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Hybrid machine learning model using gorilla troops optimizer for accurate prediction of interlayer bonding strength in 3D-printed concrete

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Abstract

Interlayer bonding strength (IBS) plays a pivotal role in 3D-printed concrete (3DPC), emphasizing the need for a reliable predictive model. A new hybrid model is proposed in this study, which leverages the gorilla troops optimizer (GTO) to fine-tune the hyperparameters of the extreme gradient boosting (XGBoost) algorithm. For comparison, XGBoost and decision tree (DT) models were also developed. To enhance interpretability, SHapley Additive exPlanations (SHAP) were employed to highlight the most influential factors affecting IBS. The proposed GTO-XGBoost model outperformed the other approaches, attaining a correlation coefficient of 0.974, compared to 0.958 for XGBoost and 0.930 for DT. The findings demonstrate that the GTO-XGBoost model offers a reliable solution for predicting IBS, contributing to the advancement of 3D printing technology in construction.

Keywords: Interlayer bonding strength; 3D concrete printing; machine learning; gorilla troops optimizer; intelligent prediction

1. Introduction

Conventional construction methods are costly, time-consuming, and offer limited design flexibility. They also require a large labor force, which can be difficult to use in remote or dangerous areas [1,2]. To solve these problems, the construction industry started exploring automation in the 1950s. In the mid-1990s, Khoshnevis introduced one of the first ideas for 3D-printed concrete (3DPC) at the University of Southern California [3]. Since then, interest in 3DPC has increased a lot, leading to more research and projects around the world. However, a major problem is the weak bonding between the printed layers [4]. The layer-by-layer printing process often causes weak bonding, creating cold joints. These are poorly connected areas that reduce the structure’s strength, stiffness, and ability to carry loads [5]. Therefore, enhancing interlayer bonding strength (IBS) is vital to ensure the reliability and longevity of 3D-printed structures [6]. To address this, researchers have investigated various strategies to improve IBS. For instance, Wolfs et al. [7] conducted experimental studies to analyze how printing factors like layer interval, nozzle height, and surface moisture influence bonding performance. Likewise, Moelich et al. [8] designed a computational model to investigate how surface moisture affects IBS. However, these approaches face inherent limitations: experimental methods require significant time and resources, while simulation

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outcomes can be sensitive to initial assumptions and parameter configurations, potentially impacting their reliability.

Lately, the use of machine learning (ML) has gained importance as a promising approach for advancing concrete research. It helps improve the accuracy of predicting different concrete properties. ML has been used to predict compressive strength, flexural and tensile behavior, flow properties, and how well concrete can be printed [9–12]. However, using ML to predict the IBS of 3DPC is still relatively unexplored. Most studies focus on other properties, so there is still a gap in predicting IBS of 3DPC. Traditional methods such as empirical correlation-based models [7], numerical simulations [8], and thermo-fluid dynamics analyses [6] are often constrained by their inability to identify globally optimal solutions. This highlights the increasing importance of applying robust ML-based models capable of accurately predicting IBS and advancing 3DPC technology.

This study introduces a hybrid predictive model that combines the gorilla troops optimizer (GTO) with the extreme gradient boosting (XGBoost) algorithm, where GTO is used to optimize the model's hyperparameters. For comparative purposes, standalone decision tree (DT) and XGBoost models were developed. A total of 146 data points, sourced from existing experimental studies, were used to train and evaluate the models. To interpret the model's output and identify the most influential variables affecting the IBS of 3DPC, SHapley Additive exPlanations (SHAP) were applied. This work demonstrates the value of applying advanced ML techniques to improve the structural performance assessment of 3DPC, thereby supporting further innovation in 3D construction practices.

2. Research approach

2.1. Data description

To accurately estimate the IBS of 3DPC, a dataset with 146 records was collected from published experimental studies. The model uses 16 input variables [13]. These variables include both the material mix and the printing process settings (**Figure 1**). These comprehensive inputs aim to capture the key factors influencing IBS in 3D-printed concrete. **Table 1** presents the statistical summary variables used in this study.

