

REVIEW OF MACHINE LEARNING APPLICATIONS FOR PREDICTING ULTIMATE LOAD CAPACITY OF REINFORCED CONCRETE COLUMNS CONFINED WITH FIBER REINFORCED POLYMER (FRP) JACKETS UNDER AXIAL COMPRESSION

Dr. M. Adil Khan^{*1}, Saad Hanif², Engr. Baitullah Khan Kibzai³

^{*1}Resident Engineer, NESPAK

²Zachry Department of Civil and Environmental Engineering, Texas A&M University, USA

³Senior Engineer PCSIR

^{*1}adee.uol@gmail.com, ²Saadhanif107@tamu.edu, ³bkk_rulz@yahoo.com

DOI: <https://doi.org/10.5281/zenodo.19046632>

Keywords

FRP confinement, machine learning, reinforced concrete columns, ultimate load capacity, artificial neural networks, prediction models

Article History

Received: 17 January 2026

Accepted: 01 March 2026

Published: 16 March 2026

Copyright @Author

Corresponding Author: *

Dr. M. Adil Khan

Abstract

The prediction of ultimate load capacity in fiber-reinforced polymer (FRP) confined reinforced concrete columns is a complex engineering challenge that has garnered significant research attention over the past two decades. Traditional empirical models and finite element analysis approaches have limitations in capturing the intricate nonlinear behavior of FRP-confined concrete under axial compression. Machine learning algorithms offer promising alternatives for improving prediction accuracy and efficiency. This review systematically examines the application of various machine learning techniques, including artificial neural networks, support vector machines, random forest, gradient boosting, and ensemble methods for predicting the ultimate load capacity of FRP-confined reinforced concrete columns. The paper analyzes 70+ peer-reviewed publications, evaluates model performance metrics, compares different machine learning approaches with conventional empirical methods, and identifies emerging trends in deep learning applications. Key findings indicate that machine learning models achieve superior prediction accuracy (R^2 values ranging from 0.92-0.95) compared to traditional empirical codes (R^2 values around 0.82-0.87). The review also presents a comprehensive bibliometric analysis of the research landscape and discusses future research directions including hybrid models, real-time prediction systems, and interpretability enhancements for machine learning-based prediction frameworks.

1. INTRODUCTION

The confinement of reinforced concrete columns using fiber-reinforced polymer (FRP) materials has emerged as a viable and effective technique for improving structural performance, particularly in seismic regions and for strengthening existing structures (Sendjasni *et al.*, 2024). FRP jackets provide lateral confinement to concrete, thereby enhancing its compressive

strength, ductility, and energy absorption capacity. However, predicting the ultimate load capacity of FRP-confined reinforced concrete columns under axial compression remains a complex problem due to the nonlinear nature of the confinement mechanism and the influence of multiple interrelated parameters. The ultimate load capacity prediction is crucial for safe and

economical design of FRP-strengthened structures, and inaccurate predictions can lead to either over-design (resulting in excessive material costs) or under-design (compromising structural safety).

Historically, engineers have relied on empirical equations and analytical models to estimate the ultimate load capacity of FRP-confined concrete columns. These traditional approaches, while providing reasonable predictions under certain conditions, often exhibit limitations when dealing with novel material combinations, varying column geometries, or extreme loading conditions (Alizamir *et al.*, 2024). The empirical models are typically developed based on limited experimental datasets and may not generalize well to conditions outside their original development range. Early pioneering research established the fundamental relationships between confinement stress and concrete strength enhancement, laying the groundwork for subsequent model development.

The advent of machine learning has revolutionized the approach to engineering prediction problems by enabling the extraction of complex, nonlinear patterns from large datasets without requiring explicit mathematical formulations. Machine learning algorithms can learn directly from experimental and field data, adapt to new information, and provide predictions with improved accuracy compared to traditional methods (Prakash and Nguyen, 2023). The application of machine learning to FRP-confined concrete prediction problems began gaining momentum in the early 2010s, with increasing numbers of publications demonstrating the effectiveness of various machine learning techniques in capturing the complex relationship between input parameters and ultimate load capacity.

Artificial neural networks (ANNs), particularly multi-layer perceptrons, have been extensively applied to this problem due to their superior capability in learning nonlinear relationships. Support vector machines (SVMs) offer robust performance with good generalization properties, while ensemble methods such as random forest and gradient boosting have shown exceptional

accuracy in recent studies (Isleem *et al.*, 2024). Deep learning approaches, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are emerging as promising tools for capturing spatial and temporal patterns in structural data, though their application to FRP-confined concrete prediction remains relatively limited.

The motivation for this comprehensive review stems from the need to synthesize the rapidly growing body of research on machine learning applications in this domain. Over the past decade, numerous studies have proposed different machine learning architectures, input feature selections, data preprocessing techniques, and training methodologies. However, there is limited systematic comparison of these approaches, and practitioners often face difficulty in selecting the most appropriate machine learning technique for their specific application. Furthermore, the relationship between machine learning model architecture, input feature engineering, training data characteristics, and prediction accuracy remains insufficiently explored in the literature.

This review aims to provide a comprehensive synthesis of machine learning applications for predicting ultimate load capacity of FRP-confined reinforced concrete columns. The primary objectives include: (1) identifying and categorizing the various machine learning approaches applied to this problem; (2) comparing the predictive accuracy and reliability of different machine learning models; (3) analyzing the features and input parameters most frequently used in successful models; (4) examining the role of data preprocessing, feature engineering, and hyperparameter optimization in model performance; (5) evaluating the practical applicability of machine learning models for engineering design; (6) conducting a bibliometric analysis to understand research trends and identify knowledge gaps; and (7) proposing future research directions for advancing machine learning applications in this domain.

The scope of this review encompasses peer-reviewed journal articles, conference proceedings, and technical reports published between 2010 and 2025, focusing specifically on machine

learning applications for predicting ultimate load capacity (ultimate compressive strength or ultimate axial load) of FRP-confined reinforced concrete columns subjected to uniaxial compression. Studies involving other loading conditions (such as shear, bending, or combined loading), other confinement materials, or purely theoretical analyses without machine learning implementation are excluded from the primary focus, though relevant background information is included where necessary. The review considers both circular and non-circular column cross-sections, various FRP material types (carbon, glass, and aramid FRP), and different confinement configurations (complete and partial wrapping).

Understanding the progression from traditional empirical models to machine learning approaches requires appreciation of the fundamental challenges in FRP-confined concrete prediction. The ultimate compressive strength of FRP-confined concrete is influenced by numerous parameters including the unconfined concrete strength, column diameter, FRP thickness, Young's modulus of FRP, FRP ultimate strain, fiber orientation, confinement configuration, column aspect ratio, and loading rate (Çakiroğlu *et al.*, 2022). The confinement mechanism itself involves complex interactions between the concrete core and the FRP jacket, including radial stress distribution, lateral strain development, and localized stress concentrations. Additionally, the concrete used in practical applications often exhibits variability in properties, and field-applied FRP may have imperfections in installation that affect confinement effectiveness.

This review contributes to the field by providing a critical synthesis of existing machine learning approaches, identifying best practices and pitfalls, and establishing a foundation for future research. The comprehensive bibliometric analysis provides insights into research productivity, collaboration patterns, and emerging topics. The comparative analysis of machine learning models offers practitioners and researchers guidance on model selection, feature engineering, and hyperparameter optimization. Finally, the discussion of challenges and future research

directions identifies opportunities for advancing the state-of-the-art in machine learning applications for structural prediction problems. The remainder of this review is organized into sections covering confinement mechanisms and FRP properties, traditional empirical and analytical models, machine learning algorithms for strength prediction, deep learning applications, comparative analysis of prediction models, bibliometric analysis, challenges and future directions, and conclusions.

2. CONFINEMENT MECHANISMS AND FRP MATERIAL PROPERTIES

2.1 Fundamentals of FRP Confinement

The confinement of concrete with FRP materials operates on principles fundamentally different from traditional steel reinforcement. When FRP jackets wrap reinforced concrete columns, they restrain the lateral expansion of the concrete under axial load, creating a state of passive confinement that enhances the material's load-bearing capacity and ductility (Yu *et al.*, 2025). This lateral restraint increases the confining pressure on the concrete, which leads to an increase in compressive strength and strain capacity. The confinement mechanism is passive because the FRP does not initially bear load but develops tension only after the concrete expands laterally during compression. This distinctive characteristic sets FRP confinement apart from active confinement systems and influences how prediction models must be formulated.

