Split Tensile Strength prediction of Coir Fiber Reinforced Concrete using Machine Learning Technique

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Abstract - Coir fiber reinforced concrete (CFRC) is widely used nowadays due to its easily availability, economical and enhancement in strength. Many past literatures show strength enhancement of concrete when coir fiber is added to it. CFRC enhances the tensile properties of concrete. The mechanical behavior of CFRC varies with various parameters such as, fiber length, its diameter, volume of fiber added etc. It is not effective to evaluate the tensile strength of CFRC with existing empirical equations. So, a prediction model for split tensile strength is necessary for CFRC to predict the strength for any grade of concrete using various parameters. The Machine Learning models are very effective method for prediction model development that have complex relationships. So, this paper discusses about tensile strength prediction of various Machine learning models like Multiple Linear Regression (MLR), Support Vector Regression (SVR), Decision Tree (DT) Regression, K Nearest Neighbors (KNN) Regression, Random Forest (RF) Regression, etc. of CFRC by collecting data from previous existing literatures of CFRC. Among that XGBoost shows a better R^2 value of 0.95 and a lower Root Mean Square Error value of 0.348 MPa when training the data.

Key Words: Machine Learning, Coir fiber Reinforced Concrete, Split Tensile Strength, Prediction Models

1.INTRODUCTION

In recent years, there has been interest in the possible application of Coir Fibers (CFs) as building materials. It might be possible to reduce the adverse environmental effects of construction by incorporating CFs into mortar or concrete, which would promote a more sustainable and ecologically aware building industry [1], [2], [3]. Compared to natural fibers like sisal, flax, hemp, and kenaf and synthetic fibers like polypropylene, polyvinyl, and nylon fibers, CFs have a lower global warming potential of 0.2 kg equivalent CO_2 per kg. Furthermore, CFs are not expensive and widely available, especially in tropical areas of the world [3],[5]. Natural fibers like CFs can be added to cementitious composites to improve their mechanical properties [3, 6, 7, 8, 9, 10], increase their durability [5, 8, 11, 12], and lessen their environmental impact [4, 9, 12]. However, in order to fully understand and optimize the performance of materials like CF-reinforced mortar (CFRM) and in CFRC, experimental studies are required to evaluate the effects of various parameters on performance, such as fiber volume fraction, fiber length and pretreatment techniques. When mixing, long fibers have a propensity to tangle easily, leading to a high porosity and poor workability. Conversely, short fibers may not have a long enough embedded length to achieve the desired fiber bridge effect [3], [4]. So, length and volume of CF are tensile strength influencing parameters of CFRC. Oth-er parameters that can be influencing are cement, Fine Aggregate (FA), Coarse Aggregate (CA), superplasticizers (SP), water, Fly ash etc. Concrete's compressive strength is decreased when CF is added without any surface treatment [18, 19, 20]. The existence of weaker ITZ is the cause. Concrete's compressive strength is in-creased by boiled CF, but its tensile strength is decreased [21]. CF's tensile strength is decreased by alkali treatment [22]. Thus, whether the fiber is treated or not will have an impact. The split tensile strength is a mechanical property of concrete. It can be enhanced by adding fiber to it. It is experimentally tested by destructive testing in Compression Testing Machine as mentioned in various standards [13]. It is a destructive type testing. So, a prediction model will be more advantageous for CFRC. Many prediction models are developed for different other types of concrete using machine learning [14, 15, 16, 17]. There are many literatures, that predict the strength of various fiber reinforced concretes using various machine learning techniques and also with different parameters [23, 24, 25, 26, 27]. But prediction models for CFRC are absent. The prediction model is evaluated based on Coefficient of Regression (R^2) and Root Mean Square Error (RMSE).

This work focuses on the evaluation of various machine learning models developed for CFRC by its R^2 values and RMSE values.

2.METHODOLOGY

The steps involved in this work are, data collection, identification of parameters and training of the data.

2.1.DATA COLLECTION

The data for training the model are collected from various journals [23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35]. The data of each literature are collected and converted into same units. The data includes quantity of water used, volume fraction of fibers, its tensile strength etc. There are 99 data set were collected from various past literatures. The statistical summary of split tensile strength from collected data is shown in Table 1. Here, the data suggests that, the difference between mean and median are less. And the standard deviation suggests that, it's a moderately spread data. And shows a slight longer right tail and a sharper peak.

