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Evaluating the Performance of Ensemble Machine Learning Algorithms Over Traditional Machine Learning Algorithms for Predicting Fire Resistance in FRP Strengthened Concrete Beams

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Abstract

In recent years, fiber-reinforced polymers (FRP) have emerged as a highly effective solution for strengthening reinforced concrete (RC) structures. However, accurately assessing the fire resistance of FRP-strengthened members remains a significant challenge due to the limited guidance available in current building codes, often leading to conservative and cost-intensive evaluations. Experimental testing and numerical analysis required for such assessments are resource-demanding, highlighting the need for more efficient methods. This study investigates the application of machine learning (ML) techniques to predict the fire resistance of FRP-strengthened RC beams. Twelve ML models, including eight ensemble methods and four traditional approaches, were employed. The models were trained using a comprehensive dataset comprising over 21,000 data points obtained from numerical simulations and experimental tests. The dataset captured variations in geometric configurations, insulation strategies, loading conditions, and material properties. To enhance predictive accuracy, Bayesian optimization and k-fold cross-validation were applied for model tuning, while the Shapley Additive Explanations (SHAP) method was utilized to assess the relative importance of features influencing fire resistance. Among the models tested, Extreme Gradient Boosting (XGBoost), Categorical Boosting (CatBoost), Light Gradient Boosting (LGBoost), and Gradient Boosting (GRB) demonstrated superior performance, achieving accuracy rates exceeding 92%. Key factors identified as significantly affecting fire resistance included loading ratio, area of tensile reinforcement, insulation depth, concrete cover thickness, and FRP area. The findings underscore the potential of ensemble ML techniques over traditional methods for accurately predicting the fire resistance of FRP-strengthened RC beams, offering critical insights for optimizing design practices and enhancing structural fire safety.

Keywords

Ensemble Machine Learning, Fire Resistance, FRP Strengthened Concrete Beams, Machine Learning

1. Introduction

The deterioration of structural components in buildings and bridges caused by factors like aging, material degradation, insufficient maintenance, and seismic activity has spurred the search for efficient and cost-effective repair methods. Traditional approaches include member replacement, externally bonded steel plates, supplementary elements addition, external post-tensioning, and concrete jackets or steel reinforcements (Chen et al., 2020). While effective, these methods often entail increased deadload and substantial implementation time. An emerging alternative method involves the utilization of fiber-reinforced polymers (FRP) for retrofitting reinforced concrete (RC) structures. FRP strengthening has gained rapid acceptance due to its efficiency and cost-effectiveness, attributed to characteristics such as lightweight, exceptional strength, corrosion resistance, and durability. FRP materials, with their ability to be shaped conveniently, offer versatility in construction applications (Abuodeh et al., 2020). Precise prediction and assessment of the strengthening effect in RC beams using FRP are crucial for evaluating effectiveness and design comprehensively. Two principal methods, namely, externally bonded (EB) and near-surface-mounted (NSM) techniques, are commonly employed in strengthening RC beams using FRP. While these approaches have demonstrated effectiveness in enhancing the flexural and shear capacity of RC structures, it is essential to recognize that FRP reinforcement presents limitations, particularly in scenarios involving exposure to fire.

The challenges associated with FRP performance during fire exposure, including polymer matrix decomposition, loss of strength and stiffness properties, and degradation of the bond between FRP and concrete, are key considerations limiting its widespread adoption, particularly in fire-resistant building designs. Consequently, it is crucial to prioritize addressing fire resistance concerns to enable the wider application of FRP strengthening in RC structures, thereby safeguarding structural integrity and ensuring overall safety. Traditionally, the determination of fire resistance for FRP-strengthened RC beams has primarily relied on theoretical analysis and experimental studies. These approaches can also be time-consuming and prone to errors due to simplifications, such as neglecting the contribution of FRP, leading to conservative predictions.

The performance of FRP in concrete structures is significantly affected by temperature variations. As is common with many materials, the strength of FRP tends to decrease as temperature increases (Fig. 1). When FRP-reinforced concrete elements are subjected to gradual heating, failure often occurs before the FRP reaches its melting or sublimation point. This failure is typically caused by the degradation of the mechanical properties of the reinforcement as the temperature rises. Moreover, the elastic moduli of carbon fiber-reinforced polymer (CFRP) materials exhibit temperature-dependent behavior. While the longitudinal modulus remains relatively constant, the transverse and shear moduli decrease as temperature rises (Gates, 1991). This is primarily due to the sensitivity of the matrix material to temperature changes, which affects the overall behavior of the composite.

Several case studies have been conducted to investigate the effects of temperature on CFRP composites, such as AS4/PEEK (Uematsu et al., 1995). These studies have revealed that the longitudinal modulus remains nearly constant, while the transverse and shear moduli decrease significantly near the glass transition temperature (T_g) of the matrix material. The decrease in elastic constants becomes more pronounced as the temperature approaches T_g, with substantial reductions observed at higher temperatures. Additionally, analyses of stress-strain relationships for CFRP composites indicate a noticeable reduction in both tensile and compressive strength at elevated temperatures. Strength degradation occurs progressively, with significant reductions observed at temperatures exceeding 100°C (V. K. R. Kodur et al., 1996).

