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Prediction and Interpretability Analysis of Concrete Tensile Strength Using Machine Learning

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Fiber-Reinforced Concrete (FRC) is used for its improved tensile performance and crack resistance. However, accurate prediction of split tensile strength remains challenging due to the nonlinear influence of mix parameters. This study presents a machine learning–based approach for predicting the split tensile strength of FRC using experimental data. Experimental data from various FRC mix designs were used to develop predictive models using advanced machine learning techniques: Extreme Gradient Boosting (XGBoost), Gaussian Process Regression (GPR), Support Vector Regression (SVR), and Random Forest (RF). Among these models,XGBoost exhibited exceptional performance, attaining R^2 =0.97, RMSE = 0.0313, and MAE = 0.0253 during the training phase, and R^2 =0.88, RMSE = 0.0836, and MAE = 0.0665 in the testing phase. To further interpret the model predictions, sensitivity analysis was conducted using Shapley Additive exPlanations (SHAP). The SHAP-based analysis revealed that fiber content and ultimate load are the most influential parameters affecting tensile strength, followed by curing age and water–cement ratio. The results highlight the effectiveness of the XGBoost model in predicting the tensile strength of Concrete and provide valuable insights into the relative importance of key input variables. This study demonstrates that machine learning-based predictive frameworks can serve as reliable tools for optimizing material design and reducing dependence on extensive experimental testing, thereby supporting the development of more efficient and sustainable construction materials.

Keywords: XGBoost, Machine Learning, SHAP Analysis, Fiber-Reinforced Concrete, Tensile Strength.

Introduction:

Fiber-reinforced Concrete (FRC) is widely used due to itsenhanced tensile performance, improved crack resistance, and greater durability compared with conventional concrete. The tensile strength of these materials is influenced by several interacting parameters, including fiber content, water–cement ratio, curing age, and loading conditions. Accurate prediction of tensile strength is therefore essential for safe structural design and efficient mix optimization. Traditional empirical and regression-based methods often fail to capture the nonlinear relationships governing tensile behavior. Recently, machine learning techniques have been increasingly adopted to model complex material behavior with improved prediction accuracy. However, most existing studies focus on compressive strength prediction, while tensile strength prediction remains relatively underexplored. In addition, the limited interpretability of many machines learning (ML) models poses challenges for their application in engineering practice. This study addresses these issues by developing machine learning-based models for tensile strength prediction and employing explainable methods to interpret model behavior.

In addition, the interpretability of ML models has gained increasing attention in recent years. Explainable artificial intelligence methods, including Shapley Additive explanations (SHAP), have been introduced to provide quantitative insights into feature contributions and to enhance the transparency of model predictions [1][2][3][4][5].

Literature Review:

Previous studies have shown that fiber reinforcement significantly improves the tensile strength and crack resistance of cement-based composites [1][2][3]. Experimental investigations have highlighted the importance of parameters such as fiber content, curing age, and water–cement ratio in governing tensile behavior [4][5]. However, experimental testing is often time-consuming and may exhibit variability due to material heterogeneity.

To overcome these limitations, researchers have explored empirical and machine learning-based prediction models. While empirical models provide limited accuracy, machine learning approaches such as Support Vector Regression, Random Forest, and Gaussian Process Regression have demonstrated improved performance in predicting strength-related properties of cement-based materials [1][2][3][4][5][6]. Nevertheless, studies focusing specifically on tensile strength prediction using interpretable ML frameworks remain limited, highlighting the need for further research in this area.

Research Methodology:

Data Collection:

This study acquired a comprehensive experimental dataset regarding the Fiber-Reinforced Concrete from an unpublished Bachelor's thesis by Imran Ali Channa at the Laboratory of Structural Engineering, Quaid-e-Awam University of Engineering, Science and Technology, Nawabshah. In total, 120 records were collected. The dataset was split 80/20, with 96 samples (80%) allocated to train the ML algorithms, while the remaining 20% (24 data points) were reserved for testing. Following standard AI model practices, the training stage initially assesses the model's prediction quality, gauging the accuracy of output predictions. Subsequently, the testing phase, using a separate dataset, verifies the model's reliability in predicting the output. In this study, four parameters, including Fiber_Content, Ultimate Load, W/C ratio, and Curing Age (Days), were selected as input features for the ML models. The Tensile Strength (TS) values were identified as the output data for prediction. Fiber-reinforced concrete was prepared using controlled mix proportions to evaluate its tensile strength performance. The experimental materials used in this study, including fiber and the tested concrete cylinder, are shown in Figure 1.