Table -1: Statistical Summary of Split Tensile Strength

	Values
Mean	3.497
Median	3.25
Standard Deviation	1.434
Skewness	1.872
Kurtosis	4.536
Maximum	8.75
Minimum	1.4

2.2. IDENTIFICATION OF PARAMETERS

From previous studies, it is understood that, some components of cementitious materials will influence more on its compressive strength and some will be less. Such highly influencing parameters has to be identified for CFRC. The parameters that can be added for describing coir fiber are its length and volume fraction. Water to cement ratio (w/c), fine aggregates to cement ratio, coarse aggregate of 12 mm to cement ratio, coarse aggregate of 20 mm to cement ratio, the specific gravity of aggregates, silica fume to cement ratio, coir fiber volume, coir fiber length used, percentage of superplasticizer, whether the coir fiber is treated with any surface treatment materials like alkali method, boiling, etc., and its corresponding tensile strength are the parameters chosen for training the models. There are 12 parameters are chosen for predicting tensile strength. The correlation heatmap of the data is shown in Fig 1. Here, the values vary from -1 to 1 and is represented with dark green and red respectively.

	w/b	FA/b	CA12/ b	CA20/ b	SG of FA	SG of CA12	SG of CA20	fibre volum e	SP %	length	silica fume/ c	SS
w/b	1	0.4792	-0.535	0.3942	-0.035	-0.294	0.3661	-0.317	0.0829	-0.002	0.0275	-0.247
FA/b	0.4792	1	-0.133	0.2220	-0.314	-0.012	0.0736	-0.364	-0.015	-0.023	0.0687	0.2611
CA12/ b	-0.535	-0.133	1	-0.906	0.3139	0.8717	-0.975	0.1322	-0.176	-0.071	0.3032	0.1379
CA20/ b	0.3942	0.2220	-0.907	1	-0.290	-0.850	0.9286	-0.102	0.1487	0.0965	-0.350	0.1581
SG of FA	-0.035	-0.314	0.3139	-0.290	1	0.2982	-0.359	0.1022	0.2458	0.1793	0.1718	-0.017
SG of CA12	-0.294	-0.012	0.8717	-0.850	0.2982	1	-0.895	0.0774	-0.215	-0.182	0.3267	-0.003
SG of CA20	0.3661	0.0736	-0.975	0.9286	-0.358	-0.895	1	-0.110	0.1973	0.1023	-0.377	-0.018
fibre volum e	-0.317	-0.364	0.1322	-0.102	0.1022	0.0774	-0.111	1	-0.014	0.3029	-0.127	-0.197
SP %	0.0829	-0.015	-0.176	0.1487	0.2458	-0.215	0.1973	- 0.0143 6	1	0.4834	-0.094	0.0732
length	-0.003	-0.023	-0.071	0.0965	0.1793	-0.181	0.1023	0.3029	0.4834	1	-0.136	0.1116
silica fume/ c	0.0275	0.0687	0.3032	-0.350	0.1718	0.3267	-0.377	-0.127	-0.094	-0.136	1	-0.175
SS	-0.248	0.2611	0.1378	0.1581	-0.017	-0.003	-0.018	-0.197	0.0732	0.1116	-0.176	1

Fig. 1: Correlation heatmap of collected data

2.3. TRAINING OF DATA

The regression models adopted are multi-linear regression (MLR) model, decision tree regression (DT) model, Random Forest (RF) Regression Model, Support Vector Regression (SVR), Artificial Neural Network (ANN), eXtreme Gradient Boosting (XGBoost) and k Nearest Neighbors (KNN) Regression model. 80% of data collected will be used for training and 20% of the data for testing. The hyperparameters are selected based on better result of hyperparametric tuning. Then the comparison is carried out with the obtained Coefficient of Determination R^2 value and RMSE value.

3.RESULTS AND DISCUSSION

The training and testing of data were carried out using Python programming. 20% of collected data is used for testing were 80% for making model. The R^2 value and RMSE obtained after all regression tests are shown in Table 2.

3.1. MULTIPLE LINEAR REGRESSION

The assumption made was, all data are linearly depending on the tensile strength and each variable are independent to each other. The R^2 value obtained after testing was 0.62. The RMSE value obtained after testing is 0.814. The predicted value and the actual values of tested data were plotted to a graph and is shown in Fig 2. This deviation is due to non-linear behaviour of some parameter used for generation of the models.