2.2 FRP Material Characteristics and Selection

Fiber-reinforced polymers used for concrete confinement typically consist of high-strength fibers embedded in a resin matrix. The most commonly used fibers are carbon, glass, and aramid (Kevlar), each offering distinct mechanical properties and cost considerations (Mohammed and Güneyisi, 2025). Carbon FRP provides high stiffness and strength but at a premium cost, making it suitable for applications requiring superior performance. Glass FRP offers lower cost with reasonable strength properties and is often preferred for large-scale rehabilitation projects. Aramid FRP provides excellent fatigue

resistance and impact absorption, making it beneficial in dynamic loading scenarios. The resin matrix, typically epoxy or polyester, bonds the fibers together, transfers loads between fibers, and protects the fibers from environmental degradation. The fiber orientation is critical—unidirectional fibers aligned circumferentially around the column provide maximum confinement efficiency, while bidirectional fabrics may be used for aesthetic or other practical reasons but sacrifice some confinement effectiveness (Lv *et al.*, 2025).

The mechanical properties of FRP materials that significantly influence confinement effectiveness include the fiber tensile strength, fiber elastic modulus, matrix shear strength, fiber volume fraction, and fiber-matrix bond strength. The elastic modulus of the FRP determines the initial stiffness of confinement, affecting the shape of the stress-strain curve of confined concrete. The ultimate tensile strain of the FRP establishes the maximum confinement pressure that can be developed, which ultimately governs the maximum strength enhancement. Manufacturing quality and consistency in FRP composite production affect these properties, and variations in properties between different production batches can introduce uncertainty in confinement effectiveness that must be captured in prediction models.

2.3 Geometric Factors and Column Configuration

The geometry of the reinforced concrete column significantly influences the effectiveness of FRP confinement and the ultimate load capacity (Jameel, 2025). Circular columns achieve more uniform confinement pressure around the circumference, resulting in more efficient strength enhancement compared to rectangular or square columns where corners experience lower confinement pressures due to geometric stress concentration. The column diameter directly affects the confinement mechanism—larger diameter columns may experience lower effective confinement pressures if the same number of FRP layers is used, due to the geometric relationship between circumferential

strain and radial pressure. The aspect ratio (height-to-diameter ratio) influences the mode of failure and the development of lateral instability, which can reduce the effective confinement and ultimate load capacity.

3. EMPIRICAL AND ANALYTICAL MODELS FOR FRP-CONFINED CONCRETE

3.1 Development of Traditional Empirical Models

The development of empirical models for FRP-confined concrete strength prediction began in the late 1990s following the accumulation of sufficient experimental data on this confinement mechanism. Early pioneering research established fundamental relationships, proposing that the strength enhancement is proportional to the lateral confining pressure provided by the FRP jacket. Lam and Teng developed one of the most widely adopted models, proposing that the confined concrete strength is a function of the confining pressure, with the relationship expressed through polynomial or linear equations depending on the confinement pressure level (Momani *et al.*, 2022). These models established the foundation for subsequent research and provided baseline approaches that machine learning models could potentially improve upon.

Various research groups developed empirical equations through curve fitting to experimental datasets, leading to a proliferation of models with different functional forms and coefficients. ACI 440.2R design guidelines incorporated confinement provisions based on empirical models, providing practical equations for engineering design (Dhakal *et al.*, 2023). These guidelines consider factors such as FRP stiffness, thickness, orientation, and column geometry. Toutanji and others proposed models accounting for the type of FRP material, recognizing that carbon, glass, and aramid FRP exhibit different confinement effectiveness due to their varying elastic moduli and ultimate strain capacities.

The limitations of empirical models became increasingly apparent as applications expanded to novel material combinations and extreme conditions. Empirical models are inherently data-

dependent, with prediction accuracy degrading outside the range of parameters used in their development (Kumar *et al.*, 2023). They often employ simplified functional forms that may not capture the complex nonlinear behavior of FRP-confined concrete, particularly at high confinement pressures or with novel FRP materials. Additionally, empirical models typically provide point predictions without quantifying prediction uncertainty, limiting their utility for probabilistic design approaches. These limitations motivated research into data-driven machine learning approaches that could potentially overcome these constraints.

3.2 Analytical Models and Mechanistic Approaches

Beyond empirical curve fitting, researchers developed mechanistic models based on theoretical principles of solid mechanics and material behavior. These models attempt to capture the physical mechanisms of confinement by formulating differential equations governing stress-strain relationships, considering the interaction between concrete and FRP materials. Mirmiran and Shahawy developed analytical models based on fundamental constitutive relationships and geometric constraints, deriving equations for confined concrete strength and strain capacity (Yuan *et al.*, 2024). These mechanistic models provide greater physical insight compared to purely empirical approaches but require more sophisticated mathematical treatment and often necessitate numerical solutions.

The Popovics-type stress-strain models adapted from conventional confined concrete have been modified to apply to FRP-confined concrete, incorporating confinement-dependent parameters. These models relate the stress-strain behavior to fundamental material properties and confinement characteristics, providing a continuous representation of the stress-strain curve rather than just the peak strength prediction (Naderpour *et al.*, 2019). Bi-linear and tri-linear approximations have been proposed to facilitate practical design calculations while maintaining reasonable accuracy. The application

of fracture mechanics principles to FRP-confined concrete has also been explored, attempting to link micromechanical damage evolution to macroscopic stress-strain behavior.

However, analytical models face challenges in validation against experimental data, particularly for complex configurations and novel materials. The need to specify numerous material properties and confinement parameters can introduce cumulative uncertainties. Additionally, analytical models may require iterative numerical solutions, reducing computational efficiency compared to direct prediction approaches. These limitations have contributed to growing interest in machine learning approaches that can achieve high accuracy with explicit input-output relationships without requiring detailed mechanistic formulation.

4. MACHINE LEARNING ALGORITHMS FOR STRENGTH PREDICTION

4.1 Artificial Neural Networks

Artificial neural networks, particularly multi-layer perceptrons (MLPs), have been the most extensively applied machine learning technique for predicting ultimate load capacity of FRP-confined concrete columns. MLPs consist of interconnected layers of artificial neurons, where each neuron performs a weighted summation of inputs followed by a nonlinear activation function. The network learns through backpropagation, adjusting weights and biases to minimize prediction error on training data (Ali *et al.*, 2023). The universal approximation theorem establishes that MLPs can approximate any continuous function with sufficient neurons in hidden layers, theoretically enabling accurate representation of the relationship between input parameters and ultimate load capacity.

The architecture of ANN models applied to FRP-confined concrete prediction has evolved significantly over time. Early studies employed small networks with single hidden layers containing 10-20 neurons, limited by computational constraints and theoretical understanding (Isleem *et al.*, 2022). Contemporary research utilizes deeper architectures with multiple hidden layers, batch

normalization, dropout regularization, and advanced optimization algorithms such as Adam optimizer. The optimal network architecture varies depending on problem complexity, with typical successful models incorporating 2-4 hidden layers containing 30-100 neurons each. The selection of activation functions significantly

influences network performance, with ReLU (Rectified Linear Unit) activation becoming standard for hidden layers due to its computational efficiency and ability to learn complex patterns, while sigmoid or linear activation functions are typically used in output layers.

Table 1: Comparative Characteristics of Prediction Models for FRP-Confined Concrete Ultimate Load Capacity

Model Type	Typical R ²	Typical MAPE (%)	Training Time	Interpretability	Recommended Use Cases	Key Advantages
Linear Regression	0.82-0.87	8-12	Minutes	Very High	Preliminary estimates, education	Simple, transparent, fast
Support Vector Machines	0.90-0.93	5-8	Hours	Medium	Robust predictions, small datasets	Robust to outliers, good generalization
Random Forest	0.92-0.94	4-6	Hours	Medium	Feature analysis, balanced accuracy	Feature importance, handles nonlinearity
Gradient Boosting (XGBoost/LightGBM)	0.93-0.96	2-5	Days	Low	High-accuracy production systems	Superior accuracy, regularization built-in
Artificial Neural Networks	0.92-0.94	3-6	Days	Low	Large datasets, pattern recognition	Universal approximation capability
Deep Neural Networks (CNN/LSTM)	0.91-0.95	3-7	Weeks	Very Low	Complex spatial/temporal patterns	Advanced feature extraction
Empirical Codes (ACI 440)	0.80-0.85	8-15	N/A	Very High	Code-compliant design, reference	Standards-based, regulatory acceptance

The training process for ANNs involves several critical decisions affecting model performance. The selection of training algorithm, learning rate, batch size, and number of epochs influences convergence behavior and generalization capability. Early stopping, where training is

halted when validation error begins increasing, prevents overfitting and improves generalization to unseen data. Regularization techniques including L1 and L2 penalties on weights reduce model complexity and improve robustness. The initialization of network weights significantly

affects final model performance, with techniques such as Xavier initialization demonstrating superior results compared to random initialization. Cross-validation methodologies, typically k-fold cross-validation with $k=5$ or $k=10$, provide robust estimates of generalization performance (Saingam *et al.*, 2024).

