant input influencing FRC compressive strength. It exhibited the highest mean SHAP value (6.06), highlighting its strong effect on the hydration process and the development of the concrete's microstructure. Further, [12, 62] reported that the w/c ratio has shown the highest influence on compressive strength prediction. The ANFIS model resulted in a coefficient of determination (R^2) of 0.974, demonstrating its strong potential and efficient for accurate strength prediction in most engineering applications.

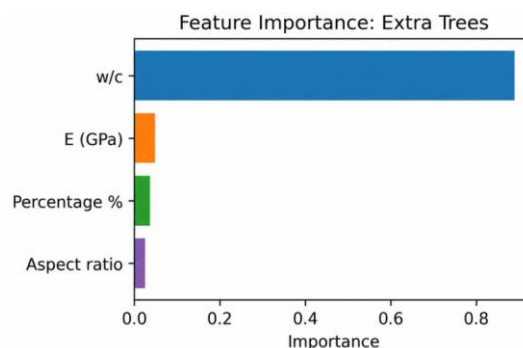


Fig. 9. Native feature importance for Extra Trees.

5 Conclusion

This study assessed different ML algorithms for predicting FRC compressive strength. Eight regression algorithms including linear models, Ridge regression, support vector regression, k-nearest neighbours, CART, random forest, gradient boosting, and Extra Trees were performed and assessed. Based on ML results discussed in this study, the following can be drawn:

1. Extra Trees model presented outperformed other evaluated ML models under random holdout validation with R^2 of 0.984, RMSE of 4.79 MPa, and MAE of 3.37 MPa.
2. Five-fold cross-validation of Extra Trees demonstrated strong internal predictive capability associated to an average R^2 of 0.966.
3. By using the grouped validation based on data source, the performance of Extra Trees model noticeably decreased to R^2 value of 0.193, indicating that random data partitioning may lead to an overestimation of the model's capability on generalizing unseen data.
4. The w/c ratio was identified as the most influential input on the compressive strength compared to fibre modulus of elasticity, fibre percentage, and aspect ratio. While fibre s aspect ratio presented the least influence on the compressive strength of concrete.

5. The w/c ratio is negatively correlated with the compressive strength of FRC.

6 Research Limitations

Although this study highlights the importance of predicting concrete compressive strength through different ML algorithms using the best performance models, various limitations are associated to this research. Firstly, the input parameters adopted in this study were limited to fibre type, aspect ratio, fibre volume fraction, and water-to-cement ratio. These parameters were chosen based on the studies available in literature that reported that these parameters are the most influential inputs affecting the FRC compressive strength. However, this is valid for concrete with normal strength values where different factors such as fly ash, silica fume slags and other supplementary cementitious materials, admixture characteristics, and curing conditions have not been considered due to the limited availability of experimental datasets. The limited input parameters influenced the predictive performance for unseen experimental sources; this can be noticed in the results of grouped validation which demonstrated R^2 value of 0.193.

Future research should focus on employing diverse databases that incorporate innovative materials, mix-design, and curing conditions to improve model robustness, interpretability, and accuracy. In addition, although this study performed feature importance analysis to identify the sensitivity of target to the input parameters, more advanced artificial intelligence techniques including SHAP values, feature interaction analysis, and partial-dependence plots, were not evaluated. The incorporation of these techniques in future studies would provide better understanding of the relationships between concrete constituent and its compressive strength.

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Author contributions. The author collected the dataset, performed the data analysis, and prepared the draft and final copy of the manuscript.

Use of artificial intelligence. No AI tools were used beyond language editing.

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