Prediction of Fire Resistance of Fiber-Reinforced Polymer-Strengthened Concrete Beams Using Machine Learning Techniques

Cesar P. Malenab Jr.
College of Computer Studies
De La Salle University
Manila, Philippines
cesar_malenabjr@dlsu.edu.ph

***Abstract*—Fiber-reinforced polymer (FRP) has gained widespread adoption as a structural retrofitting solution, leveraging its benefits such as durability, lightweight, high strength, and adaptability. However, its limited performance at elevated temperatures constrains its applicability as a retrofitting option. Prescriptive, experimental, and numerical approaches, while either overly conservative or impractical, demand significant time and specialized equipment to perform. Consequently, this study investigates the potential of utilizing five machine learning (ML) models - Linear Regression (LR), Support Vector Regressor (SVR), Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Deep Neural Networks (DNN)- to predict the fire resistance of FRP-strengthened concrete beams. The hyperparameters of the ML models were optimized using random search (RandomizedSearchCV) with five-fold cross-validation. XGBoost gives the best results in the overall prediction of the fire resistance with RMSE = 17.82 and MAE = 9.87 but Deep Neural Network is more robust in predicting at extreme values of fire resistance with RMSE = 17.62 and MAE = 12.15. SHAP method was utilized to determine the importance of each feature in the prediction. The analysis showed that the load ratio, insulation depth, steel area, concrete cover, and total load are the top features that impact the prediction of the models.**

Keywords—Fiber-reinforced polymer, structural retrofitting, machine learning, fire, neural networks,

I. Introduction

Concrete structures undergo retrofitting due to deteriorations and damages incurred through their service life. The need for structural strengthening arises from the degradation of concrete and steel due to aging, changes in occupancy requiring higher load-carrying capacity of members, compliance due to code update requirements, structural damages sustained from earthquakes, and even construction mistakes that may occur at the early stage of building development. A wide range of strengthening techniques have been adopted to address these deficiencies such as concrete jacketing of beams, external steel plate bonding, and application of Fiber-Reinforced Polymers (FRP). Among these, FRP has been gaining wide acceptance due to its significant advantages [1] such as short installation resulting in minimizing disruption of building operations, lightweight material needing less labor and equipment, high durability to corrosion, and versatility that can be easily adaptable to any architectural orientations [2]. However, one of the major disadvantages of FRP is its poor performance when subjected to elevated temperatures as its continued capability to sustain design loads can easily diminish at rapidly increasing temperatures [3]. Moreover, adhesion failure between concrete members and FRP is likely due to its exposure to the external environment unless insulation devices are rendered to protect it [4].

Evaluation of fire resistance of FRP-strengthened concrete beams is conducted using prescriptive approaches from code requirements, experimental testing, and numerical analysis using finite element software. American Concrete Institute (ACI) recommends disregarding the contribution of FRP in calculating the resistance of members to load effects at elevated temperatures [5]. In addition, the existing methodology from ACI 216.1 does not extend to the calculation of fire resistance of concrete structures strengthened with FRP [6]. The recommendations from ACI documents were already proven to be too conservative as various experimental studies have shown that with proper thermal insulations, FRP-strengthened concrete beams can maintain their enhanced capacities [7][8]. On the other hand, full-scale fire tests were conducted by scientists to validate hypotheses regarding the behavior of concrete members under increasing temperatures. These experiments are costly and tedious such that their practicality in real-world design situations is limited as engineers have limited access to sophisticated equipment to conduct full-blown fire tests [9]. Numerical analysis using finite element models is also one of the alternative means of analyzing the nonlinear nature of the fire performance of strengthened beams [10]. These are usually implemented using commercially available software, namely ABAQUS, and ANSYS, and require special training in higher-order mathematics as well as intensive computing resources to reduce the processing time of various parameters. Therefore, the practicality of employing numerical analysis within the context of design offices is also limited.

The oversimplification and infeasibility of existing methodologies in determining the fire performance of FRP-strengthened concrete beams call for a more pragmatic approach such as the use of machine learning (ML) algorithms and artificial intelligence (AI). The use of ML techniques in FRP-strengthened members has gained significant traction over the past four years [11]. The primary objectives of the adaptation of ML and AI tools in Fire Engineering and Sciences (FES) include developing modern fire assessment tools, supplementing knowledge-based approaches, and leveraging computational power to solve multi-dimensional problems in FES [9]. These ML-based approaches can significantly include all parameters influencing the performance of FRP-strengthened members which can easily be retrained as new data becomes available.

