Materials Research Proceedings 63 (2026) 47-55 https://doi.org/10.21741/9781644904053-6

Evaluation of Compressive Strength of Fibre Reinforced Concrete using Randomizable Filtered Classifier

Abideen Adekunle GANIYU

Department of Civil Engineering, British University of Bahrain, Saar 527, Bahrain

a.ganiyu@bub.bh

Keywords: Fibre-reinforced Concrete, Compressive Strength, Machine Learning, Randomizable Filtered Classifier

Abstract. Fibre reinforced concrete (FRC) is a matrix material that adds discrete fibres to mixed concrete with the aim of increasing its mechanical properties. Conventional techniques for the evaluation of compressive strength of concrete entail time-consuming, laborious laboratory tests. Machine Learning (ML) models have the capabilities to utilise data on mix proportions to train a model that can accurately estimate strength outcomes for new mixes. This research employs a codeless ML tool to predict the compressive strengths of FRC using 173 datapoints with 7 input features of binder, water, fine aggregate, coarse aggregate, volume fraction of steel, aspect ratio and age. An 80:20 data split was adopted for training and testing sets, while pre-processing of data, visualisation, hyper-parameter optimisation, and feature selection were all done in the model development stage. Randomizable Filtered Classifier (RFC) algorithm yielded the optimal model, with a coefficient of determination, R^2 of 0.9886 and root-mean-square-error of 14.4529 as values of the performance measures. This implies that the model's predictions are closely aligned with the true values, underscores the strong correlation between the input features and the compressive strength, and asserts the model's validity. The study leverages data-driven soft computing methods to provide timely, cost-effective, accurate and reliable processes for the design of compressive strength of fibre-reinforced concrete for practical usage.

Introduction

The inclusion of discrete fibres into normal concrete to form Fibre reinforced concrete (FRC) is a significant advancement in concrete technology. In comparison with normal concrete, FRC exhibits enhanced mechanical and durability properties[1, 2], increased toughness and ductility[3], reduced micro-cracks resulting from shrinkage and other volume changes[4], reduced permeability [5], improved resistance to acid, alkali, and sulphate attacks [4], enhanced longevity in harsh environments [6], and reduced maintenance costs over the lifespan of a structure [7]. FRC is suitable for a wide range of structural applications, and can be tailored for specific applications by varying the type and amount of fibres used [8]. Compressive strength is a fundamental property for the structural design of concrete; it helps in understanding the stress-strain behavior which is crucial for predicting the structural behavior of concrete members. The compressive strength test of FRC is a critical evaluation of the material's ability to withstand axial loads [9]. FRC superior performance over conventional concrete is associated with increased peak stress, yield strain, ultimate strain, toughness index, and fracture toughness [10, 11] induced by fibre inclusion, these properties make FRC suitable for high performance structural applications[12, 13].

Fibres in FRC could be natural or synthetic, and are distributed throughout the concrete matrix, proper distribution can prevent fire balling, which can negatively impact fibre's effectiveness [14]. Steel, glass, carbon, basalt, polypropylene, polyester, coir, sisal, jute, hemp, flax, kenaf, bamboo, and hybrid fibres have been used in FRC matrix [15-18]. Long, short, crimped, hooked, hooked-end, twisted, milled, mil-cut, copper-coated, wave-shaped are examples of steel fibres used in FRC [19-21]. Steel fibres are commonly associated with the enhancement of tensile and flexural

Content from this work may be used under the terms of the Creative Commons Attribution 3.0 license. Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI. Published under license by Materials Research Forum LLC.

strength of FRC, however, their impact on compressive strength increments have been reported from moderate (13.69%) [22] to as high as marking a 233.1% (355.0 MPa) increase over the control mix [23]. The volume fraction of fibres in FRC is crucial to its compressive strength, increasing fibre content generally improves compressive strength, but there is an optimal range[24]. The composition of the concrete mix, including the cement content, aggregate type, water-cement ratio, use and type of admixtures, superplasticizers, etc. also influences the compressive strength[25].