The influence of creep on the behavior of FRP-reinforced concrete structures at elevated temperatures is substantial. Gate's findings (Gates, 1991) illustrate this effect, showing the creep strain of an off-axis CFRP composite at a constant stress of 76 MPa. Notably, the increase in creep strain becomes significantly pronounced above 150°C. For instance, after

150 seconds, the creep strain at 200°C is approximately 18 times higher than that at 150°C. Thermal expansion, another crucial deformation property affecting the fire behavior of structural members, plays a vital role in understanding material behavior. The coefficient of thermal expansion (CTE) quantifies the change in the unit length of a material per unit temperature change, which is crucial for calculating dimensional changes and thermal stresses due to temperature variations (V. K. R. Kodur et al., 1996). Unlike steel, the CTEs of composite materials, varying with fiber type, orientation, and volume fraction, are generally higher at room temperature (Gudonis et al., 2014). This discrepancy in thermal expansion between FRP reinforcements and concrete poses challenges. Tensile stresses in concrete members reinforced with FRP may lead to cracking due to thermal expansion incompatibility, potentially causing concrete spalling and compromising structural integrity, especially in fire scenarios (Silverman, 1983). Several experimental studies have been conducted to assess the fire resistance of FRP-strengthened RC beams. Deuring evaluated the fire performance of CFRP- and steel-strengthened RC beams under ISO 834 fire (Deuring, 1994). Observing reduced FRP-concrete interaction early in fire exposure, they recommended external thermal insulation to maintain bond effectiveness. Blontrock et al. tested FRP-strengthened RC beams with fire insulation, underlining the importance of keeping the FRP/concrete interface below the glass transition temperature (T_g) in a critical range of 60–82 °C for epoxies where the adhesive weakens (Blontrock H, 2000). Williams et al tested FRP-strengthened T-beams with VG-EI-R insulation under standard fire (Williams B, 2008). Despite exceeding the glass transition temperature of the adhesive, a 38 mm thick insulation layer ensured a 4-hour fire resistance for the beams, highlighting the effectiveness of proper insulation. Ahmed and Kodur found that FRP-strengthened RC beams with a 25 mm fire protection system could resist failure for 3 hours under ASTM E119 fire conditions (Ahmed & Kodur, 2011). Failure occurred after the glass transition temperature of FRP, and it was influenced by rebar temperature, insulation, and cooler anchorages. Their study highlights the importance of fire-induced restraint, insulation for deflection control, and proper configuration to prevent debonding for strong fire resistance.

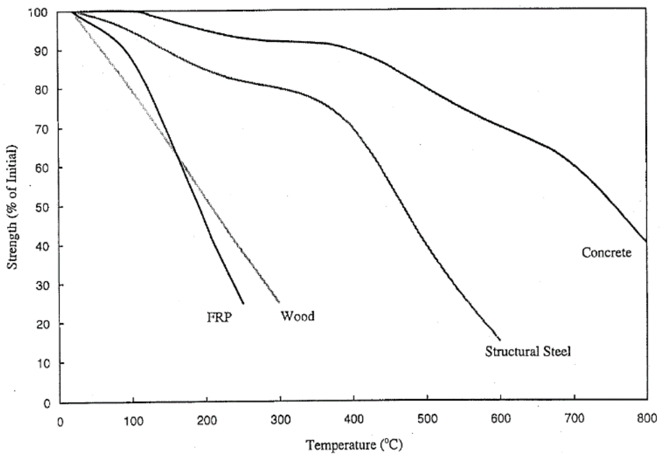

Fig. 1 Variation of strength with temperature for different materials (V. K. R.; B. D. Kodur, 1996)

Several numerical models have been explored to predict fire behavior in FRP-strengthened RC members. Kodur V. et al. proposed a numerical model to analyze the behavior of FRP-strengthened RC beams exposed to fire (V. K. R. Kodur & Ahmed, 2010). This model, presented in their study, demonstrates the capability to predict the response of FRP-strengthened RC beams under fire conditions. Kodur V. with Yu B. presented a rational approach for evaluating the fire resistance of FRP-strengthened concrete beams, but the equations are validated for specific types of FRP-strengthened RC beams and under standard fire conditions only (V. K. R. Kodur & Yu, 2016). El-Mahdy et al. successfully developed a finite element model for simulating fire response in FRP-strengthened beams with thermal insulation, validated against experimental data (El-Mahdy et al., 2018). However, a notable challenge associated with these numerical models is their high computational cost and time-consuming nature.

The emergence of machine learning (ML) techniques, driven by advancements in soft computing, has fostered their application in various domains of structural engineering, including design optimization (Alabdullh et al., 2022), damage detection (Baduge et al., 2023), structural member resistance, fire resistance assessment and structural health monitoring (Baduge et al., 2022). ML algorithms enable the analysis of vast datasets, uncovering intricate patterns that improve the accuracy and efficiency of structural predictions and assessments. In a related study, Naser et al. proposed a methodology for developing and testing supervised ML algorithms against structural and fire engineering databases, including Decision Trees (DT), Extreme Gradient Boosted Trees (ExGBTs), Light Gradient Boosting (LGBoost), Random Forest (RF), TensorFlow Deep Learning (TFDL), and Keras Deep Residual Neural Network (KDPNN) (M. Z. Naser et al., 2021). Their investigation laid the groundwork for a comprehensive framework to accelerate the adoption of ML in structural and fire engineering fields, demonstrating the capability of these algorithms to capture the phenomena under investigation accurately. Zhongnan Ye et al. conducted research on real-time prediction of structural fire response using a finite element-based machine learning approach. Their study revealed that RF and Gradient Boosting (GRB) models outperformed DT and Support Vector Machine (SVM) models in predictive accuracy (Ye et al., 2022).