Figure 1. Fiber and demolished Cylinder

Table 1. Statistical description of the dataset

Statistic	Fiber Content (%)	Ultimate Load (N)	W/C ratio	Curing Age (Days)	Tensile Strength (N/mm²)
Count	120.00	120.00	120.00	120.00	120.00
Mean	2.50	120354.25	0.50	28.00	3.84
Std	1.71	6553.87	0.00	0.00	0.20
Min	0.00	103696.00	0.50	28.00	3.37
25%	1.00	117385.25	0.50	28.00	3.76
50%	2.50	121283.50	0.50	28.00	3.88
75%	4.00	125511.50	0.50	28.00	3.98
Max	5.00	131611.00	0.50	28.00	4.19

Parameters: Fiber Content (%), Ultimate Load (N), W/C ratio, Curing Age (Days), Split Tensile Strength (N/mm^2)

Table 1 summarizes the statistical characteristics of the experimental dataset used in this study. The data reflect a wide range of fiber content levels and applied load conditions. The water–cement ratio and curing age were maintained at constant values to ensure controlled experimental conditions. The effectiveness of machine learning models largely depends on the quality and distribution of input variables. Therefore, parameters with a direct influence on tensile strength were selected as model inputs. Table 1 provides detailed descriptive statistics, including the total number of samples, mean, standard deviation, quartiles (25th, 50th, and 75th percentiles), and the minimum and maximum values of each parameter. These statistics indicate adequate variability in the key influencing factors, supporting reliable ML model training and tensile strength prediction.

Figure 2 illustrates the frequency distribution of the experimental dataset and its relationship with the tensile strength of concrete using combined scatter and histogram plots. The left vertical axis represents the tensile strength (N/mm²), while the right vertical axis indicates the frequency of samples. The horizontal axis corresponds to the selected input parameters, including fiber content (%), ultimate load (N), water-to-cement (W/C) ratio, and curing age (days).

For fiber content, the highest sample concentration lies between 1% and 4%, where tensile strength shows a noticeable increasing trend, indicating the beneficial role of fibers in enhancing tensile performance. The ultimate load parameter exhibits a strong positive correlation with tensile strength, with peak frequency occurs between 115 and 125 kN, corresponding to higher tensile strength values. The W/C ratio remains constant across most samples; however, its influence is reflected through minor variations in tensile strength, highlighting its indirect effect on material performance. Curing age is fixed at 28 days for the majority of samples, ensuring consistency in hydration and strength development. Figure 2. illustrates the frequency distribution of the experimental dataset and its relationship with tensile strength using scatter and histogram plots.

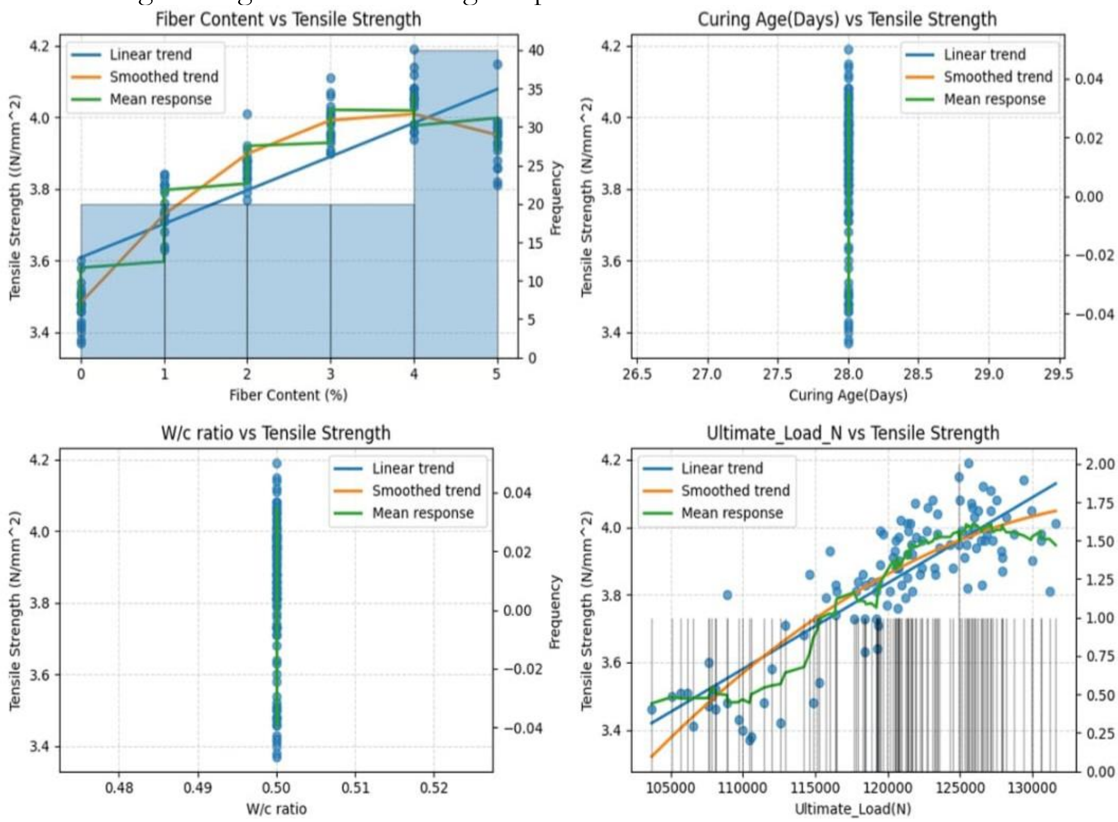

Figure2. Relationship between input and output

Data Preprocessing:

Before developing the machine learning models, a systematic data preprocessing procedure was carried out to ensure the reliability and consistency of the dataset. All input variables, including fiber content (%), ultimate load (N), water–cement ratio, and curing age (days), were examined for missing values and anomalies. The dataset was found to be complete, with no missing observations. Outliers were assessed using boxplots and Z-score analysis; no statistically significant outliers ($|Z| > 3$) were found.

