Data-Driven PSO-CatBoost Machine Learning Model to Predict the Compressive Strength of CFRP- Confined Circular Concrete Specimens

MIAMI

ACI Concrete Convention (Fall 2023-Boston)

Open Topic Session

October 31st

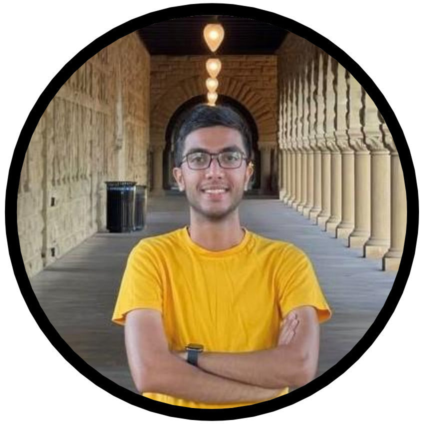
Team

Antonio Nanni

Nima Khodadadi

El-Sayed M. El-kenawy

Francisco De Caso



Hossein Roghani

Yelena Yesha

INTRODUCTION

FRP-Confined Concrete

- Rising interest in using FRP in the construction sector.
- Significant amount of experimental and analytical research.
- Lateral confinement of concrete columns increases ductility and strength.
- Enhances the durability and service life concrete elements.
- Two major categories of research: 1) experimental investigations; and 2) analytical investigations (model development)

Fig.1. CFRP wrap[1] and filament wound FRP tubes[2].

Fig.2. CFRP-wrapped Columns for bridge retrofitting[3,4].

[1] FRP Carbon Fibre Reinforcing Systems | Strong-Tie | Together we're helping build safer stronger structures (strongtie.com.au).
[2] Ahmed, A. A., & Masmoudi, R. (2018). Journal of Composites Science, 2(4), 57.
[3]ctech-carbon-wrap-frp-Columns-bridge-Retrofitting-concrete | CTech-LLC

FRP-Confined Concrete

- Cylindrical concrete elements subjected to triaxial compressive stresses.
- Subjected to compression, confined concrete tends to expand in the radial direction.
- Expansion generates a reactively confining radial pressure at the interface between FRP and concrete.

$$\boxed{\sigma_l = \frac{2t_f\sigma_f}{D}}$$

- D is diameter, t_f is thickness of FRP, σ_l is confining pressure, and σ_f is hoop tensile stress of FRP.

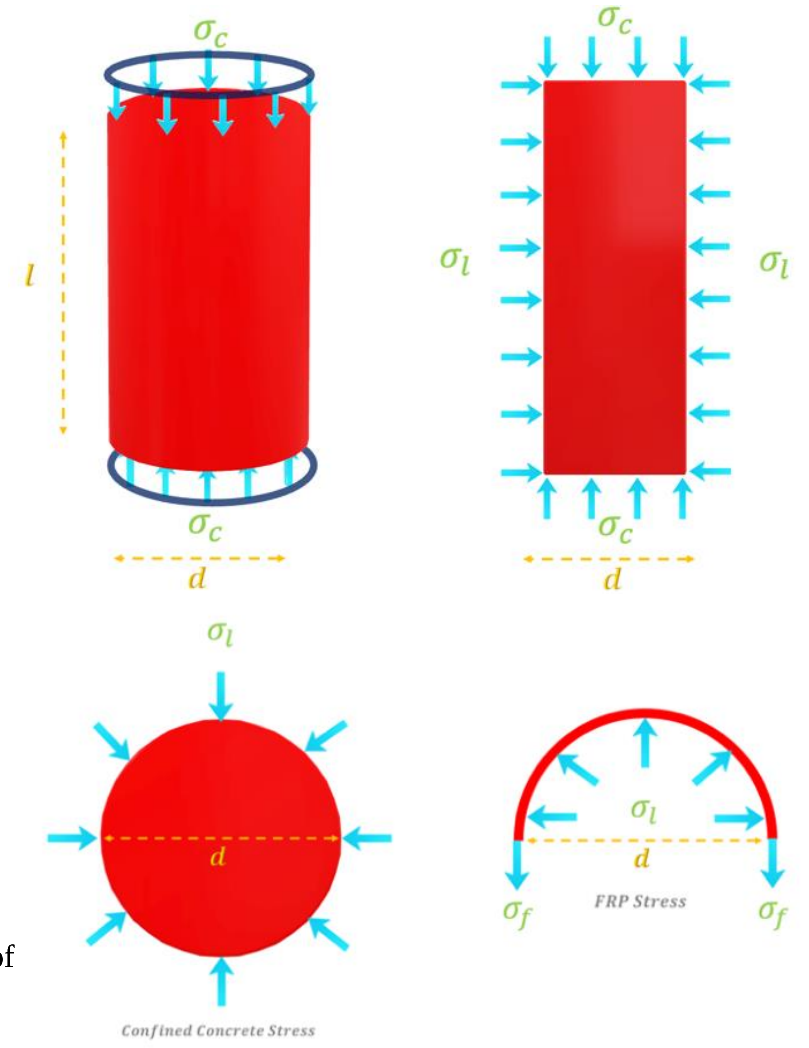


Fig.3. Schematic view of FRP-confined circular concrete specimen.

INTRODUCTION

Machine Learning

- In recent times ML methods gained significant recognition.
- Primary benefit: doesn't require the user to understand a problem comprehensively.
- Sufficient data and domain knowledge, an ML model assists in predicting outcomes in a complex system.
- Developing a resilient ML model: a complex and time-consuming endeavor.
- Process: appropriate algorithm, development of an efficient model, and optimization of hyperparameters.
- Algorithms: tree-based ML algorithms and deep neural networks, possess multiple hyperparameters that substantially impact the accuracy of predicted values by model.
- Precise adjustment of hyperparameters using an optimization technique holds significant importance.

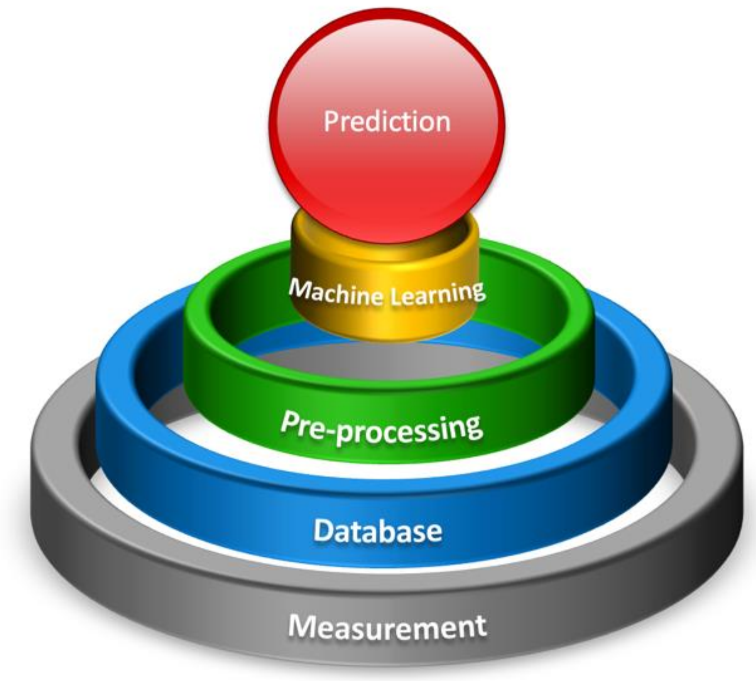


Fig.4. Prediction process with ML.

INTRODUCTION

Primary advancements and contribution

- A data-driven ML model based on PSO and the CatBoost algorithm (PSO-CatBoost) is proposed.
- Goal: to predict the compressive strength of CFRP-CC under axial compression.
- Extensive dataset on CFRP-CC specimens from 1991 to mid-2023.
- Evaluate effectiveness of CatBoost in estimating compressive strength of CFRP-CC under axial compression.
- CatBoost methods are rarely used in ML issues, although PSO is increasingly used.