Naser et al. utilized an artificial neural network (ANN) model to predict the temperature distribution of RC T-beams reinforced with CFRP plates under fire conditions (M. Naser et al., 2012). Additionally, Mashrei et al. introduced a back-propagation neural network (BNN) approach to estimate the bond strength between FRP and concrete joints (Mashrei et al., 2013). Chen et al. utilized Gradient Boosting Decision Tree (GBDT) and RF algorithms to predict the bond strength of CFRP-steel interfaces, achieving a remarkable R^2 of 0.98 with the GBDT model (Chen et al., 2021). This demonstrates the superior ability of ensemble models to capture intricate data relationships, enhancing the design and evaluation of CFRP-strengthened steel structures. Similarly, Milad et al. employed XGBoost, Multivariate Adaptive Regression Spline (MARS), and RF for predicting FRP composite strain (Milad et al., 2022). These models outperformed traditional empirical models, underscoring their reliability and effectiveness in civil engineering applications. Further reinforcing the benefits of ensemble models, Kim et al. developed a CatBoost-based model for predicting FRP-concrete bond strength, achieving superior performance metrics compared to other ensemble methods and existing models (Kim et al., 2022). Amin et al. estimated the flexural capacity of FRP-reinforced concrete beams using decision tree (DT) and gradient boosting tree (GBT) models, with the GBT model showing greater accuracy and robustness (Amin et al., 2022). These studies collectively highlight the transformative potential of ensemble ML models in civil engineering, providing enhanced predictive capabilities and accuracy over traditional empirical approaches. Bhatt and Sharma developed a data-driven deep neural network (DNN) to evaluate the fire resistance time of RC beams strengthened with FRP (Bhatt & Sharma, 2021). They utilized both scaled and unscaled datasets, incorporating various geometry, insulation configurations, applied loads, and material properties. After extensive hyperparameter tuning and ten-fold cross-validation, the DNN model demonstrated a relatively accurate assessment of the fire resistance of FRP-strengthened concrete beams. Their analysis underscored the critical role of insulation thermal properties in influencing fire resistance, achieving an impressive R^2 value of almost 92%.

Furthermore, building upon existing research in fire resistance prediction of FRP-strengthened RC beams, Kumarawadu et al. (Kumarawadu et al., 2024) explored the performance of six machine learning (ML) models. These models encompassed ensemble methods like LGBoost and RF alongside traditional ML algorithms such as K-Nearest Neighbor (KNN), DT, Polynomial Regression (PR) and Linear Regression (LR). Grid Search optimization was employed to optimize the hyperparameters of each model. Notably, the LGBoost model achieved the highest accuracy (R^2 value), reaching 92.3%. This finding suggests that ensemble methods hold promise for predicting fire resistance in FRP-strengthened concrete beams. This study clearly demonstrates that exploring ensemble learning techniques presents a promising approach for predicting the fire resistance of FRP-strengthened concrete beams.

Ensemble ML models have proven to be powerful tools in solving complex engineering problems, offering significant advantages over traditional empirical models. Existing research extensively employs experimental and numerical methods to assess the fire resistance of FRP-strengthened concrete beams. While achieving acceptable accuracy, these approaches are often time-consuming, resource-intensive, and computationally expensive, hindering their practical application. ML offers a promising alternative for fire resistance prediction, but current research is limited, with only a few studies achieving a maximum accuracy of 92.3%. This highlights the need to explore further ML techniques to enhance predictive capabilities and achieve superior accuracy. This study endeavors to address this gap by developing an improved ML model for fire resistance prediction, ultimately contributing to more efficient and accurate fire safety assessments in FRP- RC structures. This study investigates the development of accurate predictive models for fire resistance in FRP-strengthened RC beams. The investigation employs twelve ML models both traditional and ensemble ML techniques. The performance of these models will be evaluated through comparison with established experimental and numerical results. The coefficient of determination (R^2 values) will serve as the primary metric for assessing model accuracy. Furthermore, the Shapley Additive explanation (SHAP) technique will be utilized to gain insights into the relative significance and influence of various input features on the predicted fire resistance.

2. Dataset

Table 1. Range of values considered for the parameters used for generating the database (Bhatt et al., 2024)

Parameter Category	Description	Minimum	Maximum
Geometrical parameters	Length of beam - L (m)	1	6
	Area of concrete beam – A_c (mm²)	12,000	157,500
	Concrete cover – C_c (mm)	10	38
	Total area of tensile steel reinforcement – A_s (mm²)	157	1473
	Area of FRP – A_f (mm²)	1.1	640
	Thickness of Insulation – t_{ins} (mm)	0	38
	Depth of insulation on sides – h_i (mm)	0	115
Material property parameters	Compressive strength of concrete – f_c (MPa)	25	45
	Yield strength of steel – f_y (MPa)	414	460
	Elastic modulus of steel reinforcement – E_s (MPa)	200,000	210,000
	Tensile strength of FRP – f_u (MPa)	900	4900
	Elastic modulus of FRP – E_{frp} (MPa)	66,000	255,530
	Glass transition temperature of polymer - T_g (⁰C)	60	80
	Thermal conductivity of insulation - k_{ins} (W/mK)	0.037	0.228
	Specific heat capacity of insulation - $r_{ins}c_{ins}$ (J/⁰Cm³)	240,000	1,031,000
Loading parameters	Total load applied on beams - L_d (kN)	3	220
	Applied load ratio - L_R (%)	15	75

In this study, a comprehensive dataset developed by Bhatt et al. (2024), comprising over 21,384 experimental and numerical data points, was utilized. The dataset contains extensive information regarding the fire performance of FRP-strengthened reinforced concrete (RC) beams, including variations in geometric dimensions, levels of FRP-strengthening, steel reinforcement ratios, insulation thickness and configurations, material properties, and applied load levels. The parameters are classified into four main categories: geometrical, material properties, loading, and fire resistance parameters. The first three categories (geometrical, material properties, and loading) span a broad range of values, encompassing the practical applications commonly encountered in the field, as shown in Table 1. These value ranges were determined through consultations with industry experts and the practical experience of the authors of the study (Bhatt et al., 2024).