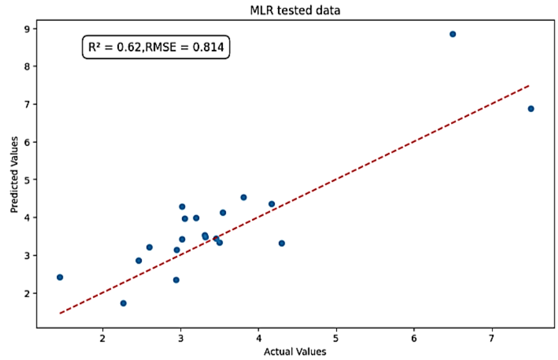

Fig. 2: Actual to Predicted values of MLR

3.2. DECISION TREE REGRESSION

Hyperparametric tuning was done to identify the best parameters. Eight is deter-mined to be the maximum depth, minimum number of leaves needed as 1 and minimum split as 2. The assumption made was, all data variables are independent and strength can be approximated by a series of piecewise constant functions. The R^2 value obtained after testing was 0.86. The RMSE value obtained after testing is 0.388. The predicted value and the actual values of tested data were plotted to a graph and is shown in Fig 3.

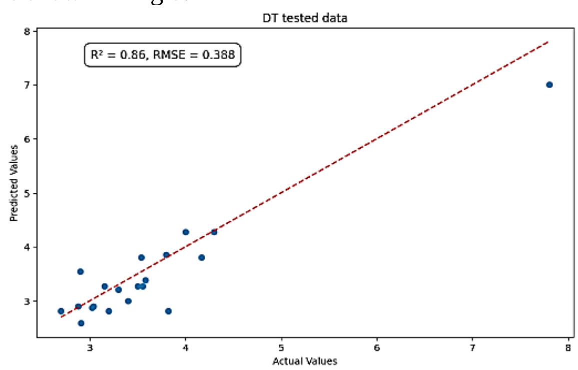

Fig. 3: Actual to Predicted values of DT

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3.3. RANDOM FOREST REGRESSION

RF is a machine learning technique that combines many DTs. Hyperparametric tuning was done to identify the best parameters. Eight is determined to be the maximum depth. The number of estimators is 500. And minimum number of leaves needed as 1 and minimum split as 2. The R^2 value obtained after testing was 0.92. The RMSE value obtained after testing is 0.302. Fig 4 shows the predicted and the actual values of tested data.

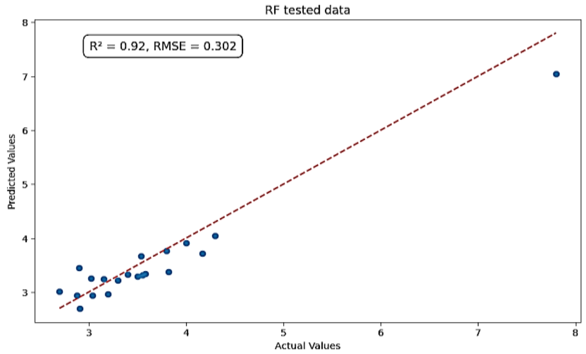

Fig. 4: Actual to Predicted values of RF

3.4. ARTIFICIAL NEURAL NETWORK

The hyperparameters identified are alpha as 0.01, maximum number of iterations is 500, rectified linear unit as activation function and Adam as optimizer. The R^2 value obtained after testing was 0.67. The RMSE value obtained after testing is 0.607. The predicted value and the actual values of tested data were plotted and is shown in Fig 5.

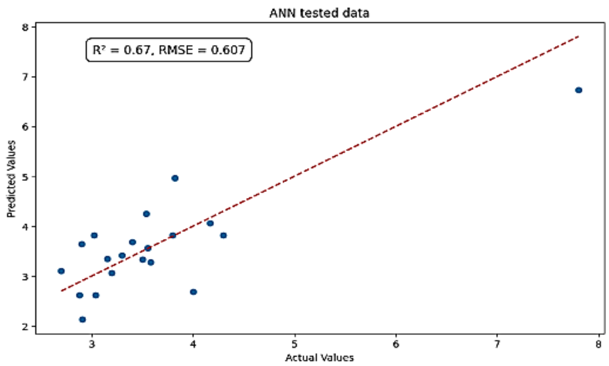

Fig. 5: Actual to Predicted values of ANN

3.5. SUPPORT VECTOR REGRESSION

Hyperparametric tuning was done to identify the best parameters. The parameters identified are regularization parameter as 100, width of margin as 0.1 and the kernel function is radial basis function. The R^2 value obtained after testing was 0.83. The RMSE value obtained after testing is 0.811. The predicted value and the actual values of tested data were plotted to a graph and is shown in Fig 6.

3.6. XGBOOST REGRESSION

The hyperparameters identified are number of estimators as 500, maximum depth as 7, percentage of rows used for each tree construction is 0.9 and alpha and lambda as 0.1. The R^2 value obtained after testing was 0.95. The RMSE value obtained after testing is 0.348. The predicted value and the actual values of tested data were plotted to a graph and is shown in Fig 7.

