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SHEAR STRENGTH PREDICTION OF POST-FIRE REINFORCED CONCRETE BEAMS USING NUMERICAL METHODS AND MACHINE LEARNING ALGORITHMS

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ABSTRACT

Fire exposure significantly degrades the mechanical and structural performances of reinforced concrete beams, leading to a reduction in residual load-carrying capacity with associated safety concerns for post-fire structures. The conventional numerical models can identify residual capacity but are usually computationally expensive and time-consuming. To address this limitation, the present study proposes a data-driven framework that integrates machine learning techniques for fast and reliable prediction of post-fire shear strength in RC beams. A parametric dataset of 246 samples was compiled using fire-related parameters adopted from published literature and supplemented with numerical and analytical calculations incorporating temperature-dependent material degradation. In the training, six different input parameters were considered: beam width, height, concrete cover, stirrup spacing, stirrup area, and fire exposure time. In this paper, four popular supervised ML algorithms, such as Random Forest, Extreme Gradient Boosting, or XGBoost, K Nearest Neighbour, Support Vector Regression are trained and tested by using statistical performance metrics such as the coefficient of determination, R^2; root mean square error, RMSE; mean absolute error, MAE; and mean absolute percentage error, MAPE. Among the models developed, XGBoost demonstrated the highest predictive accuracy, achieving R^2 = 0.951, RMSE = 21.10 kN, MAE = 12.63 kN, and MAPE = 6.17%, considerably superior to traditional numerical methods (R^2 = 0.369, RMSE = 56.01 kN, MAE = 37.83 kN, MAPE = 23.30%). The results show that ML models based on ensemble algorithms capture non-linear relationships among geometric, material, and thermal variables much better than conventional models. This study further corroborates that the integration of artificial intelligence with structural fire engineering could offer a robust, fast, and precise means for the evaluation of post-fire shear performance in RC beams. In particular, the XGBoost model of the proposed ML framework can serve as a practical tool for post-disaster assessment and structural safety decisions that contribute to enhanced resilience and efficiency within fire-affected infrastructures.

Keywords: *Machine Learning, Post-Fire Shear Strength, Structural Assessment, Reinforced Concrete Beams, XGboost*

1. INTRODUCTION

The high temperatures caused by fire deteriorate the mechanical qualities of RC beams. A reinforced concrete (RC) beam undergoes considerable structural deterioration after being exposed to fire over extended periods of time(Kodur & Dwaikat, 2008). For example, concrete can crack and spall, while the steel reinforcement inside it becomes weaker and less flexible, both of which reduce the building's shear resistance (Kodur & Dwaikat, 2008). The reduction in residual shear strength depends on multiple parameters including fire exposure duration, stirrup ratio, longitudinal reinforcement, concrete strength, and shear span-to-depth ratio (Liu et al., 2022).

Predicting residual shear resistance is of great importance for post-fire evaluation, however, conventional approaches are complex and time-consuming, as a large number of variables are considered, including geometry, material properties, and fire duration (Cai et al., 2019). Numerical modeling has played an important role in the understanding and prediction of residual shear capacity of reinforced concrete beams after exposure to fire conditions (Cai et al., 2019; Song et al., 2023). In this regard, Finite Element analysis has become an important tool for simulating thermal and mechanical behavior of post-fire RC beams with the capability for detailed assessment of temperature distributions, material property degradations, and the subsequent failure mechanisms that control residual shear strength (Cai et al., 2019; Liu et al., 2022). For example, Cai et al. (2019) used ABAQUS software to simulate the heat conduction within beams exposed to standard ISO 834 fire curves and captured temperature gradients with an important bearing on the subsequent adjustment of mechanical properties. Liu et al. (2022) modeled Q690 HSS plate girders under fire exposure; the web thickness-to-height ratio and cooling methods imposed a significant influence on post-fire shear resistance. The finite element results showed that nonlinear post-buckling behavior and strain hardening effects should be considered for accurate capacity predictions. This hybrid approach leverages the predictive power of ML to approximate FE outcomes efficiently, aiming for real-time post-fire assessments with high accuracy (Cai et al., 2019; Feng et al., 2021; Song et al., 2023).

