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## Article

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# Gradient Boosting-Based Computational Method for Predicting Uniaxial Compressive Strength of Cemented Hydraulic Backfill

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**Abstract:** For an accurate prediction of the uniaxial compressive strength (UCS) of cemented hydraulic backfill (CHB), it is important to fine-tune the mix design and ensure the safety and stability of underground mining operations. However, most empirical approaches fail to capture the nonlinear relationships among mixture properties, thus sacrificing interpretability. This study proposes novel explainable gradient boosting models, including light gradient boosting model (LightGBM), CatBoost, adaptive boosting (AdaBoost), and gradient boosting machine (GBM), to predict UCS based on inputs such as cement content (CT) in %, curing time (CD) in days, solids concentration (SD) in %, and aggregate to tailings ratio (AT). This study employs various statistical metrics to evaluate model performance. The results indicate that the GBM model demonstrates greater potential for predicting UCS values than the other studied models, with training metrics of  $R^2 = 0.93$ , RMSE = 0.1590, and MAE = 0.1130, and testing metrics of  $R^2 = 0.86$ , RMSE = 0.2289, and MAE = 0.1395. To compare and evaluate the robust GBM model, this study also implemented and tested LightGBM, CatBoost, and AdaBoost models. Consequently, the GBM model provides a balanced and reliable solution for predicting UCS values. To construct a more interpretable model, SHapley additive exPlanations (SHAP) analysis was employed to evaluate the effect and direction of influence of each input parameter on the prediction of UCS values. In addition, the study employed sensitivity analysis to investigate the effects of various inputs on the output UCS. The findings indicate that, in the design of CHB mix proportions, cement content and curing time are the factors that most significantly influence the predicted UCS values. This study has multiple practical applications in the field of mine stability and contributes to providing a safe working environment for underground mining operations.

**Keywords:** mining stability; underground mining operations; uniaxial compressive strength; cemented hydraulic backfill; gradient boosting machine

## Highlights

- This study presents the explainable gradient boosting models for accurate prediction of uniaxial compressive strength of cemented hydraulic backfill.
- The gradient boosting machine model established excellent predictive accuracy, expressively outperforming other models.
- Sensitivity analysis revealed that cement duration and cement content were identified as the most significant input parameters affecting output.

## 1. Introduction

Waste rocks and tailings represent the major waste streams associated with mineral processing plants. Due to various environmental and safety issues, there is considerable interest in using waste rocks and tailings for backfilling underground void spaces created by underground mining activities instead of stockpiling them at surface locations. CHB is defined as crushed waste rocks, tailings, water, and cement. By facilitating the use of primary waste streams in underground mines, CHB is gaining popularity as an integral part of underground mining activities. During underground mining activities, CHB is injected into mined stopes to create a stable working platform and support mined areas. In addition, it helps in maximizing pillar recovery and minimizing dilution. UCS is considered one of the essential parameters for designing CHB. The parameters that control short- and long-term backfill strengths may be broadly classified into two groups: extrinsic and intrinsic factors. Extrinsic factors relate to in situ conditions such as underground temperature and humidity levels, underground drainage conditions, stope geometry, and groundwater conditions. These factors are considered controllable parameters. Intrinsic factors relate to various physical and chemical properties of backfill constituents and the mixing behavior of constituents.

Recently, considerable progress has been achieved in computer programming and data analysis techniques. In this context, data mining, artificial intelligence (AI), and machine learning (ML) techniques have been successfully applied in various engineering and technology fields. ML methods have been successfully applied in the construction industry to forecast concrete slump flow [1,2], the compressive strength of concrete materials [3,4,5,6], and crack formation in concrete surface materials [7]. In various studies, ML techniques were used to estimate the UCS of mortars containing fly ash and other materials [8]. Advanced algorithms such as extreme learning machines (ELM), random forests (RF), and XGBoost are described in the related work to provide improved accuracy in prediction. Hybrid and ensemble techniques are also stated to provide improved robustness and accuracy in generalization. However, less emphasis is seen on the integration of optimization algorithms with ensemble techniques in the prediction of UCS and *E*. [9]. In another study, ML techniques were used for forecasting fracture toughness of rocks in the mining industry [10]. In a study by He et al. [11], a novel evolved random forest (RF) model using a bio-objective optimization method was proposed. The first evolved RF model was developed using a beetle search algorithm (BAS) to predict the UCS of cemented paste backfill (CPB). Mishra et al. [12] investigated the influence of partial replacement of ordinary portland cement (OPC) by fly ash (FA) on CPB strength using a bayesian network (BN) to identify an optimal mixture to attain a specific strength of 1 MPa at 28 days of curing in a cost-effective way.

