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Ensemble Machine Learning for Predicting Flexural Capacity of FRCM-Strengthened RC Beams

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Abstract

Fabric reinforced cementitious matrix (FRCM) composites are progressively applied to strengthen reinforced concrete (RC) members because they offer improved compatibility, durability and fire resistance compared with epoxy-bonded fibre reinforced polymer (FRP) systems. However, predicting the ultimate flexural capacity of FRCM-strengthened beams remains challenging due to the complex interaction of material, geometric and loading parameters. Here, we develop and evaluate ensemble machine learning (ML) models to predict the ultimate load-carrying capacity of FRCM-strengthened RC beams. A curated database of 244 experimental tests from the literature was compiled, comprising 16 input features describing concrete compressive strength, reinforcement ratios, FRCM properties and specimen geometry. After systematic preprocessing and feature encoding, several ensemble regressors were benchmarked and three models Extra Trees, XGBoost and AdaBoost were analysed by 5 fold cross-validation with grid search for hyperparameter optimization. Among them, the Extra Trees regressor achieved the best performance, with a coefficient of determination $R^2 = 0.898$, root mean square error RMSE = 21.5 kN and mean absolute error MAE = 11.7 kN. Feature-importance analysis and SHAP-based explainability consistently identified concrete compressive strength, reinforcement ratio and cracking load as dominant predictors, in agreement with structural mechanics. These results demonstrate that ensemble ML models provide a reliable and interpretable tool for assessing the flexural capacity of FRCM-strengthened RC beams, also highlight the potential of data-driven methods to complement empirical and code-based design approaches in structural strengthening.

Keywords:

‘Fabric-reinforced cementitious matrix’, ‘Reinforced concrete beams’, ‘Flexural strengthening’, ‘Ensemble machine learning’, ‘Extra Trees’, ‘Explainable AI’

Abbreviations

FRP	Fibre reinforced polymer
FRCM	Fabric-reinforced cementitious matrix
MAE	Mean absolute error
ML	Machine learning
RC	Reinforced concrete
RMSE	Root mean square error
SHAP	SHapley Additive exPlanations

Introduction:

The existing methods for retrofitting reinforced concrete (RC) structures have been improved through research which developed new techniques to strengthen these structures. The rehabilitation process becomes essential when environmental conditions damage existing infrastructure and design defects and operational needs and seismic threats increase [1]. The engineering field requires advanced techniques which can help engineers to enhance their existing concrete structures. The combination of increasing loads and stricter design regulations and earthquake damage results in building and bridge deterioration over time [2,3]. FRPs provide corrosion resistance because they possess lightweight yet strong characteristics which make them appropriate for their intended applications. The successful use of carbon fiber composites and glass fiber composites and basalt fiber composites has been demonstrated in various applications [4]. The use of epoxy-bonded FRPs presents multiple challenges, Epoxy-bonded FRP systems encounter operational challenges because their bond performance decreases when exposed to wet or rough concrete contact and high-temperature conditions and concrete surfaces [5]. The systems of Fabric-reinforced cementitious matrix (FRCM) composites solve multiple existing problems through their design which uses fiber meshes as embedded elements in cement-based matrices [1,6] to create stronger materials which work better with existing substrates and still maintain their structural integrity under extreme temperatures while preventing moisture damage [7]. The experimental research on FRCM strengthening operations has demonstrated their ability to increase the flexural capacity and shear resistance and ductility characteristics and crack distribution patterns of RC beams [8]. The advanced configurations which include mechanical anchorage and multilayer fabrics and hybrid fiber combinations have improved structural performance [9]. Research scientists currently investigate the development of novel binding agents which use industrial waste materials as their primary component [10].

The standard binder methods face their main challenge because they need to stop all carbon emissions which these methods generate while in operation [6,11]. Machine learning (ML) will function as the strength evaluation method which enables the systems to deliver better results according to [12] because it enables testing of structural response to nonlinear interactions through multiple input parameters [13]. The method enables both load capacity prediction and crack detection and estimation of bond strength [14]. The ML operations will analyze expenses which occur during testing with an outcome prediction method that requires testing of all cases [15,16]. Engineers have stopped using steel plate bonding methods for structural retrofitting because of recent advancements which provide better tensile strength and lightweight design and advanced protection against corrosion through fiber-reinforced polymer (FRP) systems [17]. The use of epoxy-bonded FRPs provides several advantages but the material contains specific limitations. The material operates poorly because its interface fails to maintain strength at high temperatures and humidity conditions which results in early bond failure that shortens its operational lifespan and restricts its usage in large-scale strengthening projects [18]. FRCM composites have achieved recognition as a legitimate replacement for traditional materials. The FRCM systems use inorganic cement-based matrices to create materials which achieve better fire resistance properties while maintaining low brittleness and strong chemical and mechanical bond to concrete surfaces [19]. The research found that FRCM strengthening substantially improved crack control flexural shear strength and energy dissipation capacity of reinforced concrete beams [20]. The implementation of hybrid fiber systems together with newer anchorage techniques has strengthened the performance of FRCM retrofits according to [21,22].

Researchers investigate sustainable strengthening materials that use geopolymer binders together with industrial by-products like sugarcane bagasse ash to achieve environmental benefits while maintaining structural performance [23]. The construction practices establish circular economy systems which support the transition to environmental-friendly building methods. Geopolymer-based fiber composites have demonstrated flexural and compressive strengths comparable to, and in some cases exceeding, those of conventional cementitious systems, supporting their use in sustainable retrofitting applications [24]. The existing herelths approach develops methods that help build structures which need rehabilitation from severe exposure damage. The FRCM systems successfully restore reinforced concrete elements that experienced fire damage [25,26] and corrosion [27,28]. The combination of hybrid near-surface embedded reinforcement together with ultra-high-performance concrete (UHPC) jacketing produces better results in load capacity and deformation resistance according to research findings [29,30] and interpretations [31–33]. The method demonstrates improved resistance against deformation while its load capacity testing results show better performance than before [34–38]. Researchers discovered that fabric selection together with matrix composition and interfacial behavior determined how different reinforcing systems performed during various structural tests which used composite materials based on cementitious materials [39]. In this recent work the research team applied ML tools which used ensemble methods to achieve dependable predictions regarding bond strength and crack detection and ultimate load estimation through gradient boosting and random forest and extreme gradient boosting methods [4,40]. End users can better comprehend the effects of design variables through SHAP-based analysis because it enables the clear interpretation of model outcomes [12].