These challenges can be overcome using machine learning techniques, which have emerged to model complex nonlinear relationships among a number of influencing factors with the shear resistance results intrinsically, without explicit physical assumptions.(Cai et al., 2019; Feng et al., 2021). Considering post-fire RC beams, an ANN model was developed by Cai et al. (2019) for rapid prediction of residual shear strength. The temperature distributions from FE analyses and material strength degradation factors are combined in the input layer with beam height, width, fire exposure time, stirrup cross-sectional area, stirrup spacing, concrete compressive strength, and concrete cover thickness as inputs (Cai et al., 2019). Erdem (2015) used ANNs to predict the moment capacity of RC beams under elevated temperatures. He demonstrated that the ANN model provides computational efficiency and high accuracy, thus reducing the dependency on time-consuming numerical simulations by modeling the nonlinearity caused by fire (Erdem, 2015). Support Vector Regression is preferred due to its robust theoretical background, the possibility of dealing with small dataset sizes, and robustness against overfitting, which generally makes the method attractive for structural engineering applications where only a limited number of high-quality experimental results may be available (Liu et al., 2022; Ni & Duan, 2022). Ni and Duan (2022) conducted research on predicting shear strengths of UHPFRC beams using SVR, ANN, and XGBoost. Liu et al. (2022) utilized SVR with genetic algorithm (GA) optimization to predict post-fire shear resistance reduction factors for Q690 high-strength steel (HSS) plate girders. Feng et al. (2021) collected a large experimental dataset involving 434 squat RC walls and then applied both RF and XGBoost models for predicting the shear strength. They showed that the XGBoost model, when combined with SHAP analysis, provides both accurate shear strength predictions and interpretable insights into feature contributions for squat RC walls (Feng et al., 2021).

The purpose is to investigate how shear resistance is influenced by some significant factors, including beam width and height, fire exposure period, stirrup cross-sectional area and spacing, concrete strength, and concrete cover thickness. This paper applies ML to provide a trustworthy and effective alternative to established approaches, allowing for quicker and more precise evaluations of post-fire structural performance. The present study demonstrates that integrating artificial intelligence with structural mechanics, particularly the pattern-identifying and function-estimating capability of machine learning, provides a faster and smarter alternative to traditional engineering calculations. This demonstrates that machine learning provides a practical and effective tool for engineering applications but also a workable and usable solution in structural and civil engineering in enhancing safety evaluations, streamlining design procedures, and saving time in critical situations such as fire aftermaths.

2. METHODOLOGY

The approach in this study used a three-tier methodological framework: numerical and analytical modeling and the generation of a parametric dataset based on published literature, machine-learning model development and training, and performance evaluation and validation.

2.1 Parametric Study on Shear Resistance of Post-Fire Reinforced Concrete Beams

Safety assessment and structural rehabilitation require precise predictions regarding post-fire shear capacity. Fire exposure conditions and temperature-dependent material degradation parameters were obtained following previously published and validated finite element–based thermal analyses, while the remaining dataset was generated through numerical and analytical calculations. Complex computations and numerous assumptions are inherent in conventional models. However, machine learning (ML) provides a data-driven and efficient alternative for generating such nonlinear predictions (Cai et al., 2019; Erdem, 2015).
It is acknowledged that the dataset used in this study is not purely experimental in nature. Fire exposure conditions and temperature-dependent material degradation parameters were adopted from previously published experimental and numerical studies reported in the literature .The remaining data were generated through numerical and analytical calculations following established formulations for post-fire shear resistance. The compiled dataset was subsequently used for training and testing the machine learning models.