Correlation analysis was conducted to minimize redundancy and avoid multicollinearity among input variables. The correlation coefficients for all feature pairs were below the critical threshold ($|r| < 0.85$), indicating that each parameter contributed unique information to the model; no feature was excluded.

All input features were normalized using Min–Max scaling to bring them into a comparable numerical range, which enhances numerical stability and accelerates model convergence. Subsequently, the dataset was randomly divided into training (80%) and testing (20%) subsets using a fixed random state (random_state = 42) to ensure reproducibility and unbiased performance evaluation. The overall methodology adopted for data preprocessing and machine learning model development is illustrated in Figure 3.

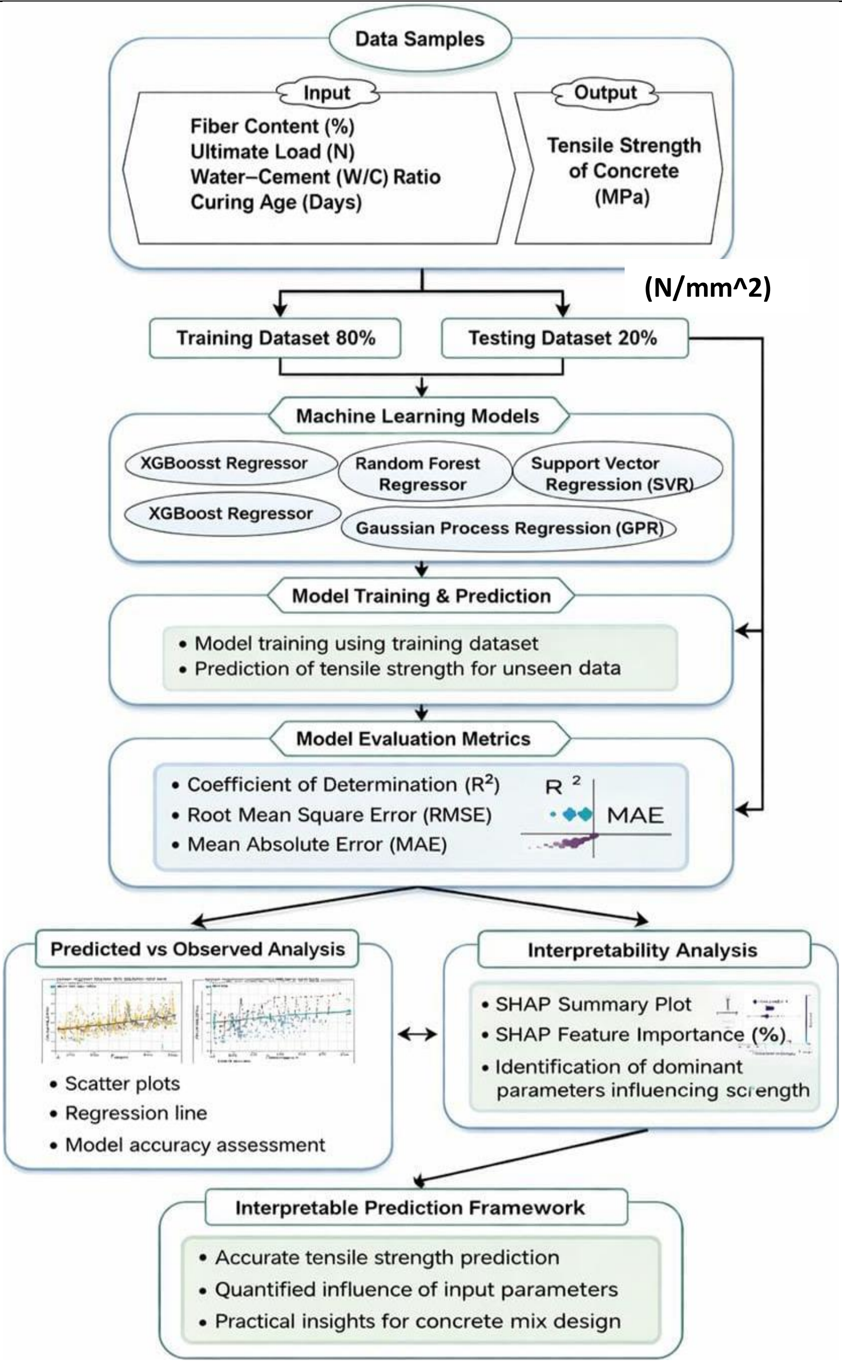

Figure 3. The methodology for constructing the ML models to predict the TS

Overview of XGBoost Model:

XGBoost employs a regularized objective function that includes both training loss and model complexity penalties, which helps prevent overfitting and improve generalization performance. Additionally, it supports learning rate shrinkage, column and row subsampling, and tree pruning, enhancing robustness and computational efficiency.

