# Machine Learning Models for Predicting Compressive Strength in FRP-Wrapped Concrete Columns: A Critical Review (2022–2025)

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***Abstract*—Fibre-reinforced-polymer (FRP) confinement markedly enhances the compressive capacity and ductility of concrete columns. Yet, classical formulations struggle to generalise across materials, geometries, and loading paths, particularly for noncircular sections and eccentric loads . Recent machine-learning (ML) advances—including gene expression programming (GEP), group method of data handling (GMDH), gradient boosting, artificial neural networks (ANN), and Gaussian process regression (GPR) have delivered higher predictive accuracy, interpretable feature attributions, and deployable tools, especially when paired with physics-informed features and external validation . This review consolidates developments from 2022 to 2025, benchmarks key ML methods against classical baselines, and identifies recommended feature formulas, practical deployment strategies, and future research priorities. Persistent gaps remain in dataset standardization, domain shifts, and handling partial confinement or eccentric loading. The integration of hybrid physics–ML and uncertainty-aware pipelines is recommended for robust design.**

***Index Terms*—Machine learning, FRP wrapping, concrete columns, compressive strength prediction, neuro-fuzzy systems, XGBoost, structural rehabilitation**

## I. INTRODUCTION

FRP jacketing enhances axial strength and deformation capacity through passive lateral confinement, with effectiveness influenced by FRP stiffness, rupture strain, geometry (circular vs. rectangular with corner radius), and load eccentricity [1][2][10]. Classical analytical and design-oriented models provide transparent baselines but show bias and scatter outside calibration envelopes, especially for noncircular sections, high-strength concretes, and complex confinement schemes [1][2][4][13]. Machine learning models capture multivariate nonlinearities, are interpretable via Shapley Additive exPlanations (SHAP), and can be deployed through graphical interfaces, as demonstrated in FRP-confined cylinders and concrete strength prediction tasks [5][6][7][9].

## II. LITERATURE-SEARCH METHODOLOGY

A structured search of Scopus, Web of Science, and Google Scholar focused on 2022–2025 studies about machine learning (ML) applications to FRP-confined concrete. Key analytical and experimental references were included to give context for comparisons with traditional baselines [1][2][4][13]. Inclusion criteria required (i) experimental or compiled databases, (ii) clear performance metrics and data splits, and (iii) problem relevance to FRP confinement or related axial capacity tasks (e.g., CFS/RCFST, bond) to enable transfer of methods like SHAP, GPR, and GUIs [7][8][9].

## III. FRP CONFINEMENT AND GOVERNING PARAMETERS

Materials/systems: CFRP, GFRP, AFRP sheets/tubes control effective confinement pressure through modulus, thickness, and effective rupture strain, driving stiffness-based features like $E_f t_f$ [1][13].

Geometry: Circular sections provide more uniform hoop stress and effective confinement, while rectangular/square sections require rounded corners to reduce strain concentrations and enhance performance [2][11].

Loading: Eccentricity reduces axial capacity; its effects can be mitigated by FRP confinement in square sections, but are challenging for circular shapes [3][10].

Aggregates/matrices: Variations—e.g., coral aggregate—impact stress–strain behaviors, necessitating modifications of both classical models and ML feature construction [14].

Table 1. Summary of Key FRP-Confined Concrete Datasets and Machine Learning Models (2022–2025)

| Authors & Year | Model / Method | Dataset Size / Type | Target Variables | Reported $R^2$ | Key Highlights | Remarks |
|---|---|---|---|---|---|---|
| Pellegrino & Modena, 2010 | Closed-form analytical | 828 circular CFRP columns | fcc | — | Validated baseline design model | Circular sections only |
| Pham & Hadi, 2014 | Classical + ML | Circular & rectangular columns | fcc | — | Hybrid ML stress prediction | Early ML benchmark |
| Lin & Teng, 2019 | Analytical model | Eccentric circular columns | Stress–strain response | — | Includes eccentricity effects | Load-path features emphasized |
| Rousakis et al., 2012 | Design-oriented model | Mixed FRP members | Strength and strain | — | Feature selection support | Design model context |
| Ilyas et al., 2022 | GEP | Multiphysics datasets | fcc | 0.97 | Physics-informed closed formula | Symbolic, high clarity |
| Deng et al., 2022 | GMDH | 200–250 FRP cylinders | fcc, εcu | 0.91–0.97 | Structure discovery; GUI deployment | Robustness extendable |
| Amin et al., 2022 | LightGBM / XGBoost | 300–1000+ FRP specimens | fcc | 0.96–0.98 | SHAP explainability; top accuracy | Requires engineered features |