2.1.1 Geometric and Material Parameters

Geometric parameters and material properties are distributed over the experimental dataset used for analysing reinforced concrete beams after a fire. Beam characteristics, differences in stirrup spacing, fire temperature, post-fire tensile strength, and cross-sectional dimensions (width and height) variables are essential input parameters for the machine learning and numerical modelling techniques used to forecast shear strength(Cai et al., 2019).The beam geometry parameters analyzed include- Beam width (b)**:** 200 mm, 220 mm, 250, 300 mm, Beam height (h): 400–700 mm, Concrete cover thickness (c): 25 mm, 35 mm, 45 mm, Stirrup spacing (s): 100 mm, 150mm, 200 mm, Stirrup cross-sectional area (Asv): 100.53 mm², 157 mm², 226.08 mm²(Cai et al., 2019).These variations reflect realistic design conditions for RC beams under fire loading, as modeled in previous studies(Cai et al., 2019). Material properties included concrete tensile strength (2.8 – 3.5 MPa) and temperature-dependent yield strength of stirrups, adjusted using Eurocode-based reduction factors(Molkens et al., 2017). When determining the shear resistance of a beam under fire, only maximum temperature of beams at different locations is needed, therefore, the ISO834 fire curve was used here, and the temperature–time relation could be expressed as follows in Eq.(1) (Cai et al., 2019).

$$T=T_0+345\lg(8t+1) \tag{1}$$

In the equation (1) where T is the temperature (°C) at time t (minutes) and T_0 is ambient temperature.

2.1.2 Computation of Residual Shear Resistance

The concrete tensile strength reduction factor at the corresponding temperature can be expressed as follows(Cai et al., 2019):

$$\varphi_{tT}=\frac{ft(T)}{ft}=0.976+\left[1.56\times\left(\frac{T}{100}\right)-4.35\times\left(\frac{T}{100}\right)^2+0.345\times\left(\frac{T}{100}\right)^3\right]\times10^{-2} \quad (2)$$

Where, $ft(T)$ is the tensile strength of post-fire concrete at T ◦C, ft is the tensile strength of concrete at normal temperature, and φtT is the tensile strength reduction factor of post-fire concrete.
Computation of Residual Resistance Based on Section Equilibrium (Cai et al., 2019):

$$\varphi_t \overline{T}=\frac{\sum\varphi_{tTi\,\Delta b\,\Delta h}}{bh} \quad (3)$$

where φ_{tTi} is the concrete tensile strength reduction factor in the i-th zone of the component section, b is the width of beams, h is the height of beams, Δb is the unit width, and Δh is the unit height.

For tensile strength reduction factor of stirrup the equation is (Cai et al., 2019)

$$\varphi_{\overline{yvT}}=\frac{\sum\varphi_{yvT_i}}{n} \quad (4)$$

Where $\bar{\varphi}_{yvT}$ is the tensile strength reduction factor of stirrup, φ_{yvT_i} is the tensile strength reduction factor at the temperature of the i-th point, n is the number of temperature distribution points on the stirrup.
Using the above deduction factor, the post-fire shear resistance of RC beams can be computed as(Cai et al., 2019):

$$V_T=\alpha_{cv}\,\varphi_{tT}f_t bh_0+\varphi_{\overline{yvT}}f_{yv}\frac{A_{sv}}{s}h_0 \quad (5)$$

Where αcv is the Shear bearing capacity coefficient of inclined plane.
Reduction Factor-Based Model: This formula adjusts the standard ACI-style shear capacity formula with temperature-dependent reduction factors(Cai et al., 2019)

$$V_{T(post\text{-}fire)}=\emptyset_{C(T)}\times V_C+\emptyset_{S(T)}\times V_S \quad (6)$$

$$V_C=\propto_{CV}\times f_t\times b\times h_0 \quad (7)$$

$$V_S=f_y\times\frac{A_S}{S}\times h_0 \quad (8)$$

Where, V_C=Concrete contribution to the post fire shear strength, V_S=Striup contribution to the post fire shear strength, λ=lightweight concrete factor 1.0 for normal weight concrete), f_c'=concrete compressive strength (MPa), b=width of beam (mm), d=effective depth (mm),A_S= area of shear reinforcement within spacing s,f_y= yield strength of stirrups (MPa),s= spacing of stirrups (mm),$\emptyset_{S(T)}$= temperature reduction factors.

Regression-Based Model: It’s a regression-based temperature decay model inspired by Erdem(2015)

$$V_T=V_0\times\left(1-a\times T^b\right) \quad (9)$$

$$V_0=V_C+V_S \quad (10)$$

V_C and V_S are computed as defined in Eqs. (7) and (8).