The training dataset contains information which extends until the month of november in the year 2025, also the present method establishes a link between mechanical comprehension and the techniques which use data for forecasting outcomes. The complete research analysis of all available studies demonstrates that FRCM serves as an effective strengthening solution which improves concrete structure compatibility and provides enhanced durability and fire protection while solving all issues that arise from epoxy-bonded FRP system usage [41–45]. ML operation creates a precise system which assesses performance while it improves design and predicts outcomes without requiring expensive time-consuming testing methods [46–51]. Data-driven decision-making which combines sustainable material innovation with transparent computer modeling establishes a new standard for retrofit engineering which enables infrastructure projects to achieve improved resilience and sustainability [52–59].

Scientists need to demonstrate how data-driven predictions connect with mechanics-based understanding through their work on FRCM materials development and ML method development. The research team created ensemble machine learning models to predict the maximum flexural strength of RC beams that have been reinforced with FRCM. The research team conducted tests on Extra Trees XGBoost and AdaBoost regressors by using cross-validation and hyperparameter tuning methods to evaluate 244 experimental tests from their database. SHAP interpretation together with feature importance analysis enables the creation of prediction models which establish ties between physical parameters. The goal is to deliver precise predictions which maintain transparency and serve as support for both design processes and decision-making in retrofit engineering.

Methods

Dataset Collection and Features

The study created an experimental database which contained 244 FRCM-strengthened RC beam tests that researchers had previously published as well as the system design shown in figure 1, as well as the entry included 16 input features which explained material properties [60] through physical attributes that included compressive strength and fibre tensile strength and reinforcement ratio and through geometric dimensions that included effective depth and cross-sectional area and through the description of loading conditions. The structural system reached its maximum sustaining capacity at the ultimate flexural load which engineers measured in kilonewtons (kN). The following section provides descriptions of the 16 selected input parameters.

- Compressive Strength (MPa): Uniaxial compressive strength of the concrete matrix.
- Longitudinal Reinforcement Ratio (%): Ratio of longitudinal steel reinforcement to the cross-sectional area.
- Fiber Content (%): Volumetric proportion of fibres in the cementitious matrix.
- Tensile Strength of Fibers (MPa): Maximum tensile stress the fibers can withstand.
- Young's Modulus of Fibers (MPa): Stiffness of the fiber material.
- Specimen Geometric Properties: Height (mm), Cross-sectional Area (mm²), Effective Depth (D) (mm), Overall Depth (h) (mm).
- A/D Ratio: Shear span-to-effective depth ratio.
- Reinforcement Ratio: Ratio of total steel reinforcement area to the gross cross-sectional area.
- Cracking Load (kN): Load at which initial visible cracking occurs.

The dataset establishes the basis for ML model development which extracts nonlinear structural performance relationships from input feature data through model flow established in figure 2 [12,60].

Data Preprocessing

This piece of work adapted the scikit-learn's label encoding method to transform their categorical variables into numerical formats. The dataset contained non-predictive columns which included Reference, Beam ID, Paper Title, Eccentric Load, and Axial Load. Yield Load from the dataset have been excluded because of the higher possibility of data leakage [14]. The researchers used column means to fill missing numbers and applied mode values to substitute missing categories [2,13]. The dataset divided into training and testing sets using an 80/20 split while they standardized numerical features through z-score normalization, also established a fixed random seed to ensure their results could be duplicated.