Fire resistance evaluation of FRP-strengthened beams under ASTM E119 (American Society for Testing and Materials, n.d.) considers both structural strength and serviceability. Failure under the strength criterion occurs when the bending moment from applied loads exceeds the capacity of the beam. Serviceability failure is defined by mid-span deflection exceeding $L^2/400d$ and a deflection rate surpassing $L^2/900d$ per minute over a minute (where L is span length and d is effective depth). The fire resistance duration is the time at which any of these criteria are first met, ensuring a comprehensive assessment of the performance of the beam under fire.

3. Methodology

3.1 Parameter Correlations Map

In this study, the geometrical, material, and loading parameters were selected as input parameters, while the failure time of the beam which represents the fire resistance of the beam, was considered as the output. To identify the relationships between these input parameters and the fire resistance (output), a heat map visualization was employed (Fig. 2). The heat map was generated using Google Collab and Python which is better at revealing correlations between variables using Pearson's correlation coefficient. The intensity and color coding of each cell in the heat map represent the strength and direction (positive or negative) of the correlation between two parameters. By analyzing Fig. 2, which depicts the heat map for input parameters of this study, valuable insights were gained regarding the interdependencies between these features. This visualization aided in focusing subsequent data analysis efforts on the most impactful parameters, leading to a more efficient and targeted investigation.

3.2 Development of ML Models

Ensemble learning methods in ML involve the integration of multiple learning algorithms to enhance predictive performance. It has been observed that combining multiple learning models often results in significantly improved performance compared to individual base learners, both in theory and through empirical experimentation. The application of ensemble ML techniques for predicting the behavior of FRP-strengthened RC beams represents a novel and significant advancement in the field of structural engineering. The integration of advanced ML in predicting fire resistance of FRP-strengthened RC beams is relatively unexplored and offers substantial improvements in prediction accuracy and reliability.

This study pioneers the use of these ensemble methods to capture the complex interactions between material properties, loading conditions, and geometric configurations inherent in FRP-strengthened RC beams. By combining multiple base learners, these techniques overcome the limitations of single predictive models, ensuring more robust and generalizable outcomes (Fig. 3). This innovative approach not only addresses a critical gap in the existing literature but also enhances the precision of structural performance predictions, leading to safer and more efficient design practices. The findings of this research are poised to significantly impact the field, providing new insights and methodologies for the analysis and optimization of FRP-strengthened RC beams, thereby advancing both theoretical understanding and practical applications in structural engineering.

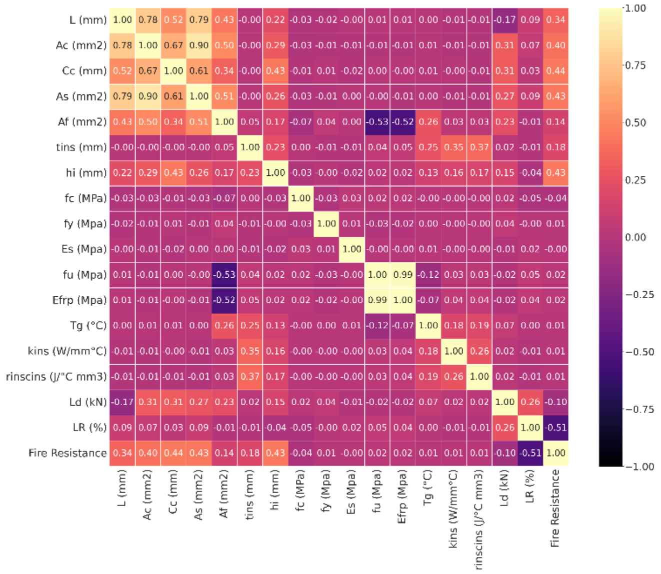

Fig. 2 Correlation heat map of the variables

In developing the ML framework, the accessible and user-friendly 'Google Colaboratory' platform was utilized. This web-based interactive computing platform is widely used globally for its convenience and versatility. To determine the most suitable ML techniques for the framework, a comprehensive literature review was conducted, and twelve techniques were carefully selected, encompassing both ensemble methods and traditional ML algorithms. The study employed various ensemble models, including adaptive boosting (AdaBoost), extreme gradient boosting (XGBoost), gradient boosting (GRB), categorical boosting (CatBoost), RF, histogram gradient boosting (HGBoost), bagging regressor (BR), and light gradient boosting (LGBoost). These models utilized different ensembling techniques to enhance performance and robustness. Specifically, AdaBoost, GRB, XGBoost, CatBoost, and LGBoost applied boosting techniques with decision trees as their base learners.

AdaBoost incrementally focused on correcting the errors of previous models, while GRB and XGBoost sequentially combined weak learners' outputs. CatBoost optimized performance on categorical features, and LGBoost aimed for computational efficiency. RF and BR employed bagging, training multiple decision trees on bootstrapped subsets of the data to reduce variance and improve generalization. HGBoost used histogram-based techniques with decision trees for efficient large dataset handling. Fig. 3 illustrates the fundamental concepts underlying bagging and boosting ensemble techniques.

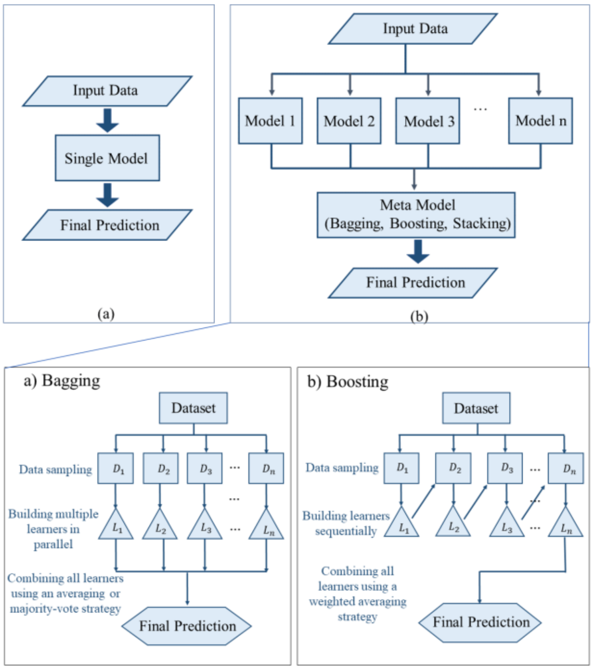

Fig. 3 Conceptual representation of traditional and ensemble learning techniques

Additionally, four empirical machine learning models were evaluated: artificial neural network (ANN), decision tree (DT), support vector machine (SVM), and polynomial regression (PR). This diverse selection explored a range of approaches to ensure robustness and effectiveness in the machine learning framework. The structured methodology leveraged the strengths of both ensemble and empirical methods, providing a robust framework for fire resistance prediction.