In this study, XGBoost was utilized to predict the tensile strength of concrete using key input parameters such as fiber content and ultimate load. Its ability to handle multicollinearity, nonlinear interactions, and limited datasets makes it particularly suitable for modeling experimental concrete data.The model's predictions were further analyzed using sensitivity analysis to identify the relative influence of input parameters on tensile strength. The graphical structure and working mechanism of the XGBoost model are illustrated in Figure 4.

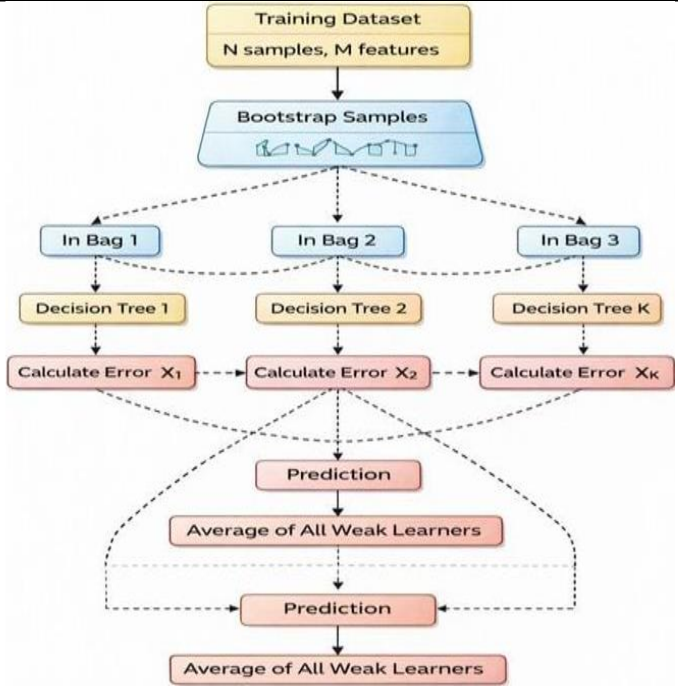

Figure 4. Graphical Representation of XGBoost

Gaussian Process Regression (GPR) Model:

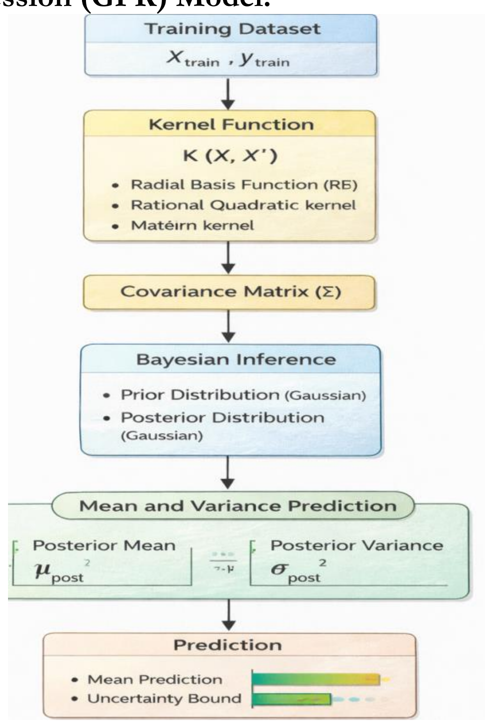

Figure 5. Graphical representation of the GPR algorithm

Gaussian Process Regression (GPR) is a probabilistic, non-parametric machine learning method based on Bayesian inference. Unlike traditional regression models that estimate fixed parameters, GPR defines a distribution over possible functions that can fit the data. This allows the model to provide not only predictions but also uncertainty estimates associated with those predictions.

GPR assumes that the target variable follows a multivariate Gaussian distribution governed by a covariance function (kernel), which defines the similarity between data points. Common kernels, such as the Radial Basis Function (RBF), enable GPR to effectively capture nonlinear relationships between input features and the output response. The kernel parameters are optimized by maximizing the marginal likelihood during training. The graphical representation of the Gaussian Process Regression (GPR) model is illustrated in Figure 5.

In this study, GPR was applied to predict the tensile strength of concrete using experimentally measured input variables, including fiber content and ultimate load. Its strong performance on small- and medium-sized datasets, along with the ability to quantify uncertainty, GPR is particularly suitable for experimental material science applications. Sensitivity analysis was subsequently performed to assess the relative influence of the input parameters on tensile strength predictions.

Support Vector Regression (SVR):

Support Vector Regression (SVR) is a kernel-based supervised learning technique derived from Support Vector Machines and is specifically designed to handle regression tasks. The core principle of SVR is to approximate a regression function that predicts the target variable within a predefined tolerance margin, referred to as the ε-insensitive region. Errors occurring within this margin are ignored, while deviations exceeding ε are penalized, allowing the model to focus on significant prediction errors.