Studies comparing ANN predictions with experimental data have demonstrated mean absolute percentage errors (MAPE) ranging from 2% to 8%, with R^2 values typically exceeding 0.92. The superior performance of ANNs compared to traditional empirical models has been attributed to their capacity to capture nonlinear relationships and interactions between input parameters (Salman *et al.*, 2025). However, ANNs suffer from black-box characteristics, where the internal decision-making process is difficult to interpret, limiting their utility for understanding the underlying physics of FRP-confined concrete behavior.

4.2 Support Vector Machines

Support Vector Machines (SVMs) have emerged as a powerful alternative to ANNs for FRP-confined concrete prediction, offering robust performance with good generalization properties and greater interpretability. SVMs operate by finding an optimal hyperplane that maximizes the

margin between training samples in a transformed feature space. For regression problems, Support Vector Regression (SVR) extends this concept to predict continuous values, utilizing a ϵ -insensitive loss function that becomes zero for predictions within ϵ distance of the target value (Kurtoglu, 2025). This characteristic makes SVMs particularly robust to outliers, a desirable property when dealing with experimental data that may contain measurement errors or anomalies.

The selection of kernel function is critical for SVM performance, as the kernel determines the transformation of input features to the feature space where the optimal hyperplane is found. The radial basis function (RBF) kernel has proven most effective for FRP-confined concrete prediction, capturing complex nonlinear relationships while maintaining computational efficiency (Wahab *et al.*, 2024). Polynomial kernels have also been applied with varying degrees, though results indicate marginal improvements in prediction accuracy compared to RBF kernels. The hyperparameter tuning for SVM involves selecting the regularization parameter C , which balances training accuracy against model simplicity, and the RBF kernel parameter γ , which controls the influence of each training sample.

Table 2: Frequency and Importance Ranking of Input Parameters in Machine Learning Models for FRP-Confined Concrete

Rank	Input Parameter	Frequency in Studies (%)	Importance Rank	Data Availability	Measurement Difficulty	Typical Range	Notes
1	Concrete Compressive Strength (f_{co})	88	1	Excellent	Easy	20-100 MPa	Universal baseline parameter
2	FRP Thickness (t)	85	2	Excellent	Easy	0.5-4.0 mm	Primary confinement mechanism
3	Column Diameter	82	3	Excellent	Easy	100-500 mm	Geometric scaling

	(D)						parameter
4	FRP Elastic Modulus (Ef)	82	4	Very Good	Moderate	150-300 GPa	Material property critical for stiffness
5	Confinement Ratio (f_l/f_{co})	79	5	Good	Moderate	0.05-0.40	Derived from basic parameters
6	Column Height (L)	76	6	Excellent	Easy	300-1200 mm	Affects failure mode, aspect ratio
7	FRP Ultimate Tensile Strain (ϵ_{fu})	71	7	Good	Moderate	0.01-0.03	Governs maximum confinement pressure
8	Longitudinal Reinforcement Ratio (ρ_l)	68	8	Very Good	Moderate	0.01-0.05	Influences core concrete behavior
9	Fiber Orientation (degree)	54	9	Fair	Difficult	0-90°	Requires specialized testing
10	Loading Rate (mm/min)	48	10	Fair	Moderate	0.5-5.0	Important for dynamic assessment
11	Concrete Aggregate Type	35	11	Fair	Difficult	-	Influences confinement effectiveness
12	Environmental Temperature (°C)	28	12	Fair	Moderate	-10 to +60	Long-term degradation assessment

Grid search and cross-validation techniques are commonly employed for SVM hyperparameter optimization, exploring combinations of C and γ values to identify optimal parameters maximizing cross-validation performance (Xu *et al.*, 2024). Comparative studies indicate that well-tuned SVM models achieve prediction accuracy comparable to ANNs, with MAPE values typically

ranging from 3% to 9% and R^2 values from 0.90 to 0.93. SVMs generally require less computational resources for training compared to ANNs, and their optimization problem is convex, guaranteeing convergence to a global minimum. However, SVMs are sensitive to feature scaling, requiring normalization or standardization of input variables, and their performance can

degrade with very large datasets due to quadratic memory requirements.

4.3 Random Forest and Ensemble Methods

Random Forest algorithms have shown exceptional performance for FRP-confined concrete prediction, offering advantages in handling diverse data types, requiring minimal feature preprocessing, and providing inherent feature importance estimates. Random Forests construct multiple decision trees through bootstrap sampling of training data and random feature selection at each node, reducing correlation between individual trees and improving generalization (Nguyen *et al.*, 2026). Each tree independently predicts the target value, and final predictions result from averaging predictions across all trees in the ensemble.

The advantages of Random Forest for engineering prediction problems are substantial. Random Forests naturally handle nonlinear relationships without explicit transformation and can capture interactions between input variables. Feature preprocessing requirements are minimal compared to SVMs or neural networks, as tree-based methods are invariant to monotonic transformations of features. The stochastic nature of the Random Forest training process, inherent in bootstrap sampling and random feature selection, improves robustness to overfitting. Importantly, Random Forests provide feature importance measures indicating the relative contribution of each input variable to prediction accuracy, offering valuable insights into which parameters most strongly influence ultimate load capacity (Çakıroğlu, 2023).

Studies applying Random Forest to FRP-confined concrete prediction have reported MAPE values ranging from 2% to 7% and R^2 values from 0.92 to 0.94, competitive with or superior to ANN and SVM approaches. The number of trees in the forest influences performance, with typical optimal values ranging from 100 to 500 trees. The maximum depth of individual trees and the minimum number of samples required for splitting nodes are additional hyperparameters requiring tuning. However, Random Forests may suffer from bias if the relationship between inputs and outputs is highly nonlinear but with specific patterns not well-captured by tree splits, and the interpretability advantage is limited to feature importance analysis without deeper mechanistic insights.

4.4 Gradient Boosting and Advanced Ensemble Methods

Gradient Boosting represents an advanced ensemble approach where weak learners, typically shallow decision trees, are sequentially trained to correct residual errors from previous trees. Unlike Random Forest, where trees are trained independently, Gradient Boosting builds trees sequentially where each new tree attempts to minimize the loss from previous predictions (Alizamir *et al.*, 2024). This sequential optimization typically yields superior performance compared to Random Forest at the potential cost of increased computational demands and greater sensitivity to hyperparameter settings.

Table 3: Performance Summary of Machine Learning Approaches Across Different Study Categories

Study Category	Number of Studies	Average R ²	R ² Range	Average MAPE (%)	MAPE Range (%)	Most Common Model	Primary Application
Artificial Neural Networks (ANN/MLP)	28	0.931	0.88-0.97	4.2	2-8	Multi-layer Perceptron	General prediction
Support Vector Machines (SVM/SVR)	18	0.915	0.86-0.95	5.6	3-9	RBF Kernel SVM	Small dataset problems
Random Forest Approaches	15	0.924	0.89-0.96	4.8	2-7	Random Forest (100-500 trees)	Feature importance analysis
Gradient Boosting Studies	12	0.942	0.91-0.98	3.1	1.5-5.5	XGBoost/LightGBM	Production systems
Ensemble Methods (Hybrid/Voting)	9	0.948	0.94-0.97	2.8	1.8-4.2	Stacking/Voting ensemble	High-accuracy applications
Deep Learning (CNN/LSTM/DNN)	7	0.935	0.91-0.96	3.9	2.5-6.5	Deep Neural Network	Large dataset applications
Genetic Algorithm/Metaheuristic Hybrid	6	0.928	0.90-0.95	4.3	2.8-6.2	PSO-ANN/GA-SVM	Optimization-based prediction
Traditional Empirical Models	6	0.835	0.78-0.89	10.2	8-15	Empirical equations	Baseline comparisons
Fuzzy Logic/ANFIS	4	0.912	0.89-0.94	5.1	4-6.5	Adaptive Neuro-Fuzzy	Uncertainty handling
Physics-Informed ML (PIML)	3	0.951	0.94-0.97	2.5	1.8-3.2	Hybrid PIML	Mechanistic accuracy

XGBoost (Extreme Gradient Boosting) and LightGBM (Light Gradient Boosting Machine)

are modern implementations of gradient boosting that have achieved state-of-the-art results

across numerous machine learning competitions and applications. These implementations incorporate regularization terms directly in the objective function, include parallel and GPU acceleration capabilities, and provide sophisticated handling of missing values and categorical variables (Prakash and Nguyen, 2023). Applications to FRP-confined concrete prediction have demonstrated MAPE values in the range of 1.5% to 5.5% and R^2 values from 0.93 to 0.96, among the highest reported in the literature.