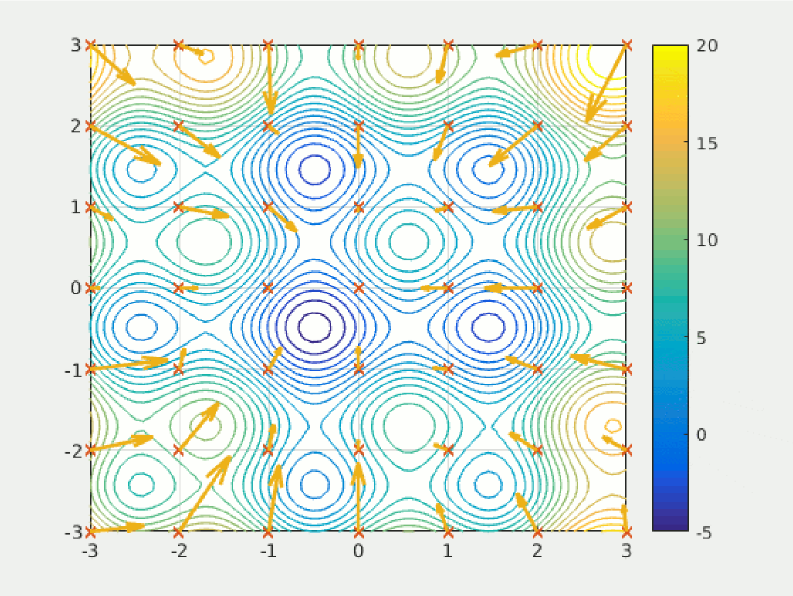


Fig.5. A Particle Swarm searching for the global minimum of a function.

Existing Compressive Strength of FRP-CC Models

1. Mandal et al.'s Model:

$$f'_{cc} = 0.0017 f'_{co} \left(\frac{E_f t_f}{D/2} \frac{f_f}{f'_{co}} \right)^2 + 0.0232\, f'_c \left(\frac{E_f t_f}{D/2} \frac{f_f}{f'_{co}} \right) + f'_{co}$$

2. Karbhari et al.'s Model:

$$f'_{cc} = f'_{co} + 2.1 f'_{co} \left(\frac{2 f_f t_f}{D f'_{co}} \right)^{0.87}$$

3. Lilliston and Jolly's Model:

$$f'_{cc} = 0.83 f'_{co} + 0.05 f'_{co} \left(\frac{2 E_f t_f}{D f'_{co}} \right)$$

These models have been employed for comparison purposes in this study.

CONSTRUCTION OF DATABASE

- 916 test results from 116 studies published between 1991 and mid-2023.
- Seven critical parameters: D, H, f'_{co}, ρ_f, E_f, f_f, t_f, and $Layers$. The target value is f'_{cc}.
- Normalization is an essential preprocessing step to address scale sensitivity.

$$\boxed{x_{i,normal} = 2 \times \left[\frac{x_i - min\,(x)}{Max(x) - Min(x)}\right] - 1}$$

- Database only includes studies on circular concrete specimens.
- Without any internal or external reinforcement.
- Height-to-diameter ratio of specimen is less than or equal 5.
- Subjected to a monotonic concentric compressive load.
- Failure mode in all specimens was FRP rupture.

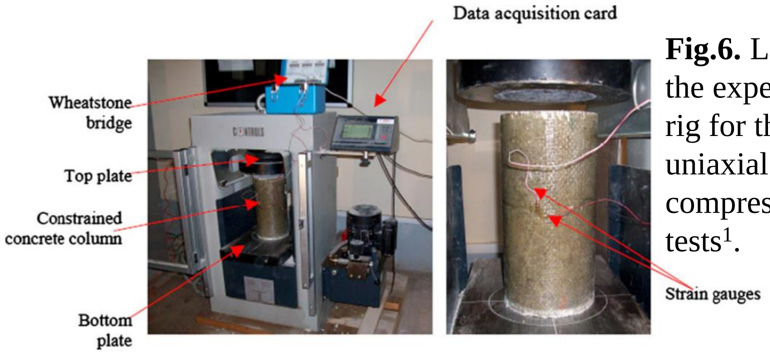


Fig.6. Layout of the experimental rig for the uniaxial compressive tests[1].

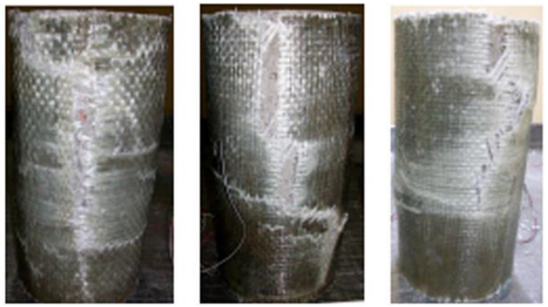


Fig.7. Failure modes of confined cylinders[1].

Table 1. Geometric and material properties of FRP-confined specimens.

Group	*Notation*	*Description*	*Unit*
Specimen geometry	D	Diameter of compression member	*mm*
	H	Height of compression member	*mm*
Concrete	f'_{co}	Compressive strength of unconfined concrete	*MPa*
FRP properties	ρ_f	FRP reinforcement ratio	-
	E_f	Tensile modulus of elasticity of FRP	*GPa*
	f_f	Ultimate tensile strength of FRP	*MPa*
	t_f	Nominal thickness of FRP reinforcement	*mm*
	$Layers$	Number of FRP layers	-
Result	f'_{cc}	Compressive strength of confined concrete	*MPa*

[1]Bouchelaghem, H., Bezazi, A., & Scarpa, F. (2011).. Composites Part B: Engineering, 42(7), 1987-1993.

CONSTRUCTION OF DATABASE

- Concrete strengths between 6.2 MPa to 169.7 MPa.
- CFRP composites with a modulus of elasticity between 16 GPa to 640 GPa.
- CFRP composites with an ultimate tensile strength from 174 MPa to 4900 MPa
- Reinforcement ratio from 0.001 to 0.162.
- Total nominal thickness of 0.09 mm to 5.84 mm.
- Compressive strength of confined concrete from 12.8 MPa to 303.6 MPa

Table 2. Statistical range of database parameters.

Parameter	*Minimum*	*Maximum*	*Mean*	*Standard Deviation*
H/D	1.6	5	2	0.36
f'_{co} (MPa)	6.2	169.7	45.3	24.8
ρ_f	0.001	0.162	0.016	0.018
E_f (GPa)	16	640	221.6	102.9
f_f (MPa)	174	4900	3128	1228
t_f (mm)	0.09	5.84	0.60	0.69
f'_{cc} (MPa)	12.8	303.6	86.3	40.7

CONSTRUCTION OF DATABASE

- 800 data points on CFRP-wrapped and 116 on CFRP-filled concrete tubes.
- 23 data points with a f'_{co} lower than 15 MPa (L), 687 data points with a f'_{co} between 15 MPa and 55 MPa (N), and 206 data points with a f'_{co} above 55 MPa (H).
- 825 data points with the E_f lower than 340 GPa (CFRP), 73 data points with E_f between 340 GPa and 520 GPa (HM_CFRP), and 18 data points with E_f above 520 GPa (UHM_CFRP).

Table 3. Classification of database.

Confinement Type	*CFRP Type*	*Concrete classification*	*No. of datapoints*
Wrap	CFRP	L	22
		N	581
		H	120
	HM CFRP	L	0
		N	40
		H	29
	UHM CFRP	L	0
		N	8
		H	0
Tube	CFRP	L	1
		N	50
		H	51
	HM CFRP	L	0
		N	4
		H	0
	UHM CFRP	L	0
		N	4
		H	6
Total Experiments		916	

CONSTRUCTION OF DATABASE

- Distribution of input and output parameters, frequency of occurrence, and correlation between these parameters.