In predicting the behavior of FRP-strengthened RC beams, the extensive number of input parameters necessitated an initial step to enhance computational efficiency and reduce sensitivity to outliers and noise. Hence, parameters with an absolute correlation value less than 0.1 with the output parameter (see Fig.2 for details), including f_c, f_y, E_s, f_u, E_{frp}, T_g, k_{ins}, and $r_{ins}c_{ins}$, were excluded from the analysis. This preliminary exclusion aimed to streamline the computational process. However, contrary to initial expectations, retaining all input parameters yielded better model accuracies in subsequent testing. Consequently, it was decided to proceed with the full set of seventeen input parameters for the analysis. The development of the machine learning models adhered to a rigorous and systematic procedure. This process, as illustrated in Fig. 4 ensured the models were both reliable and interpretable. First, the relevant dataset was imported, and the key variables were defined. These included the input features (X), representing the various material and fire-related properties, and the output variable (Y), which corresponded to the fire resistance of the FRP-strengthened concrete beams. Following data preparation, the dataset was strategically partitioned into training and testing sets. A common split of 70% for training and 30% for testing was employed. The training set played a crucial role in the learning process of the model. By analyzing the patterns within the training data, the model established relationships between the input features and the desired fire resistance outcome (Y). Once trained, the performance of the model was thoroughly evaluated using the unseen testing set. This evaluation process was vital in assessing the ability of the model to generalize to new data and make accurate predictions beyond the training examples. The details of the training and evaluation process are illustrated in Fig. 4.

To gain deeper insights into the behavior of the model and understand the relative importance of each input feature, explainable Artificial Intelligence (XAI) methods such as SHapley Additive exPlanations (SHAP) analysis and Feature Importance were utilized. These XAI methods provided valuable explanations for the decision-making process of the model, highlighting the most influential features driving the fire resistance predictions. Through this systematic approach, incorporating both data partitioning, training, testing, and explainability techniques, the machine learning models were effectively developed and evaluated, ensuring their reliability and interpretability for predicting fire resistance in FRP-strengthened concrete beams.

3.3 Model Optimization

To ensure optimal performance and reliability of the machine learning models, a comprehensive hyperparameter optimization (HPO) approach was adopted. GridSearch (GS) stands out as a widely adopted approach for exploring the configuration space of hyperparameters (Kumarawadu et al., 2024). Therefore, GS was initially employed to optimize all twelve machine learning models. GS systematically evaluates all possible combinations of user-defined hyperparameter values. This exhaustive search approach offers ease of implementation and parallelization. However, a key limitation of GS is its inefficiency for high-dimensional hyperparameter spaces. As the number of hyperparameters and the search spaces increase, the number of evaluations required by GS grows exponentially, a phenomenon known as the "curse of dimensionality" (Ilievski et al., 2016). For instance, with $'k'$ hyperparameters having $'n'$ distinct values each, GS computational complexity scales exponentially at $O(n^k)$ (Yang & Shami, 2020). Therefore, GS can be considered effective for HPO when the hyperparameter space remains relatively small.

While GS was initially employed for HPO due to its prevalence in fire resistance prediction of FRP-strengthened RC beams as observed by Kumarawadu et al. (Kumarawadu et al., 2024), its computational limitations became apparent. GS systematically evaluates all possible combinations within a predefined hyperparameter space, and this exhaustive approach can lead to significant execution time and needs substantial memory usage which limits its applicability for large datasets.

To address this challenge and potentially achieve better model performance, the HPO method was transitioned to Bayesian optimization (BO). Unlike GS, BO is an iterative HPO technique that leverages past evaluations to guide future exploration. It utilizes two key components: a surrogate model that approximates the objective function based on observed data points, and an acquisition function that balances exploration which is searching for potentially better configurations and exploitation which is focusing on promising regions identified by the surrogate model (Hazan et al., 2017). This balanced approach allows BO to efficiently navigate the hyperparameter space and potentially identify configurations that outperform those found by GS. Notably, employing BO significantly reduced execution time while potentially achieving satisfactory model accuracies.