II. Review of Related Literature

Numerous attempts to incorporate ML techniques in fire performance predictions have been undertaken to overcome the shortcomings of existing approaches. Naser et al. [12] performed a comparative assessment of supervised ML algorithms, including Decision Trees (DT), Random Forest (RF), Extreme Gradient Boosted Trees (ExGBT), Light Gradient Boosted Trees (LGBT), TensorFlow Deep Learning (TFDL), and Keras Deep Residual Neural Network (KDP) utilizing their baseline hyperparameters on six databases. The study aims to set a benchmark for comparison of future development of algorithms in the field of FES. A five-fold cross-validation procedure was adopted in all analyses and models were compared across multiple metrics to have a holistic view of their performance. ExGBT and LGBT outperformed other algorithms while DT demonstrated the lowest performance across the majority of the tested databases. In addition, Hisham et al. [13] applied artificial neural networks (ANN) to predict temperature profiles for FRP-wrapped concrete columns. The dataset was obtained from numerical simulations of 1200 specimens resulting in 512,400 data points, and the data was divided into 70-15-15 for training, validation, and test set. Furthermore, the data underwent normalization to expedite the training and prediction process. The model was able to achieve an optimal state after 751 epochs with an overall accuracy of predicting the temperature from 85-90%.

Bhatt utilized regression models, including Support Vector Regression (SVR), Random Forest Regressor (RFR), and Deep Neural Networks (DNN) to predict the fire resistance rating of FRP-strengthened flexural members [14]. The dataset was obtained from experimental testing of 49 concrete beams with the failure time as the fire resistance rating of the beams. Feature engineering involves reducing the 29 input parameters from the original dataset to just 16 parameters that were standardized using Gaussian normalization. Hyperparameter tuning was performed using GridSearchCV and the DNN structure was determined using a tenfold cross-validation analysis. Root Mean Square Error (RMSE), coefficient of determination (R^2), and Pearson correlation coefficient (R) are the evaluation metrics used to compare the three algorithms. The study showed that DNN exhibited the highest accuracy while RFR demonstrated the lowest performance.

Previous studies in the fire performance of concrete structures show that ML and AI tools can capture the nonlinear behavior of structural members under elevated temperatures. However, most of these studies are limited in either the data points or models used or were not able to perform hyperparameter tuning to the algorithms. Thus, this project aims to build on the previous studies by extending the ML algorithms in a more comprehensive dataset of FRP-strengthened concrete beams and performing hyperparameter tuning to push the predictive power of the models. This study will further the application of AI and ML techniques in the domain of fire engineering, exploring its potential and eventual adoption in the industry.

III. Methodology

A. Data Source

The dataset was published last December 2023 containing 21,384 experimental and numerical data of FRP-strengthened concrete beams [15]. The data contains 20 parameters including geometrical, material property, loading, and fire resistance. The parameters for the numerical data were adjusted to incorporate values that align with field implementation, following consultations with construction personnel. A subset of the data was used in a prior study [14], but the complete dataset has not been employed in subsequent machine learning applications.

With access to a more recent and extensive dataset, the present study can concentrate on constructing and comparing machine learning models. This is a deviation from prior studies that also involved the generation of datasets as part of their research. Moreover, the availability of a larger dataset allows for a more robust hyperparameter tuning which can capture a broader range of patterns in the data. In addition, the effort of the authors to include a more representative dataset through consultations ensures that the model generalizes well to unseen data.

B. Data Preprocessing

The dataset is largely clean, though a few discrepancies were present, such as beam lengths denoted in varying units, duplicate beam names, and negative values for insulation thickness. These issues have been rectified during the data cleaning process. Moreover, to enhance the robustness of the machine learning models during training, all features within the dataset have been scaled using a standard scaler so that each feature has a mean of 0 and a standard deviation of 1.

C. Machine Learning Models

a) Linear Regression (LR) with Regularization

A linear regression model is a statistical tool that captures the linear association between a target feature and one or multiple independent variables. Through analytical or approximate techniques, such as gradient descent, the model determines the optimal intercept and coefficients that minimize the loss function. Incorporating ridge or lasso regularization ensures the model's ability to generalize well to unseen data by preventing overfitting [16].

b) Support Vector Regression (SVR)

Support Vector Regression extends the principles of Support Vector Machines (SVMs) to regression tasks. SVR seeks to identify the hyperplane that best fits the data while allowing for a margin of error within an ε-insensitive tube. Instances lying outside this tube are termed slack variables, and the regularization parameter C penalizes the distance of these slack variables from the hyperplane tube. Much like SVM, SVR can address non-linear regression challenges by leveraging kernel functions to map data points into a higher-dimensional space, where the search for an optimal hyperplane is facilitated, ensuring better fitting to the data [17].

c) Random Forest

Random Forest employs an ensemble learning technique by training multiple decision trees independently on different subsets of the dataset, employing bootstrapping methods. To prevent overfitting and ensure generalization, each tree can be pruned using specified parameters such as maximum depth, minimum sample split, maximum leaf nodes, and minimum impurity split. The final output is determined by aggregating the predictions of all individual trees, often through averaging, resulting in a robust and reliable model [18].

d) Extreme Gradient Boosting (XGBoost)