SVR transforms the original input space into a higher-dimensional feature space through kernel functions such as linear, polynomial, and radial basis function (RBF) kernels. This transformation enables the model to capture complex nonlinear relationships between the input parameters and the output response. The RBF kernel is commonly preferred for its flexibility and generalization ability.

To control model complexity and prevent overfitting, SVR incorporates a regularization parameter (C), which balances the trade-off between minimizing training error and maintaining a smooth regression function. The final regression model relies on support vectors—training points lying on or outside the ε-insensitive margin—which are critical in defining the regression hyperplane.

Due to its robustness to noise, effectiveness with limited datasets, and strong nonlinear modeling capability, SVR has been extensively applied in civil engineering and material science applications. In this study, SVR was employed to model the relationship between experimental input variables and the tensile strength of concrete, providing reliable predictions and serving as a benchmark model for comparison with advanced machine learning techniques. The graphical representation of the Support Vector Regression (SVR) model is illustrated in Figure 6.

Random Forest (RF):

Random Forest (RF) is an ensemble-based machine learning algorithm that operates by constructing a large number of decision trees during the training phase and combining their outputs to produce a final prediction. Unlike a single decision tree, which may suffer from overfitting, Random Forest improves predictive accuracy and robustness by averaging the predictions of multiple independently trained trees.

The algorithm introduces randomness in two ways: (i) bootstrap sampling, where each decision tree is trained on a randomly selected subset of the training data, and (ii) random feature selection, where only a subset of input variables is considered at each split. These mechanisms reduce correlation among individual trees and enhance the model's generalization capability.

In regression problems, such as tensile strength prediction, the final output of the Random Forest model is obtained by averaging the predictions from all decision trees. Due to its ability to capture nonlinear relationships, handle multicollinearity, and perform well on small to medium-sized datasets, Random Forest has been widely adopted in civil engineering and material science applications. The graphical representation of the Random Forest (RF) model is shown in Figure 7.

In this study, the Random Forest model was employed to predict the tensile strength of concrete using experimental input parameters. Additionally, sensitivity analysis was conducted to evaluate the relative influence of key parameters, providing insights into the governing factors affecting tensile strength.

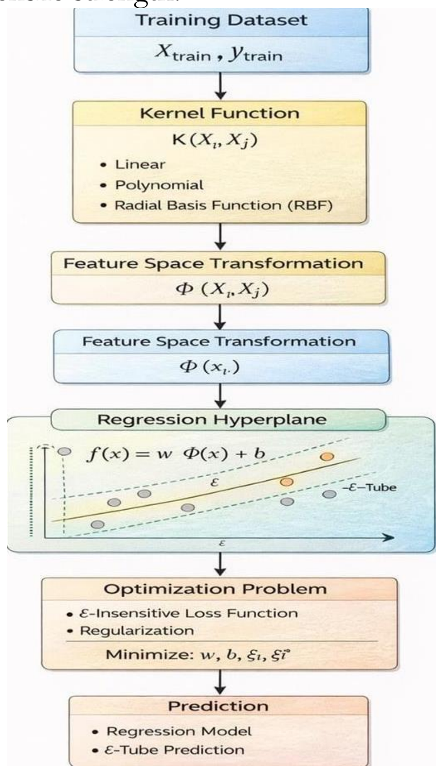

Figure 6. Graphical Representation of SVR

Statistical Analysis:

To evaluate the predictive accuracy and generalization capability of the developed machine learning models for tensile strength estimation, three widely accepted statistical performance indicators were employed: the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE). These indicators quantify the agreement between experimentally observed tensile strength values and the corresponding model predictions during both the training and testing phases.

Name of goodness criteria	Expression	Standard range
R-square	$R = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$	0–1
Root mean square error	$RMSE = \sqrt{(1/n \sum(y_i - \hat{y}_i)^2)}$	0 is the best value
Mean absolute error	$MAE = (1/n) \sum\lvert y_i - \hat{y}_i\rvert$	0 is the best value

The coefficient of determination (R^2) measures the proportion of variance in the tensile strength that is explained by the input variables, with values closer to unity indicating superior model performance. RMSE represents the standard deviation of prediction errors and penalizes larger deviations, while MAE provides the average magnitude of prediction errors without considering their direction. Together, these metrics provide a comprehensive assessment of model accuracy, robustness, and reliability. The mathematical formulations and acceptable ranges of the employed goodness-of-fit criteria are summarized.