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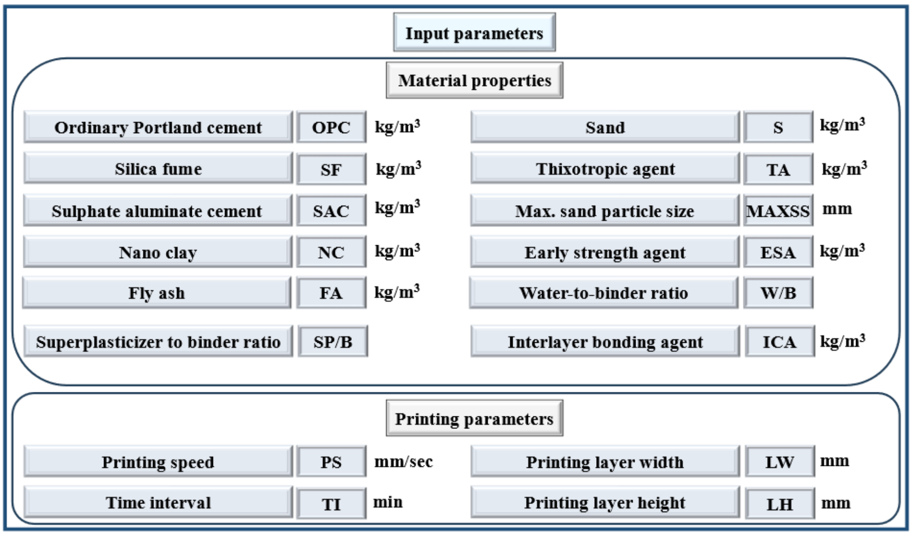


Figure 1. Overview of input parameters

Table 1. Statistical description of the dataset

Statistics	OPC	SAC	SF	FA	NC	S	MAXSS	TA
Mean	787.77	73.17	81.62	8.45	17.90	1123.28	1.48	1.46
Median	850.00	50.00	0.00	0.00	0.00	1200.00	0.80	0.00
Mode	850.00	0.00	0.00	0.00	0.00	1500.00	0.60	0.00
SD	326.51	83.38	112.52	36.18	62.16	520.74	1.57	4.81
Maximum	1400.00	405.00	250.00	162.00	400.00	1750.00	5.00	30.00
Minimum	270.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Statistics	**ESA**	**SP/B**	**W/B**	**ICA**	**TI**	**PS**	**LH**	**LW**
Mean	1.04	0.00	0.38	21.99	99.63	102.17	14.47	30.70
Median	0.00	0.00	0.39	0.00	20.00	80.00	10.00	20.00
Mode	0.00	0.00	0.44	0.00	0.00	120.00	10.00	20.00
SD	1.44	0.00	0.08	43.55	293.18	78.54	8.87	26.64
Maximum	3.30	0.02	0.50	160.00	1440.00	300.00	50.00	145.00
Minimum	0.00	0.00	0.23	0.00	0.00	4.23	6.00	10.00

2.2. Model development

A hybrid model was developed by using the GTO to fine-tune the settings of the XGBoost algorithm. This helped improve the model's accuracy and prediction results. To compare performance, separate XGBoost and DT models were also built. The dataset used had 146 values taken from published experiments and included important factors that affect the IBS of 3DPC. The data was split into two parts: 80% was used to train the models, and 20% was used for evaluating their performance. **Table 2** shows the settings (hyperparameters) used for the GTO-XGBoost, XGBoost, and DT models during training. These settings were carefully chosen to help the models better understand the data and improve their predictions.