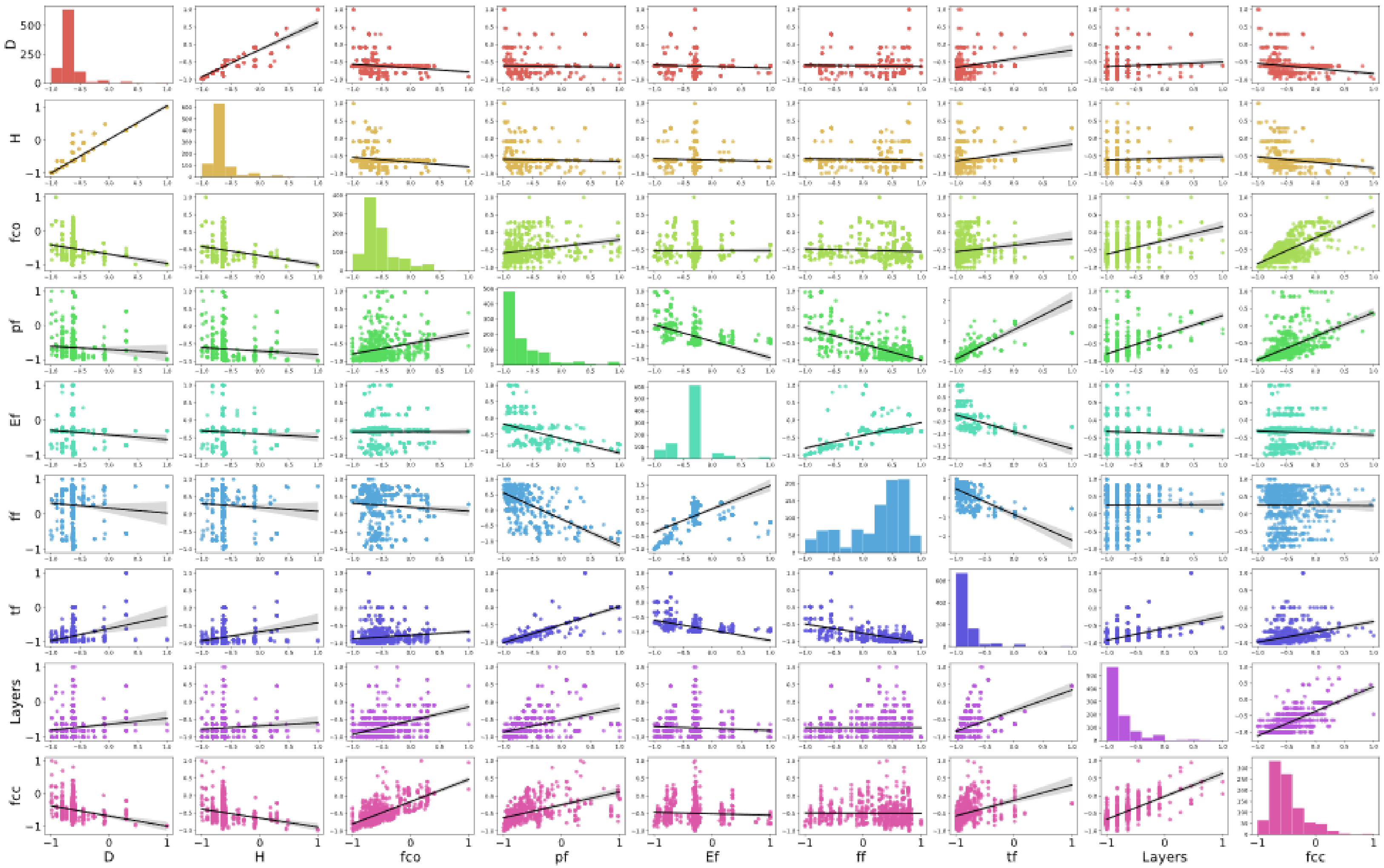


Fig.8. Multi-correlation among input and output variables.

PERFORMANCE MEASURES

1. Residual Error

$$e = x_{Experimental} - x_{Predicted}$$

2. Coefficient of Determination

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(x_{exp,i} - x_{mod,i})^2}{\sum_{i=1}^{N}\left(x_{exp,i} - \bar{x}\right)^2}$$

3. Mean Square Error

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(x_{exp,i} - x_{mod,i}\right)^2$$

4. Root Mean Square Error

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_{exp,i} - x_{mod,i})^2}{N}}$$

5. Mean Absolute Error

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|x_{exp,i} - x_{mod,i}\right|$$

CONSTRUCTION OF MODEL

Particle Swarm Optimization- Categorical Boosting (PSO-CatBoost)

- Gradient Boosted Decision Trees (GBDTs), an ensemble method based on decision trees.
- This study is focused on one of the GBDT variations, namely Categorical Boosting (CatBoost), which is improved to generate a prediction model.

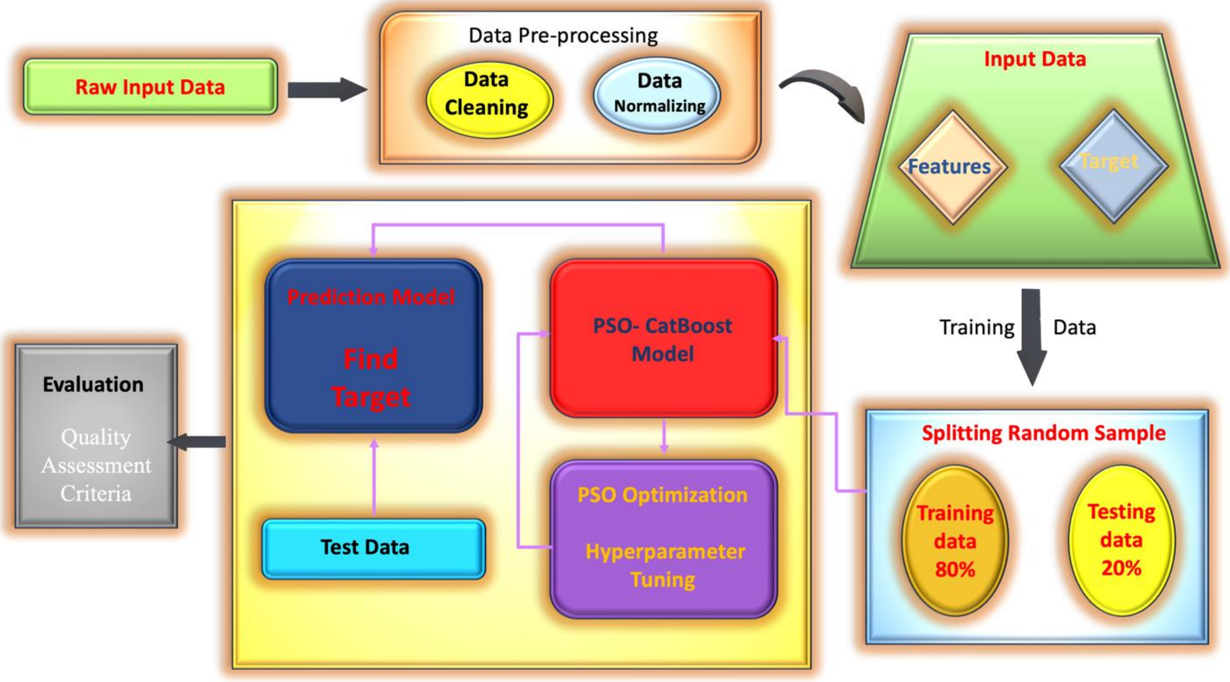


Fig.9. The architectural detail PSO-CatBoost Model.

RESULTS AND DISCUSSION

Hyperparameters and Optimum Values

- Optimized hyperparameters utilized in the process of training the model.
- Model was run on a personal computer equipped with an Apple M2 Max processor, 96GB of RAM, and utilizing the macOS Ventura operating system.

Table 4. Optimum hyperparameters value for PSO-CatBoost model.

Algorithm	*Hyperparameters*	*Optimum Value*
PSO	Local coefficient (c_1)	*0.5*
	Global coefficient (c_2)	*0.3*
	Inertia coefficient (w)	*0.9*
	Maximum iteration count (max_{iter})	*500*
	Population/swarm size (s)	*10*
CatBoost	Depth	*4.046*
	Learning rate	*0.1*
	L2-regularization	*1.959*

RESULTS AND DISCUSSION

Interpretation of Model Results

- Model was trained using 80% of the data, while 20% used for testing.
- Spearman correlation technique to find correlations.
- Strong positive correlation between the t_f and ρ_f of (s=0.94)
- Strong positive correlation between and *D and H* (s=0.93).
- No. of layers has moderate correlations with t_f (s=0.68) and ρ_f (s=0.65).
- PSO-CatBoost model achieved R^2 scores of 0.9898 and 0.9571 in training and testing, respectively.
- PSO-CatBoost model showed comparatively lower error values (training and testing).

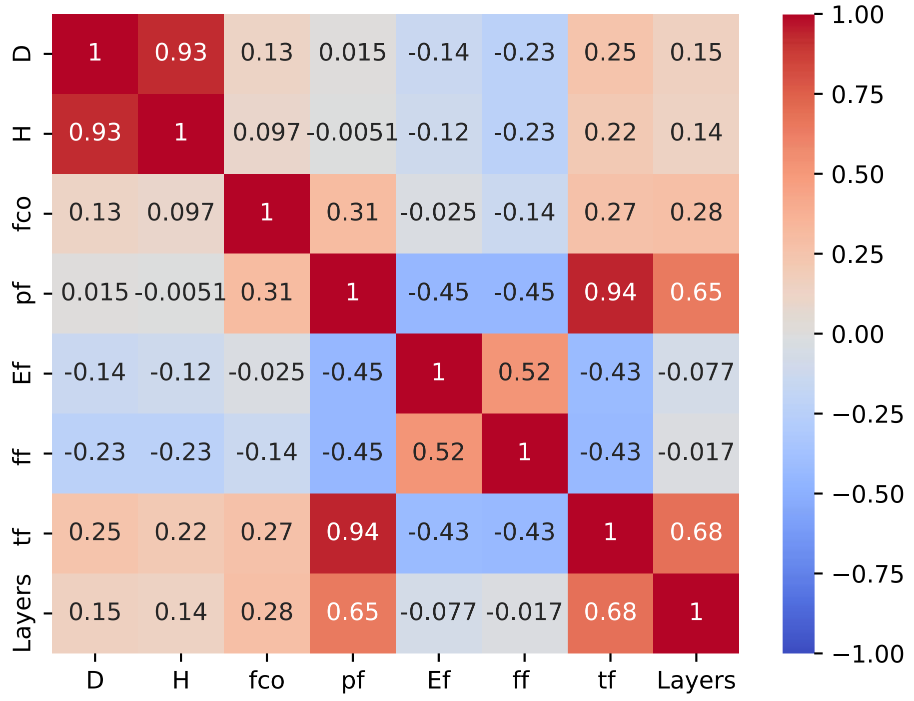


Fig.10. Heatmap for the correlation coefficient between variables.