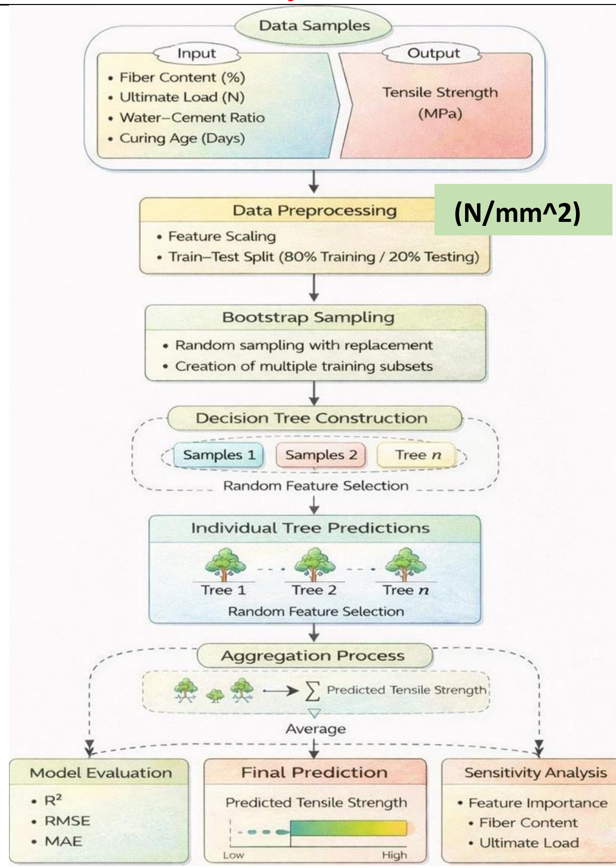

Figure 7. Graphical Representation of RF

Sensitivity Analysis:

Sensitivity analysis was conducted to quantify the influence of input variables on the predicted tensile strength of concrete and to enhance the interpretability of the machine learning models. Two complementary approaches were employed: SHAP (Shapley Additive ex Planations) values and feature importance analysis.

The analysis focused on evaluating the relative contribution of key input parameters— fiber content (%) and ultimate load (N)—across the developed machine learning models, including XGBoost, Support Vector Regression (SVR), Gaussian Process Regression (GPR), and Random Forest (RF). These parameters were selected based on their direct relevance to tensile strength behavior and their statistical significance within the dataset.

SHAP values provide a consistent, model-agnostic explanation by assigning contribution scores to each input feature for individual predictions. This approach enables both global and local interpretability, illustrating how variations in fiber content and ultimate load affect tensile strength predictions. In parallel, feature importance analysis was applied to rank the input variables based on their overall impact on model performance.

The combined sensitivity analysis results offer valuable insights into the governing factors influencing tensile strength, thereby improving model transparency and supporting the reliability of the proposed predictive framework.

Results and Discussion:

Comparison Analysis of ML Models:

In Figure 8. presents the comparative performance of Extreme Gradient Boosting (XGBoost), Gaussian Process Regression (GPR), Support Vector Regression (SVR), and Random Forest (RF) models using R^2, RMSE, and MAE in both the Training and Testing Phases. These evaluation metrics collectively assess model accuracy, error magnitude, and generalization capability. During the training phase, the Extreme Gradient Boosting (XGBoost) model demonstrated the strongest predictive ability, achieving the highest R^2 of 0.971, RMSE of 0.0313, and MAE of 0.0253. These metrics indicate excellent agreement between predicted and observed values. The Gaussian Process Regression (GPR) model showed strong performance, with an R^2 of 0.99, RMSE of 0.0020, and MAE of 0.0014. The Support Vector Regression (SVR) model has an R^2 of 0.91, RMSE of 0.2993, and MAE of 0.2233, while the Random Forest (RF) model has an R^2 of 0.93, RMSE of 0.0522, and MAE of 0.0408.

In the testing phase, Extreme Gradient Boosting (XGBoost) achieved an R^2 of 0.88, RMSE of 0.0836, and MAE of 0.0665. The Gaussian Process Regression (GPR) model achieved an R^2 of 0.83, RMSE of 0.5117, and MAE of 0.4278. Support Vector Regression (SVR) achieved an R^2 of 0.88, RMSE of 0.3431, MAE of 0.2825, and Random Forest (RF) achieved an R^2 of 0.87, RMSE of 0.0669, MAE of 0.0547.