Table 2. Configured hyperparameters of the models

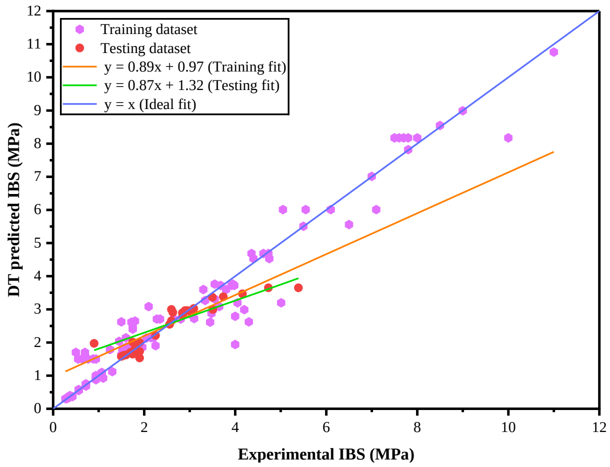
Parameter	Setting	Optimized value
XGBoost		
Max tree depth	3-10	6
Data subset for training each tree	0.5-1	0.7521
Features for training a tree	0.5-1	0.07521
Increment per each iteration	0.01-0.3	0.0122
Drop in loss during a split	0-5	0.0972
GTO		
Candidate solution in each iteration	20-100	20
Max optimization iterations	10-100	50
Reproducibility seed	Any integer	42
Perturbation range	+/- 0.1	+/-0.1
Candidate solution adjustment	Random uniform perturbation	Exploitation and exploration base
DT		

Reproducibility random seed	Any integer	42
Splitting at each node	Random, best	Best
Features for ideal split	Sqrt, auto, none, log2	None
Min samples for a leaf node	1-50	5
Samples to divide internal node	2-50	10

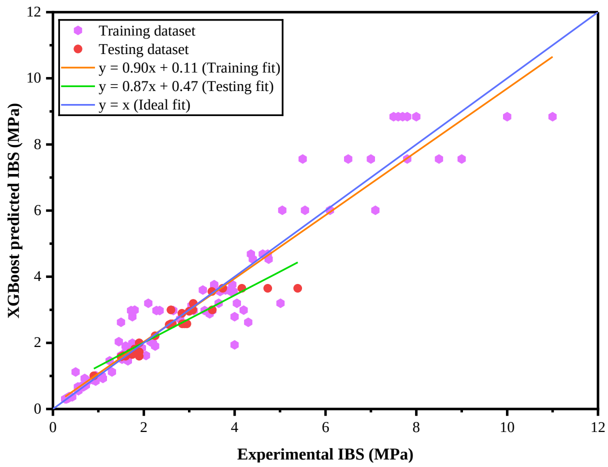
3. Results and discussions

3.1. Regression analysis

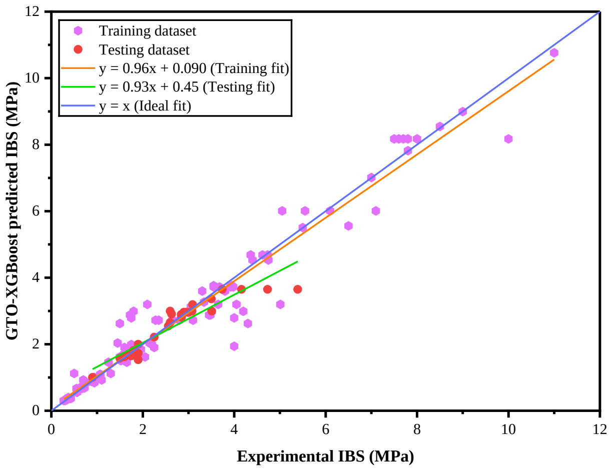
The regression slopes of the developed machine learning models demonstrate their predictive accuracy (**Figure 2**). The GTO-XGBoost model demonstrated the best performance, achieving regression slopes of 0.96 (training) and 0.93 (testing). The XGBoost model followed with regression slopes of 0.90 during training and 0.87 during testing, showcasing its robustness but slightly lower accuracy compared to the hybrid model. Similarly, the DT model demonstrated reliable performance, highlighting its reliable yet less optimized performance relative to the other models. These results emphasize the effectiveness of hybrid approaches, such as GTO-XGBoost, in improving predictive capabilities.