Extreme Gradient Boosting extends gradient-boosted trees by enabling parallel computation of trees, enhancing both speed and scalability. It employs ensemble learning, sequentially training multiple weak classifiers using the residual errors of preceding trees. Additionally, XGBoost integrates L1 and L2 regularization terms, regulated by alpha and lambda parameters respectively, to prevent overfitting. Furthermore, it introduces a gamma hyperparameter that controls tree pruning based on the gain score, ensuring optimal tree complexity. Each weak learner's output is multiplied by a learning rate, and the final prediction is derived by summing the outputs of multiple trees, resulting in a robust and accurate model [19].

e) Deep Neural Networks

Neural Networks consist of numerous neurons organized in layers and interconnected to form a network. Each neuron incorporates an activation function, introducing non-linearity to capture intricate patterns within complex datasets. Through the process of back-propagation, the network computes prediction errors and propagates them backward to adjust the corresponding weights and biases in the layers, employing an optimizer with a specified learning rate [20].

Deep Neural Networks extend traditional Multi-Layer Perceptrons (MLPs) by incorporating more hidden layers, enabling them to learn complex features from data. However, this depth makes them more prone to overfitting and instability. To mitigate these challenges, various techniques are employed, such as:

- Weight Initialization: Proper initialization of weights helps prevent issues like vanishing or exploding gradients during training, aiding in stable and efficient optimization.
- Batch Normalization: This technique normalizes the activations of each layer, stabilizing the training process, accelerating convergence, and improving generalization performance.
- Dropout: Dropout randomly deactivates a fraction of neurons during training, effectively reducing overfitting by introducing noise and encouraging robustness in the network's learned features.

Training a neural network involves iteratively presenting the dataset to the network in batches or epochs, and adjusting the model parameters to minimize the prediction error. Careful selection of the number of epochs is crucial to prevent overfitting, ensuring that the network learns the underlying patterns of the data without memorizing noise or irrelevant details.

D. Performance Metrics and Hyperparameter Tuning

The study adopted three quantitative measures to evaluate the performance of the various models in a regression task:

a) Root Mean Squared Error

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}{n}} \tag{1}$$

b) Mean Absolute Error (MAE)

$$MAE = \frac{\sum_{i=1}^{n}|y_i - \widehat{y_i}|}{n} \tag{2}$$

c) Coefficient of Determination

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}{\sum_{i=1}^{n}(y_i - \overline{y_i})^2} \tag{3}$$

RMSE and MAE both assess the accuracy of a model's predictions by comparing them to the actual values. Lower values of RMSE and MAE indicate better performance, with RMSE being more sensitive to outlier data compared to MAE. RMSE penalizes larger errors more heavily due to the squaring operation, making it particularly useful when dealing with datasets containing outliers. In contrast, MAE provides a more straightforward measure of average error magnitude and is less influenced by extreme values.

R-squared measures the proportion of variance in the target variable that is explained by the model's predictions. It ranges between 0 and 1, with higher values indicating better model fit. An R^2 value closer to 1 suggests that the model can explain a larger portion of the variability in the target variable using the input features. R^2 is particularly useful for assessing the overall goodness of fit of the model.

The dataset was divided into 80-20 train-test-split to determine both training and testing performance where the train data is further divided into a validation set for hyperparameter tuning. To identify the optimal parameters based on a chosen performance metric, a systematic approach involves conducting a randomized search across the hyperparameter space, employing five-fold cross-validation. This entails testing 100 randomly selected combinations of hyperparameters, each evaluated across five validation sets. The overall error is then calculated as the average across these validation groups. The optimal hyperparameters are determined by selecting the combination that yields the most satisfactory performance according to the specified metric.

E. Feature Importance

Beyond merely achieving high predictive performance, understanding the features influencing predictions is crucial in model development. This paper adopts the Shapley method, a technique designed to discern the relative impact of input features on the overall model predictions. By computing predictions across all conceivable feature subsets and monitoring the model output with each feature's inclusion or exclusion, the Shapley method extracts the marginal contribution of each feature. The calculated Shapley values serve as quantitative measures, revealing both the strength and direction of the feature's impact on predictions [21].

IV. Results and discussion

A. Hyperparameter Tuning Results

The hyperparameter tuning results for various models are detailed in Table I.

For linear regression with Elastic Net regularization, the default regularization leans towards Lasso regularization, resulting in certain parameter coefficients, particularly those related to glass transition and steel strength, being reduced to zero. This reduction suggests that these variables do not significantly contribute to the predictive capability of the linear regression model.

Support Vector Regressor yield optimal performance in predicting the fire rating of strengthened beams when employing the radial basis function kernel with the kernel coefficient set equal to the inverse of the number of features. This kernel effectively captures nonlinear relationships by identifying support vectors across infinite dimensions [22]. To enhance robustness against overfitting, a relatively low value of the epsilon tube is paired with a high regularization parameter, creating a large margin hyperplane.