Machine learning (ML) is a branch of artificial intelligence which mimics human-like learning processes in a structured, mathematical framework. It enables computer models to learn patterns from historical data and make informed decisions about new, unseen data based on patterns it learned [26]. ML has emerged as a powerful tool for predicting the compressive strength of concrete by offering a more efficient and accurate alternative to traditional experimental methods [27]. This approach leverages data-driven models to capture complex interactions between various concrete components, enabling precise predictions that are crucial for structural safety and material optimization [28].

Pal et. al. [29] assessed thirteen different machine learning models for the prediction of compressive strength of fibre-reinforced rubberized concrete using 905 experimental data points collated from diverse datasets. It deploys grid search and 10-fold cross-validation for hyperparameter tuning to optimize each model and provides an in-depth feature importance analysis to tackle the complex relationship between diverse concrete constituents. The results reveal that rubber content and the water/cement ratio are the major contributors to compressive strength, and CatBoost algorithm, with R^2 value of 0.865, and lowest error values emerged the best model. This analysis informs engineers which mix components to prioritize or modify when designing rubberized recycled aggregate FRC, and the viability of CatBoost algorithm as a reliable data-driven model for the compressive strength prediction.

An innovative framework for the prediction of compressive strength of recycled aggregate FRC combining ML with optimization algorithms was presented by Duan [30]. XGBoost algorithm was coupled with Tunicate Swarm Algorithm (TSA) to yield an outstanding result of R^2 value of 0.9897 and low error measures. Through extensive simulations, the research explicates the effects of steel fibre types on compressive strength, highlights the optimal fibre dosage, and offers insights into the trade-offs between material performance and fibre content. The research delves into the microstructural analysis of the FRC pore structures and explains the relationship between the internal structural characteristics and its compressive behavior. This link between microscopic observations and macroscopic strength provides a more holistic understanding of concrete performance.

Li et. al. [31] develops ML models to predict the 28-day compressive strength of steel FRC exploring both individual algorithms and ensemble techniques. The SVR AdaBoost model demonstrated the highest accuracy with an R^2 value of 0.96, and lowest error values of 4.4 MPa & 8 MPa for mean absolute error (MAE), and root mean square error (RMSE), respectively. The sensitivity analysis revealed that cement, silica fume, water, and superplasticizer have the most significant impact on the strength predictions, and this highlights the FRC constituents that must be closely controlled in practice to achieve reliable strength predictions. The research provides strong evidence that ML techniques could replace time-consuming traditional methods of estimating compressive strength of FRC.

WEKA is an open-source ML software with a wide array of algorithms for analyzing both qualitative and quantitative datasets [32]. The Random Filtered Classifier algorithm addresses both feature selection and classification simultaneously, it uses a randomization technique to filter out less relevant features, thereby focusing on the most informative ones for building the classifier, the approach is particularly effective in reducing the initial search space, which can significantly

enhance the computational efficiency of the classification process, and lead to more interpretable models [33].

The application of ML to compressive strength of FRC determination saves time, materials and costs. Using a codeless tool like WEKA for the prediction enables concrete materials experts without coding background to carry out the prediction. This research explores multiple algorithms in WEKA to develop and validate predictive models for the estimation of compressive strength of FRC. All the important modelling steps were undertaken before the optimal model was established. The correlation analysis of the input attributes with the output attribute were determined, likewise is the sensitivity analysis of the input attributes with the developed model.

Methodology

The dataset was obtained from GitHub, a public data repository. It was gathered from 12 experimental research on concrete collated by Hoang [34]. It contains 173 datapoints and 9 features namely, binder, water, fine aggregate, coarse aggregate, volume fraction of steel fibre, aspect ratio, age, splitting tensile strength, and compressive strength. The attributes are mainly the constituent materials in FRC with details about the steel fibre i.e. volume fraction, aspect ratio, and testing age of concrete. The only exception is the splitting tensile strength, which is a mechanical property of FRC. The statistical analysis of the features is presented in Table 1.