2.2 Machine-Learning Model Development

Four supervised learning algorithms were implemented to predict the residual shear strength: K-Nearest Neighbors (KNN), Random Forest (RF), Support Vector Regression (SVR), and Extreme Gradient Boosting (XGBoost).

2.2.1 K-Nearest Neighbors (KNN)

KNN makes predictions by averaging the values of the k most proximate training samples in feature space, according to a distance metric(Cover & Hart, 1967). It is a non-parametric algorithm that makes no assumptions on data distribution and can work well for regression and classification tasks.(Liu et al., 2022).

2.2.2 Random Forest (RF)

Random Forest (RF) is an ensemble algorithm that builds multiple decision trees using bootstrap samples and random feature selection(Breiman, 2001). It averages the model predictions from all trees with an aim to improve accuracy and reduce overfitting. Consequently, this method provides really robust performance in complex nonlinear datasets(Liu et al., 2022).

2.2.3 Extreme Gradient Boosting (XG Boost)

XG Boost operates similarly to traditional boosting with sequential training of decision trees; improvement is made through gradient-based optimization and regularization to reduce error (Liu et al., 2022).It supports parallel processing , handles missing data effectively, and delivers strong predictive performance, particularly in engineering applications (Feng et al., 2021).

2.2.4 Support Vector Regression (SVR)

Support Vector Regression extends the concept of SVR to regression by fitting a function within an acceptable error margin, known as epsilon(Vapnik, 1995).Using kernel transformations, SVR captures nonlinear relationships efficiently (Rahman et al., 2021).

2.2.5 Hyperparameter tuning and model selection

To avoid model-specific bias and to ensure fair comparison, hyperparameters of each machine learning model were selected through systematic tuning on the training dataset only. A k-fold cross-validation (CV) strategy was adopted within the training set to search for optimal hyperparameters by minimizing prediction error (RMSE/MAE) and maximizing goodness-of-fit (R^2). For KNN, the number of neighbors (k), distance metric, and weighting scheme (uniform vs. distance) were tuned. For Random Forest, the number of trees, maximum depth, maximum features, and minimum samples per split/leaf were tuned. For XGBoost, the number of estimators, learning rate, maximum tree depth, subsampling ratio, column sampling ratio, and regularization terms were tuned. For SVR (RBF kernel), the penalty parameter (C), epsilon-insensitive zone (ε), and kernel width (γ) were tuned. After selecting the best hyperparameter set from CV, the final model was retrained using the full training set and then evaluated once on the held-out test set.

2.2.6 Software and implementation details

All numerical and machine learning computations were carried out using standard engineering and data-science tools. Finite element/numerical model development and data generation were performed using ABAQUS (or the specific FE platform used in this study). Finite element thermal analysis for temperature distribution and corresponding degradation parameters was conducted using ABAQUS, following previously published and validated modeling procedures (e.g., Cai et al., 2019). Detailed FE model documentation (e.g., mesh discretization and boundary-condition sensitivity) is not included here due to the primary focus of this study on machine-learning-based prediction and space limitations. Machine learning implementation was conducted in Python (version X.X) using NumPy and Pandas for data handling, scikit-learn for KNN/RF/SVR modeling and cross-validation utilities, and the XG Boost library for gradient boosting regression. Model interpretation was carried out using SHAP (Shapley Additive Explanations). Figures and plots were generated using Matplotlib.

2.3 Model training and testing

The dataset was divided into training and testing subsets using an approximately 80/20 split (196 samples for training and 50 samples for testing). This split was selected to preserve a sufficiently large training set for learning nonlinear relationships while retaining an independent test set for unbiased generalization assessment. To reduce the dependence on a single random split and to improve robustness, k-fold cross-validation was applied within the training set during hyperparameter tuning and model selection. The final reported test performance was obtained only after fixing hyperparameters and retraining the model on the complete training set.