DT



XGBoost



GTO-XGBoost

Figure 2. Regression analysis

3.2. Statistical assessment

The statistical indicators demonstrate the performance of the developed ML models (**Table 3)**. In the training phase, GTO-XGBoost model showed the highest accuracy, with a coefficient of correlation (R^2) value of 0.972, an adjusted R^2 value of 0.975, a mean absolute error (MAE) of 1.54, and a root mean square error (RMSE) of 1.23. The XGBoost model followed with R^2 at 0.956, adjusted R^2 at 0.953, RMSE at 1.76, and MAE at 2.67. The DT model demonstrated comparatively lower performance, with R^2 at 0.924, adjusted R^2 at 0.932, RMSE at 2.76, and MAE at 2.98.

In the testing phase, the GTO-XGBoost model continued to outperform the others, with R^2 at 0.974, adjusted R^2 at 0.981, RMSE at 1.34, and MAE at 1.23. The XGBoost model maintained consistent performance with R^2 at 0.958, adjusted R^2 at 0.953, RMSE at 1.87, and MAE at 2.43. The DT model, while reliable, displayed lower accuracy compared to the hybrid models, with R^2 at 0.93, adjusted R^2 at 0.941, RMSE at 2.43, and MAE at 2.78. These results indicate that the GTO-XGBoost model outperformed both the XGBoost and DT models during training and testing (**Figure 3**). This proves that the hybrid model is strong and dependable when dealing with complex data.

Table 3. Performance of the developed models

	R^2	Adj R^2	RMSE	MAE
Training phase				
GTO-XGBoost	0.972	0.975	1.23	1.54
XGBoost	0.956	0.953	1.76	2.67
DT	0.924	0.932	2.76	2.98
Testing phase				
GTO-XGBoost	0.974	0.981	1.34	1.23
XGBoost	0.958	0.953	1.87	2.43
DT	0.93	0.941	2.43	2.78

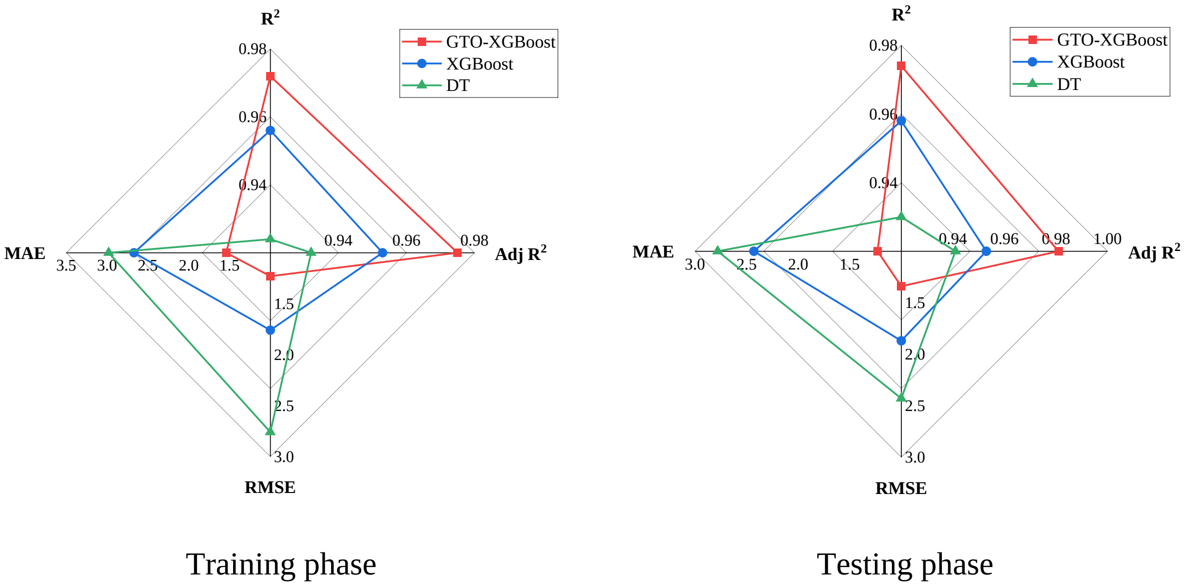


Figure 3. Spider plots of statistical indicators

3.3. SHAP interpretation

Figure 3 presents the mean SHAP plot, illustrating the contributions of various parameters to the model's predictions. Among these parameters, PS exhibited the greatest mean SHAP value of