Table 1: Statistical Summary of the dataset

Variables	Unit	Min	Mean	Max	Standard deviation	Skewness
Binder	kg/m^3	230.00	403.59	651.00	105.92	0.24
Water	kg/m^3	133.00	205.61	762.00	120.90	3.98
Fine aggregate	kg/m^3	400.00	699.72	1049.20	122.69	-0.17
Coarse aggregate	kg/m^3	293.30	976.41	1236.00	234.99	-1.59
Volume fraction of steel fibre	%	0.20	0.99	5.00	0.54	2.55
Aspect Ratio	-	32.42	64.18	82.67	14.52	-0.45
Age	Day	7.00	27.68	91.00	11.74	3.26
Compressive strength	MPa	7.75	54.99	145.84	29.16	0.43
Splitting tensile strength	MPa	0.79	4.52	11.50	1.79	0.45

The dataset appears clean, with no missing values. The first preprocessing step was to remove the split tensile strength values from the dataset; this is essential because the value of compressive strength is independent of it both theoretically and in practice. This step ensured that the model learns patterns specific to the required output without interference from unrelated features. Next, the correlation between the remaining seven input features and the output feature was determine using the "*CorrelationAttributeEval*" feature of WEKA which was paired with a Ranker search method to list features in order of correlation strength.

For the model development, the dataset was randomly split into 80:20 ratio for training and testing, respectively. The random split is to ensure unbiased evaluation and generalization of the model's performance. In essence, 138 datapoints were used for the training, and 35 datapoints were used for the testing. N-folds of 5-fold and 10-fold, and Random splits of 66/34; 70/30, 75/25, 80/20; and 85/15 were simulated for available algorithms under lazy, meta, functions, rules, and trees classifiers. The effects of data standardization and normalization were later investigated on leading algorithms.

Further, hyperparameters were tuned for the leading algorithms to improve predictive accuracy, optimize learning efficiency, and enhance the robustness of the leading models. The evaluative

metrics for the constructed model encompass the correlation coefficient R, which assesses the statistical relationship between actual and predicted values, the coefficient of determination R^2, which elucidates the extent of variability accounted for by the fitted model, the mean absolute error (MAE) which quantifies the average magnitude of the errors in a set of predictions, and the root mean squared error (RMSE), which signifies the sample standard deviation of the discrepancies between observed and predicted values. Mathematical representations of *RMSE, MAE* and R^2 are presented in equations (1-3).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (1)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \quad (3)$$

where y_i, $\hat{y}_i$, $\bar{y}_i$ and n are the experimental output, model output, mean of the experimental output, and number of samples, respectively. The lower the values of *RMSE* and *MAE*, the better the model, the closer the value of R and R^2 value to 1, the better the model. Sensitivity analysis was also done using the optimal model to identify how each input feature influenced the model's prediction.

Results and Discussions

Figure 1 presents the outcome of correlation analysis done; it is observed that the order of linear dependence of the attributes on compressive strength is binder, coarse aggregate, age, water, aspect ratio, and volume fraction. Water and volume fraction have negative correlations, i.e. their increase leads to a decrease in compressive strength, while increase in other features leads to an increase in compressive strength as they are positively correlated.

	Binder	Water	Fine aggregate	Coarse aggregate	Volume fraction	Aspect Ratio	Age
Water	-0.424						
Fine aggregate	0.145	-0.578					
Coarse aggregate	0.152	-0.212	0.235				
Volume fraction	-0.089	0.261	-0.249	0.007			
Aspect Ratio	-0.117	0.213	-0.019	-0.405	-0.036		
Age	0.235	-0.080	0.242	0.200	-0.065	-0.011	
Compressive strength	0.686	-0.291	0.249	0.397	-0.031	0.129	0.341

Figure 1: Pearson correlation between features

The most promising results of the simulations were obtained for the 80/20 split; the top five algorithms are presented in Table 2. Randomizable Filtered Classifier (RFC) led the pack with R = 0.9861, and RMSE = 5.3382. Hence, it was applied for the testing stage where it yields R = 0.9943 corresponding to R^2 of 0.9886, this implies 98.86 % of compressive strength is accurately predictable from the input variables using the RFC model, and this underscores its' accuracy. The error values are MAE = 10.5868, and RMSE = 14.4529 which are higher than the values obtained from the training stage but are highly reasonable. The hyperparameters of the RFC – filter, filter options, base classifier and seed - were tuned, and the default values yield the best results. Figure 2 shows the relationship between the actual values and the predicted values of the compressive strength for the testing dataset.