| Authors & Year | Model / Method | Dataset Size / Type | Target Variables | Reported $R^2$ | Key Highlights | Remarks |
|---|---|---|---|---|---|---|
| Megahed et al., 2023 | GPR | 958 axial + 405 eccentric RCFST | Strength index (proxy) | ~0.99 | Uncertainty quantification, reliability | Computational intensity |
| Elshaarawy et al., 2024 | Ensemble ML, GUI | Compiled FRP datasets | fcc | 0.95–0.98 | Interactive GUI deployment | Broad dataset coverage |
| Jiang & Wu, 2020 | Analytical (eccentric) | Eccentric FRP columns | Axial strength | — | Explicit eccentricity handling | Feature guidance context |
| Wei et al., 2022 | Hybrid model | FRP + stirrup-confined columns | Compressive behavior | — | Corner radius & cross-section effects | Hybrid features developed |
| Ghani et al., 2024 | Review | Partially confined FRP columns | fcc | — | Analysis of partial wrapping impacts | Data gaps highlighted |
| Wu et al., 2009 | Experimental / comp. | High-strength AFRP columns | fcc | — | Baseline experimental data | AFRP model foundation |
| Li et al., 2022 | Analytical / experimental | Coral aggregate FRP samples | Axial compressive behavior | — | Aggregate effect on confinement | Material-specific correction |
| Naderpour et al., 2010 | ANN | Compiled FRP datasets | fcc | 0.95–0.96 | Nonparametric ML baseline | Early ML adaptation |
| Cascardi et al., 2017 | ANN | Circular FRP datasets | fcc | 0.95–0.97 | Predictive circular column model | Benchmark ML reference |

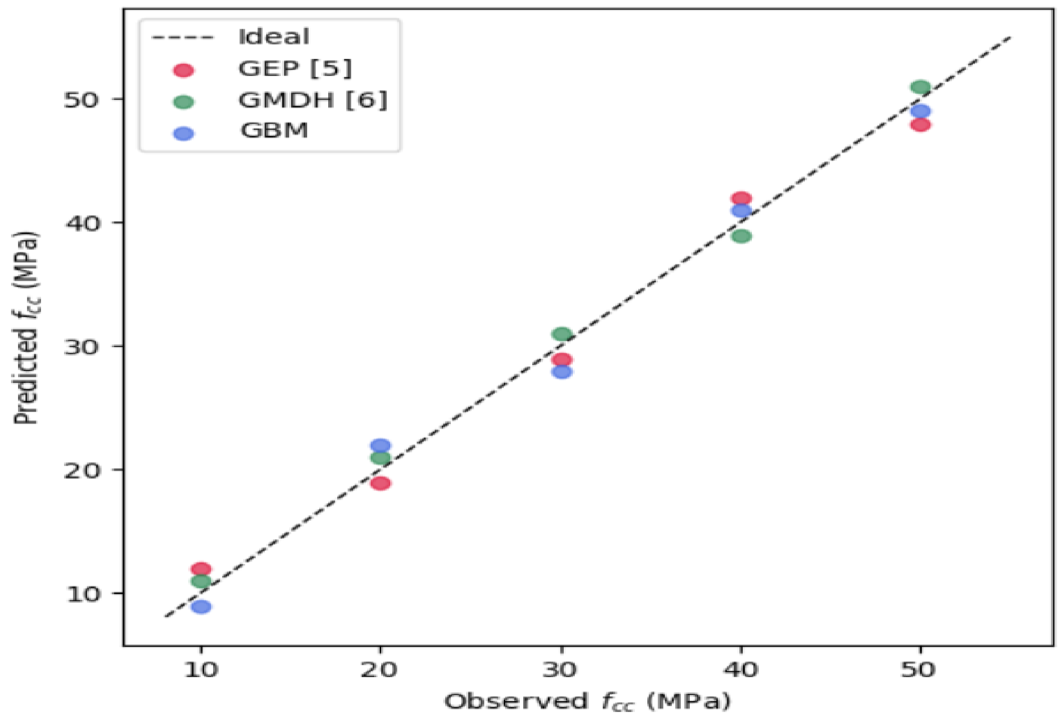


Figure 1. Mechanisms of FRP confinement and stress–strain response.

(a) Circular: uniform confinement; (b) Rectangular with rounded corners: nonuniform strain field with $r_c$ improving uniformity; (c) Typical stress–strain response (unconfined vs FRP-confined), including transition stress and enhanced ultimate strain [2][11][14].