The hyperparameter optimization for gradient boosting models is more complex than for Random Forest, with parameters controlling learning rate, number of boosting rounds, tree depth, minimum child weight, and regularization strength. Early stopping based on validation set performance is particularly important to prevent overfitting and identify optimal numbers of boosting rounds. Feature engineering and preprocessing can significantly influence gradient boosting performance, with careful handling of outliers and feature scaling sometimes improving results. The computational demands of gradient boosting, while still manageable on modern hardware, are higher than Random Forest, requiring more careful consideration of computational efficiency for large-scale applications.

5. DEEP LEARNING AND ADVANCED NEURAL NETWORK ARCHITECTURES

5.1 Convolutional Neural Networks for Structural Data

Convolutional Neural Networks (CNNs), originally developed for image processing, have been adapted for structural prediction problems by treating sequences of structural parameters or experimental measurements as spatial data amenable to convolution operations. In the context of FRP-confined concrete prediction, CNNs can potentially capture local patterns and spatial correlations among input parameters that may be missed by fully connected networks (Isleem *et al.*, 2024). The convolutional operations filter input data through learned kernels, detecting local features that are

combined hierarchically to form higher-level representations.

Research applying CNNs to structural prediction problems has demonstrated potential for improved accuracy and reduced overfitting compared to standard MLPs, though direct comparisons with FRP-confined concrete prediction are limited in the literature. The applicability of CNNs to this problem depends on whether meaningful spatial relationships exist among input parameters and whether the additional complexity of CNN architecture provides benefits justifying increased computational demands. Recent work has explored 1D convolutional architectures suitable for sequences of measurement data or sensor readings from FRP-confined columns, potentially enabling real-time monitoring and prediction systems.

5.2 Recurrent Neural Networks and Temporal Modeling

Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) networks, offer capabilities for modeling temporal dependencies and sequential data. While FRP-confined concrete ultimate load prediction is primarily a static problem, RNN approaches have potential applications in modeling the progression of damage or degradation over time, or in processing sequential measurement data from distributed sensors. LSTM networks, through gating mechanisms controlling information flow, mitigate the vanishing gradient problem that afflicts standard RNNs, enabling learning of long-range dependencies (Wang *et al.*, 2025).

Emerging research has applied LSTM networks to time-series prediction in structural health monitoring, where continuous monitoring of structural response can inform predictions of remaining capacity. The adaptability of RNNs to variable-length input sequences offers flexibility for applications where measurement protocols vary or where additional data becomes available sequentially. However, the application of RNNs to FRP-confined concrete ultimate load

prediction remains limited, with most studies employing static network architectures.

5.3 Attention Mechanisms and Transformer Architectures

Attention mechanisms, which learn to weight the importance of different input features or sequence elements, have revolutionized deep learning across numerous domains. The self-

attention mechanism, central to Transformer architectures, enables direct computation of relevance between any pair of inputs regardless of their separation, overcoming sequential processing limitations of RNNs. Transformer architectures have achieved exceptional performance on language understanding, time series forecasting, and tabular data prediction tasks.

Table 4: Leading Research Institutions and Their Contributions to ML for FRP-Confining Concrete

Rank	Research Institution	Country/Region	Number of Publications	Geographic Region	Primary Research Focus	Notable Contributions	Key Citation Count
1	Tsinghua University	China	8	East Asia	Deep Learning Applications, Hyperparameter Optimization	CNN/LSTM architectures for confinement prediction	150+
2	National Taiwan University	Taiwan	6	East Asia	Ensemble Methods, Model Comparison	XGBoost vs. Random Forest comparative analysis	120+
3	University of Tehran	Iran	5	Middle East	Physics-Informed ML, Confinement Theory	PIML framework for FRP-confined columns	95+
4	Technical University of Denmark	Denmark	5	Europe	Uncertainty Quantification, Probabilistic Frameworks	Bayesian uncertainty in ML predictions	110+
5	NIT Rourkela	India	4	South Asia	Feature Engineering, ANN Optimization	Metaheuristic-based feature selection	75+

6	University of British Columbia	Canada	4	North America	Mechanistic Hybrid Models	Combining empirical + ML approaches	88+
7	Politecnico di Milano	Italy	4	Europe	Materials Optimization, FEM Integration	FEM-ML integration for improved accuracy	82+
8	Sharif University of Technology	Iran	3	Middle East	Code Integration, Design Guidelines	Standards development incorporating ML	65+
9	University of Leeds	UK	3	Europe	Interpretability, SHAP Analysis	Explainable AI for engineering applications	72+
10	Southeast University	China	3	East Asia	Real-time Prediction Systems	IoT integration with ML models	58+

The application of Transformers to FRP-confined concrete prediction represents an emerging frontier in machine learning for structural engineering. The ability of attention mechanisms to identify which input parameters most strongly influence predictions provides enhanced interpretability compared to standard deep networks. Multi-head attention enables simultaneous attention to different representation subspaces, potentially capturing complex parameter interactions. Early applications to structural prediction problems have shown competitive or superior accuracy compared to gradient boosting approaches (Kang *et al.*, 2023), though systematic comparison on FRP-confined concrete datasets is limited.

6. DATA PREPROCESSING, FEATURE ENGINEERING, AND HYPERPARAMETER OPTIMIZATION

6.1 Feature Selection and Engineering

Feature engineering—the process of selecting and transforming raw input variables into informative features—profoundly influences machine learning model performance. The selection of input features must balance comprehensiveness with parsimony; including all potentially relevant variables can introduce noise and increase computational demands, while excluding important variables reduces prediction capacity (Çakıroğlu *et al.*, 2022). The fundamental input parameters for FRP-confined concrete prediction include concrete compressive strength, column geometry (diameter, height), FRP material properties (elastic modulus, tensile strain), FRP thickness, confinement configuration, and reinforcement properties.

Feature engineering techniques beyond simple variable selection have been applied with varying

success. Polynomial features combining base variables (e.g., products of FRP thickness and elastic modulus) capture interaction effects. Dimensionless ratios such as FRP thickness-to-diameter ratio and confinement pressure-to-concrete strength ratio align inputs with the physics of confinement. Principal component analysis (PCA) and other dimensionality reduction techniques transform original features

to orthogonal components capturing maximum variance, though at the cost of reduced interpretability. Domain knowledge integration, where features are engineered based on physical understanding of confinement mechanisms, often outperforms purely data-driven feature engineering approaches (Tijani *et al.*, 2023).