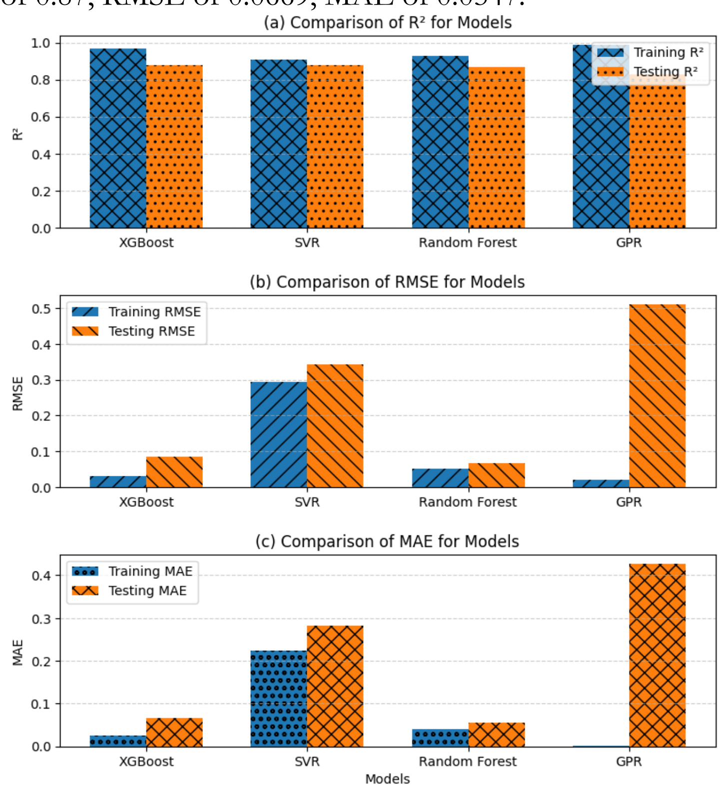

Figure 8. (a) R^2 Score Comparison, (b) MAE Comparison, and (c) RMSE Comparison

Comparison with Conventional Models:

To evaluate the effectiveness of the proposed machine learning models, their predictive performance was compared with several conventional regression techniques, including Linear Regression (LR), Decision Tree Regression (DTR), Support Vector Regression (SVR), Random Forest Regression (RFR), and Gaussian Process Regression (GPR). All models were trained and tested on the same dataset using identical evaluation criteria, namely the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE).

Conventional models generally exhibited lower predictive accuracy than the advanced machine learning approaches. Linear Regression and Decision Tree Regression showed limited capability in capturing nonlinear relationships between input parameters and tensile strength, resulting in relatively lower R^2 values and higher RMSE and MAE. SVR and Random Forest Regression provided improved performance due to their nonlinear learning ability; however, their prediction accuracy remained inferior to that of the proposed models.

Among all models, the XGBoost-based framework demonstrated superior predictive performance, achieving the highest R^2 and the lowest RMSE and MAE values on the testing dataset. The strong performance of XGBoost can be attributed to its gradient boosting mechanism and its effective handling of complex nonlinear interactions. These results confirm that advanced ensemble learning models outperform conventional regression techniques in accurately predicting the tensile strength of concrete.

Sensitivity Analysis:

Sensitivity analysis is essential for understanding how input variables influence the predicted output of machine learning models. In this study, the SHAP (Shapley Additive exPlanations) algorithm was employed to interpret the contribution of input parameters to the prediction of concrete tensile strength using the XGBoost model. SHAP values provide both global feature importance and local interpretability by quantifying the individual impact of each input variable on model predictions.

In Figure 9. presents the feature importance ranking based on the mean absolute SHAP values of all input parameters. The results indicate that fiber content (%) is the most influential variable affecting tensile strength, exhibiting the highest mean absolute SHAP value. This highlights the critical role of fiber dosage in enhancing tensile performance. The ultimate load parameter follows as the second most significant contributor, reflecting its strong association with tensile resistance. In contrast, curing age and water–cement (W/C) ratio showed relatively lower influence, which can be attributed to their limited availability across the experimental dataset.

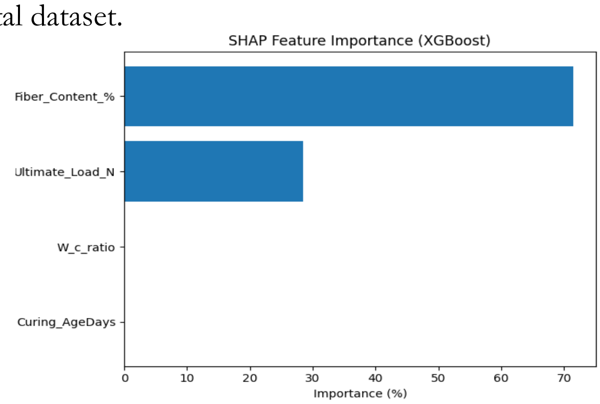

Figure 9. Mean absolute SHAP values

In Figure 10. illustrates the global SHAP summary plot, demonstrating how high and low values of each input feature affect tensile strength predictions. In the plot, red markers represent higher feature values, while blue markers indicate lower values. The analysis reveals that higher fiber content consistently contributes positively to tensile strength, as reflected by positive SHAP values. Similarly, higher ultimate load values have a strong positive impact on predicted tensile strength. Conversely, lower fiber content is associated with negative SHAP values, indicating a reduction in tensile performance.