The Random Forest model, with 300 trees and minimal pruning, constructs trees without depth restrictions and with a minimum sample split of 2. Despite featuring 14 dataset features, only five are selected for each tree, and 99% of the data is utilized for bootstrapping. Although individual trees are prone to overfitting, the ensemble nature of Random Forest mitigates this risk effectively [18].

In contrast, XGBoost requires a higher number of decision trees but counteracts overfitting with stricter regularization. This includes limiting the maximum tree depth at 7 levels, integrating L1 and L2 regularization terms on weights, and enforcing a minimum reduction of 5 in the loss function.

Meanwhile, the deep neural network architecture comprises three hidden layers, with ReLU activation functions and batch normalization applied to each neuron. Weight initialization utilizes He initialization techniques, with bias values set to 0. Dropout regularization randomly deactivates 25% of neurons during training to prevent overfitting. Each epoch involves training on batches of 512 samples, continuing for 700 epochs. The Adam optimizer with a learning rate of 0.001 is employed. Notably, Fig. 1 illustrates that training and validation loss converge closely by the last epoch, indicating effective prevention of overfitting in the model.

TABLE I. HYPERPARAMETER OF ML MODELS

Model	Hyperparameter	Value
Linear Regression	regularization parameter	0.1
	mixing parameter	1
Support Vector Regressor	kernel	Radial Basis Function
	gamma	auto
	epsilon	1
	regularization parameter	1000
Random Forest	number of trees	300
	maximum depth of the tree	None
	minimum samples for split	2
	maximum fraction of observations	0.99
	maximum number of features	5
Extreme Gradient Boosting	number of trees	400
	maximum depth of the tree	7
	learning rate	0.1
	maximum fraction of observations	0.95
	maximum fraction of features	0.8
	minimum split loss	5
	L1 regularization	3
	L2 regularization	4
Deep Neural Networks	input size	15
	output size	1
	hidden layers	[200,300,200]
	activation function	ReLU
	initialization method	He
	dropout	0.25
	batch normalization	True
	learning rate	0.001
	epoch	700
	optimizer	Adam
	batch size	512

B. Model Results

Table II provides a comprehensive overview of the machine learning model performances, while Fig. 2 visually depicts prediction errors and residual plots for each model's predictions. The prediction error plots highlight the effectiveness of each model in accurately forecasting the fire resistance of FRP-strengthened concrete beams while the residual plots demonstrate that the prediction errors are randomly distributed, suggesting that the prediction errors of the models can be attributed to inherent randomness in the data.

Ensemble learning, specifically through XGBoost and Random Forest, emerged as the top-performing models, exhibiting superior predictive capabilities. Deep Neural Networks and Support Vector Regressors followed, with Linear Regression being the least effective in prediction accuracy.

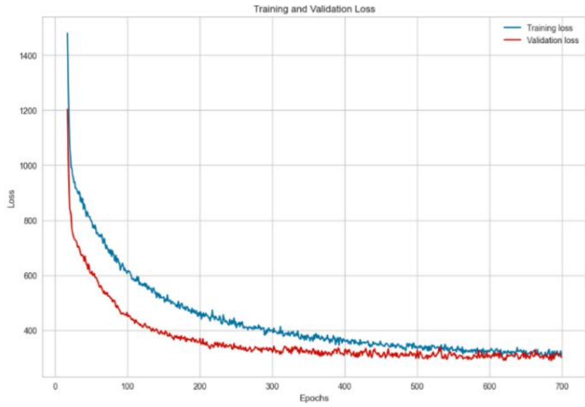

Fig. 1. Training loss and validation loss of neural networks per epoch.

Notably, XGBoost achieved a coefficient of determination of 0.942 in the test set, signifying its ability to explain approximately 94% of the variance in fire resistance. The residual plots indicated that the remaining 6% unexplained variance stemmed from inherent data randomness. Previous research in fire engineering domains has similarly highlighted the efficacy of gradient-boosted trees, affirming XGBoost's prominence in capturing complexity relating to fire engineering databases [12].

While Deep Neural Network demonstrated superior RMSE, its MAE was higher compared to XGBoost and Random Forest, suggesting its proficiency in accurately predicting data points with larger errors. Conversely, XGBoost provided more consistent and accurate predictions across all samples.

Despite Deep Neural Network trailing slightly behind Random Forest and XGBoost, its performance could potentially be enhanced through techniques such as learning rate scheduling and Bayesian optimization for parameter tuning. However, the trade-off lies in the considerable development time required for neural network execution compared to the efficient performance of ensemble methods like Random Forest and XGBoost.

Support Vector Machines exhibited the longest training time among all models, yielding only average performance with a prediction error of approximately 26 minutes for the test set. However, a separate analysis focusing solely on experimental data demonstrated its robustness, albeit indicating poor performance in large datasets due to prolonged training time and difficulty in capturing nonlinear data patterns [23].