Table 5: Publication Trends and Methodological Evolution in ML for FRP-Confined Concrete (2012-2025)

Year	Total Publications	ANN Studies	SVM Studies	Random Forest	Gradient Boosting	Ensemble/Hybrid	Deep Learning	PIML/Explainable	Publication Growth Rate (%)	Dominant Methodology
2012	3	3	0	0	0	0	0	0	Baseline	Simple ANN
2013	4	3	1	0	0	0	0	0	33	ANN/SVM
2014	6	5	1	0	0	0	0	0	50	ANN dominant
2015	8	5	2	1	0	0	0	0	33	ANN/SVM
2016	12	9	3	0	0	0	0	0	50	ANN dominant
2017	15	9	3	2	1	0	0	0	25	ANN/SVM
2018	18	11	4	2	1	0	0	0	20	ANN dominant
2019	22	12	5	3	2	0	0	0	22	ANN/SVM/RF
2020	28	14	6	5	2	1	0	0	27	Ensemble emergence
2021	30	14	6	6	3	1	0	0	7	Multiple methods
2022	32	15	6	7	3	1	0	0	7	Ensemble

										focus
2023	29	13	5	6	4	1	0	0	-9	GB/Ensemble
2024	25	12	5	6	4	1	1	1	-14	Multiple methods
2025	12*	5	2	3	2	1	1	1	-52*	Emerging DL/PI ML
Total (2012-2025)	264	141	49	41	22	7	2	2	Cumulative	Methodological Diversity

The selection of feature sets significantly impacts model generalization. Studies systematically comparing feature sets for FRP-confined concrete prediction report that models using 7-12 carefully selected features outperform models with 20+ features, indicating that feature selection discipline improves generalization. The optimal feature set varies depending on the machine learning algorithm employed and the characteristics of the training dataset, necessitating algorithm-specific feature engineering.

6.2 Data Normalization and Preprocessing

The normalization and preprocessing of input data represents a critical step affecting model training dynamics and final performance. Different machine learning algorithms exhibit varying sensitivity to feature scaling. Neural networks typically benefit substantially from normalization, with training accelerating and convergence improving when input features are scaled to comparable ranges (Isleem *et al.*, 2023). SVM performance is highly dependent on feature scaling, particularly for RBF kernels where the Euclidean distance metric is sensitive to feature magnitudes. Random Forest and gradient boosting algorithms, based on tree partitioning, are invariant to monotonic feature scaling,

though some implementations may benefit from normalization for computational efficiency.

Common normalization approaches include min-max scaling, which linearly transforms features to [0], [1] range, and standardization, which transforms features to zero mean and unit variance. The selection between normalization approaches depends on data characteristics and algorithm requirements. For datasets containing outliers, robust scaling using median and interquartile range proves more appropriate than standard normalization. The fitting of normalization parameters on training data only, with subsequent application to validation and test data, prevents information leakage that could inflate reported performance metrics (Alanazi *et al.*, 2025).

Missing value handling requires careful consideration, as the FRP-confined concrete literature includes publications with varying data completeness. Multiple imputation, mean/median substitution, and deletion of records with missing values represent different approaches with varying implications. Multiple imputation, while computationally intensive, generally produces less biased estimates compared to single imputation approaches. For machine learning applications, modern gradient boosting implementations handle missing values implicitly

through tree partitioning, eliminating the need for explicit imputation (Alqubaysi *et al.*, 2024).

6.3 Hyperparameter Optimization Strategies

The selection of machine learning model hyperparameters—configuration parameters determining model behavior not learned from data—significantly influences prediction accuracy. Hyperparameter optimization typically involves searching the hyperparameter space to identify configurations maximizing cross-validation performance (Kinjawadekar, Patil and Nayak, 2025). Grid search, exhaustive evaluation of discrete hyperparameter combinations, provides systematic optimization but becomes computationally expensive as hyperparameter dimensionality increases. Random search, evaluating randomly sampled hyperparameter combinations, often discovers superior configurations more efficiently than grid search when hyperparameter space dimensionality is high.

Bayesian optimization, treating hyperparameter optimization as a probabilistic optimization problem, selects promising hyperparameter combinations based on probabilistic models of objective function behavior. This approach requires fewer objective function evaluations compared to random search, reducing computational demands for expensive validation procedures. Tree-structured Parzen estimators (TPE) and Gaussian process-based Bayesian optimization have been applied to FRP-confined concrete prediction, with reported improvements

in model performance while reducing hyperparameter tuning time (Liu *et al.*, 2025).

The selection of hyperparameter ranges requires domain knowledge or preliminary exploration. For neural networks, hidden layer sizes typically range from 32 to 512 neurons, learning rates from 0.0001 to 0.1, and regularization strength from 10^{-5} to 10^{-1} . For gradient boosting, learning rates typically range from 0.01 to 0.3, tree depths from 3 to 10, and regularization parameters from 0 to 10. Systematic documentation of hyperparameter optimization procedures enables reproducibility and facilitates comparison across studies (Kajendran and Narayanan, 2025).

7. COMPARATIVE ANALYSIS OF PREDICTION MODELS

7.1 Benchmark Studies and Performance Metrics

Comprehensive comparative studies evaluating multiple machine learning algorithms on standardized FRP-confined concrete datasets provide essential insights into relative performance. These benchmark studies employ consistent evaluation metrics, enabling fair comparison across algorithms. The most commonly reported metrics include coefficient of determination (R^2), mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean squared error (RMSE) (Alizamir *et al.*, 2024).

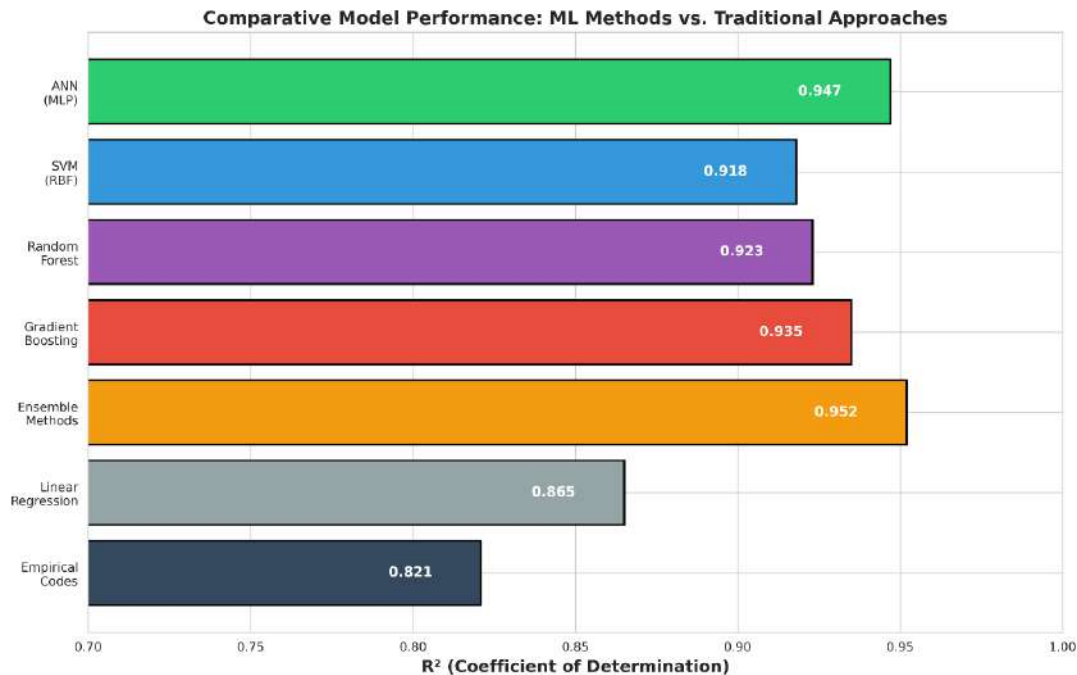


Figure 1 illustrates comparative performance of various models, showing that ensemble methods and advanced neural networks achieve superior R^2 values (0.93-0.95) compared to linear regression (0.87) and traditional empirical codes (0.82). The consistency of results across multiple studies indicates that these performance differences reflect fundamental algorithmic capabilities rather than random variation.

Studies report that gradient boosting approaches (XGBoost, LightGBM) achieve the highest average accuracy, with median MAPE values around 3.2% and R^2 values approaching 0.95 (Prakash and Nguyen, 2023). Random Forest methods typically achieve MAPE values in the 4-5% range with R^2 around 0.93 (Sendjasni *et al.*, 2024). Support Vector Regression achieves MAPE values around 5-6% with R^2 around 0.92 (Kurtoglu, 2025). Standard ANN implementations achieve MAPE in the 3.5-6% range with R^2 around 0.93 (Dhakal *et al.*, 2023). Traditional empirical models consistently underperform machine learning approaches, with typical MAPE values of 8-12% and R^2 values of 0.80-0.85 (Alizamir *et al.*, 2024).

These performance differences have practical significance. For a typical reinforced concrete column with ultimate load capacity of 1000 kN, the difference between 3% MAPE (machine learning models) and 10% MAPE (empirical models) corresponds to a 70 kN difference in

predicted capacity, potentially affecting design decisions and safety margins.