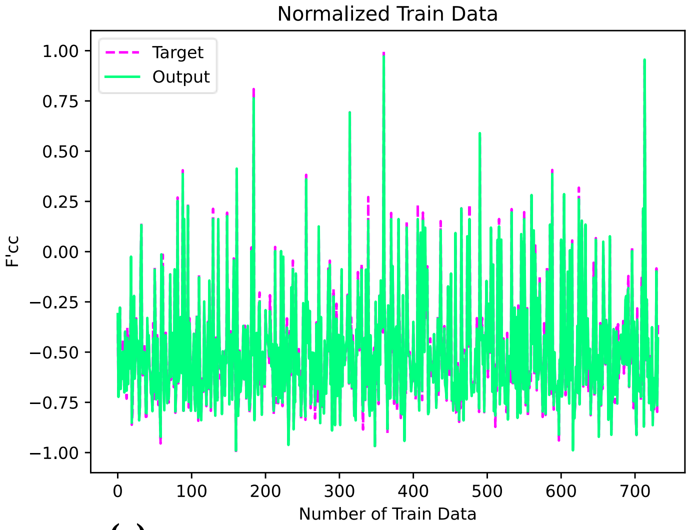
Table 5. Performance metric results for the employed method.

Data	R^2	*MSE*	*MAE*	*RMSE*
Train	0.9898	0.0008	0.0219	0.0290
Test	0.9571	0.0026	0.0373	0.0514
All	0.9847	0.0012	0.0250	0.0347

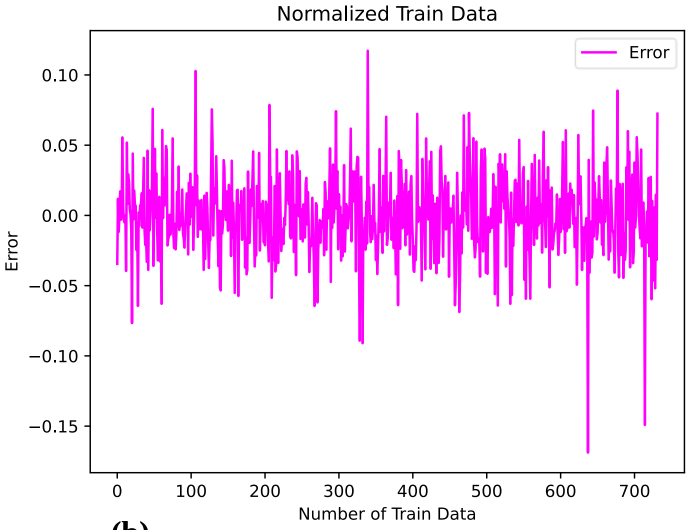
RESULTS AND DISCUSSION

Predicted Vs. Observed (training data)

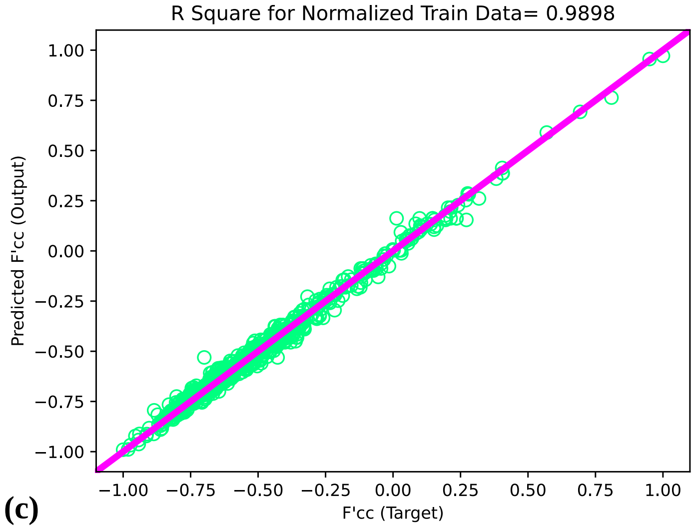
- Training data and the prediction model exhibit exceptional congruence.
- High degree of overlap indicates the model's ability to accurately reflect and predict the underlying patterns.
- Error margins for the training data indicate a high level of accuracy (most errors are less than 0.025).
- High R-squared value of 0.9898, signifying a strong relationship between independent and dependent variables.



(a)



(b)

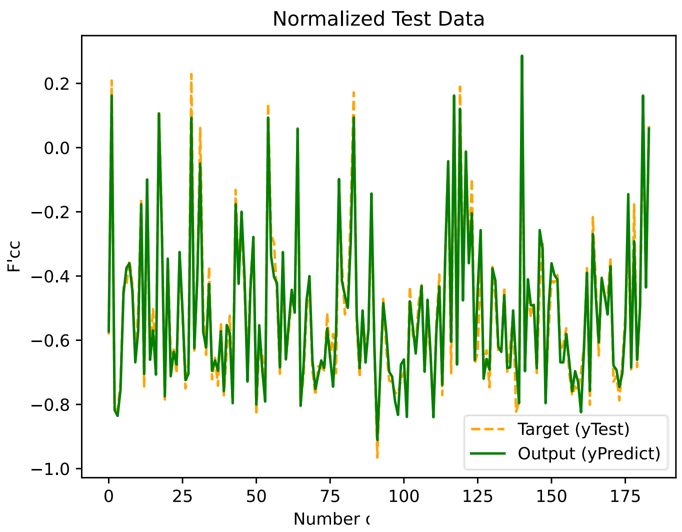


(c)

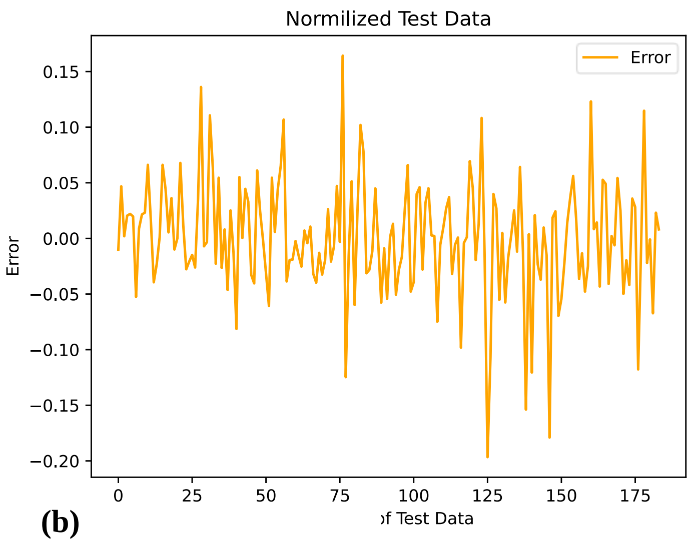
Fig. 11. Estimator result analysis of compressive strength for train data.

Predicted Vs. Observed (test data)

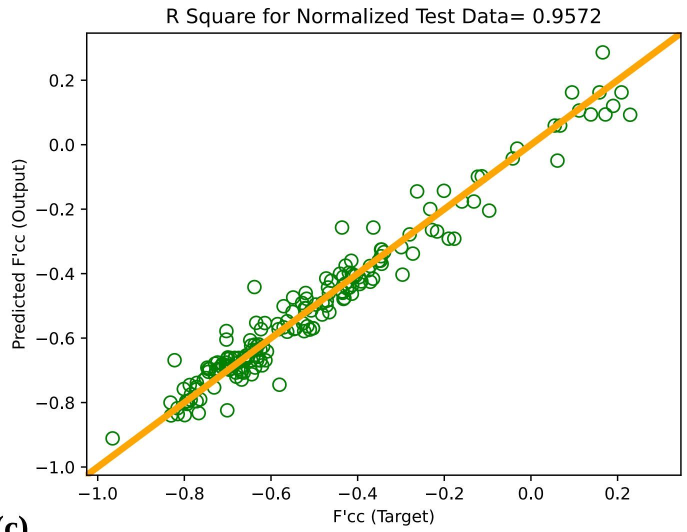
- Test data closely matches the target or desired output (model has been effectively trained and is able to generalize well to unseen data).
- Model is not overfitting to the training data.
- Error is evaluated by comparing predicted outcomes with actual data.
- R-squared value of 0.9572 obtained for the test data.