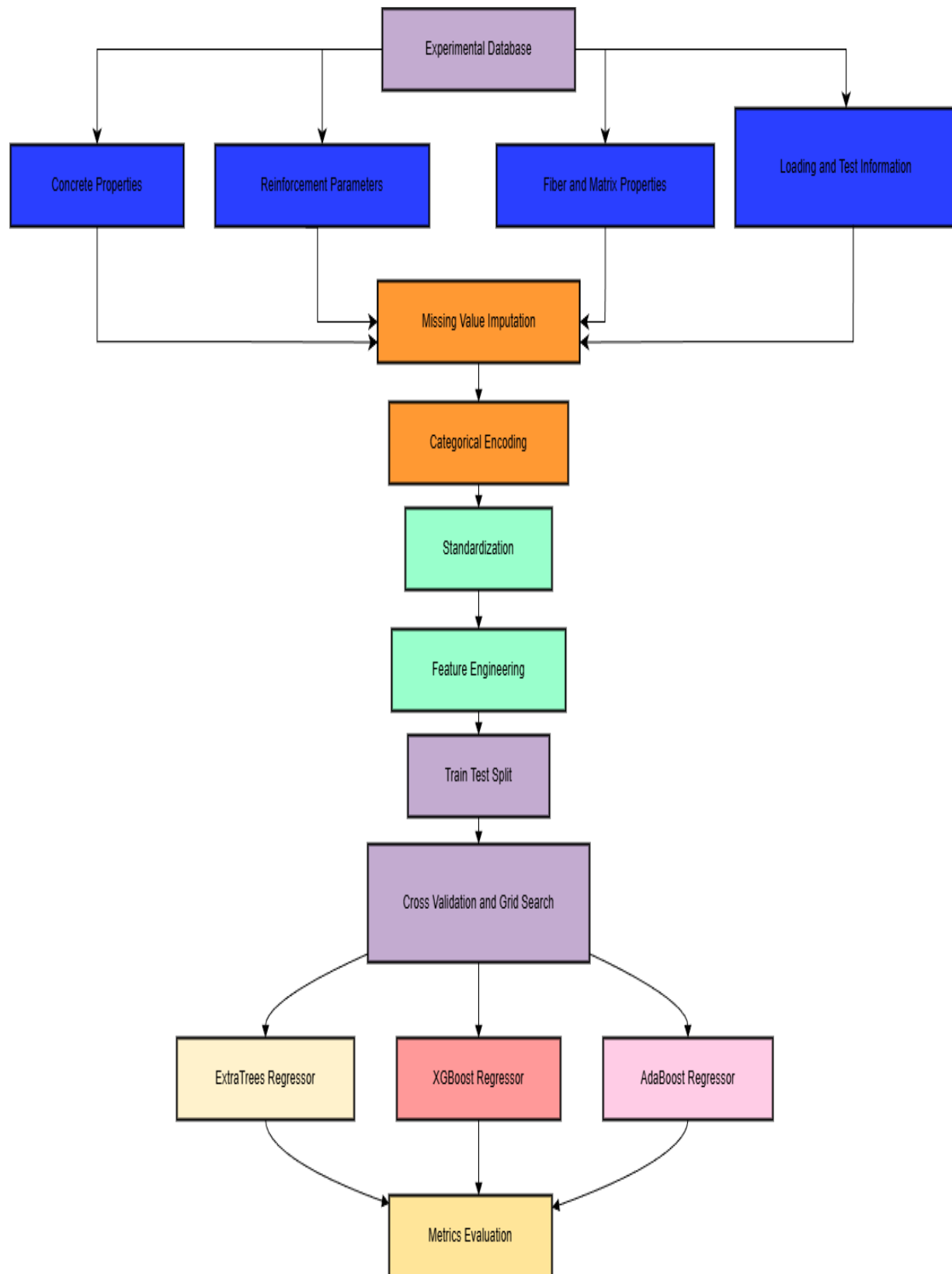


Figure 1 Overall system architecture used in this study

Model Selection and Benchmarking

The LazyPredict benchmarking tests proved that ensemble models outperformed all other modeling methods through their testing process. The automated benchmarking tool performed its assessment of multiple regression models by testing both training data and testing data. The best three models according to their RMSE and R^2 results were AdaBoost Regressor Extra Trees Regressor and XGBoost Regressor. The research team selected these three algorithms for in-depth examination. The input features were standardized through training by using the ‘StandardScaler’ tool from scikit learn. The process required this step to establish equal feature scales which proved essential for XGBoost model operation.

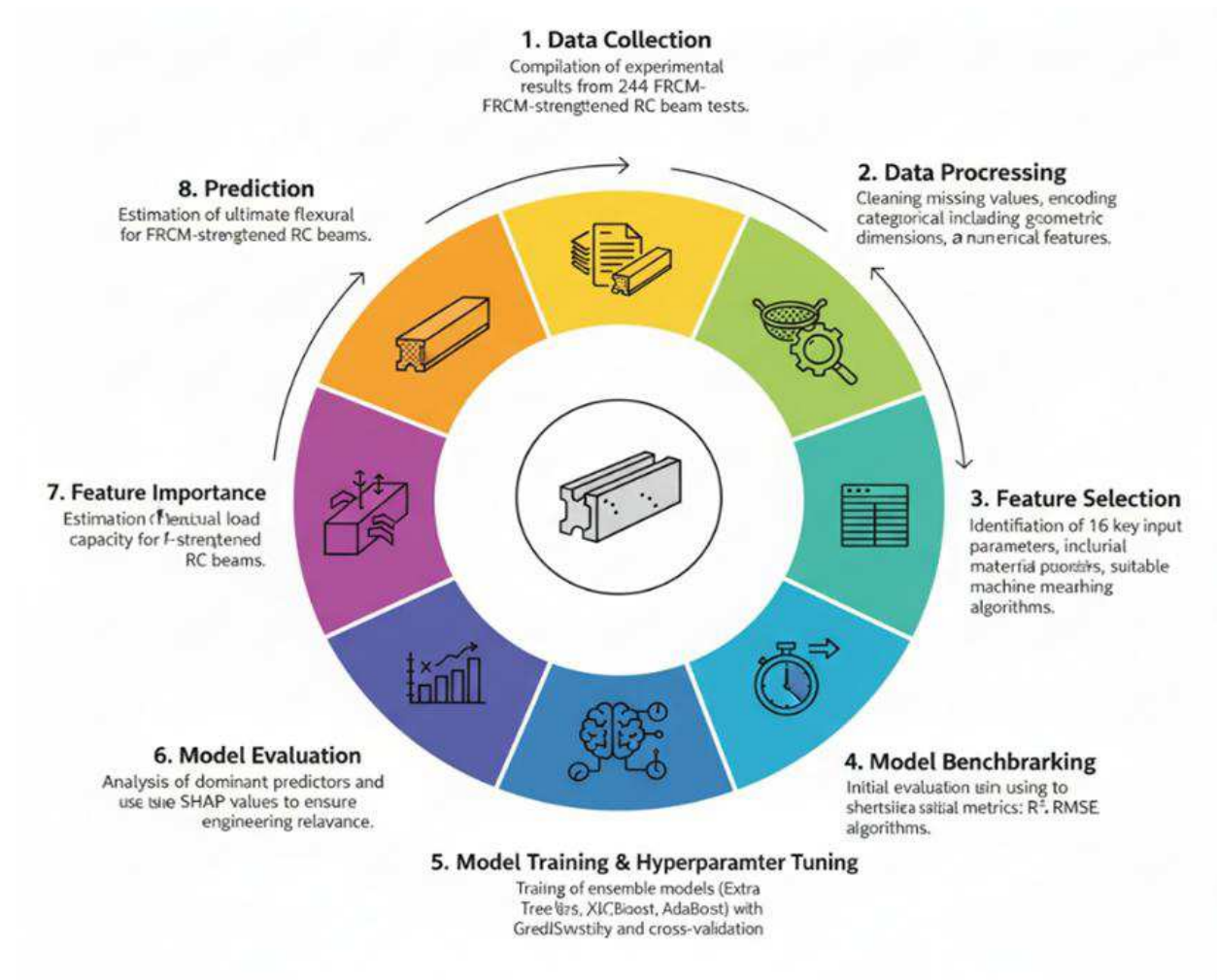


Figure 2 Model Flow

Machine Learning Models

The accurate prediction of FRCM-strengthened RC beam load-carrying capacity requires models that can simulate intricate nonlinear relationships. The benchmarking results showed that three ensemble learning algorithms achieved success which included both AdaBoost Regressor and Extra Trees Regressor and XGBoost Regressor as shown in figure.3