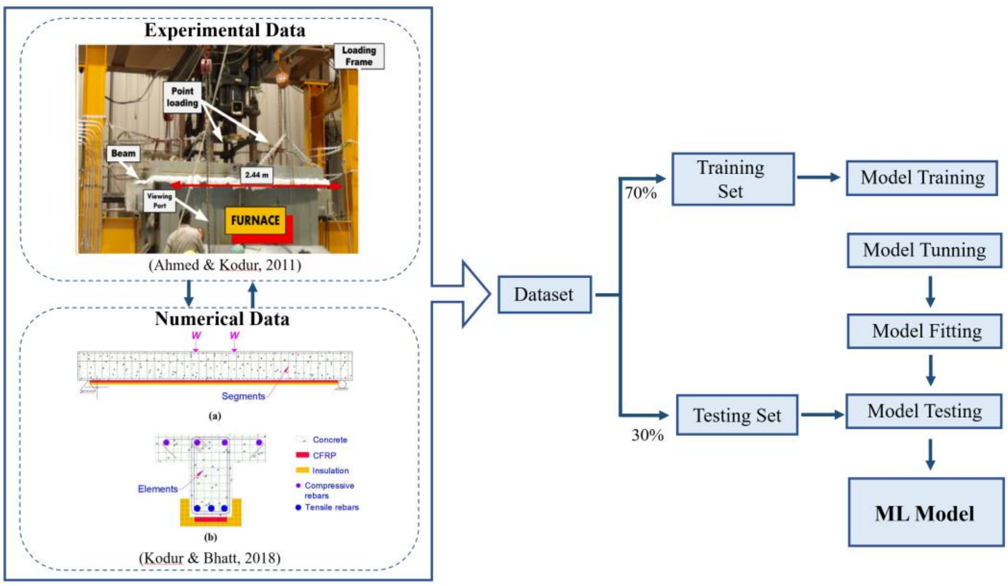

Fig. 4 Development of Finite Element based ML model

To ensure the generalizability and robustness of the developed ML models, a rigorous 10-fold cross-validation strategy was implemented as illustrated in Fig. 5. This technique effectively mitigates the risk of overfitting and enhances the ability of the model to perform well on unseen data, crucial for real-world applications in structural engineering. In 10-fold cross-validation, the dataset is randomly partitioned into ten equal folds. The model is iteratively trained on nine folds and validated on the remaining fold. This process is repeated ten times, with each fold serving as the validation set once. Finally, the performance metrics are averaged across all ten iterations, providing a comprehensive and reliable evaluation of the generalizability of the model. This approach ensures the model is not overly reliant on specific data points, enhancing its adaptability to diverse datasets commonly encountered in structural engineering practice.

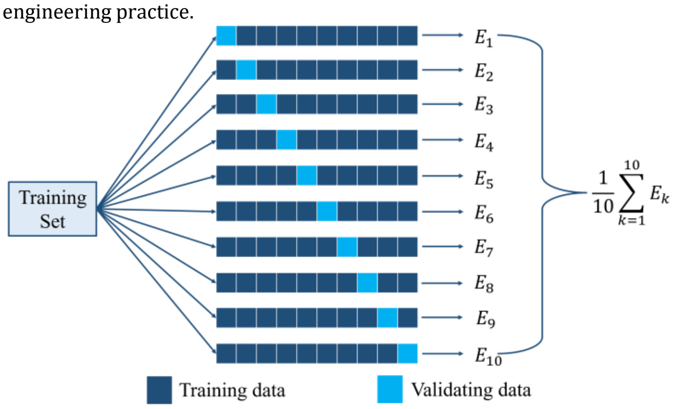

Fig. 5 Working principal of K-fold cross validation

4. Results and Discussion

4.1 Effect of Excluding Weakly Correlated Features on the Accuracy of the Model

Contrary to expectations, retaining all input parameters over filtering out the input parameters which have a less correlation value with the output parameter generally resulted in superior model performance, highlighting the complex relationships between inputs and fire resistance. While individual features may show low correlation, their combined effects can significantly enhance predictive power. Thus, correlation analysis alone may be insufficient for high-dimensional datasets, and excluding features based solely on correlation thresholds may discard relevant information, reducing model accuracy. This finding underscores the necessity of a more holistic approach to feature selection in machine learning models.

4.2 Results of Models under Bayesian Optimization

In evaluating regression models, a single metric like accuracy can be misleading. Instead, two key metrics have been used in this study to comprehensively assess performance. The R^2 score, also known as the coefficient of determination, reflects the proportion of variance in the target variable that the model can explain. R^2 value of '1' indicates a perfect fit, while '0' suggests the model offers no explanatory power. Furthermore, the mean standard deviation of the Cross-Validation score (CV score) is crucial for assessing the ability of a model to generalize to unseen data. Here, the data is split into training and testing sets, with the performance of model evaluated on unseen data in multiple random splits. The average performance across these splits provides a more robust estimate of generalizability compared to a single training-testing split. This CV score offers valuable insights into the ability of the model to perform well on real-world data beyond the training set, reflecting its overall robustness and reliability.

The results from all twelve ML models under BO are presented below in Fig. 6. From the data presented in Fig. 6, it is evident that XGBoost and LGBoost exhibit an accuracy level, surpassing R^2 value 92.3%. The analysis revealed another key strength of the employed ML models which is remarkably low variability in performance across different data subsets. This was evidenced by the standard deviation of all ten cross-validation scores remaining consistently below 1% for all models. A low standard deviation in cross-validation scores signifies minimal performance fluctuation across different training and testing set splits within the data. This observation suggests a high degree of robustness in the models, implying their ability to generalize well to unseen data beyond the training set.

Another key observation that could make is that notable ensemble ML models like XGBoost, CatBoost, GRB, HGBoost and BR demonstrate superior performance compared to traditional machine learning techniques in predicting the fire resistance of FRP-strengthened RC beams. This underscores the enhanced predictive accuracy and efficiency of ensemble machine learning techniques over conventional models in this application.

4.3 Enhanced Interpretability with SHAP

As ML models become increasingly complex, interpreting their decision-making processes becomes crucial. This study employed SHAP to provide post-hoc explanations for model predictions. SHAP operates similarly to parametric analysis, isolating the individual contribution of each input variable to the output of the model. This allows us to understand the underlying reasoning behind predictions and discern the relative influence of each feature on the predicted fire resistance of FRP-strengthened concrete beams.