(a)



(b)



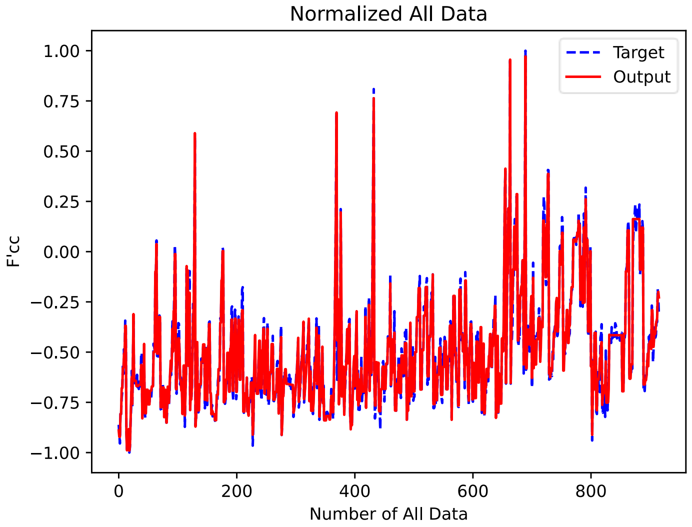
(c)

Fig. 12. Estimator result analysis of compressive strength for test data.

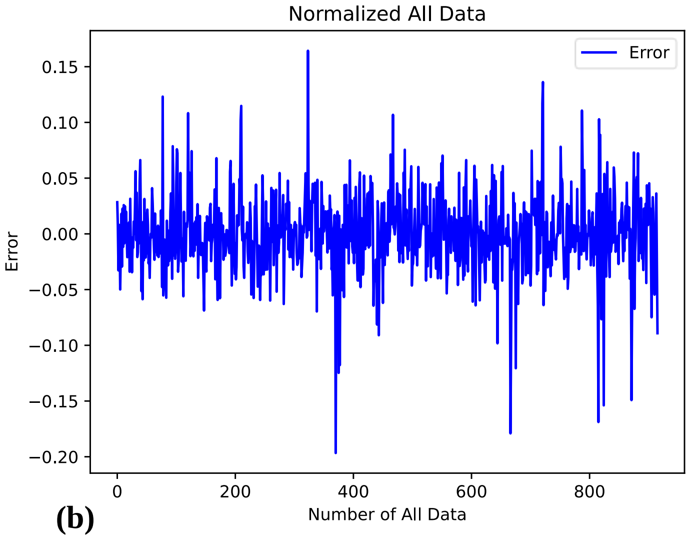
RESULTS AND DISCUSSION

Visualize Model Outcomes

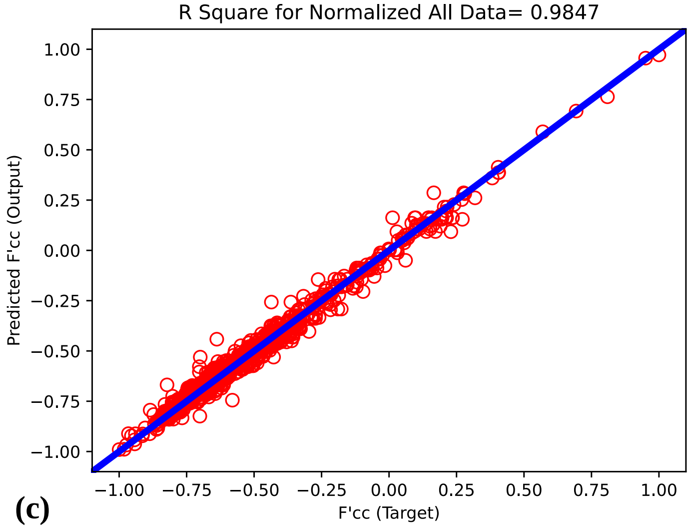
- Scatter plot Figure 13a. visualizes the differences between the predicted and actual values.
- Figure 13b. show patterns in the model's residuals.
- R-squared value of 0.9847 obtained and represented in Figure 9c.
- Line of correlation very closely resembled the ideal scenario of y = x (high degree of accuracy in predictions).



(a)



(b)



(c)

Fig. 13. Estimator result analysis of compressive strength for all data.

RESULTS AND DISCUSSION

Kernel Density Estimation (KDE)

- Visual representation of distribution of prediction errors is provide through KDE curve and histogram.
- Combined graphical representation with mean and standard deviation values present overall quality of model's predictions, performance, and reliability.

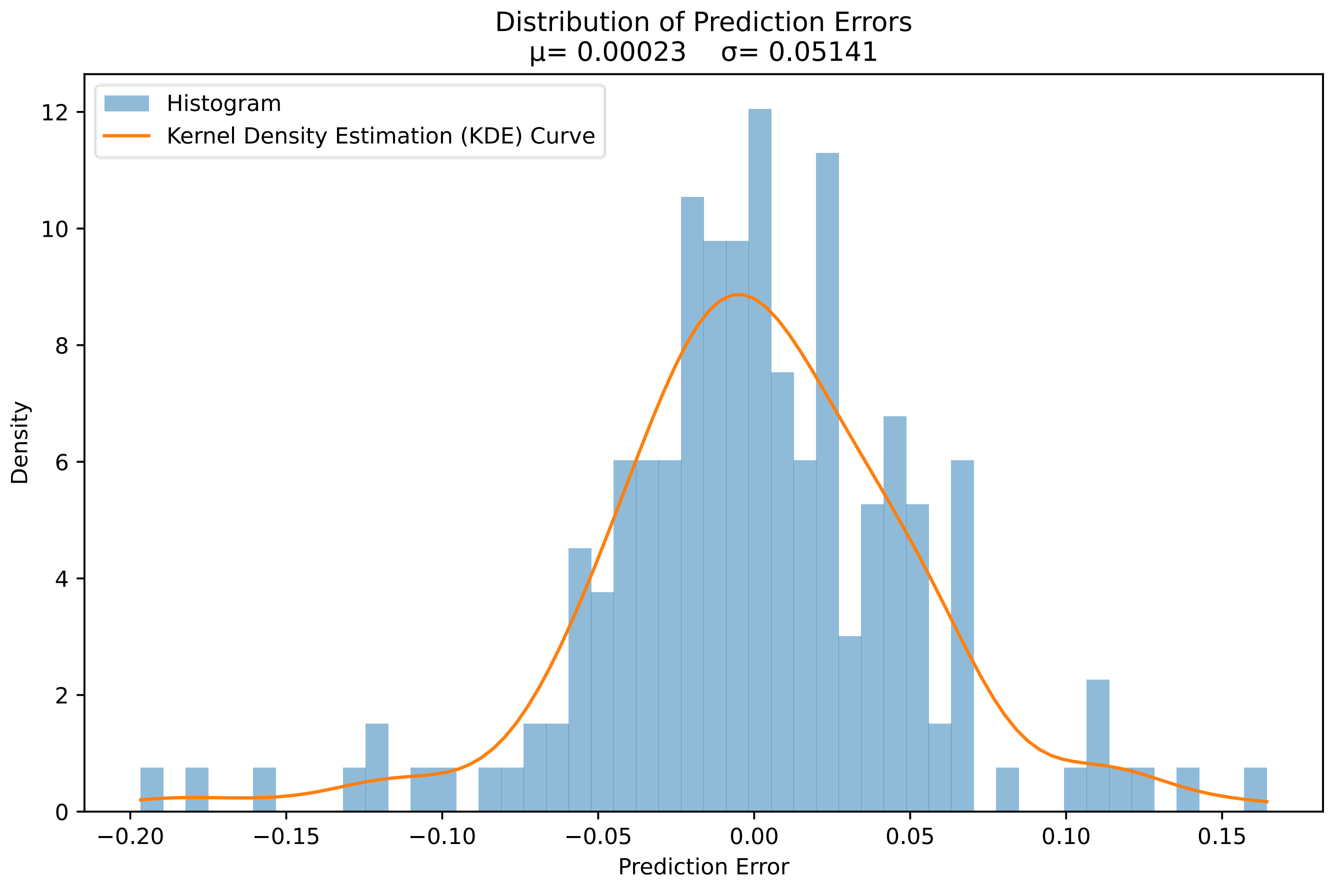


Fig. 14. Distribution of prediction error for model.