Extra Trees Regressor	XGBoost Regressor	AdaBoost Regressor
Bagging (Randomized) Builds an ensemble of deep, de-correlated decision trees by introducing randomness in both feature selection and split thresholds. Averages predictions to control overfitting.	Gradient Boosting Builds trees sequentially. Each new tree is trained to correct the residual errors of the previous ones, using a second-order gradient optimization for higher accuracy.	Adaptive Boosting Builds shallow trees (weak learners) sequentially. Focuses on difficult samples by increasing their weights in subsequent iterations, aiming to reduce bias.
<ul style="list-style-type: none"> • Strong predictive accuracy. • Effectively reduces model variance. • Computationally efficient. • Robust against overfitting with less tuning. 	<ul style="list-style-type: none"> • Typically high performance and speed. • Highly scalable and precise. • Built-in regularization prevents overfitting. • Offers fine-grained parameter control. 	<ul style="list-style-type: none"> • Excellent at reducing model bias. • Good at capturing non-linear patterns. • Can be sensitive to outliers and noise. • Conceptually simple and effective.
Applications requiring high accuracy with strong generalization, especially on smaller or complex datasets where extensive hyperparameter tuning may not be feasible.	Tasks where performance is critical and computational resources allow for careful tuning. Widely used in competitive machine learning and industry.	Problems where simple models underperform. Often used to boost the performance of weak learners in classification and regression tasks with complex decision boundaries.

Figure 3 Juxtaposition of ensembled ML models

Extra Trees Regressor

The Extra Trees Regressor creates a tree-based model through its method of building decision tree ensembles which employs both random split thresholds and random feature selection. The model achieves better general performance through its prediction aggregation method which combines outputs from a forest of trees that have been specially designed to produce independent predictions. The prediction is an average of the outputs from all trees in the ensemble:

$$\hat{y}(x) = \frac{1}{T} \sum_{t=1}^T f_t(x) \quad (1)$$

where $f_t(x)$ is the prediction from the t -th randomised decision tree, and T is the total number of trees in the forest. The model provided essential insights through its feature importance score computations which identified compressive strength axial load reinforcement ratio and cracking load as the key factors that explain model performance.

XGBoost Regressor

The XGBoost Regressor (eXtreme Gradient Boosting) was configured to minimise squared error using a second-order approximation to the loss function. Scalability and accuracy are hallmarks of XGBoost, which provides fine control over hyperparameters like tree depth, learning rate, and strength of regularisation. The objective function $Obj(t)$ at iteration t is the sum of the loss and a regularization term Ω :

$$Obj^{(t)} = \sum_{i=1}^n \left[l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) \right] + \Omega(f_t) \quad (2)$$

where l is the loss function, and the regularization term Ω penalizes model complexity:

$$\Omega(f_t) = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T \omega_j^2 \quad (3)$$

In the present study, the model had strong predictive abilities, with high R^2 values and low RMSE scores.

AdaBoost Regressor

AdaBoost Regressor was trained. This boosting method is an ensemble of many weak models, such as decision trees, which are built iteratively based on the errors of the previous model. The adaptive and bias-correcting abilities of AdaBoost Regressor make it highly efficient in handling non-linear and interaction relationships between features. The final prediction $F(x)$ is a weighted sum of the weak models $h_t(x)$, where the weights α_t are calculated during the iterative learning process:

$$F(x) = \sum_{t=1}^T \alpha_t h_t(x) \quad (4)$$

Model Training and Validation

The training and testing process was done to ensure the generalisability of the models, statistical validity, and reproducibility [60]. The preprocessed dataset was divided into a training and testing dataset with an 80:20 split. The models were trained on the training dataset only and then tested on the testing dataset. To avoid overfitting, k fold cross-validation was used during the hyperparameter search with 5 folds in this approach [6]. The hyperparameter search was done using 'GridSearchCV' for models such as XGBoost, which helped in searching for the best hyperparameters. For AdaBoost and Extra Trees, the same hyperparameters were searched [2].

Performance Evaluation

The performance of the models was evaluated using three measures:

- R^2 (Coefficient of Determination): This is the proportion of the variance in the target variable that is explained by the model. The closer to 1, the better the fit..
- RMSE (root mean square error): Penalises larger errors more heavily, making it suitable for safety-critical structural predictions.
- MAE (mean absolute error): Provides an interpretable average error magnitude in kilonewtons (kN), facilitating engineering-based evaluation.

Apart from the numerical evaluation, graphical methods of diagnosis were employed. The graph of predicted values versus actual values was employed to determine the accuracy of the predictions, as depicted in figure 4. The research utilized visual diagnostic instruments and generated feature importance rankings to pinpoint vital structural parameters.

Results

Table 1 shows the cross-validation performance results for five ensemble regressors which were evaluated on the FRCM beam database. The three performance metrics used by the study included R^2 coefficient of determination and RMSE root mean square error and MAE mean absolute error. Extra Trees achieved the highest R^2 value of 0.898, indicating that it had a very good fit between the actual and predicted values, and it had the lowest RMSE and MAE values of 21.46 kN and 11.74 kN, respectively, which indicate that it was accurate and consistent. The randomized tree-building strategy reduces variance while avoiding overfitting, particularly valuable given the moderate dataset size and high-dimensional feature space.

Table 1 Machine Learning Model Performance (Cross Validated).

Level	Model	R^2	RMSE	MAE
0	Extra Trees	0.898414	21.457190	11.737365
1	XG Boost	0.865919	25.818541	13.127922
2	Hist Gradient Boosting	0.864483	25.704411	15.576869
3	Gradient Boosting	0.857913	26.467786	14.026257
4	Ada Boost	0.836645	28.536172	14.721704

XGBoost and HistGradientBoosting were also competing models, as shown in Table 1. XGBoost was a generalising model with a stable error distribution because of its strong regularisation methods and strong control over the learning process. HistGradientBoosting, although not as accurate, had a stable prediction and was robust over the folds, hence meeting the criteria of a potential model for a structural analysis task [9]. GradientBoosting had a balanced result with moderate error values and a stable interpretation of variance. AdaBoost, although still a good model, had higher RMSE and MAE values, showing higher susceptibility to noise and outliers in the data [21].