Table 2: Performance Evaluation of Different Algorithm at Training

Name	R	R^2	MAE	RMSE
Meta- Randomizable Filtered Classifier	0.9861	0.9724	3.7144	5.3382
Meta- Regression by Discretization	0.9767	0.9539	5.5017	7.0973
Functions - Multilayers Perceptron	0.967	0.9351	11.1129	13.6195
Rules - M5Rules	0.9564	0.9147	6.8387	9.3252
Lazy - KStar	0.9463	0.8955	6.6291	10.3352

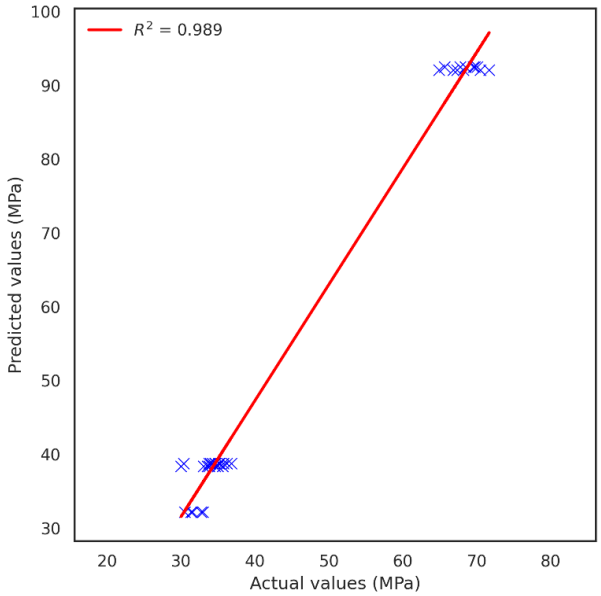


Figure 2: Actual vs. Predicted values of Compressive strength of RFC model

The result of the RFC model along with the outcome of the sensitivity analysis carried out on the features are presented in Table 3. According to the table, binder is the most important feature influencing the developed model, and the accuracy of the model will drop to 9.35% if it is removed from the input features. The next significant features are the volume fraction of fibre, water, and coarse aggregate, which will reduce the accuracy of the developed model to 25%, 30% & 36%, respectively when removed from the input features before modelling. Table 4 presents the R^2 values of RFC model developed in this research in comparison with other published research on ML prediction of FRC using WEKA software. The RFC model deployed in this research has the highest value of R^2, thereby yielding the highest accuracy.

Table 3: Sensitivity Analysis for Randomizable Filtered Classifier Algorithm

Name	R	R^2	MAE	RMSE
Randomizable Filtered Classifier, RFC (All features)	0.9943	0.9886	10.5868	14.4529
RFC (Excluding Binder)	0.3058	0.0935	17.3727	24.0887
RFC (Excluding Water)	0.5496	0.3021	17.2384	21.074
RFC (Excluding Fine Aggregate)	0.7146	0.5107	13.1953	15.7042
RFC (Excluding Coarse Aggregate)	0.6036	0.3643	16.0004	19.4675
RFC (Excluding Volume fraction of fibre)	0.5012	0.2512	19.0693	22.4879
RFC (Excluding Aspect Ratio)	0.8603	0.7401	20.2381	24.0631
RFC (Excluding Age)	0.8596	0.7389	19.7281	22.8833

Table 4: Comparison of Performance with Previous Models

Reference	Algorithm	R^2
[35]	Support Vector Machine	0.6801
[36]	K-Nearest Neighbour	0.984
[37]	Multilayer Perceptron	0.9107
This study	Randomizable Filtered Classifier	0.9886

Conclusions

The research utilised codeless software to develop an accurate model for the prediction of compressive strength of FRC. The dataset has 173 instances and seven input features which are important in the determination of compressive strength. A comprehensive approach was adopted for the modelling which produced the optimal RFC model with a R^2 of 0.9886. Binder is the most consequential input features in the developed model. The study demonstrates that data-driven soft computing techniques offer a reliable, cost-effective, and efficient approach for predicting the compressive strength of FRC, supporting their practical application in structural design.