Comparison of Models

- Proposed model compared with Mandal et al., Karbhari et al. and Lilliston and Jolly.
- PSO-CatBoost model shows much better performance.

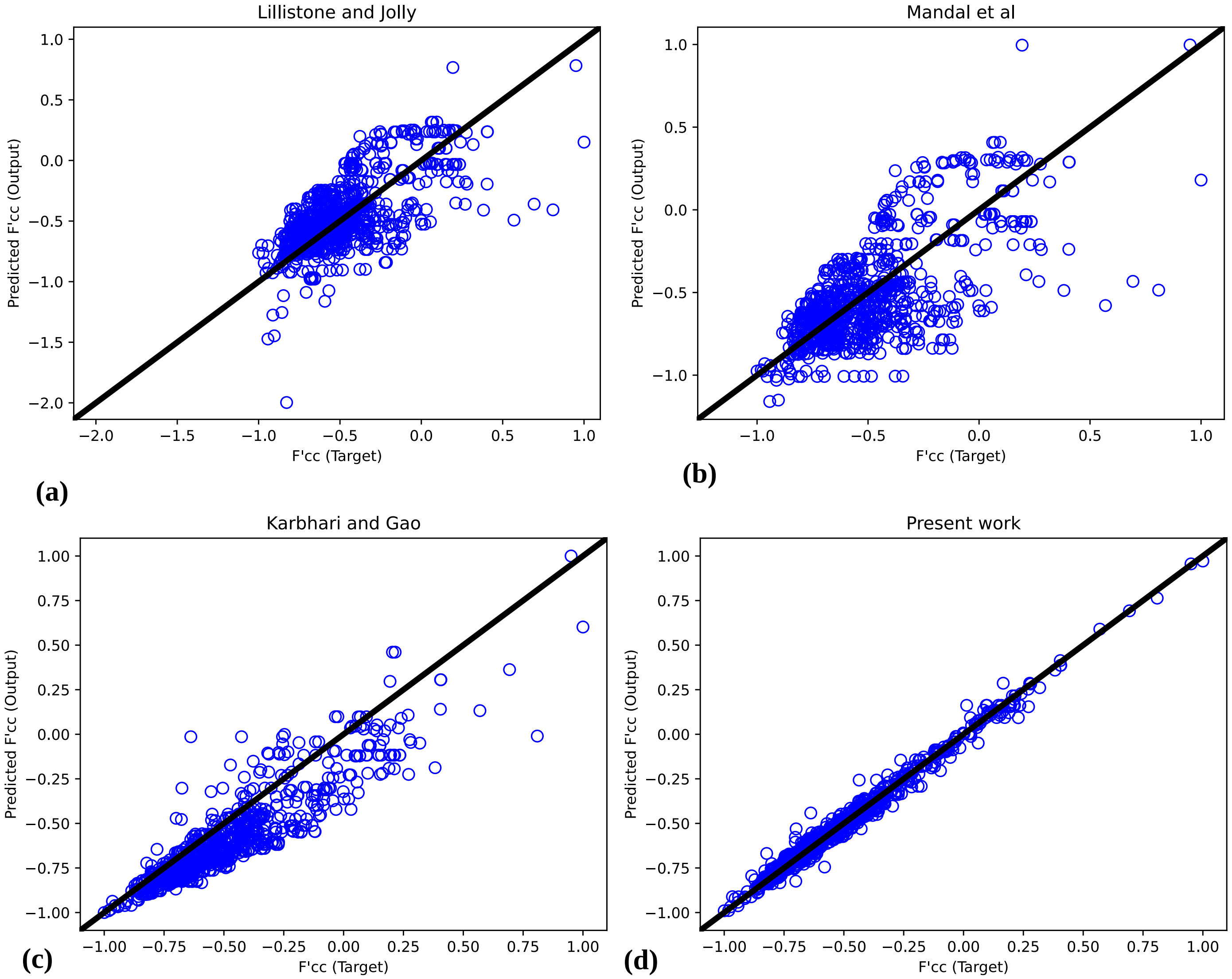


Fig. 15. Comparison of present work with other methods.

RESULTS AND DISCUSSION

Comparison of Models

- PSO-CatBoost predicts quite accurately and outperforms other models.
- Proposed model obtains an RMSE of 0.0347, an MSE of 0.0012, and an MAE of 0.0250.
- These values are noticeably lower than those for empirical equations.
- R-squared value of the proposed model is noticeably higher than those for empirical equations.

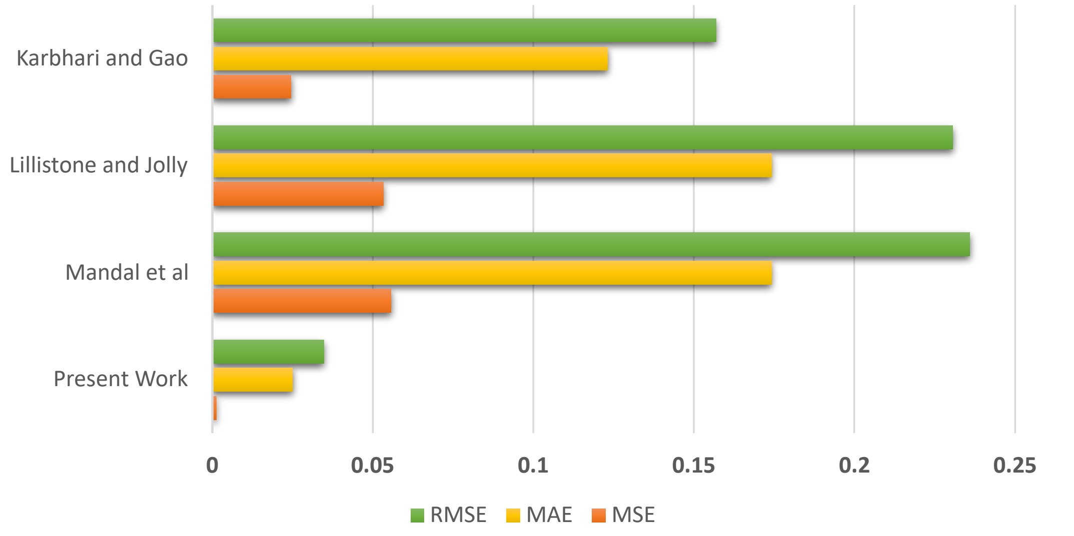


Fig. 16. Comparing RMSE, MAE, and MSE metrics for all data with all models.

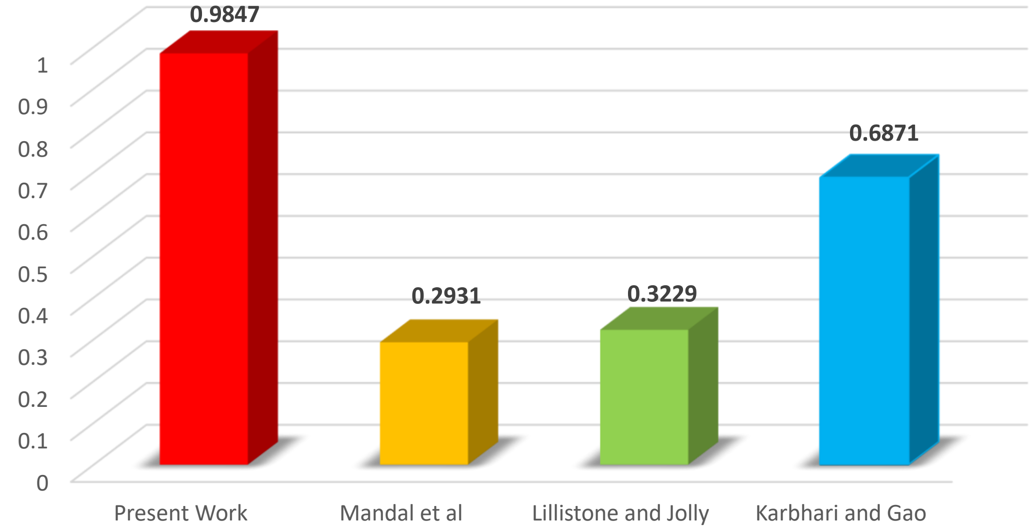


Fig. 17. Comparing R-Squared metric for all data with all models.