This can be attributed to its boosting algorithm, which could have increased the effect of noisy data points. These findings were further confirmed by the visual inspection in figure 5. The scatter plots of predicted vs. actual in figure 6 indicated that Extra Trees had the most clustering around the ideal prediction line, followed by XGBoost and Gradient Boosting, who both had a similar trend but slightly more variation.

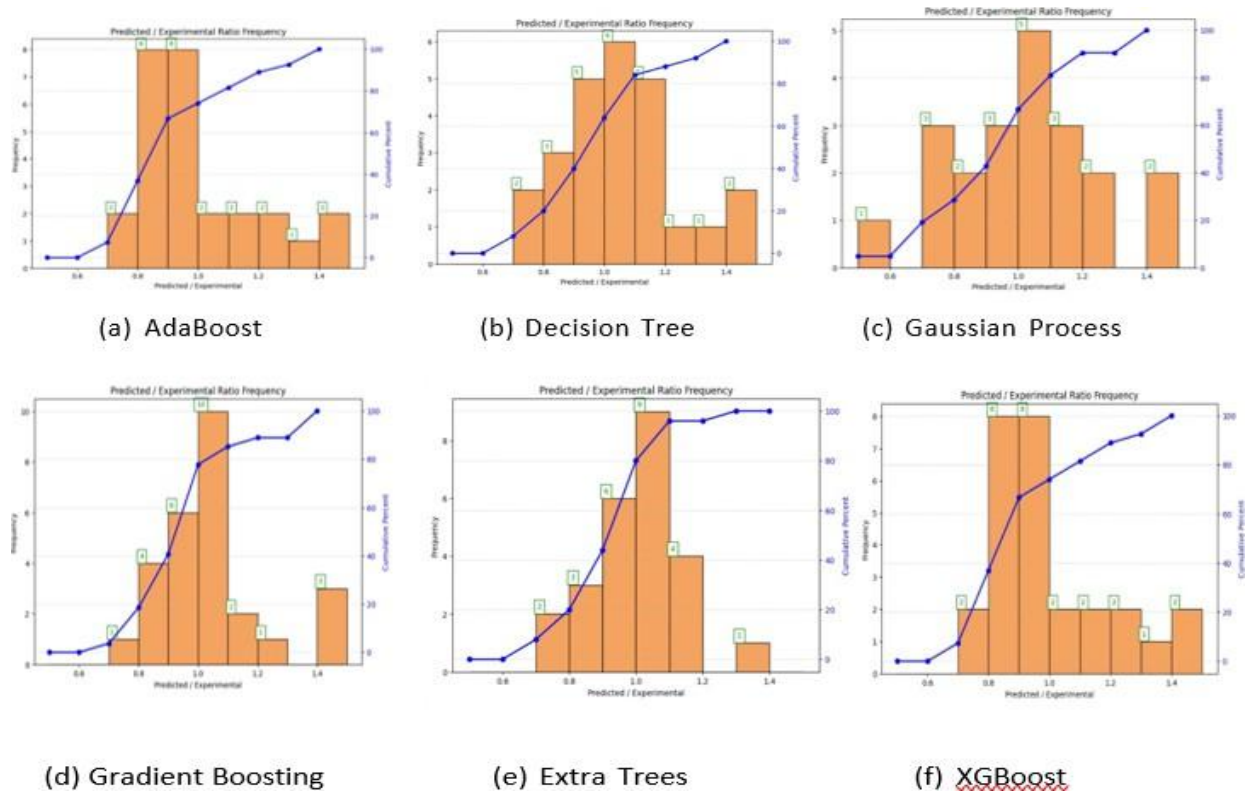


Figure 4 Comparison of Predicted/Experimental Ratio Frequencies for Different ML Models.

AdaBoost demonstrates its prediction errors with a distribution pattern that shows more variation because its prediction accuracy is inferior to other prediction methods. Figure 5 displays cross-validated residual plots which show that Extra Trees model residuals maintain a central concentration pattern with symmetrical distribution patterns that extend from a zero point. The XGBoost and Gradient Boosting models produce residuals that show no pattern of bias, whereas the residuals from AdaBoost display wider distribution patterns, which indicate that its predictive accuracy remains unstable.

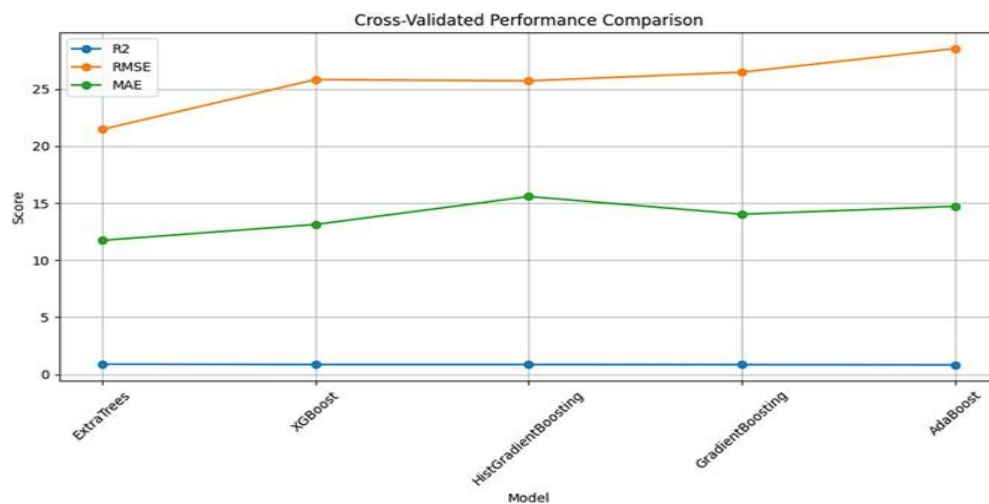


Figure 5 Machine Learning Model Performance Comparison (Cross-Validated).