TABLE II. ML MODEL PERFORMANCE

Model	Measure		
	RMSE (min)	*MAE (min)*	*R^2 (%)*
XGBoost	17.82	**9.87**	**0.942**
RF	18.58	10.33	0.937
DNN	**17.66**	12.15	**0.942**
SVR	26.49	14.71	0.871
LR	44.10	33.77	0.650

Linear Regression fared the poorest among all models, reflecting its high bias and inability to capture the complexities of predicting fire ratings for strengthened beams. While linear regression may be the simplest to implement, its lack of performance underscores its inadequacy in discerning data patterns effectively.

Analyzing the performance of all models reveals a trend where the majority of data points with significant residuals are clustered around fire resistance levels of approximately 15 or 300 minutes, as depicted in Fig. 2. This phenomenon likely arises due to the scarcity of training data within these specific ranges, as illustrated by the distribution of fire resistance in Fig. 3. At these extreme points, it is evident that DNN outperforms XGBoost and RF models, resulting in a superior RMSE score. Conversely, ensemble learning methods demonstrate stronger performance within intermediate fire resistance ranges.

Fig. 4 provides additional insight through the histogram displaying the top 100 data points with the highest errors for both XGBoost and DNN. This visualization reinforces the observation that while XGBoost tends to exhibit its highest errors at the extremes, DNN errors are more evenly distributed across the range. Table 3 further clarifies this, showcasing the top 5 errors by DNN within the 95 to 105-minute fire resistance range. It becomes apparent that the model's inaccurate predictions stem from discrepancies between the actual values and the model's expectations, particularly concerning crucial features, which will be explored in the subsequent section. For instance, examining I2_B2453 and I5_B3087 reveals high load ratios of approximately 60% to 70% without any insulation provided. One would expect such scenarios to result in poor performance; however, the actual fire resistance values were higher than expected. This considerable discrepancy suggests that the values with the largest residuals may be outliers in the dataset.

C. Feature Importance

Fig. 5 illustrates the mean SHAP values, providing insights into the feature importance of the best-performing model, XGBoost. Among the top five crucial features identified are load ratio, insulation depth, steel area, concrete cover, and total load.

TABLE III. DNN TOP 5 PREDICTION MISTAKES WITH FIRE RESISTANCE BETWEEN 95 TO 105 MINUTES

Beam name	Features			DNN Prediction	
	Insulation Depth	*Load Ratio*	*Actual Fire Resistance*	*Fire Resistance*	*Absolute Difference*
I3_B4464	76	69.93	95	180.28	85.28
I2_B2453	0	59.65	100	24.23	75.67
I3_B4463	76	57.39	100	166.55	66.55
I5_B3087	0	71.80	95	42.31	52.69
I4_B1236	25	71.25	105	59.59	45.41