RESULTS AND DISCUSSION

Taylor Diagram

- R-squared, RMSD, and SD of the patterns are represented in Taylor diagram.
- Proposed model performs better than other models in most cases (greater correlation coefficient, smaller standard deviation, and lower RMSE).

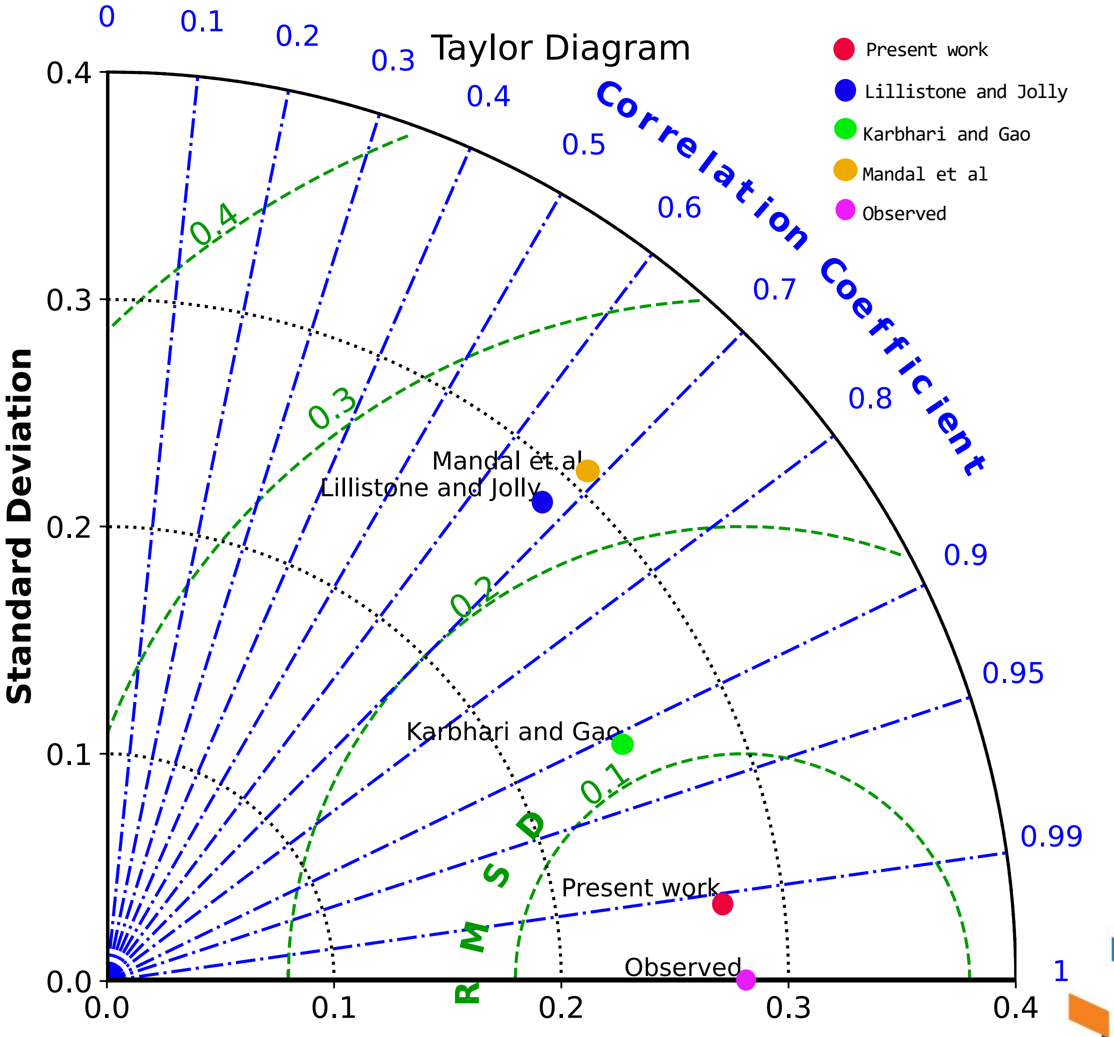


Fig. 18. Taylor Diagram.

RESULTS AND DISCUSSION

Feature Importance Analysis of Model

- ML models: difficult to interpret, frequently seen as black boxes.
- Explainable ML approaches are essential to identify key features.
- SHAP-based feature contribution (SHapley Additive exPlanations) and Permutation Feature Importance (PFI)

SHapley Additive exPlanations

- Positive value denotes a potential influence that might be beneficial to prediction, negative value denotes a potential contribution that could be negative.
- Higher values of f_{co} and f_f have a positive impact on the prediction.
- Lower values of FRP reinforcement ratio and thickness of FRP have a negative impact.

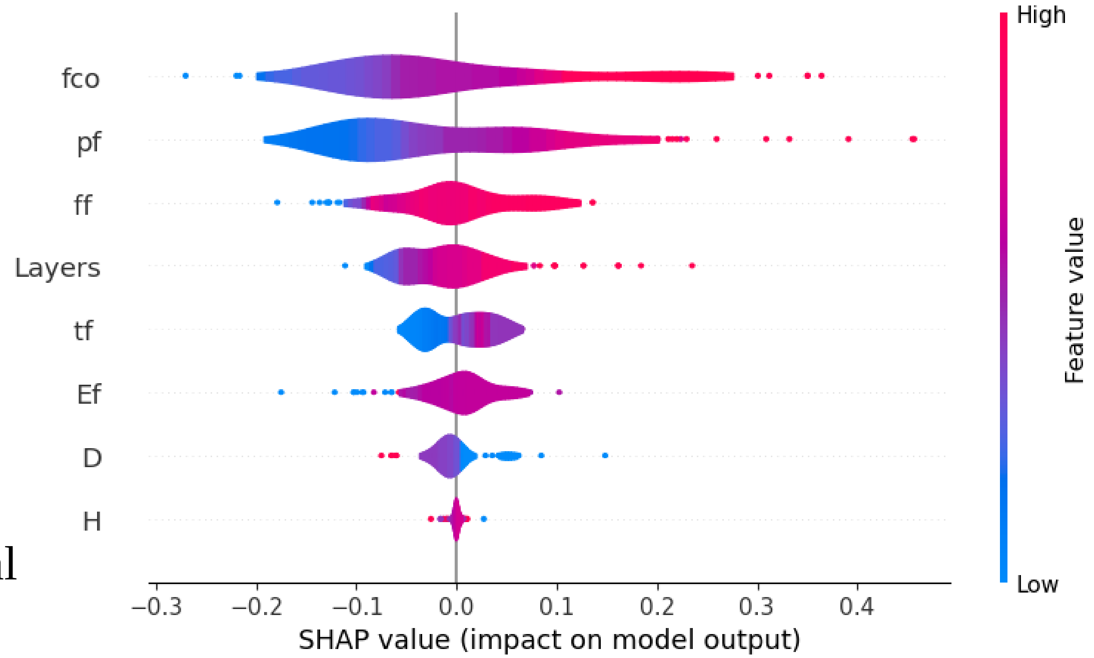


Fig. 19. The SHAP diagram for impact of features.

RESULTS AND DISCUSSION

SHapley Additive exPlanations (Cont'd)

- Mean SHAP value offers a comprehensive assessment of the significance of a feature.
- Determining the average of absolute SHAP values for a specific feature across all instances.
- High mean SHAP value indicates substantial influence (regardless of whether positive or negative).

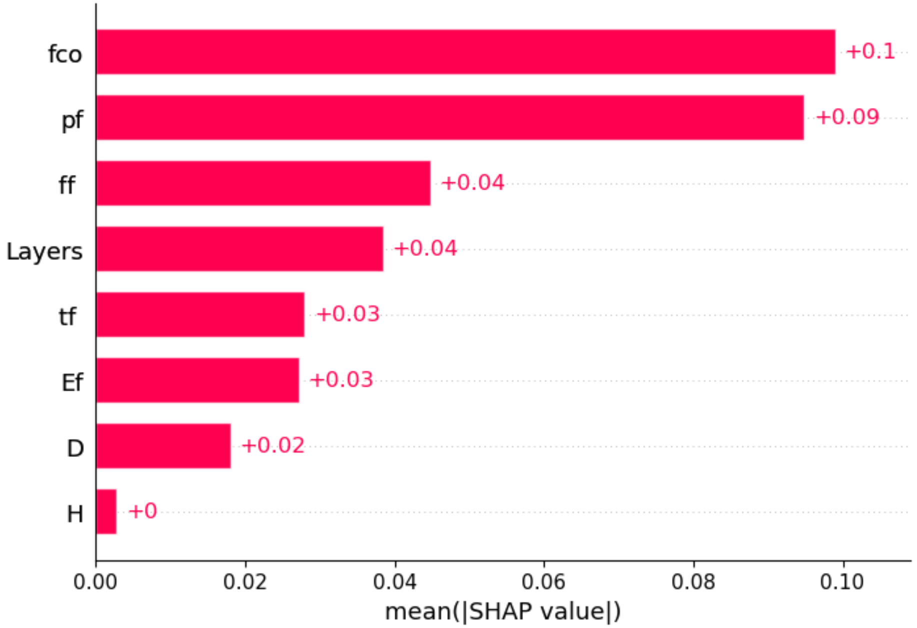


Fig. 20. Effects of all features for compressive strength of CFRP concrete.