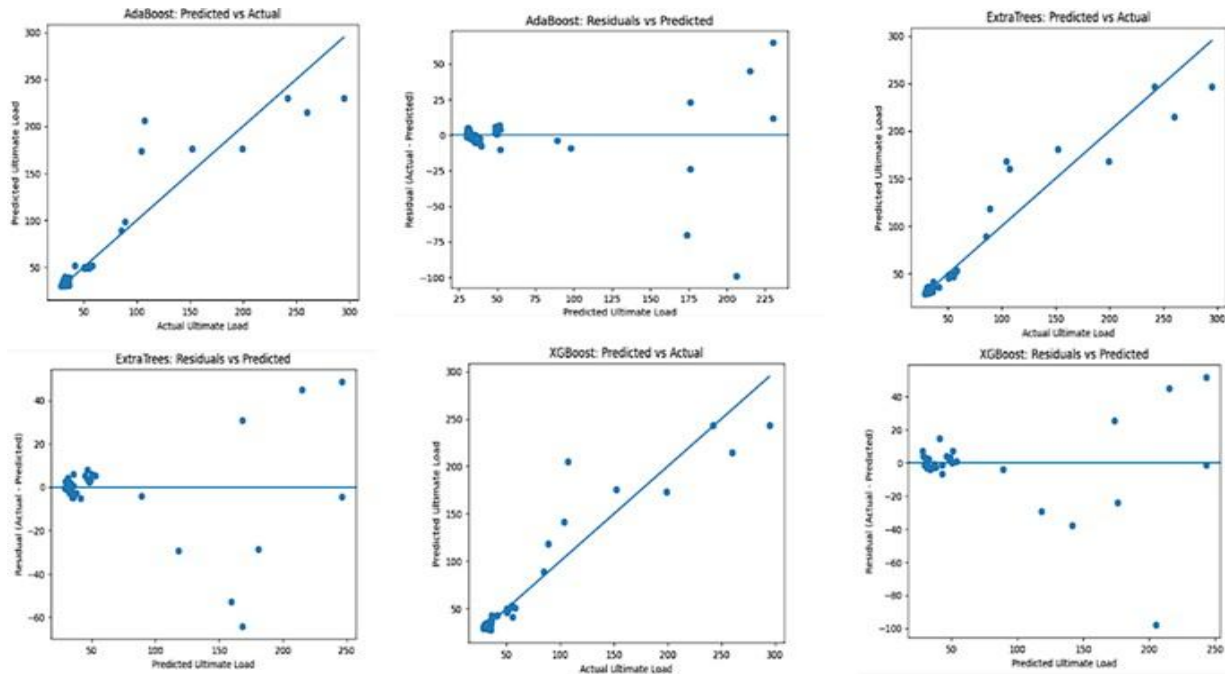


Figure 6 Residual with comparative correlation graph between predicted and actual outcomes by using AdaBoost, ExtraTrees, and XGBoost.

Figure 6 displays correlation plots which show predicted results against actual results together with residual distributions for the AdaBoost and Extra Trees and XGBoost models. Figure 6 shows correlation plots that compare predicted values with actual values and provides residual distribution measurements for the AdaBoost and Extra Trees and XGBoost models. The modeling results for feature importance consistently identify compressive strength and reinforcement ratio and cracking load as the three most critical factors which supports established structural mechanics understanding [2]. The SHAP summary shown in Figure 7 provides a more precise representation of how features contribute to the outcome:

- **Global trends:** Features such as compressive strength (Feature 4) and reinforcement ratio (Feature 5) had the largest positive SHAP values, meaning higher values of these features consistently increased the predicted ultimate load.
- **Nonlinear effects:** The Crack Load (Feature 2) and depth-specific traits (Features 11 and 12) demonstrate non-linear behavior through their Non-linear effects. The variables create SHAP values which extend from positive values to negative values because their prediction effect depends on their magnitude and their interactions with other inputs.
- **Engineering alignment:** The results match established mechanics which state that higher concrete strength and reinforcement ratios should be used as preferable construction materials while the geometric ratios (a/d ratio and effective depth) determine which failure mode will prevail.

The model establishes SHAP value verification because the system detects proper physical phenomena while it refrains from establishing false links which makes it trustworthy for structural design applications. Better understanding requires additional graph types which include figure 5 ratio frequencies figure 7 parameter distributions and figure 8 correlation patterns.