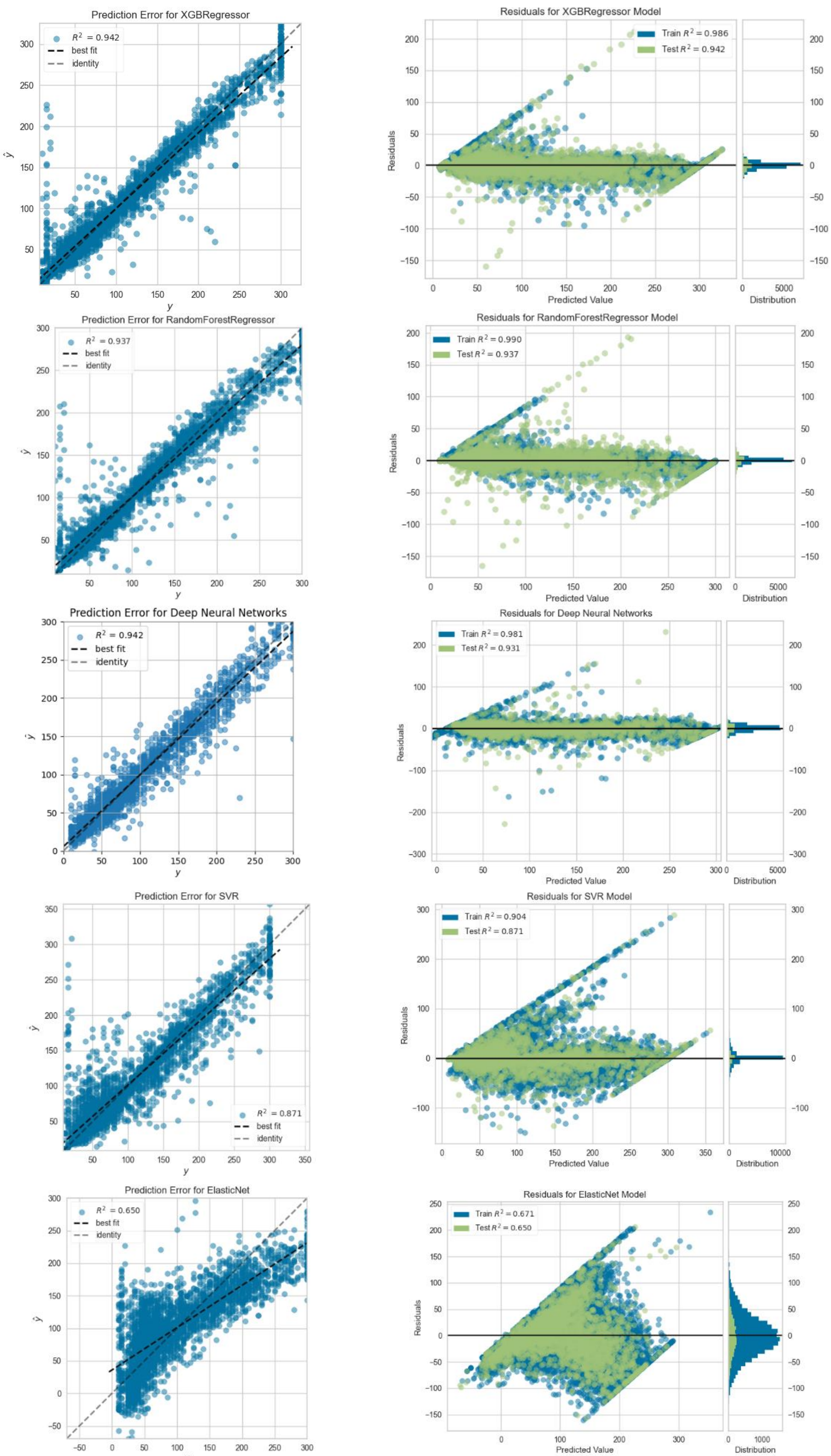

Fig 2. Prediction error plots and residual plots of XGBoost, Random Forest, Deep Neural Networks, Support Vector Regressor, and Linear Regression (*from top to bottom*)

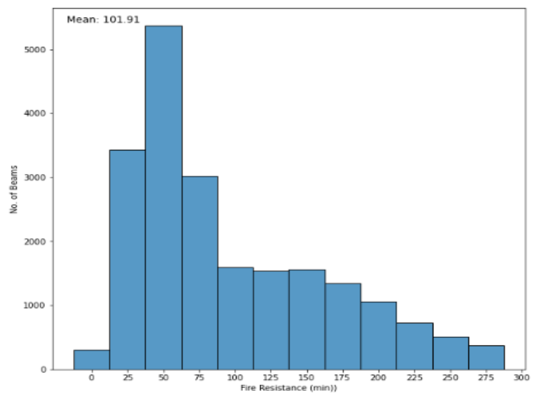

Fig. 3. Historgram plot of fire resistance.

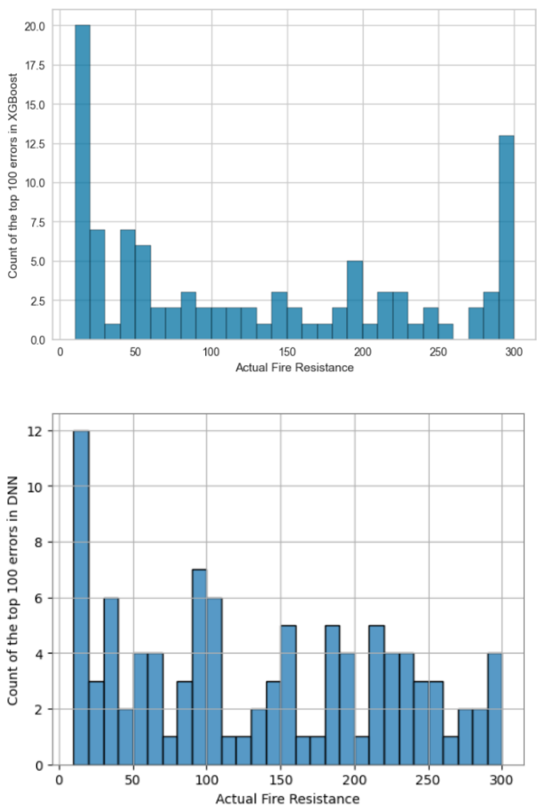

Fig. 4. Count of top 100 errors identified in XGBoost and DNN models

Bhatt explains that beams subjected to a higher load ratio result in faster degradation of the bond in the interface of FRP and concrete resulting in greater loss of capacity over time [14]. Moreover, a load ratio of less than 50% was recommended to achieve a capacity of three hours for fire resistance. The resulting SHAP values derived from XGBoost affirm the exceptional importance of the load ratio, with an absolute SHAP value of +34.7, indicating its strong influence on the fire resistance of strengthened concrete beams. Similarly, the total load also plays a crucial role, suggesting that beams under higher loads have reduced reserve strength.

Insulation depth emerges as another significant parameter for enhancing the fire performance of strengthened members.