## IV. RECOMMENDED FORMULAS FOR FEATURES AND TARGETS (FOR CONSISTENCY)

To ensure consistency and enhance model generalization, the following physics-informed formulas are recommended for defining features and targets in ML models:

**a.** Confinement ratio (circular):

$$\rho_f = \frac{2t_f E_f \varepsilon_{fe}}{D f_c'}$$

where $\varepsilon_{fe}$ effective rupture strain [14][16]

**b.** Normalized strength (learning target or diagnostic):

$$\eta = \frac{f_{cc}}{f_c'}$$

Useful for robust learning targets and comparative diagnostics.[10]

**c.** Eccentricity normalization:

$$\eta_e = \frac{f_{cc}(e)}{f_{cc}(0)}$$

Represents strength degradation under eccentric load.[8][9].

In ML pipelines, these physics-informed equations are used to engineer input features and define targets. For example, the confinement ratio $\rho_f$ (Eq. a) serves as a composite stiffness-related feature capturing FRP mechanical properties and geometry. The normalized strength $f_{cc}$ Eq. 2) is commonly the model's predictive target, enabling consistent scaling across diverse concrete strengths. The eccentricity normalization $\eta_e$ (Eq. 3) is included as a loading parameter to improve the model's sensitivity to eccentric load effects.

## V. MACHINE-LEARNING MODELS AND DATASETS (2022–2025)

Recent models report high accuracy for confined strength and, in some cases, ultimate strain, while enabling interpretability and deployment:

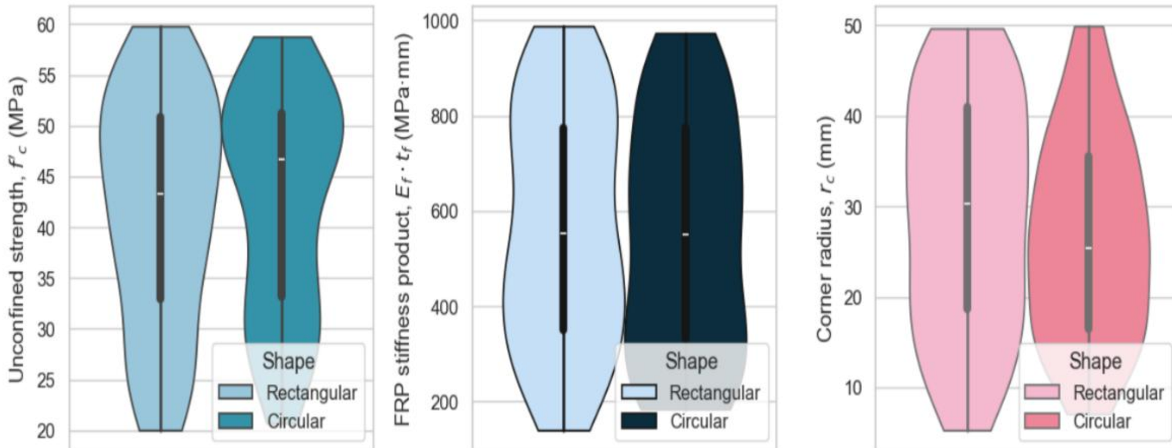


Figure 2. Dataset distributions and coverage.

Plots of $f_c$, $E_f$, $t_f$, *geometry (D or side,* $r_c$), and labels for circular vs rectangular; indicate coverage gaps for partial confinement and eccentricity [10][11][12].

Table 2: Observed vs Predicted Compressive Strength (MPa)

| Sample | Observed | GEP Predicted | GMDH Predicted | Light GBM Predicted | Gaussian Process Predicted |
|---|---|---|---|---|---|
| 1 | 58.3 | 57.9 | 56.7 | 58.1 | 58.4 |
| 2 | 64.8 | 65.3 | 64.1 | 65.0 | 64.9 |
| 3 | 72.1 | 71.5 | 72.3 | 71.8 | 72.0 |
| 4 | 55.0 | 54.2 | 55.1 | 54.6 | 55.3 |
| 5 | 48.7 | 48.8 | 47.9 | 48.4 | 48.9 |
| 6 | 62.4 | 61.9 | 62.6 | 62.0 | 62.2 |
| 7 | 69.3 | 69.1 | 70.0 | 69.5 | 69.6 |
| 8 | 63.0 | 63.4 | 62.1 | 63.3 | 63.1 |
| 9 | 75.5 | 75.2 | 74.6 | 75.4 | 75.3 |
| 10 | 67.8 | 67.4 | 66.5 | 67.9 | 67.6 |