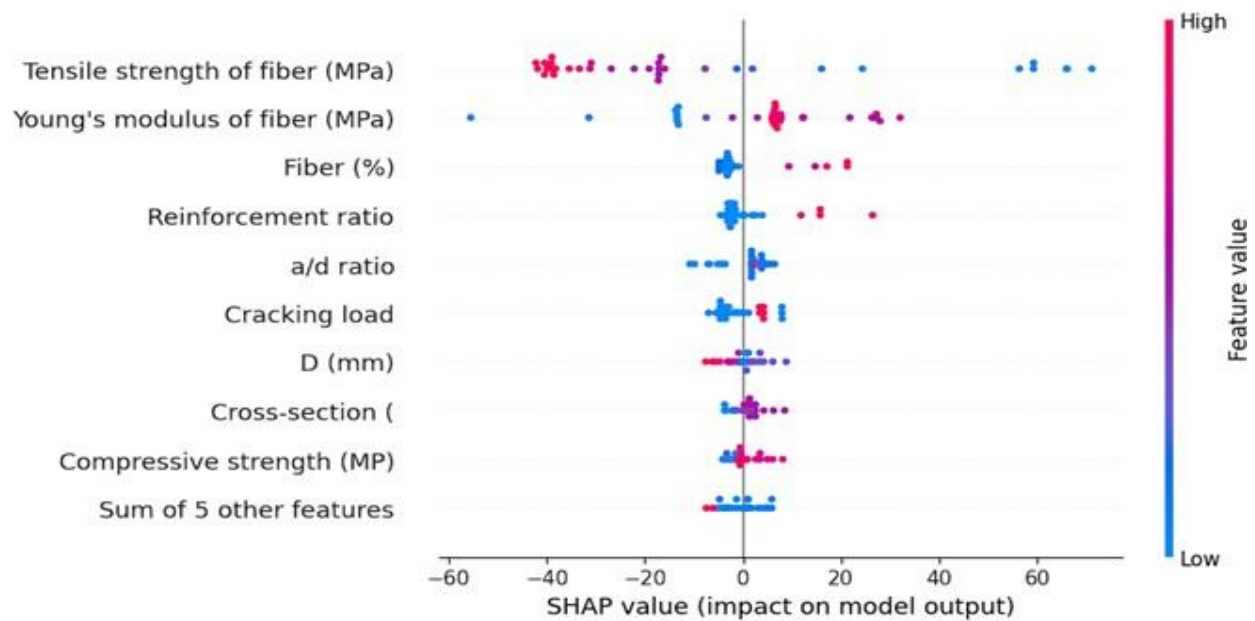


Figure 7 SHAP analysis plot showcasing feature importance and model output impact.

Discussions

Engineers can now use machine learning systems to discover the maximum load capacity of FRCM-strengthened RC beams. Ensemble learning methods successfully constructed models which could represent the complicated nonlinear connections between material properties and geometric dimensions and loading conditions. The Extra Trees regressor showed the highest level of dependable performance among all tested methods. The model demonstrates strong capacity to generalize across various experimental situations which is evident from its high coefficient of determination and its low prediction errors.

The ensemble models achieved prediction accuracy which satisfied practical engineering standards for estimating the ultimate flexural capacity of FRCM-strengthened RC beams. The Extra Trees model delivered the best performance with $R^2 = 0.898$ and $RMSE = 21.46$ kN and $MAE = 11.74$ kN as it provided a precise and consistent assessment throughout the validation process. The randomized tree-building strategy creates independent trees which decrease prediction uncertainty while enabling feature significance determination through interpretative analysis. The AdaBoost Regressor, although doing well, had slightly higher RMSE and MAE values compared to the other models. The adaptive boosting system of AdaBoost, which concentrates on the difficult-to-predict samples, might have further exaggerated the effect of noise or outliers in the data. However, AdaBoost was still able to maintain a strong R^2 value and was helpful in modeling variance, particularly in the presence of varied data distributions.

The scatter plots in figure 8 indicated that Extra Trees had the strongest clustering around the optimal prediction line, Whereas XGBoost and GradientBoosting followed a consistent trend with slightly higher dispersion. The residual plots showed that Extra Trees had negligible error dispersion and no bias, whereas XGBoost had well-distributed residuals and AdaBoost had wider error dispersion.

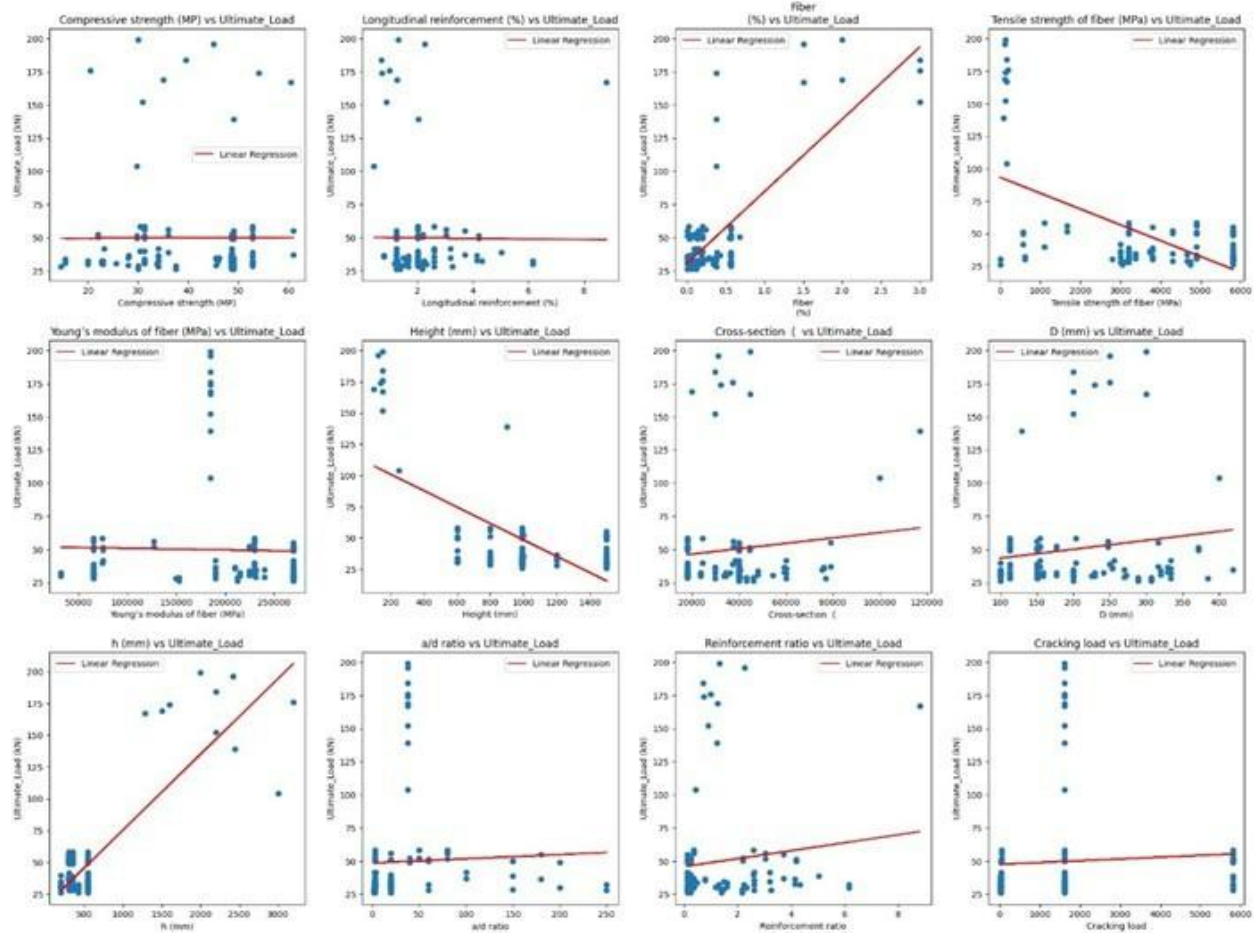


Figure 8 Correlation between the input parameters and Ultimate Load.