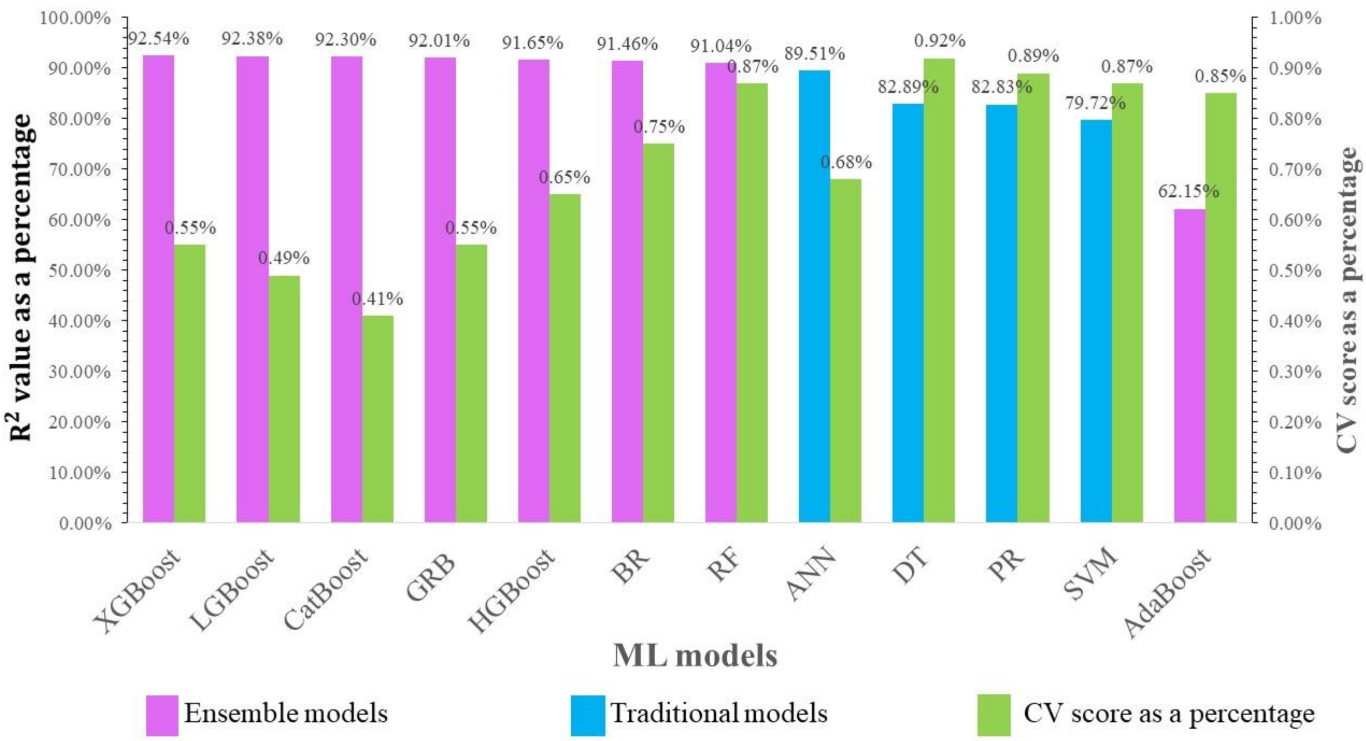

Fig. 6 Results obtained from the ML models

Given its superior performance in this study, XGBoost was chosen for the SHAP analysis. Fig. 7 depicts the mean SHAP values for all input features across the entire dataset, highlighting their relative importance in predicting fire resistance of FRP-strengthened concrete beams. The results reveal that Loading Ratio (LR), total area of tensile steel reinforcement (A_s), and depth of insulation on beam sides (h_i) are the most significant contributors to the predictions of the model. Conversely, other input features have a comparatively lower impact on the predicted fire resistance. This information is valuable for gaining insights into the factors that most critically influence the fire performance of FRP-strengthened beams.

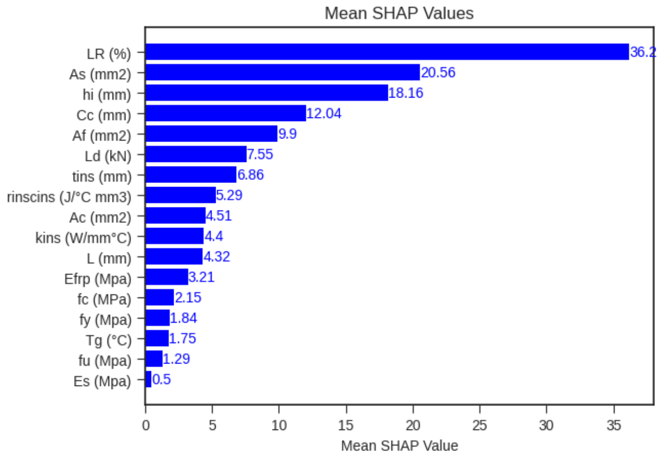

Fig. 7 SHAP Feature Importance Plot

Fig. 8 presents a summary plot of the SHAP analysis, visually depicting the impact of each input attribute on the predicted fire resistance of FRP-strengthened concrete beams. This plot facilitates the interpretation of feature importance by correlating input parameters with their respective influence on the predictions of the model. The y-axis ranks the variables in descending order of significance, with the most influential features positioned at the top. The x-axis displays SHAP values, representing the magnitude of influence of each variable. The color of the dots further emphasizes this influence, ranging from blue (low impact) to red (high impact).

Each data point in the plot corresponds to a sample from the dataset. The horizontal extent of the dot on the x-axis signifies the range of predictions for that sample based on its individual SHAP values. This range visually demonstrates the varying impact of different input attributes from blue (low impact) to red (high impact) on the predicted fire resistance for each sample.