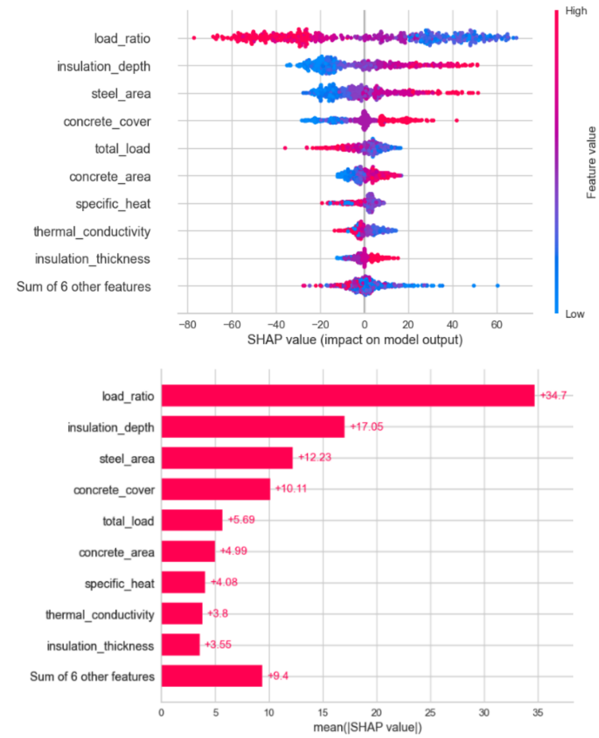

Fig. 5. Beeswarm plot and bar plot from the SHAP analysis of the most important features in the XGBoost model

Studies by Kodur and Bhatt demonstrate that thermal insulation can significantly prolong the fire resistance of beams, potentially by 60 to 90 minutes, by impeding material degradation and bond deterioration between FRP and concrete [24]. This underscores the critical role of thermal insulation in sustaining beam capacity, often overlooked in traditional approaches.

Likewise, increased steel area improves both the reserve strength capacity of the beam as well as prevents bond slip which helps maintain the capacity of beams in fire scenarios [14] with its importance validated using feature analysis from ML models. Concrete cover follows closely as an important parameter, aligning with the prescriptive and analytical methods outlined in ACI 216 Chapter 2.4. A concrete cover of 19mm, as prescribed, can provide up to 4 hours of fire resistance in concrete beams.

Remarkably, consistent across all models, the same parameters consistently rank within the top 5 or 6 in feature importance, as revealed by the SHAP values. This consistency highlights the robustness and reliability of these key features in predicting the fire performance of FRP-strengthened concrete beams.

V. Conclusion

The existing methods for assessing the fire resistance of FRP-strengthened concrete beams typically involve experimental testing, numerical modeling, or prescriptive approaches. However, these methods often suffer from drawbacks such as expensive testing setup, high computational resource requirements, or overly conservative estimations of fire performance. In response, this study explores machine learning models to accurately predict the fire resistance of strengthened beams to capture the nonlinear nature of material degradation during fire scenarios.

The findings of this research indicate that XGBoost demonstrates strong performance in overall fire resistance prediction, while Deep Neural Networks excel particularly in capturing extreme values of fire resistance. Key factors influencing fire resistance prediction include load ratio, insulation depth, steel area, concrete cover, and total load. By showcasing the effectiveness of machine learning methods, this paper emphasizes their potential to address highly nonlinear problems in classical engineering domains where conventional knowledge-based approaches may prove impractical or unfeasible. The automated nature of these approaches holds promise for significant time and resource savings, reducing reliance on manual effort.

REFERENCES

[1] Alkhrdaji, T. (2015, June). "Strengthening of concrete structures using FRP composites". Structure Magazine. Retrieved February 5, 2024, from https://www.structuremag.org/?p=8643#:~:text=FRP%20composites%20can%20be%20manufactured,an%20externally%20bonded%20reinforcing%20system.

[2] Aqueel. (2010). "Behavior of FRP-strengthened reinforced concrete beams under fire conditions". Retrieved February 5, 2024, from https://d.lib.msu.edu/etd/697

[3] Protchenko, K., & Szmigiera, E. (2020, March 10). "Post-Fire Characteristics of Concrete Beams Reinforced with Hybrid FRP Bars". Materials, 13(5), 1248. https://doi.org/10.3390/ma13051248

[4] Seo, S. Y., Lim, J. W., & Jeong, S. H. (2021, January 27). "Evaluation on the Bond Capacity of the Fire-Protected FRP Bonded to Concrete Under High Temperature". International Journal of Concrete Structures and Materials, 15(1). https://doi.org/10.1186/s40069-020-00448-3

[5] ACI 440.2R-17. (2017). "Guide for the Design and Construction of Externally Bonded FRP Systems for Strengthening Concrete Structures". American Concrete Institute: Farmington Hills, MI, United States.