Data Availability Statement

The dataset utilised in this study is available at https://github.com/NHDDTUEDU/DE_XGBoost_SFRC_fspt

References

[1] D.A. Joshi, G. Mounika, S. Sai Teja, V. Sarayu, K. Narendar, N.B. Ibrahim, D.M. Sangeetha, Novel Mechanical Strength Prediction Models of Fibre Reinforced Concrete Using Statistical Analysis, E3S Web of Conferences, 559 (2024). https://doi.org/10.1051/e3sconf/202455904019

[2] Z. Wang, H. Li, X. Zhang, Y. Chang, Y. Wang, L. Wu, H. Fan, The Effects of Steel Fiber Types and Volume Fraction on the Physical and Mechanical Properties of Concrete, Coatings, 13 (2023). https://doi.org/10.3390/coatings13060978

[3] G. Plizzari, S. Mindess, Fiber-reinforced concrete, in: Developments in the Formulation and Reinforcement of Concrete, 2019, pp. 257-287. https://doi.org/10.1016/B978-0-08-102616-8.00011-3

[4] F.M.D.S. More, S.S. Subramanian, Impact of Fibres on the Mechanical and Durable Behaviour of Fibre-Reinforced Concrete, Buildings, 12 (2022). https://doi.org/10.3390/buildings12091436

[5] T.E.T. Buttignol, J.L.A.O. Sousa, T.N. Bittencourt, Ultra High-Performance Fiber-Reinforced Concrete (UHPFRC): a review of material properties and design procedures, Revista IBRACON de Estruturas e Materiais, 10 (2017) 957-971. https://doi.org/10.1590/s1983-41952017000400011

[6] F. Kassimi, K.H. Khayat, Mechanical properties of fiber-reinforced concrete with adapted rheology, Cement and Concrete Composites, 118 (2021). https://doi.org/10.1016/j.cemconcomp.2021.103958

[7] N. Nassif, M. Talha Junaid, K. Hamad, Z. Al-Sadoon, S. Altoubat, M. Maalej, Performance-Based Prediction of Shear and Flexural Strengths in Fiber-Reinforced Concrete Beams via Machine Learning, Structural Engineering International, 34 (2024) 651-656. https://doi.org/10.1080/10168664.2024.2310520

[8] R. Wang, J. Zhang, Y. Lu, J. Huang, Towards Designing Durable Sculptural Elements: Ensemble Learning in Predicting Compressive Strength of Fiber-Reinforced Nano-Silica Modified Concrete, Buildings, 14 (2024). https://doi.org/10.3390/buildings14020396

[9] M. Amar, Comparative use of different AI methods for the prediction of concrete compressive strength, Cleaner Materials, 15 (2025). https://doi.org/10.1016/j.clema.2025.100299

[10] H. Alguhi, D. Tomlinson, Experimental and analytical study of steel and chopped glass fibre reinforced concrete under compression, Construction and Building Materials, 418 (2024). https://doi.org/10.1016/j.conbuildmat.2024.135421

[11] H. An, Y. Song, L. Liu, X. Meng, Experimental Study of the Compressive Strengths of Basalt Fiber-Reinforced Concrete after Various High-Temperature Treatments and Cooling in Open Air and Water, Applied Sciences, 11 (2021). https://doi.org/10.3390/app11188729

[12] M. Pourbaba, R. Chakraborty, M. Pourbaba, A. Belarbi, J. Yeon, A New Insight into the Design Compressive Strength of Ultra-High Performance Concrete, Buildings, 13 (2023). https://doi.org/10.3390/buildings13122909

[13] A.U. Abubakar, Statistical Evaluation of Compressive Strength in High Performance Concrete (HPC) with Steel Fiber Addition, Sustainable Structures and Materials, An International Journal, 2 (2019) 14-31.