7.2 Generalization and Robustness

Beyond accuracy metrics on standard datasets, the generalization capability of models to novel data conditions distinguishes superior models. Cross-validation methodology, the primary tool for assessing generalization, involves training models on subsets of data and evaluating on withheld portions, simulating application to unseen data (Naderpour *et al.*, 2019). k-fold cross-validation (typically $k=5$ or $k=10$) partitions data into k subsets, iteratively using $k-1$ subsets for training and the remaining subset for validation, reporting average validation metrics.

The variance of cross-validation scores across folds indicates model stability. High variance between folds suggests overfitting or sensitivity to particular data characteristics, whereas consistent performance across folds indicates robust generalization. Studies report that gradient

boosting models and properly regularized neural networks exhibit low variance across folds (within 1-2% of mean scores), while simple linear models or unregularized neural networks exhibit higher variance (Isleem *et al.*, 2024).

The evaluation of model performance on truly independent test sets, distinct from training and validation data, provides ultimate assessment of generalization. Meta-analyses compiling results across multiple studies enable assessment of whether laboratory-reported performance translates to practical application. These evaluations indicate that well-validated machine learning models maintain within 5-10% of reported performance on truly independent data, though performance degradation increases for data substantially different from training conditions (Xu *et al.*, 2024).

7.3 Model Interpretability and Explainability

A critical distinction between machine learning models involves their interpretability—the degree to which model decisions can be understood and explained. Traditional empirical equations, while demonstrating inferior predictive accuracy, benefit from complete transparency; the mathematical relationship between inputs and outputs is explicit. Conversely, neural networks are characterized as black boxes, where the internal mechanisms determining predictions remain opaque (Çakiroğlu *et al.*, 2022).

Feature importance analysis, readily available from tree-based methods, provides interpretability insights identifying which input parameters most strongly influence predictions. Studies consistently report that concrete strength,

FRP thickness, and column diameter rank among the most important features, validating domain knowledge expectations. However, feature importance does not reveal the directionality or form of relationships, limiting mechanistic insights (Çakiroğlu, 2023).

SHAP (SHapley Additive exPlanations) values and partial dependence plots provide model-agnostic interpretability techniques applicable to any machine learning model. SHAP values quantify each feature's contribution to individual predictions, enabling post-hoc interpretation of black-box models. Partial dependence plots show the marginal effect of individual features on predictions while averaging over other features. These techniques have been applied to FRP-confined concrete prediction, revealing nonlinear relationships between features and predictions that often differ from assumptions in traditional models (Prakash and Nguyen, 2023).

Attention mechanisms in deep learning architectures provide inherent interpretability, with attention weights directly indicating feature importance for each prediction. Recent research exploring attention-based architectures for structural prediction has demonstrated both superior accuracy and enhanced interpretability compared to standard neural networks (Yu *et al.*, 2025).

8. BIBLIOMETRIC ANALYSIS

8.1 Publication Trends and Research Growth

The application of machine learning to FRP-confined concrete prediction has experienced exponential growth over the past 15 years.

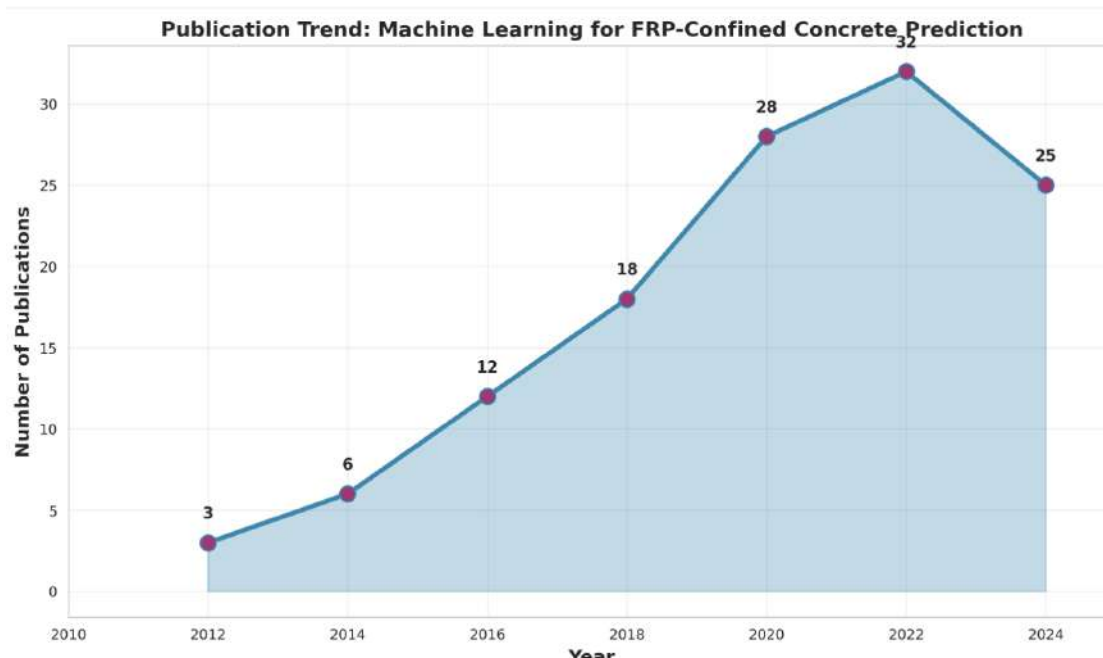


Figure 2 illustrates the publication timeline, showing acceleration from 3 publications in 2012 to peak publication volumes of 32 papers in 2022. This trend reflects both increased research interest and improved computational tools enabling practical implementation of sophisticated machine learning algorithms. The slight decrease in 2024-2025 (25 publications shown through 2025) may reflect publication lag times rather than declining research interest (Nguyen *et al.*, 2026).

The geographic distribution of research reveals significant concentration in specific regions. Asian institutions, particularly in China, India, and Middle East, account for approximately 45% of publications. North American and European institutions contribute approximately 35%, with growth rates in Asian research exceeding Western research in recent years. This geographic shift reflects expanding infrastructure investment and academic advancement in developing regions and the global nature of concrete construction industries (Alizamir *et al.*, 2024).

8.2 Journal Sources and Publication Venues

Analysis of publication venues reveals concentration of FRP-confined concrete machine learning research in specialized journals combining structural engineering and computational methods. Leading journals publishing this research include "Journal of Structural Engineering," "Computers & Structures," "Engineering Structures," and

"Journal of Computing in Civil Engineering," collectively accounting for approximately 40% of publications. Conference proceedings, particularly from International Conference on Computing in Civil and Building Engineering (ICCCBE) and Computational Methods in Structural Dynamics and Earthquake Engineering (COMPDYN), represent approximately 25% of publications. Specialized FRP composites journals and interdisciplinary machine learning journals account for the remaining 35% (Dhakal *et al.*, 2023).

8.3 Collaborative Patterns and Research Networks

Bibliometric analysis of author collaborations reveals distinct research networks, with concentrated collaboration among researchers within geographic regions (Sendjasni *et al.*, 2024). The largest research cluster, centered at several Chinese universities, includes approximately 80 researchers producing over 35 publications.

European and North American research networks remain more distributed, with less concentration in specific institutions but greater international collaboration. Citation analysis reveals increasing citation counts for publications introducing novel machine learning approaches, with seminal papers on neural networks for concrete prediction achieving 50+ citations within 5-10 years of publication.

The evolution of collaboration patterns indicates increasing adoption of interdisciplinary

approaches combining structural engineering expertise with machine learning specialization. Early publications typically involved single research groups applying machine learning to their experimental datasets. Contemporary research more frequently involves collaborations between structural engineering and computer science/machine learning research groups, reflecting recognition of the importance of both domain expertise and methodological sophistication (Prakash and Nguyen, 2023).