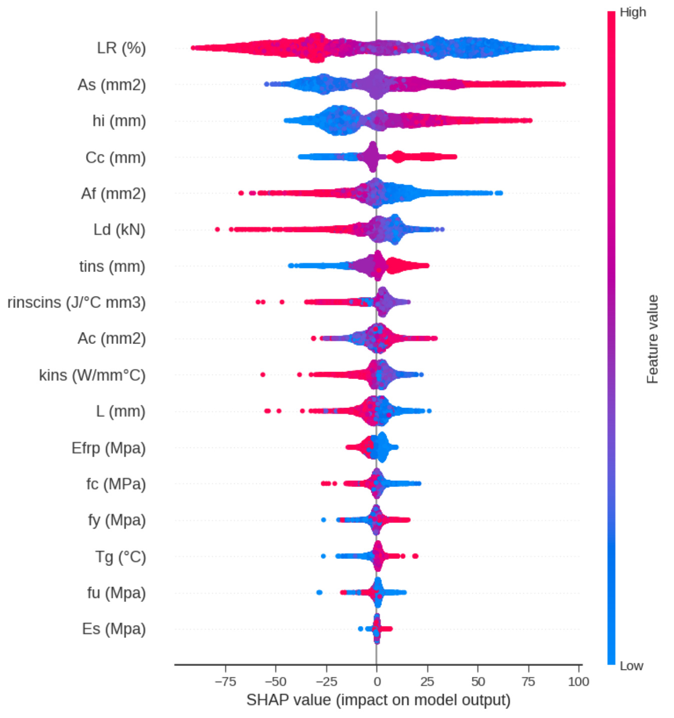

Fig. 8 SHAP Summary Plot

The SHAP summary plot shown above provides valuable insights into how each input parameter influences the predicted fire resistance of FRP-strengthened concrete beams. For parameters like Loading Ratio (LR), Area of FRP (A_f), and Load (L_d), a negative correlation with fire resistance is observed. This is reflected by a concentration of red dots which depict high SHAP values on the negative side of the x-axis and blue dots which depict low SHAP values on the positive side, indicating that increasing these parameters leads to a decrease in predicted fire resistance. Conversely, features like total area of tensile steel reinforcement (A_s), depth of insulation on beam sides (h_i), and cover to steel reinforcement (C_c) exhibit a positive influence. Here, red dots on the positive side and blue dots on the negative side suggest that increasing these parameters is associated with higher predicted fire resistance.

Interestingly, material properties such as elastic modulus of FRP (E_s), ultimate tensile strength of FRP (f_u), glass transition temperature of FRP (T_g), yield strength of steel rebars (f_y), compressive strength of concrete (f_c), and elastic modulus of steel reinforcement (E_{frp}) appear to have a lesser impact on the predictions of the model. This is reflected by their positioning lower in the ranking in Fig. 8 with a narrower range of SHAP values manifested by the horizontal spread of data points.

5. Conclusion

The application of finite element-based machine learning techniques for predicting the fire resistance of FRP-strengthened RC beams was investigated in this study. A comprehensive dataset exceeding 21,000 data points, combining numerical and experimental results, was utilized to train and validate the prediction models. Ensemble and traditional ML algorithms were employed to develop fire resistance prediction models using this dataset. The coefficient of determination (R^2 value) was used as the primary metric to assess model performance and accuracy. SHAP analysis was further implemented to interpret the models by analyzing the contribution and direction of each feature impacting the predicted fire resistance.

It was found that fire resistance prediction can be achieved with a high level of accuracy exceeding 90% using ensemble learning techniques such as XGBoost, CatBoost, LGBoost, HGBoost, GRB, and RF. These methods were shown to outperform conventional machine learning techniques like ANN, DT, PR, and SVM, demonstrating the advantages of ensemble learning. However, it is worth noting that even conventional ML techniques like ANN exhibited an attractive accuracy level of 89.5%, showcasing their effectiveness in this predictive task.

It was determined that relying solely on correlation coefficients for feature selection may not comprehensively capture the intricate relationships between variables, particularly in datasets with numerous dimensions. While correlation analysis offered valuable insights into variable relationships, it may not adequately account for complex interactions between features. Reducing the feature space based on correlation thresholds can simplify the model and enhance interpretability, but it runs the risk of sacrificing predictive accuracy, especially in datasets with intricate interdependencies among variables.

The SHAP analysis highlighted key parameters affecting fire resistance prediction in FRP-strengthened RC beams. Loading ratio, area of FRP and total applied loading were found to negatively impact fire resistance, while parameters such as the total area of tensile steel reinforcement, depth of insulation on sides of beams, and cover to steel reinforcement positively influenced it. Material properties like the elastic modulus of FRP and ultimate tensile strength of FRP exhibited lesser influence.

Furthermore, the effectiveness of ensemble ML techniques in significantly improving the accuracy of fire resistance prediction for FRP-strengthened concrete beams was emphasized. This enhanced accuracy has significant implications for optimizing the structural fire design of concrete structures. By providing engineers with reliable data, these models can support informed decision-making. Accurate predictions enable the identification of structural weaknesses during fire scenarios, facilitating targeted reinforcement strategies to improve performance while optimizing material and resource usage. Additionally, precise predictions can aid in the development and validation of advanced computational models for simulating fire behavior and its impact on concrete structures. This comprehensive approach empowers engineers to explore various design scenarios and evaluate the effectiveness of fire protection measures, ultimately leading to the design and construction of safer and more resilient structures.

Even though a comprehensive database exceeding 21,000 data points were used in the analysis of this study, the dataset was limited to five specific insulation materials and standard fire exposure scenarios. It is recommended that a more extensive database be developed, incorporating a broader range of insulation materials and fire conditions encountered in real-world applications. Expanding the dataset to include diverse fire scenarios will enhance the reliability and generalizability of the developed fire resistance prediction models. This enrichment will significantly improve the practical utility of these models for engineers by enabling the prediction of fire performance in a wider range of real-world situations.

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