[6] ACI 216.1-07. (2007). "Code Requirements for Determining Fire Resistance of Concrete and Masonry Construction Assemblies". American Concrete Institute: Farmington Hills, MI, United States.

[7] Zarifian, A., Izadi fard, R., & Khalighi, A. (2020, July). "Experimental study on the behavior of thermally insulated RC beams strengthened with CFRP after their exposure to high temperatures compared to non-insulated ones". Canadian Journal of Civil Engineering, 47(7), 875–883. https://doi.org/10.1139/cjce-2019-0001

[8] Bhatt, P. P., Kodur, V. K. R., Shakya, A. M., & Alkhrdaji, T. (2021, February). "Performance of insulated FRP-strengthened concrete flexural members under fire conditions". Frontiers of Structural and Civil Engineering, 15(1), 177–193. https://doi.org/10.1007/s11709-021-0714-z

[9] Naser, M. Z. (2021, January 2). "Mechanistically Informed Machine Learning and Artificial Intelligence in Fire Engineering and Sciences. Fire Technology", 57(6), 2741–2784. https://doi.org/10.1007/s10694-020-01069-8

[10] Keong, Kadir, Zuhan, Mastor, & Alel. (2022). "Fire resistance of FRP strengthening concrete beams at elevated temperature using ABAQUS". DOAJ. https://doi.org/10.24425/ace.2022.140632

[11] Alhusban, M., Alhusban, M., & Alkhawaldeh, A. A. (2023, December 19). "The Efficiency of Using Machine Learning Techniques in Fiber-Reinforced-Polymer Applications in Structural Engineering". Sustainability, 16(1), 11. https://doi.org/10.3390/su16010011

[12] Naser, M., Kodur, V., Thai, H. T., Hawileh, R., Abdalla, J., & Degtyarev, V. V. (2021, December). "StructuresNet and FireNet: Benchmarking databases and machine learning algorithms in structural and fire engineering domains". Journal of Building Engineering, 44, 102977. https://doi.org/10.1016/j.jobe.2021.102977

[13] Hisham, M., Hamdy, G. A., & El-Mahdy, O. O. (2021, July). "Prediction of temperature variation in FRP-wrapped RC columns exposed to fire using artificial neural networks". Engineering Structures, 238, 112219. https://doi.org/10.1016/j.engstruct.2021.112219

[14] Bhatt. (2021). "Fire Performance of FRP-strengthened Concrete Flexural Members". MSU Libraries Digital Repository. https://doi.org/10.25335/d4ef-qv21

[15] Bhatt, P., Kodur, V., & Naser, M. (2024, February). "Dataset on fire resistance analysis of FRP-strengthened concrete beams". Data in Brief, 52, 110031. https://doi.org/10.1016/j.dib.2024.110031

[16] Pillonetto, G., Chen, T., Chiuso, A., De Nicolao, G., Ljung, L. (2022). Regularization of Linear Regression Models. In: Regularized System Identification. Communications and Control Engineering. Springer, Cham. https://doi.org/10.1007/978-3-030-95860-2_3

[17] Awad, M., Khanna, R. (2015). Support Vector Regression. In: Efficient Learning Machines. Apress, Berkeley, CA. https://doi.org/10.1007/978-1-4302-5990-9_4

[18] Breiman, L. Random Forests. Machine Learning 45, 5–32 (2001). https://doi.org/10.1023/A:1010933404324

[19] T. Chen, C. Guestrin, Xgboost: a scalable tree boosting system, in: Proceedings of the 22nd Acm Sigkdd International Conference on Knowledge Discovery and Data Mining, 2016, pp. 785–794.

[20] Manogaran Madhiarasan, Mohamed Louzazni, "Analysis of Artificial Neural Network: Architecture, Types, and Forecasting Applications", Journal of Electrical and Computer Engineering, vol. 2022, Article ID 5416722, 23 pages, 2022. https://doi.org/10.1155/2022/5416722

[21] Scott M. Lundberg, et al., A unified approach to interpreting model predictions, Adv. Neural Inf. Process. Syst. 30 (2017).

[22] Alharbi, A.G., Arif, M., 2020. Detection and classification of apple diseases using convolutional neural networks. 2020 2nd International Conference on Computer and Information Sciences, ICCIS 2020, pp. 1–5 https://doi.org/10.1109/ICCIS49240.2020.9257640.

[23] S. S. Rasheed and I. H. Glob, "Classifying and Prediction for Patient Disease Using Machine Learning Algorithms," 2022 3rd Information Technology To Enhance e-learning and Other Application (IT-ELA), Baghdad, Iraq, 2022, pp. 196-200, doi: 10.1109/IT-ELA57378.2022.10107935.

[24] Kodur, V. K. R., and Bhatt, P. P. (2018). "A Numerical Approach for Modeling Response of Fiber Reinforced Polymer Strengthened Concrete Slabs Exposed to Fire", Composite Structures, 187, 226–240. 10.1016/j.compstruct.2017.12.051