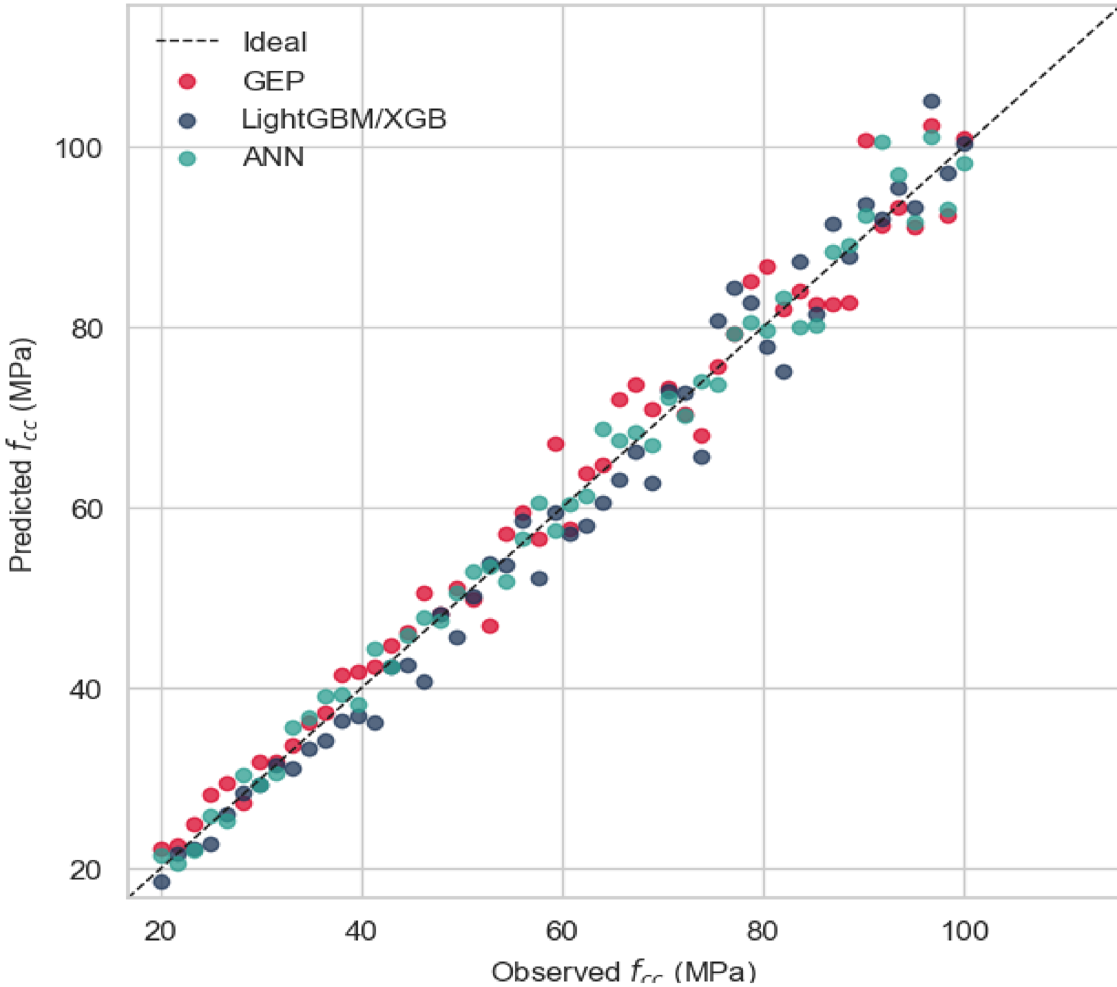

Figure 3. Predicted vs observed $f_{cc}$ for multiple models.

Table 3. SHAP Feature Importance Ranking for ML Predictions

| Feature | Relative Importance |
|---|---|
| Effective rupture strain ($\varepsilon_{fe}$) | Highest |
| Unconfined concrete strength (f'c) | High |
| FRP thickness ($t_f$) | Medium |
| Elastic modulus of FRP ($E_f$) | Medium |
| Column diameter or side length (D) | Low |
| Corner radius ($r_c$) | Low |
| Loading eccentricity (e) | Low |