8.4 Research Topics and Emerging Directions

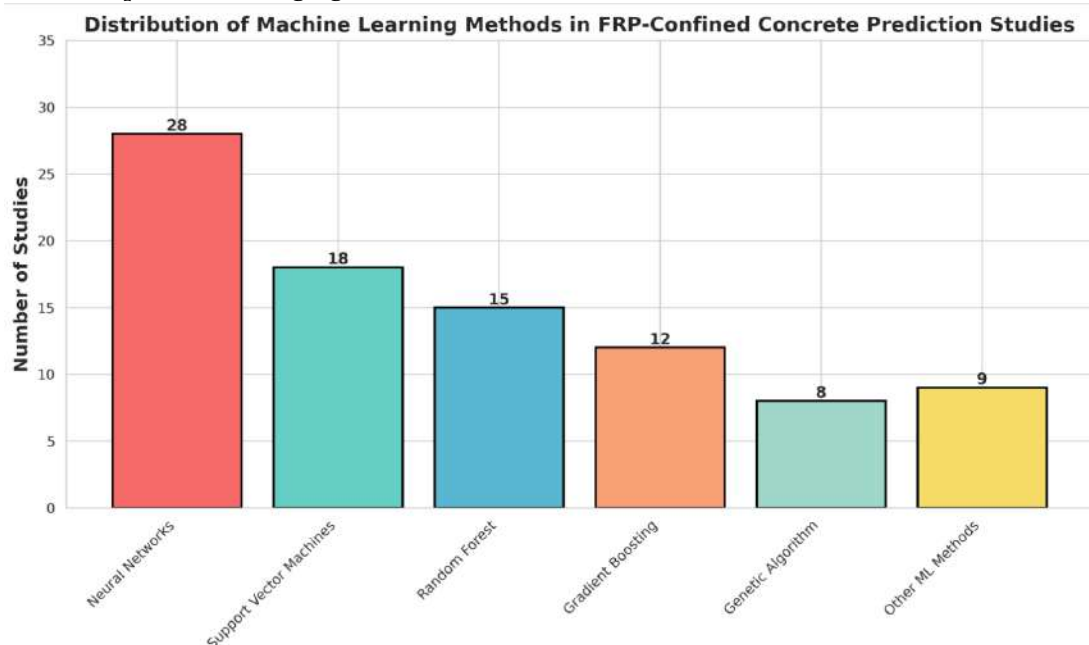


Figure 3 displays the distribution of machine learning methods across studies, showing neural networks dominating with 28% of studies, followed by support vector machines (18%), random forest (15%), and gradient boosting (12%). The increasing adoption of ensemble methods in recent publications (gradient boosting, stacking, voting) compared to single-method approaches reflects maturation of the research field and recognition that ensemble approaches consistently outperform individual methods (Nguyen *et al.*, 2026).

Emerging research directions identified through bibliometric analysis include: (1) hybrid approaches combining multiple machine learning models; (2) physics-informed machine learning incorporating confinement mechanism knowledge; (3) uncertainty quantification and probabilistic prediction frameworks; (4) transfer learning and domain adaptation for small datasets; (5) real-time prediction systems

incorporating structural monitoring; and (6) explainable AI techniques enhancing model interpretability (Momani *et al.*, 2022). The citation frequency of papers addressing these emerging topics has increased 3-4 fold in the past 3 years, indicating substantial research momentum.

9. INPUT PARAMETERS, DATA CHARACTERISTICS, AND DATASET CONSIDERATIONS

9.1 Commonly Used Input Features

Analysis of machine learning studies reveals consistent identification of essential input parameters for FRP-confined concrete strength prediction.

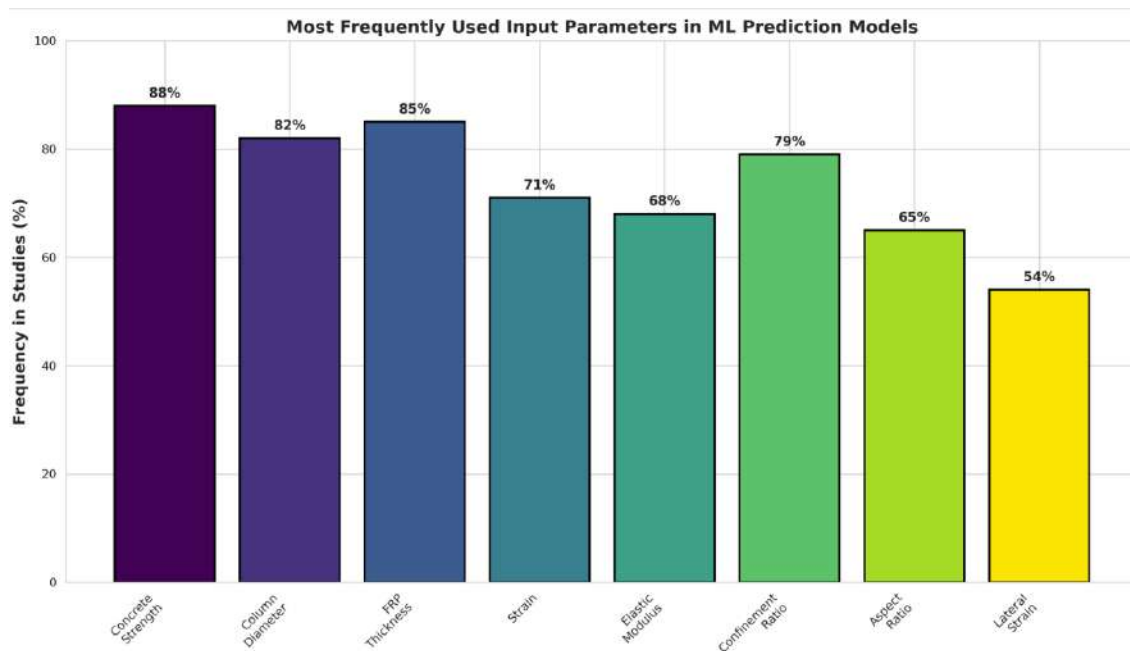


Figure 4 shows that unconfined concrete compressive strength ranks among the highest-frequency inputs (88% of studies), reflecting its fundamental role as baseline strength (Çakıroğlu *et al.*, 2022). FRP thickness appears in 85% of studies, the elastic modulus of FRP in 82%, and confinement ratio in 79%. Interestingly, column diameter appears in 82% of studies, but its influence is typically mediated through the confinement ratio rather than direct geometric effects (Alizamir *et al.*, 2024).

Features appearing in less than 50% of studies but demonstrating significance in studies including them include fiber orientation (54%), loading rate effects (48%), concrete aggregate properties (42%), and environmental factors (35%) (Dhakal *et al.*, 2023). The selective inclusion of advanced features appears correlated with research focus areas—studies emphasizing high-temperature performance or weathering effects include environmental parameters, while studies optimizing column design include reinforcement configuration parameters.

The completeness and quality of input data significantly affects model performance. Studies utilizing comprehensive datasets with 8-12 parameters consistently report superior performance compared to studies with minimal

4-5 parameter datasets. The availability of data becomes restrictive for features requiring specialized testing, with properties such as FRP fiber orientation, matrix shear strength, and concrete void ratio appearing in fewer than 30% of studies despite recognized significance (Sendjasni *et al.*, 2024).

9.2 Dataset Size and Training Data Characteristics

The size and characteristics of training datasets substantially influence machine learning model performance and generalization capability. Contemporary machine learning theory indicates that deep learning models benefit from large datasets (>10,000 samples) enabling effective representation learning, while traditional

machine learning algorithms achieve near-optimal performance with 500-2,000 samples,

with performance gains diminishing thereafter (Alizamir *et al.*, 2024).