Because conventional models based on the aleatory paradigm are inappropriate for geotechnical applications and are not consistent with conventional thinking, a BN model was developed and validated. The reliability of two classifiers in the learning model structure was analyzed, and the naive Bayes algorithm was found to be the most reliable tool. The feasibility of using a deep neural network (DNN) model for predicting the UCS of CPB was investigated by Qi et al. [13]. This study provided a first global dataset of UCS values for CPB by conducting a comprehensive literature review and laboratory tests. Hu et al. [14] observed that, under multifactorial conditions, the highest prediction accuracy for CPB strength, compared with other commonly used prediction models, was achieved with the long short-term memory (LSTM) model they had developed. Tran [15] employed eight ML methods, i.e., extreme gradient boosting (XGBoost), gradient boosting (GB), RF, decision tree (DT), k-nearest neighbors (KNN), support vector machines (SVM), multivariate adaptive regression splines (MARS), and gaussian process (GP), to develop a soft computing model for predicting the yield stress of CPB. A recent article by Pang et al. [16] proposed advanced ML models to predict UCS of alkali slag cemented tailings backfill by utilizing a comprehensive dataset. The author employed different algorithms to predict UCS values. Such as SVM, RF, radial basis function neural network (RBF), convolutional neural network (CNN), and LSTM. It is evident that some deep learning algorithms, such as RBF and SVM networks, have shown better prediction accuracy by achieving a high coefficient of determination ( $R^2 = 0.99$ ). The results show that deep learning algorithms can significantly improve efficiency while predicting UCS values. Kurniati et al. [17] applied three ML methods, i.e., simple linear model, GP, and RF model, to develop a model for predicting the UCS of CPB containing copper mining tailings as an admixture. Hyperparameters in the RF model were fine-tuned using Bayesian optimization. Following a comprehensive evaluation of the models, it was found that the RF model accurately predicted the UCS of the CPB across mixture designs. Additionally, it was noted that cement, ground granulated blast-furnace slag, superplasticizers, and curing times positively influenced compressive strength. Similarly, Zhang et al. [18] presented an LSTM method along with the optimization of aggregate gradation to forecast the UCS of CPB. The authors revealed that the cement content and slurry concentration are the most significant parameters that affect the development of UCS through the sensitivity analysis. In addition, Du et al. [19] studied the performance of hybrid models, such as genetic algorithm - support vector regression (GA-SVR) and particle swarm optimization - support vector regression (PSO-SVR), for UCS prediction of cemented backfill and observed significant improvement in the accuracy of predictions when using metaheuristic optimization for tuning the model's hyperparameters. In 2023, many studies focused on exploring the performance of ensemble learning models for UCS predictions in backfill materials. Recent studies indicate that ensemble models, including random forest, AdaBoost, and XGBoost, are likely to perform better than individual models, as they provide higher accuracy. Other techniques, including stacking and hybrid methods, have also improved the performance of the prediction model. However, the application of metaheuristic optimization coupled with ensemble regression models has not gained much popularity and needs to be explored further [20]. An additional study describes a data-driven approach based on different machine learning algorithms, such as XGBoost, GB, RF, LightGBM, SVR, KNN, etc., for predicting UCS for CPB materials [21]. In this study, XGBoost showed higher prediction accuracy compared to other algorithms, with a coefficient of determination  $R^2$  approaching 0.99, highlighting the potential of

these algorithms in solving nonlinear problems for predicting UCS. Furthermore, ensemble learning algorithms have been used for predicting early-age strength for phosphogypsum-based backfill materials. A comparative study on different algorithms, such as AdaBoost, GBDT, XGBoost, LGBM, RF, and ET, showed that ensemble learning algorithms perform better in predicting UCS with higher reliability compared to conventional algorithms. The potential of machine learning algorithms has been further explored for different backfill materials in different studies. Zhou et al. [22] used a machine learning model for predicting UCS for alkali-activated slag-based CPB materials, highlighting the potential of these algorithms in predicting complex interactions between different parameters for backfill materials, which can be difficult to establish through different experiments. Neural network algorithms for predicting UCS for different backfill materials were widely explored. In this regard, a backpropagation (BP) neural network model was used for predicting UCS for phosphogypsum composite cementitious backfill materials, highlighting the potential of these algorithms in predicting UCS for different materials, such as cementitious materials and chemical additives used in these ingredients. However, recent investigations have emphasized the need for model interpretability. Chen et al. [23] proposed a novel hybrid model based on the Grey Wolf optimizer and light gradient boosting machine (GWO-LGBM) algorithm in combination with SHAP analysis for the prediction and analysis of the effect of various parameters on the UCS of fiber-reinforced CPB. The consequences showed that the proportions of the mixture were the dominant parameters, followed by the physical properties of the tailings and the fibers. In [24], interpretable machine learning models were utilized for the prediction and analysis of the UCS of the cemented paste backfill. The fallouts showed that the curing time, water content, and chemical composition were the dominant factors in the prediction of the UCS. A recent [25] proposed the use of the Optuna algorithm in combination with the tabular prior-data fitted network (TabPFN) model and the SHAP analysis for the prediction and analysis of the UCS of the CPB. The results were highly accurate ( $R^2 = 0.98$ ). This model has the potential to provide accurate results and insights into the prediction and analysis of the UCS. From the above research articles, it is evident that the tree-based ensemble models GB, XGBoost, and LightGBM are more accurate in the prediction and analysis of the UCS of the CPB compared to the traditional statistical model. Recently, Zheng et al. [26] found that ML techniques, especially ensemble methods such as DT, RF, AdaBoost, and XGBoost, have been found to possess better predictive capabilities. The advanced techniques in the boosting family have been found to possess better accuracy than the traditional models. Additionally, optimization techniques such as genetic algorithm and grey wolf optimization (GWO) have been successfully used in combination with ML techniques for better results. However, little work has been done on adjusting ensemble techniques for small data sets. Also, Shahani et al. [27] used various indirect intelligent tools, such as multiple linear regression analysis (MLR), artificial neural networks (ANN), and adaptive neuro-fuzzy inference system (ANFIS), SVM, to predict the UCS of soft sedimentary rock. The results also prove that using ensemble tools such as random forest and XGBoost yields better accuracy. But using gradient boosting algorithms to predict UCS is still not common and requires more work.