[14] S. Kim, S. Han, C. Park, K.K. Yun, Compressive Behavior Characteristics of High-Performance Slurry-Infiltrated Fiber-Reinforced Cementitious Composites (SIFRCCs) under Uniaxial Compressive Stress, Materials (Basel), 13 (2020). https://doi.org/10.3390/ma13010159

[15] M. Abdulkareem, F. Ayeronfe, T.M. Jassam, A.H. AlAteah, K.A.A. Al-Sodani, M.M.H. Al-Tholaia, H. Yam, A. Ganiyu, S.C. Alih, Compressive and Flexural Strengths of Bio-Recycled Concrete Incorporated with Kenaf Fibre, Journal of Natural Fibers, 21 (2024). https://doi.org/10.1080/15440478.2023.2296913

[16] M. Abdulkareem, A. Ganiyu, A.H. AlAteah, K.A.A. Al-Sodani, M.M. Al-Tholaia, F. Ayeronfe, Static and Dynamic Resistance of Bio-concrete Incorporated with Kenaf Fiber, Journal of Natural Fibers, 22 (2025) 2462976. https://doi.org/10.1080/15440478.2025.2462976

[17] J. Li, J. Chang, H. Qiao, Research on optimal design of mechanical properties of hybrid fiber-reinforced concrete, Structural Concrete, 23 (2022) 1625-1641. https://doi.org/10.1002/suco.202100635

[18] H.H.Z. Khalel, M. Khan, A. Starr, N. Sadawi, O.A. Mohamed, A. Khalil, M. Esaker, Parametric study for optimizing fiber-reinforced concrete properties, Structural Concrete, 26 (2024) 88-110. https://doi.org/10.1002/suco.202300509

[19] Y.M. Abbas, M.I. Khan, Robust Machine Learning Framework for Modeling the Compressive Strength of SFRC: Database Compilation, Predictive Analysis, and Empirical Verification, Materials (Basel), 16 (2023). https://doi.org/10.20944/preprints202310.1573.v1

[20] W. Ben Chaabene, Machine Learning Prediction of Shear Capacity of Steel Fiber Reinforced Concrete, (2020).

[21] A.M. Salim, A.M. Salim, V. Gribniak, A. Rimkus, K. Holschemacher, U. Quapp, A. Singh, Mechanical Properties of Different Types of Fiber-Reinforced Concrete: Benefits and Limitations, Proceedings of International Structural Engineering and Construction, 11 (2024). https://doi.org/10.14455/ISEC.2024.11(2).MAT-09

[22] A.P. Adewuyi, O. Animbom, Performance-Based Evaluation of Steel Fibre Reinforced Normal- and High-Strength Concretes Using Statistical Analysis of Experimental Database, Journal of Civil Engineering and Urbanism, 14 (2024) 238-246. https://doi.org/10.54203/jceu.2024.25

[23] W. Ni, X. Cui, J. Yuan, W. Sun, C. Cui, Y. Wu, J. Feng, The influence of fiber, aggregate and cementitious materials on the mechanical properties of ultra-high content steel fiber reinforced reactive powder concrete, Construction and Building Materials, 431 (2024) 136530. https://doi.org/10.1016/j.conbuildmat.2024.136530

[24] M. Iqbal Khan, Y.M. Abbas, Significance of fiber characteristics on the mechanical properties of steel fiber-reinforced high-strength concrete at different water-cement ratios, Construction and Building Materials, 408 (2023). https://doi.org/10.1016/j.conbuildmat.2023.133742

[25] L.R. Mailyan, A.N. Beskopylny, B. Meskhi, S.A. Stel'makh, E.M. Shcherban, O. Ananova, Optimization of Composition and Technological Factors for the Lightweight Fiber-Reinforced Concrete Production on a Combined Aggregate with an Increased Coefficient of Structural Quality, Applied Sciences, 11 (2021). https://doi.org/10.3390/app11167284

[26] A.A. Ganiyu, F.R. Alalawi, Efficacy of instance-based learning algorithms for the prediction of ultimate bearing capacity of piles, in: 4th Asia-Pacific Conference on Physical Modelling in Geotechnics, 2024.