2.4 Model performance criteria

This study evaluated many statistical measures to determine the accuracy of machine learning models. These metrics include the coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE) and mean absolute percent error (MAPE) (Montgomery et al., 2012) .The statistical estimation methods use the following formulas (Montgomery et al., 2012)

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)}{\sum_{i=1}^{n} (Y_i - \overline{Y}_i)} \tag{13}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} / Y_i - \hat{Y}_i / \tag{14}$$

$$RMSE = \sqrt{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2} \tag{15}$$

$$MAPE = \frac{1}{n} \sum_{I=1}^{n} / \frac{Y_i - \hat{Y}_i}{Y_i} / \times 100\% \tag{16}$$

3. ILLUSTRATIONS

3.1 Figures and Graphs

The graphical results highlight the performance of different machine learning (ML) models—K-Nearest Neighbors (KNN), Random Forest (RF), Support Vector Regression (SVR), and Extreme Gradient Boosting (XGBoost)—in predicting the residual shear strength after fire exposure.

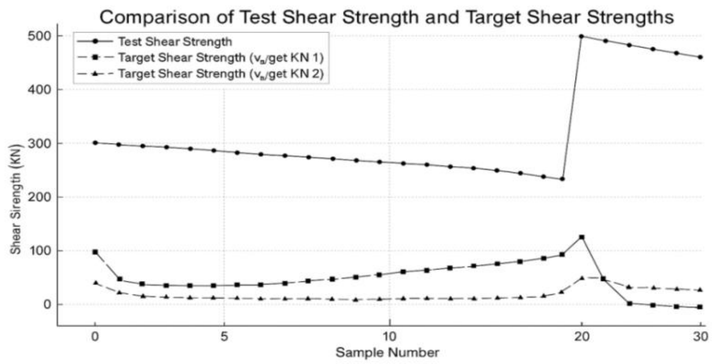
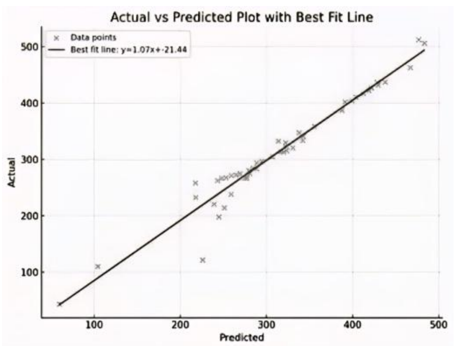


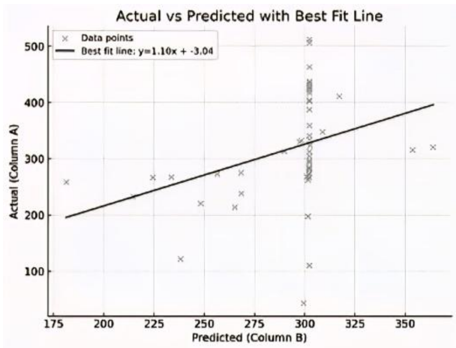
Figure 1: Comparison of test shear strength and target shear strength

Target shear strength 1 and target shear strength 2 were calculated using two distinct numerical formulations reported in the literature for post-fire shear resistance, and were used as reference values for comparison with the test shear strength. The upper line indicates the data that was obtained from the test shear strength. This graph shows the huge difference between the data on test shear strength and target shear strength.

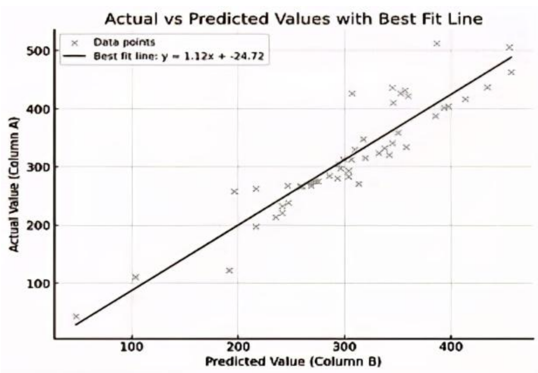
The effectiveness of four machine learning (ML) models in predicting the shear strength of post-fire reinforced concrete beams is investigated in this study. K-Nearest Neighbours (KNN), Random Forest (RF), Support Vector Regression (SVR), and XGBoost are some of these models.