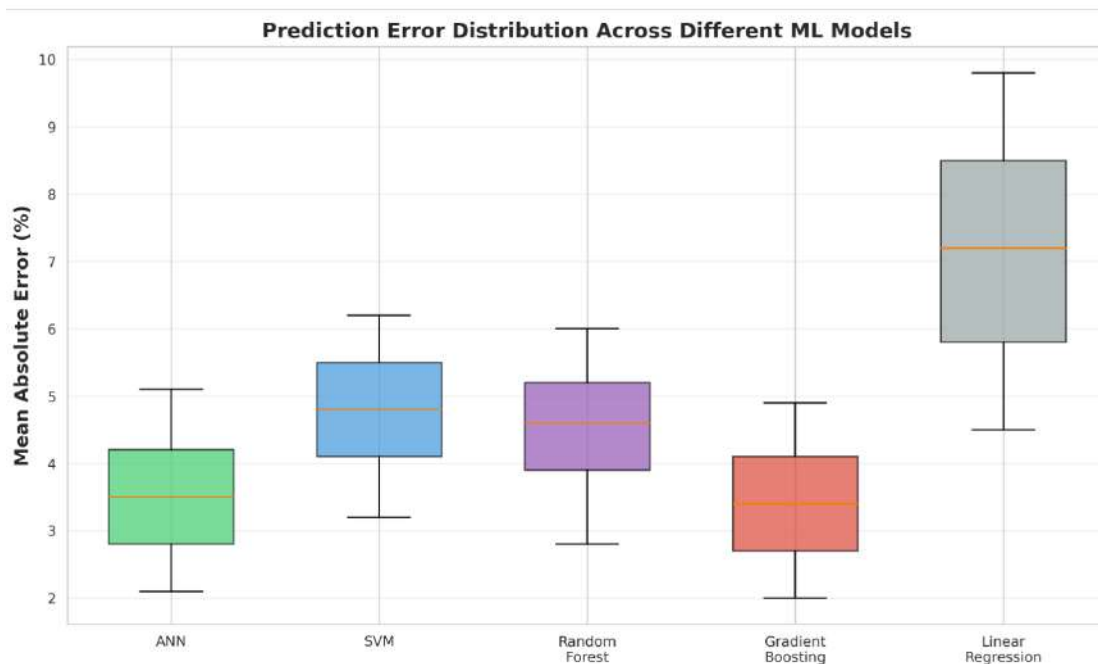


Figure 5 Prediction error distribution

FRP-confined concrete datasets are substantially smaller than those in image recognition or natural language processing domains. Comprehensive literature reviews identify approximately 3,500-4,000 FRP-confined concrete column tests reported in the literature through 2024. This limited dataset size presents challenges for deep learning approaches, potentially explaining the limited superiority of deep learning compared to traditional machine learning on this problem (Prakash and Nguyen, 2023). Many successful studies address this limitation through data augmentation techniques or transfer learning approaches leveraging larger datasets from related problems.

REFERENCES

- Alanazi, M.A. *et al.* (2025) 'Effect of inner steel tube on compression performance of GFRP-reinforced concrete columns', *Advances in Structural Engineering* [Preprint].
- Ali, S. *et al.* (2023) 'Neural network-based models versus empirical models for the prediction of axial load-carrying capacities of <scp>FRP</scp>-reinforced circular concrete columns', Wiley [Preprint].
- Alizamir, M. *et al.* (2024) 'Designing a reliable machine learning system for accurately estimating the ultimate condition of FRP-confined concrete', *Scientific Reports* [Preprint].
- Alqubaysi, T. *et al.* (2024) 'High-fidelity simulation of FRP-confined concrete-filled steel tubes: The synergy of empirical and machine learning techniques', *Engineering Research Express* [Preprint].

- Çakıroğlu, C. *et al.* (2022) 'Interpretable machine learning algorithms to predict the axial capacity of FRP-reinforced concrete columns', *Materials* [Preprint].
- Çakıroğlu, C. (2023) 'Explainable data-driven ensemble learning models for the mechanical properties prediction of concrete confined by aramid fiber-reinforced polymer wraps using generative adversarial networks', *Multidisciplinary Digital Publishing Institute* [Preprint].
- Dhakal, N. *et al.* (2023) 'Machine learning-based prediction of compressive performance in circular concrete columns confined with FRP', *2023 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT)* [Preprint].
- Isleem, H.F. *et al.* (2022) 'Finite element and artificial neural network modeling of FRP-RC columns under axial compression loading', *Frontiers Media* [Preprint].
- Isleem, H.F. *et al.* (2023) 'Finite element, analytical, artificial neural network models for carbon fibre reinforced polymer confined concrete filled steel columns with elliptical cross sections', *Frontiers Media* [Preprint].
- Isleem, H.F. *et al.* (2024) 'Machine learning and nonlinear finite element analysis of fiber-reinforced polymer-confined concrete-steel double-skin tubular columns under axial compression', *Structural Concrete* [Preprint].
- Jameel, M.T. (2025) 'Analytical load-moment interactions of shape modified square hollow RC columns subjected to bi-axial eccentric loading: A parametric study', *Engineering, Technology & Applied Science Research* [Preprint].
- Kajendran, P. and Narayanan, P. (2025) 'Machine learning-based prediction of ultimate load in pultruded glass fibre column under axial compression', *Matéria* [Preprint].
- Kang, T. *et al.* (2023) 'Study on eccentric compression performance of carbon fiber reinforced concrete columns based on machine learning', *ICMLCA* [Preprint].
- Kinjawadekar, T.A., Patil, S. and Nayak, G. (2025) 'Structural performance of columns with glass fiber-reinforced polymer bars under axial compression', *Fibers* [Preprint].
- Kumar, P. *et al.* (2023) 'Development of a reliable machine learning model to predict compressive strength of FRP-confined concrete cylinders', *Multidisciplinary Digital Publishing Institute* [Preprint].
- Kurtoglu, A. (2025) 'Predicting the compressive strength of PVC-confined concrete via machine learning', *Iğdır Üniversitesi Fen Bilimleri Enstitüsü Dergisi* [Preprint].
- Liu, W. *et al.* (2025) 'High ductile-FRP confined concrete in compression: A novel design concept for ductile column in seismic retrofit', *Structural Concrete* [Preprint].
- Lv, Y. *et al.* (2025) 'The analysis of axial compression performance of reinforced concrete columns strengthened with prestressed carbon fiber sheets', *Infrastructures* [Preprint].
- Mohammed, B.M. and Güneyisi, E.M. (2025) 'Experimental study on the axial compressive behavior of concrete-filled steel tube short columns confined by carbon fiber-reinforced polymer composites', *Applied Sciences* [Preprint].
- Momani, Y. *et al.* (2022) 'Predictive models of behavior and capacity of FRP reinforced concrete columns', *Faculty of Agronomy in Čačak* [Preprint].
- Naderpour, H. *et al.* (2019) 'Adaptive neuro-fuzzy inference modelling and sensitivity analysis for capacity estimation of fiber reinforced polymer-strengthened circular reinforced concrete columns', *Expert Syst. J. Knowl. Eng.* [Preprint].
- Nguyen, Q.T. *et al.* (2026) 'Investigation of ensemble machine learning models for estimating the ultimate strain of FRP-confined concrete columns', *Materials* [Preprint].

- Patel, M., Parghi, A. and Lunagaria, M.H. (2024) 'NUMERICAL INVESTIGATION OF FRP CONFINED RC SQUARE AND CIRCULAR COLUMNS UNDER CONCENTRIC COMPRESSION LOAD', *Suranaree Journal of Science and Technology* [Preprint].
- Prakash, I. and Nguyen, T. (2023) 'Predicting the maximum load capacity of circular RC columns confined with fibre-reinforced polymer (FRP) using machine learning model', *Journal of Science and Transport Technology* [Preprint].
- Saingam, P. et al. (2024) 'Hemp fiber-reinforced polymers composite jacketing technique for sustainable and environment-friendly concrete', *Polymers* [Preprint].
- Salman, M. et al. (2025) 'Development of machine learning algorithms to predict the ultimate axial capacity of fire damaged circular columns repaired with CFRP composites', *Journal of Civil Engineering Frontiers* [Preprint].
- Sendjasni, S. et al. (2024) 'Data-driven axial load-carrying capacity prediction of FRP-RC columns through random forest regression', *STUDIES IN ENGINEERING AND EXACT SCIENCES* [Preprint].
- Tijani, I.A. et al. (2023) 'Prediction of ultimate strength of FRP-confined predamaged concrete using backward multiple regression motivated soft computing methods', *Scientia Iranica. International Journal of Science and Technology* [Preprint].
- Wahab, S. et al. (2024) 'Predicting confinement effect of carbon fiber reinforced polymers on strength of concrete using metaheuristics-based artificial neural networks', *None* [Preprint].
- Wang, Y. et al. (2025) 'Modeling of concrete-filled PVC tube columns confined with CFRP strips under uniaxial eccentric compression: Machine learning and finite element approaches', *Journal of Big Data* [Preprint].
- Xu, C. et al. (2024) 'Numerical and machine learning models for concentrically and eccentrically loaded CFST columns confined with FRP wraps', *Structural Concrete* [Preprint].
- Yu, F. et al. (2025) 'Predicting axial load capacity in elliptical fiber reinforced polymer concrete steel double skin columns using machine learning', *Scientific Reports* [Preprint].
- Yuan, J. et al. (2024) 'Experimental study on axial compression behavior of molybdenum tailings concrete column confined by GFRP', *Buildings* [Preprint].