[27] I.B. Mustapha, Z. Abdulkareem, M. Abdulkareem, A. Ganiyu, Predictive Modeling of Physical and Mechanical Properties of Pervious Concrete using XGBoost, Neural Computing and Applications, (2024). https://doi.org/10.1007/s00521-024-09553-w

[28] I.B. Mustapha, M. Abdulkareem, T.M. Jassam, A.H. AlAteah, K.A.A. Al-Sodani, M.M.H. Al-Tholaia, H. Nabus, S.C. Alih, Z. Abdulkareem, A. Ganiyu, Comparative Analysis of Gradient-Boosting Ensembles for Estimation of Compressive Strength of Quaternary Blend Concrete, International Journal of Concrete Structures and Materials, 18 (2024). https://doi.org/10.1186/s40069-023-00653-w

[29] A. Pal, K.S. Ahmed, F.M.Z. Hossain, M.S. Alam, Machine learning models for predicting compressive strength of fiber-reinforced concrete containing waste rubber and recycled aggregate, Journal of Cleaner Production, 423 (2023). https://doi.org/10.1016/j.jclepro.2023.138673

[30] S. Duan, Compressive strength prediction of fiber-reinforced recycled aggregate concrete based on optimization algorithms, Frontiers in Built Environment, 10 (2024). https://doi.org/10.3389/fbuil.2024.1509714

[31] Y. Li, Q. Zhang, P. Kamiński, A.F. Deifalla, M. Sufian, A. Dyczko, N.B. Kahla, M. Atig, Compressive strength of steel fiber-reinforced concrete employing supervised machine learning techniques, Materials, 15 (2022) 4209. https://doi.org/10.3390/ma15124209

[32] M. Nidhya, P.K. Shah, Acquiring Knowledge by Performing Classification and Clustering of Datasets using WEKA: Intelligence through MLP, RF, DT, and RepTree, in: 2023 International Conference on Communication, Security and Artificial Intelligence (ICCSAI), IEEE, 2023, pp. 833-837. https://doi.org/10.1109/ICCSAI59793.2023.10421077

[33] V. Mhetre, M. Nagar, Classification based data mining algorithms to predict slow, average and fast learners in educational system using WEKA, in: 2017 International Conference on Computing Methodologies and Communication (ICCMC), IEEE, 2017, pp. 475-479. https://doi.org/10.1109/ICCMC.2017.8282735

[34] N.-D. Hoang, Predicting tensile strength of steel fiber-reinforced concrete based on a novel differential evolution-optimized extreme gradient boosting machine, Neural Computing and Applications, (2024). https://doi.org/10.1007/s00521-024-10458-x

[35] A.U. Abubakar, K.A. Kau, M. Hassan, M.S. Tabra, Prediction of Compressive Strength in High Strength Concrete with Steel Fiber Addition using Support Vector Machine Algorithm, Sustainable Structures and Materials, An International Journal, 3 (2020) 25-36.

[36] A.U. Abubakar, M.S. Tabra, Prediction of Compressive Strength in High Performance Concrete with Hooked-End Steel Fiber using K-Nearest Neighbor Algorithm, International Journal of Integrated Engineering, 11 (2019). https://doi.org/10.30880/ijie.2019.11.01.016

[37] A.U. Abubakar, M.S. Tabra, Predictive Capabilities of Multilayer Perceptron (MLP) in WEKA Algorithm for High Strength Concrete with Steel Fiber Addition, Journal of Cement Based Composites, 1 (2020) 13-18. https://doi.org/10.36937/cebacom.2020.002.003