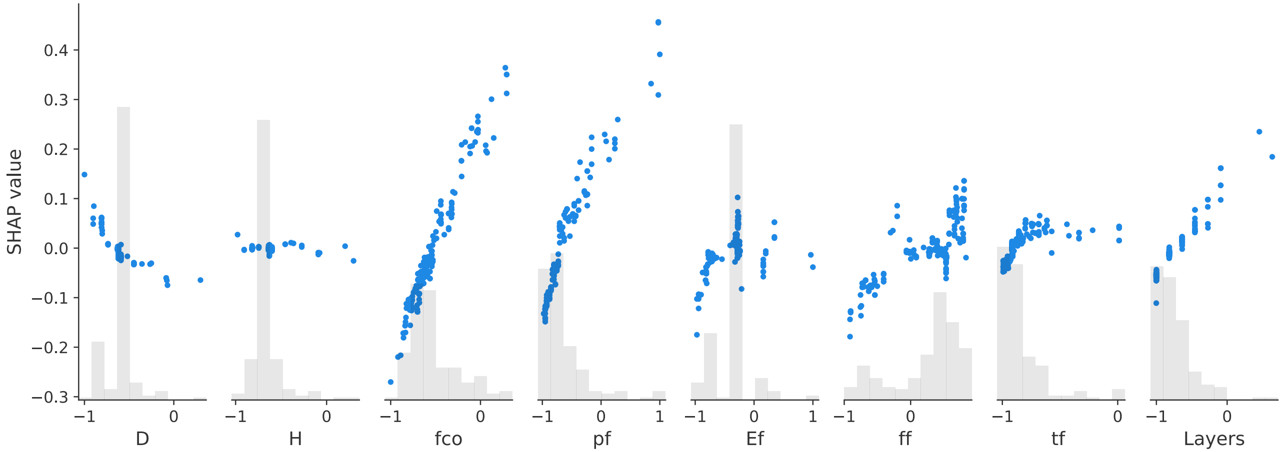


Fig. 21. Scatter plot of each feature for SHAP value

RESULTS AND DISCUSSION

Permutation Feature Importance (PFI)

- SHAP values do not reveal the specific impact of each feature.
- PFI displays the features that influence the overall performance of the model.
- Quality of predictions decrease when the information is disrupted.
- Original predictor's information is not crucial when drop is small (model still does reasonably well even without it).
- Considerable reduction shows initial predictor had a notable impact on the accuracy of predictions.
- Analysis provides a critical understanding of decision-making process of model.

RESULTS AND DISCUSSION

Feature Importance Analysis of Model

- ρ_f and f'_{co} are the most influential factors in predicting f'_{cc}.
- Lastly, it seems that the other features do not significantly impact the predictions.

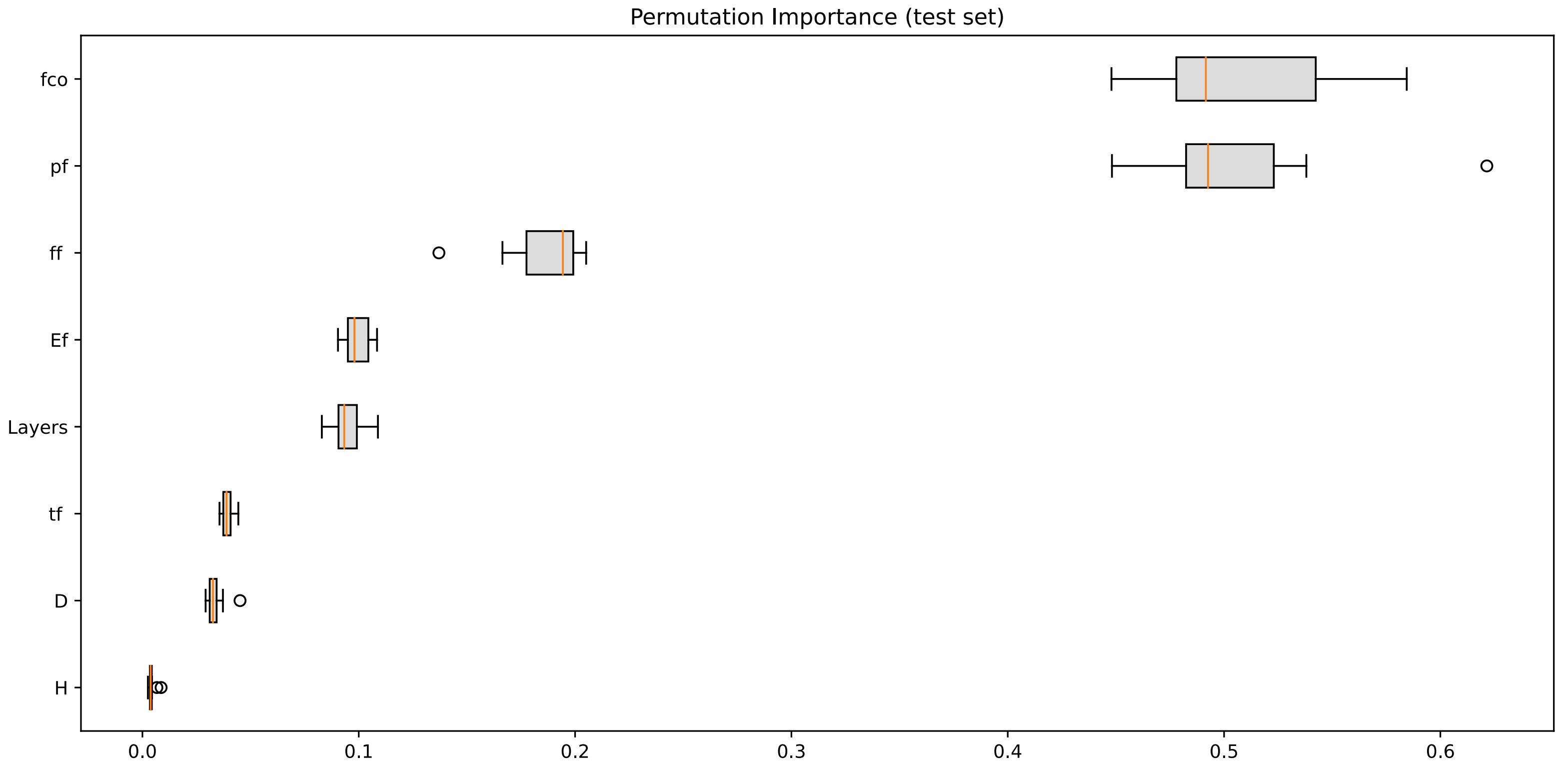


Fig. 22. The box plot of permutation importance for features of the dataset.

RESULTS AND DISCUSSION

Conclusions

- Robustness of ML algorithms, scope and details of the dataset, affect the efficacy of the algorithm.
- Boosting algorithms were proposed to increase prediction accuracy.
- Utilizing CatBoost with PSO algorithm, the accuracy of estimating f'_{co} can be significantly improved.
- PSO-CatBoost exhibited the highest level of performance, attaining a notable coefficient of determination value of 0.9597.
- Capacity of PSO-CatBoost algorithm to reduce MSE and RMSE was identified through a comparison between the experimental and proposed models.
- According to feature importance assessments, ρ_f was the most crucial characteristic.
- ML model performed better than other empirical equations and showed significant promise as a substitute strategy for dealing with complicated structural applications and forecasting design problems.

RESULTS AND DISCUSSION

Conclusions (Cont'd)

- Future research efforts are recommended to focus on using the proposed method to improve prediction accuracy using other experimental models.
- Other optimization algorithms should be tested instead of PSO to gain more accurate results.
- While machine learning is increasingly integrated into daily life, its use is still primarily limited to individuals with specialized knowledge.
- Technical complexity of machine learning, which relies on advanced mathematics, statistics, and coding skills, presents a significant barrier to entry for non-experts.

Thank U

Center for Integration of Composites into Infrastructure