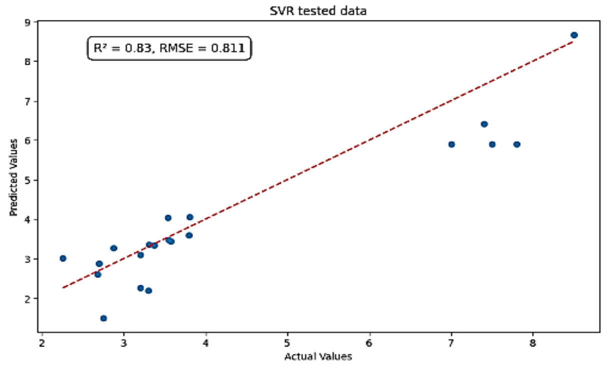

Fig. 6: Actual to Predicted values of SVR

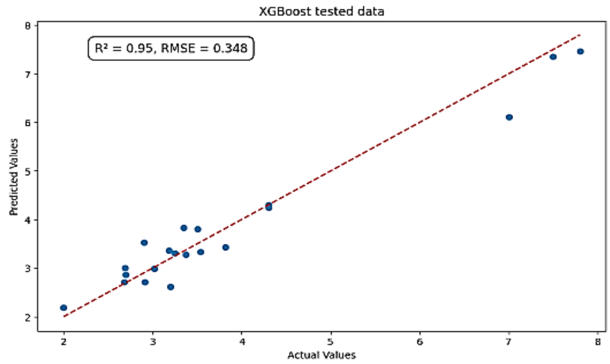

Fig. 7: Actual to Predicted values of XGBoost

3.7. K NEAREST NEIGHBORS REGRESSION

The hyperparameters identified are k value as 2, Manhattan equation for distance calculation and brute algorithm for solving. The R^2 value obtained after testing was 0.86. The RMSE value obtained after testing is 0.393. The predicted value and the actual values of tested data were plotted and is shown in Fig 8. The assumption made was, data points that are close to each other in feature space are likely to have similar target values.

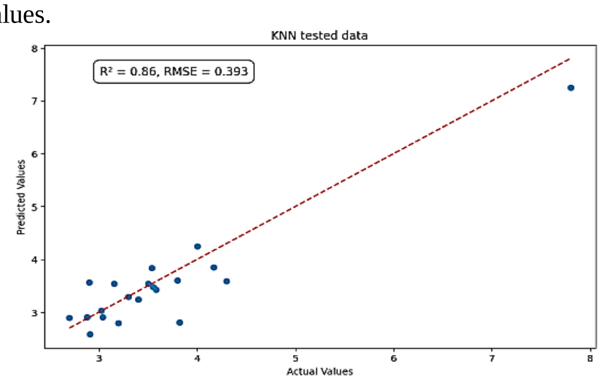

Fig. 8: Actual to Predicted values of KNN

Decision Tree Regression and KNN Regression shows a R^2 value of 0.86 and a RMSE value of 0.388 MPa and 0.393MPa respectively. This suggests that both models produced accurate tensile strength estimates by successfully capturing the non-linear connections included in the data. These models' accuracy in simulating complex patterns highlights how well suited they are for forecasting the mechanical properties of composite materials such as CFRC. MLR shows a poor result due to non linear behaviour of parameters. XGBoost shows a higher value. This shows bagging and boosting is more applicable in CFRC.

Table 2. R^2 value and RMSE of various models

	R^2 value	RMSE (MPa)
MLR	0.62	0.814
DT	0.86	0.388
KNN	0.86	0.393
RF	0.92	0.302
ANN	0.67	0.607
SVR	0.83	0.811
XGBoost	0.95	0.348

4. CONCLUSIONS

The prediction models are developed and tested the following conclusions are ob-tained:

- Multiple Linear Regression shows a lower R2 value of 0.62 and higher RMSE value of 0.814 MPa among other models. Its due to the non-linear behaviour of parameters.
- The ensembling machine learning models, RF and XGBoost gives better results. XGBoost shows higher R2 value of 0.95 than all other prediction models with a RMSE of 0.348 MPa. Random Forest Regression shows a R2 value of 0.92 and a RMSE value of 0.302 MPa. It shows the effectiveness of bagging and boosting in CFRC.
- Decision Tree Regression shows a R2 value of 0.86 and a RMSE value of 0.388 MPa and K Nearest Neighbors Regression shows a R2 value of 0.86 and a RMSE value of 0.393MPa.
- Prediction model developed by Artificial Neural Network shows a R2 value of 0.67 and a RMSE value of 0.607 MPa. And Support Vector Regression shows a R2 value of 0.83 and a RMSE value of 0.348 MPa.

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