0.90, highlighting its significant influence on the model's output. Following PS, SF had a mean SHAP value of 0.52, suggesting it also plays a notable role in predictions. Additionally, SP/B demonstrated a mean SHAP value of 0.19, reflecting its comparatively lesser impact on the model. Furthermore, the SHAP summary plot depicted in **Figure 4** reveals the relationships between various parameters and IBS. The analysis indicates that IBS increases with an increase in PS and SF, highlighting their positive influence on the model's predictions. Notably, SF exhibits a wide range of influence, with SHAP values reaching as high as 0.8 and dropping to about -0.9, indicating its significant variability in impact. Additionally, IBS increases with an increase in S, suggesting that higher sand content positively affects bond strength. Conversely, an increase in SAC correlates with a decrease in IBS, indicating a detrimental effect on bond strength as SAC content rises. Overall, these findings underscore the complex interactions among the parameters influencing IBS in the model.

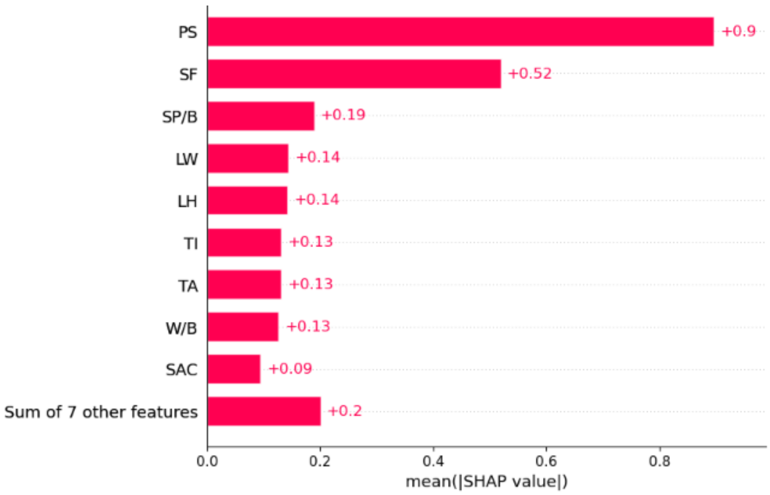


Figure 4. Mean SHAP plot

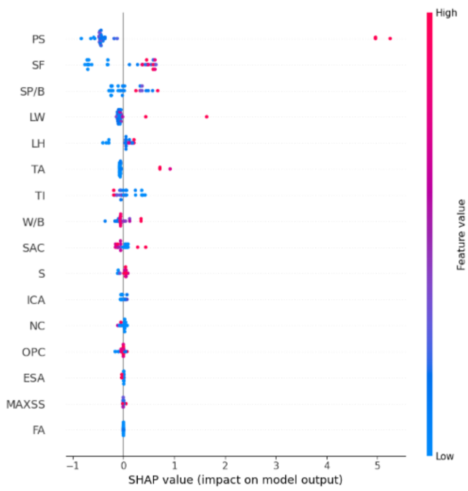


Figure 5. SHAP summary plot

4. Conclusions

This study introduces a novel hybrid model that utilizes the GTO to fine-tune the settings of the XGBoost algorithm for predicting the IBS of 3DPC. For comparison, XGBoost and DT models were also developed. The key findings are as follows.

- The study underscores the enhanced effectiveness of the GTO-XGBoost model relative to both ensemble and individual models. The developed hybrid model consistently outperformed the XGBoost and DT models, demonstrating its strength in understanding complex data patterns.
- Additionally, the ensemble model performed better than the individual model.
- The SHAP values revealed that for IBS, PS was the most critical feature, followed by SF and SP/B.

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Irfan Ullah: Conceptualization, Data curation, Formal analysis, Software, Supervision, Writing – original draft, Writing – review & editing.

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Abbreviations

The following abbreviations are used in this manuscript:

IBS	Interlayer bonding strength
DT	Decision tree
GTO	Gorilla troops optimizer
XGBoost	Extreme gradient boosting
3DPC	3D-printed concrete
SHAP	SHapley Additive exPlanations
ML	Machine learning

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