However, interpretability is still a concern in engineering. Feature importance and correlation heat maps from figure 9 above provided a global view, but for a better understanding, SHAP (Shapley Additive Explanations) analysis is preferred. SHAP provides a local explanation and assists engineers in:

- Attribute predictions to specific features.
- Detect nonlinear interactions and thresholds.
- Validate model decisions against domain knowledge.

The upcoming operational procedures will achieve better transparency through SHAP implementation which enables safety critical environments to use retrofitted design and performance monitoring together with structural optimization. The study results show that machine learning technology improves traditional analysis methods.

The research needs empirical equations and finite element models as essential components but these models face performance issues during testing with non-standard conditions and when researchers study material properties. ML models should be included in today's design tools because these models provide multiple advantages which include scalable operations and flexible functionality and automated system processes.

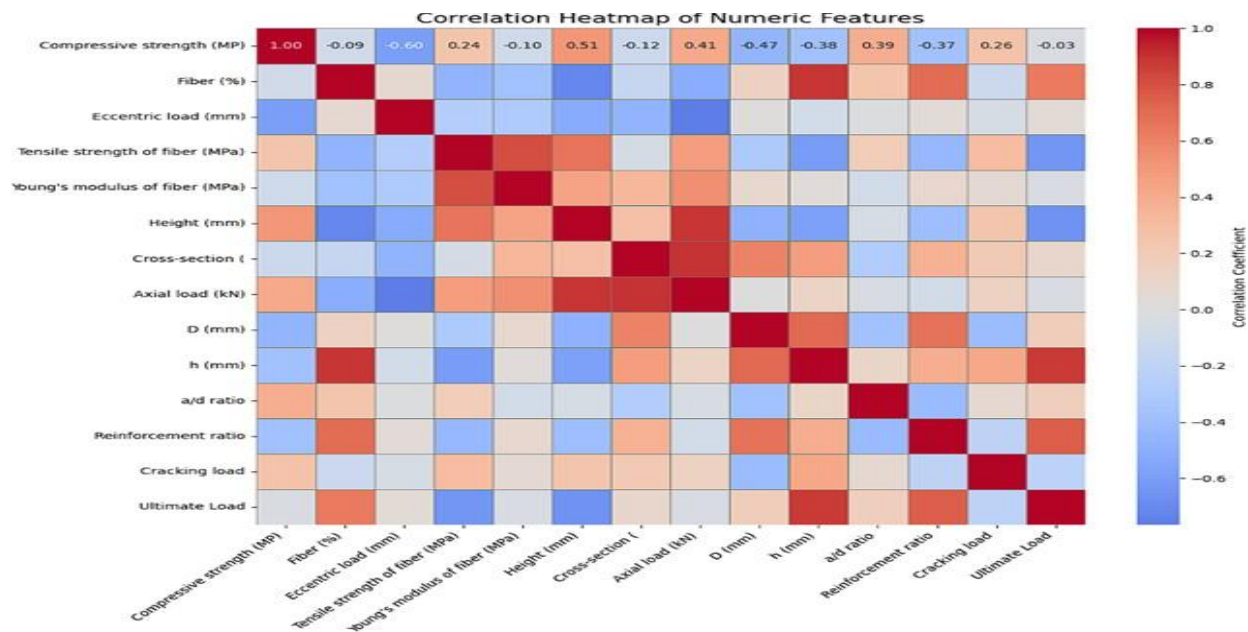


Figure 9 Relationship between numeric features depicted by correlation heatmap.

Conclusion

The study evaluated the accuracy of ensemble machine learning models in predicting flexural strength for FRCM reinforced concrete beams. Researchers established the training database through their complete experimental testing of 244 tests which included all required material properties and geometric dimensions and loading parameters. The Extra Trees and XGBoost and AdaBoost regressors completed their 5-fold cross-validation testing after they had finished all work on preprocessing and feature encoding and hyperparameter tuning activities. The Extra Trees model provided better predictive results because it achieved $R^2 = 0.898$ and $RMSE = 21.5$ kN and $MAE = 11.7$ kN by using its random tree building approach which reduced prediction variability. The feature importance rankings together with the SHAP-based interpretation method consistently showed that compressive strength and reinforcement ratio and cracking load attained the highest importance according to existing structural behavior knowledge. Retrofit design needs both empirical formulas and finite element methods which makes ensemble learning essential to practical applications because it provides precise models and interpretable model outcomes. The current study demonstrates the first use of SHAP-driven explainability to predict FRCM strength which makes the prediction process more transparent while linking data-driven models to engineering reasoning. The research results demonstrate that explainable machine learning should be used for structural assessment and retrofit planning because it leads to better design outcomes.. Key contributions of this study include demonstrating the accuracy of ensemble models for FRCM beam capacity prediction, introducing SHAP-based explainability to structural engineering analysis, and confirming that the trained models reflect physically meaningful relationships rather than incidental correlations. The upcoming research should expand the experimental database through the collection of additional laboratory and field data while researchers should investigate hybrid physics-informed machine learning frameworks which use mechanics-based restrictions to develop explainable AI systems for real-time structural health monitoring and automated decision-support systems.

Declarations

Data Availability.

Data supporting the findings of this study are sourced from the literature and are available from the corresponding author upon request.

Competing Interests.

The authors declare no conflicts of interest regarding this manuscript.

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Author Contributions.

Arnav Sharma: Software Implementation, Formal Analysis, Figures & Tables. Ronit Debnath & Sach Thadani: Writing - Original Draft, Data Curation, Sivayogaraj A: Conceptualisation, Methodology, Investigation. Raja Rajeswari G & Elavenil S: Supervision, Validation, Writing - Review & Editing.

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