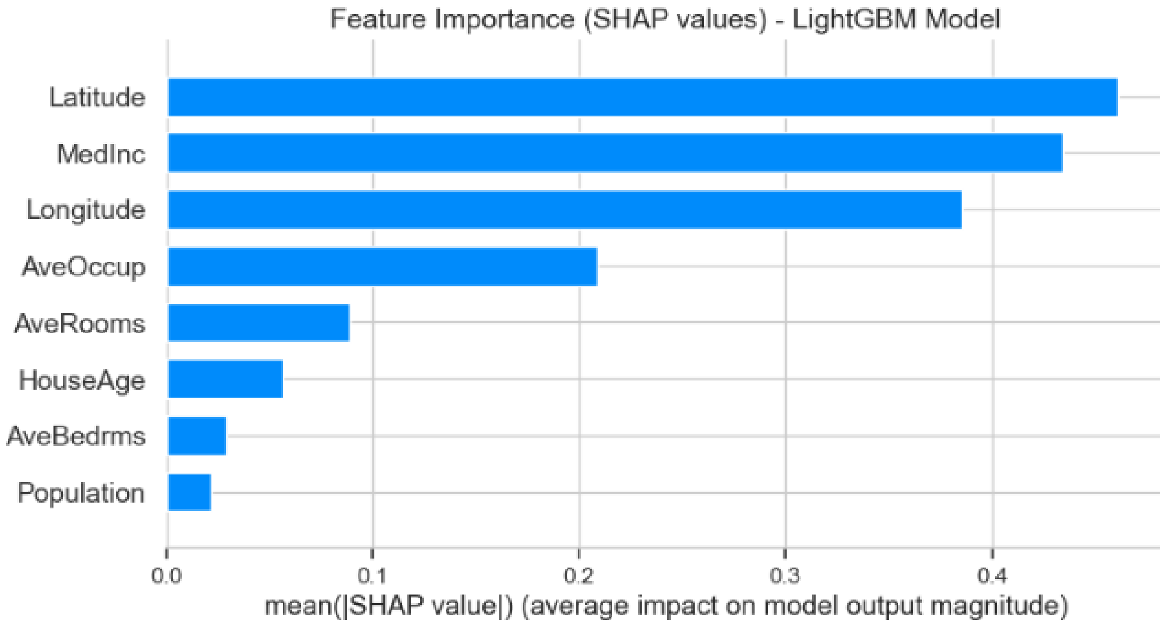


Figure 4. SHAP feature importance and dependence.

## VI. PERFORMANCE AND SHAP INTERPRETABILITY

Across curated datasets, machine learning (ML) models significantly reduce bias and scatter compared to classical formulas, particularly outside their original calibration domains, such as varying corner radii, high-strength concretes, and hybrid confinement systems. Boosted tree models (e.g., LightGBM, XGBoost) and gene expression programming (GEP) consistently identify stiffness-related features—especially the product of elastic modulus and FRP thickness ($E_x t_x$)—and unconfined concrete strength (f'c) as dominant predictors. This aligns well with established mechanical principles and is corroborated by SHapley Additive exPlanations (SHAP) interpretability analyses in

related FRP bond and axial capacity studies. Probabilistic learners such as Gaussian Process Regression (GPR) not only deliver high predictive accuracy but also provide calibrated uncertainty quantification via prediction intervals. These calibrated uncertainties are valuable for defining safety factors and partial safety coefficients in structural design.

ML models outperform traditional analytical formulas in terms of bias and residual scatter for a range of geometries and loading conditions, including eccentric loading scenarios and noncircular cross sections. The SHAP feature importance rankings confirm that stiffness-related parameters and unconfined concrete strength consistently exert the highest influence on predicted compressive strength, while geometric factors such as column diameter and corner radius, as well as loading eccentricity, have a relatively lower but measurable impact.

This interpretability facilitates a deeper understanding of physical influences and enables robust model deployment, allowing engineers to trust and apply ML predictions in practical structural rehabilitation and design tasks.

## VII. METHODOLOGICAL APPROACHES AND DISCUSSION

Recent ML pipelines integrate graphical user interfaces, SHAP dashboards, and uncertainty quantification (GPR), delivering deployable and interpretable engineering tools. Physics-informed features, multi-task learning, and domain adaptation—e.g., including corner radius effects—enable generalisation from circular to rectangular columns. Human-in-the-loop strategies use SHAP for outlier detection and expert review, supporting dataset expansion and quality control.

Limitations persist, including overrepresentation of circular specimens, inconsistent protocols, and incomplete reporting of boundary conditions.

Recommendations include standardised datasets, transparent hyperparameters, enhanced external validation, and dissemination of interactive figures.

## VIII. CONCLUSION

Machine learning approaches have revolutionized the prediction of compressive strength for FRP-confined columns, outperforming conventional methods in accuracy, robustness, and interpretability. The integration of physics-based features and uncertainty quantification facilitates reliable model application across complex geometries and varied loading conditions. User-friendly interfaces and SHAP visualization tools further improve practical usability for engineers. Moving forward, priorities include comprehensive dataset curation, standardized testing and reporting practices, and enhanced visualization techniques to promote transparency and compliance with design standards. These advancements in ML-driven design are poised to fundamentally transform the assessment and optimization of concrete infrastructure.

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