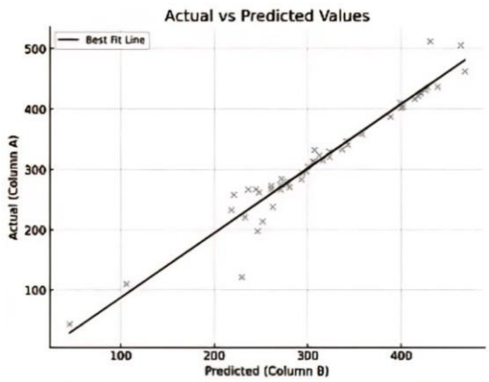
a) XGBoost



b) SVR



c) KNN



d) Random Forest

Figure 2: Comparison of machine learning-based prediction models

In the figure 2, the scatter plots show how each model's predictions and the actual shear strength values relate to one another. The line represents perfect prediction, where predicted and actual values match exactly. Among the models, XGBoost and Random Forest show the best predictive accuracy, with data points closely grouped around the ideal line. On the other hand, the SVR model shows significant deviations, indicating poorer prediction performance. The KNN model provides moderately reliable results but with slightly more spread. Overall, the ensemble methods, XGBoost and RF, perform better than the others, demonstrating their strength and dependability in predicting post-fire shear strength in structural concrete elements.

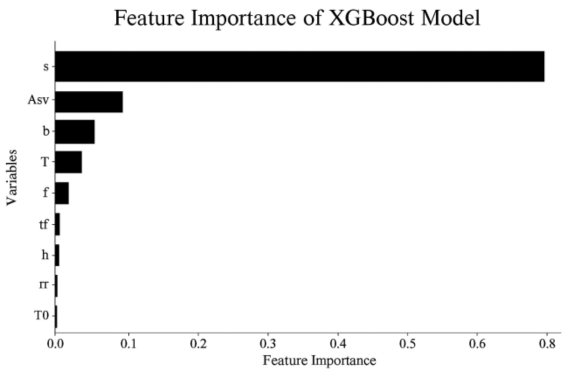


Figure 3: Relative feature importance of input using XG Boost models.

The chart in the figure 3 clearly shows that the variables have the greatest influence on the XG Boost model.This suggests that 's' (spacing) is the most important factor in predicting the final result. The next most important characteristics are 'Asv'(area of shear reinforcement), 'b'(width), and 'T'(temperature), however they are significantly less important than 's' (spacing). Other elements, such as 'ft'(tensile strength of concrete), 'Tf'(temperature after fire), 'h'(height), 'rr'(residual resistance), 'rf'(reduction factor), and 'T_0'(room temperature), have a negligible effect on the XG Boost model.

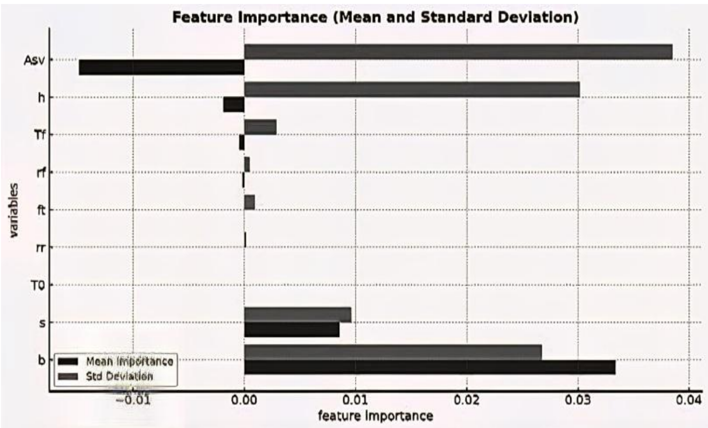


Figure 4: Relative feature importance of input using SVR models

Figure 4 shows that mean importance and standard deviation of feature significance values all over many model trials. Features such as ‘Asv’ (area of shear reinforcement), ‘h’ (height), and ‘b’ (width) have a higher average significance. On the other hand, features like ‘Tf’(temperature after fire), ‘rf’ (reduction factor), and ‘ft’ (tensile strength of concrete) are always less important and don’t help the model much.