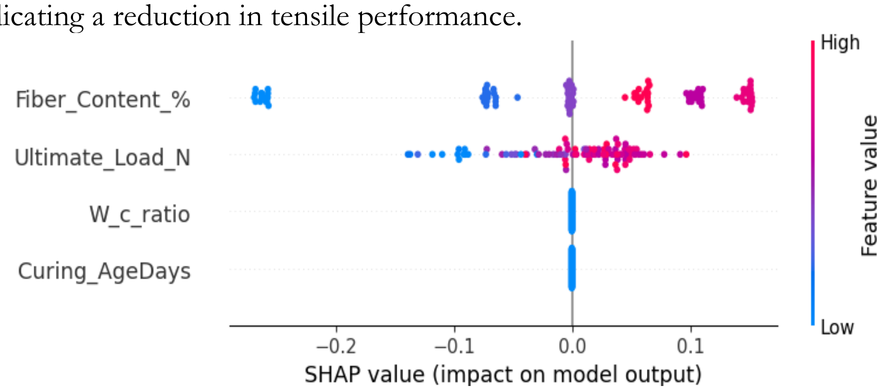

Figure 10. SHAP explanation on XGBoost Model

Overall, the SHAP-based sensitivity analysis confirms that fiber content and ultimate load are the dominant parameters governing tensile strength prediction in the developed model. This interpretability analysis enhances confidence in the model's reliability and provides valuable physical insight into material behavior, supporting its practical applicability in concrete design and optimization.

Correlation Metrics of Tensile Strength:

The correlation matrix illustrated in Figure 11. presents the relationship between the selected input parameters and the tensile strength of concrete. The matrix was developed using Pearson correlation coefficients, and visualized through a heatmap to clearly represent the strength and direction of inter-variable relationships. Correlation values range from −1 to +1, where positive values indicate direct relationships and negative values denote inverse associations.

Fiber content (%) shows a strong positive correlation with tensile strength, confirming its significant contribution to crack bridging and stress transfer mechanisms within the concrete matrix. This result highlights the effectiveness of fiber reinforcement in enhancing tensile performance. Ultimate load also demonstrates a strong positive correlation with tensile strength, indicating that specimens capable of sustaining higher loads tend to exhibit superior tensile resistance.

The water-to-cement (W/C) ratio exhibits a weak to moderate negative correlation with tensile strength, which is consistent with established concrete behavior, where higher W/C ratios increase porosity and reduce bonding strength. In contrast, curing age exhibits a negligible correlation in this dataset, primarily because all specimens had a constant curing duration, limiting statistical variability.

Inter-feature correlations reveal minimal multicollinearity among the input parameters, indicating that each variable contributes independently to tensile strength prediction. Overall, the correlation analysis confirms that fiber content and ultimate load are the most influential parameters affecting tensile strength, while the W/C ratio plays a secondary role. This analysis supports the selection of key variables used in the machine learning models and provides physical justification for the observed prediction trends.

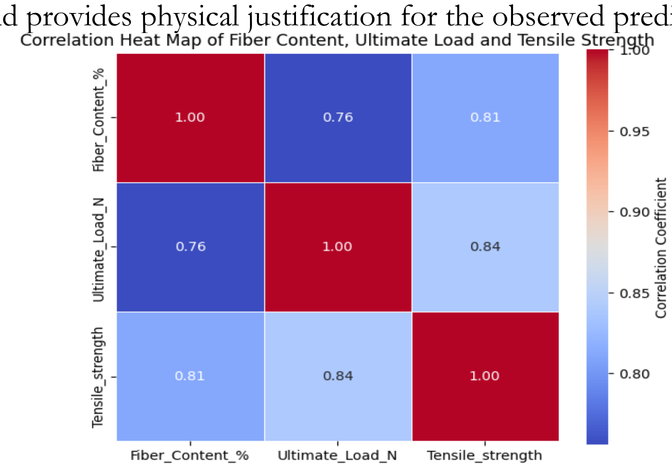

Figure 11. Correlation heat map of inputs and output variables

Conclusion:

This study demonstrated the effectiveness of artificial intelligence–based machine learning techniques in accurately predicting the tensile strength of concrete. An advanced ensemble learning model, XGBoost, was developed and evaluated to capture the complex nonlinear relationships between key input parameters and tensile strength. The model exhibited strong predictive capability, achieving a high coefficient of determination (R^2) during training. It also demonstrated acceptable generalization performance on the testing dataset, confirming its robustness and reliability.

The results indicate that XGBoost outperforms conventional regression approaches due to its gradient boosting structure, efficient handling of nonlinear interactions, and resistance to overfitting. The application of Shapley Additive exPlanations (SHAP) provided valuable insights into model interpretability, allowing a transparent assessment of the influence of each input parameter. Sensitivity analysis revealed that fiber content and ultimate load were the most dominant factors governing tensile strength, whereas other parameters had comparatively lower influence. These findings are consistent with the physical behavior of fiber-reinforced concrete, in which fibers enhance crack resistance and load-carrying capacity.

The integration of machine learning with explainability techniques offers a reliable framework for optimizing concrete mix design by focusing on the most influential variables. This approach significantly reduces the need for extensive experimental testing, saving time, cost, and material resources. Moreover, the developed methodology can assist engineers and researchers in making informed decisions during material design and quality control processes.

Overall, the proposed machine learning-based framework provides an efficient, interpretable, and practical solution for tensile strength prediction of concrete. The findings support the adoption of data-driven techniques in civil engineering applications and highlight the potential of explainable artificial intelligence for advancing sustainable and performance-oriented construction practices.

Acknowledgment:

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