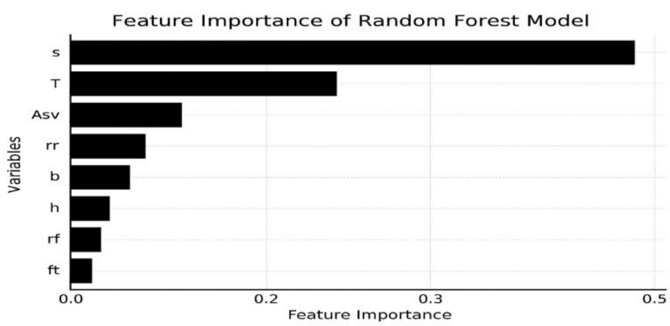


Figure 5: Relative feature importance of input using Random Forest model

In figure 5, represents the feature importance of different variables for predicting the shear strength of RCC beam.The bar chart showed that‘s’(spacing),‘T’(temperature),‘Asv’(area of shear reinforcement), ‘rr’(residual resistance**)**, ‘b’(width), ‘h’(height), ‘rf’ **(**reduction factor**)**, **‘**Tf’(temperature after fire) variables are responsible for predicting the shear resistance. On the other hand **‘**T_0**’(**room temperature) have no contribution for predicting shear strength.

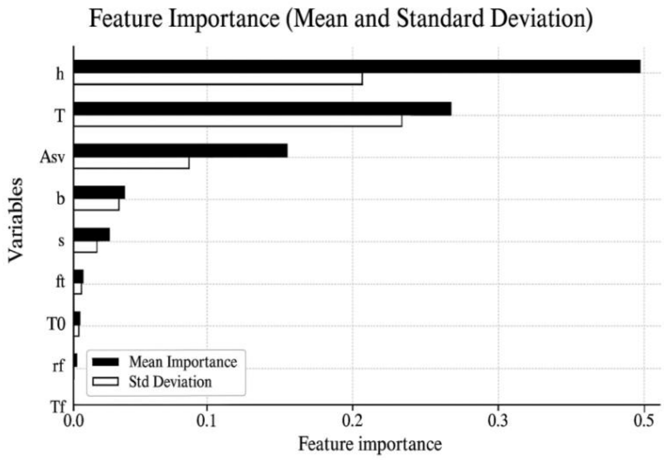


Figure 6: Relative feature importance of input using KNN model

In figure 6, the bar chart presents the feature importance analysis which highlights the variables that influence the KNN model’s predictive performance. The x-axis represents the feature importance and the y-axis lists the input variables**.** The variable ‘h’(height) exhibited the highest average importance (~0.52), moreover ‘T’(temperature) and ‘Asv’(area of shear reinforcement) indicating that these parameters are the most critical for accurate prediction of the shear strength of RCC beam. For predicting shear strength b (width) and spacing(s) had moderate contributions, while features like **‘**ft’(tensile strength of concrete)**,** ‘T_0’(room temperature), ‘rf’(reduction factor)**,** ‘rr’(residual resistance), and ‘Tf’**(**temperature after fire) showed negligible importance. Additionally, which variables had low standard deviation that suggests a high level of model stability and consistency.

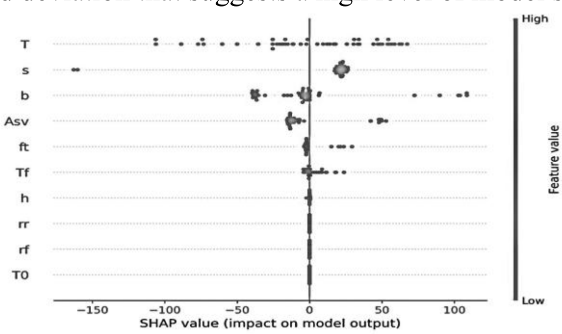


Figure 7:SHAP values (impact on model output)

The result of SHAP (Shapley Additive explanations) showed that the temperature (T) was the most important parameter to predict the shear strength of post-fire RC beam. Temperature has high SHAP values in a wide range and high position in the summary plot suggesting its fluctuations result in the highest effect on the model performance. Particularly, high-temperature data leads to a strong reduction of the predicted shear capacity, due to the detrimental influence of fire on the concrete and reinforcement properties.

3.2 Tables

Table 1: Comparison of machine learning (ML) models and the conventional numerical method on training phase

Menu	R^2	Mean	CoV	RMSE	MAE	MAPE
ML	0.99006	299.2574	29.50761	8.915811	4.588186	2.07991
Numerical Method	0.3382	2353.53	71.51	60.21	62.25	31.41

Table 2: Comparison of machine learning (ML) models and the conventional numerical method on testing phase

Menu	R^2	Mean	CoV	RMSE	MAE	MAPE
ML	0.951136	317.0296	27.59219	21.1005	12.6382	6.173047
Numerical Method	0.369	327.83	71.51	56.01	37.828	23.30

Tables 1 and 2 present a comparative evaluation of individual machine learning models and the conventional numerical method for predicting the post-fire shear strength of reinforced concrete beams. During the training phase (Table 1), the XGBoost model exhibited the highest predictive accuracy, achieving an R^2 value of 0.99006 with significantly lower error measures (RMSE: 8.92 kN, MAE: 4.59 kN, and MAPE: 2.08%). Random Forest also demonstrated strong performance, while KNN provided moderate accuracy. In contrast, Support Vector Regression (SVR) showed comparatively higher prediction errors. In the testing phase (Table 2), XGBoost continued to outperform the other models, yielding an R^2 value of 0.9511 with RMSE, MAE, and MAPE values of 21.10 kN, 12.64 kN, and 6.17%, respectively. Random Forest followed closely, whereas KNN and SVR exhibited relatively lower predictive capability. Compared to all machine learning models, the conventional numerical method demonstrated substantially lower accuracy in both training (R^2 = 0.3382) and testing phases (R^2 = 0.369), with considerably higher error values. Overall, the superior and consistent performance of XGBoost highlights its effectiveness in capturing the complex nonlinear behavior of post-fire shear resistance, justifying its selection as the most reliable model in this study. For conciseness, only the best-performing machine learning model (XGBoost) is reported in Tables 1 and 2, while the performance of the remaining models is discussed comparatively in the text and figures.

4. CONCLUSIONS

This study presented an efficient data-driven approach for predicting the residual shear strength of post-fire reinforced concrete (RC) beams using machine learning (ML) techniques. Among the models tested, XGBoost achieved the highest predictive accuracy (R^2 = 0.951, RMSE = 21.10 kN, MAE = 12.63 kN, MAPE = 6.17%), outperforming traditional numerical methods that showed lower reliability (R^2 = 0.369). The analysis identified stirrup spacing, shear reinforcement area, beam width, and fire temperature as the most influential parameters governing shear capacity. These results demonstrate that ML, particularly XGBoost, can effectively capture complex nonlinear behaviors in fire-damaged RC structures, offering faster and more accurate predictions than conventional models. Overall, the study contributes a practical and computationally efficient framework for post-fire structural assessment, enhancing safety evaluation and resilience in structural fire engineering.

Predicting post-fire residual strength quickly promotes sustainable development in a number of direct ways. First, by avoiding needless demolition and over-repair, accurate residual structural capacity estimation minimises the amount of construction materials that must be disposed of and replaced. Second, targeted strengthening and repair strategies are made possible by quick and evidence-based assessment, which prolongs the life of buildings damaged by fire and makes it possible for them to safely resume operations more quickly. Lastly, by increasing emergency response effectiveness,

cutting downtime, and facilitating a safer and quicker community recovery after fire incidents, quicker screening and prioritisation of damaged structural assets improve resilience and disaster recovery.
Although the proposed machine learning framework demonstrates strong predictive performance, future research should focus on validation using full-scale experimental fire tests and real post-fire case studies of reinforced concrete beams. Incorporating controlled laboratory fire experiments and field investigation data from fire-damaged structures would enhance the robustness, reliability, and practical applicability of the proposed models.

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DECLARATION ON THE USE OF AI

The authors acknowledge the use of AI-assisted tools solely for language editing and improvement of academic presentation. All technical content, analyses, and conclusions were developed and validated by the authors.

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