Despite the increasing use of ML tools for predicting the UCS of CPB, some significant issues need to be addressed to enhance the accuracy of existing prediction methods. Several studies

[28,29] have successfully employed various ML models, including ANN, simple regression analysis, or traditional ensemble models, to forecast UCS based on mixture parameters and curing conditions of cemented backfill materials. However, these models are generally viewed as black boxes, which limit their ability to provide insights into how different parameters, such as cement content, curing time, solid concentration, and aggregate properties, affect UCS prediction. Therefore, to improve the accuracy of existing models and gain a deeper understanding of UCS prediction, this study aims to enhance these models by incorporating robust GBM models, including LightGBM, CatBoost, AdaBoost, and GBM, to predict UCS for CHB materials. Additionally, SHAP values quantify the influence of input parameters on UCS, and sensitivity analysis evaluates how each input parameter affects UCS. The findings from this study reveal nonlinear relationships among backfill mixture parameters and UCS, enabling better mix design optimization, reducing experimental costs, and supporting more reliable decision-making for safer and more efficient underground mining operations.

## 2. Construction of a Dataset

The dataset reflects critical geomechanical properties of rock samples, including UCS in MPa, CT in %, CT in days, AT in %, and SD in %. This dataset originates from the publicly available online literature, where the application of an adaptive neuro-fuzzy inference system holds [29]. Before modeling, the dataset was cleaned. The dataset was split, with 80% used for model training and 20% used for testing. Throughout the modeling process, the hyperparameters of gradient boosting models were optimized with the assistance of LightGBM, CatBoost, AdaBoost, and GBM. The model's performance was evaluated using the coefficient of determination ( $R^2$ ), root mean square error (RMSE), and mean absolute error (MAE). Table 1 presents the statistical summary of the dataset used in the current study, comprising 1,641 data points. The availability of the data suggests the success of the ensemble models used, considering the size of the dataset.

Table 1. Statistical distribution of the dataset used in this study.

| Statistical distribution | D (%) | ATR   | CD (%) | CT (days) | UCS (MPa) |
|--------------------------|-------|-------|--------|-----------|-----------|
| No. of data              | 1641  | 1641  | 1641   | 1641      | 1641      |
| Max                      | 76    | 11.45 | 29.98  | 28        | 6.34      |
| Min                      | 67    | 1.46  | 1.92   | 7         | 0.03      |
| Range                    | 9     | 9.99  | 28.06  | 21        | 6.31      |
| Average                  | 75.40 | 4.87  | 11.70  | 16.32     | 0.89      |
| Std. Dev.                | 1.25  | 1.10  | 4.09   | 8.73      | 0.61      |

Figure 1 indicates the density distribution of four inputs (SD, AT, CD, and CT), and the output UCS. The figure disclose that the data holds a combination of normal and n-normal distributions. The distribution of SD shows a close-fitting distribution with a peak at roughly 75-76, signifying low variability with a relatively uniform distribution of the data for SD. The AT distribution, conversely, exposes a normal distribution with a peak at nearly 5-6, indicating a near-normal performance with reasonable inconsistency. The distribution of CD reveals a clear multimodal distribution with major peaks at approximately 10-12, indicating a high degree of variability with

possible effects of subdivisions. The distribution of CT exposes a multimodal distribution with peaks at approximately 7, 14, and 29, indicating possible different classes of dimensions. The distribution of UCS reveals a high degree of skewness, with most of the data determined at values less than 1.5, indicating infrequent but possibly important effects of large values. Fig. 1, therefore, reveal that a number of the variables have distributions that are not normal, indicating a possible need for robust statistical analysis.

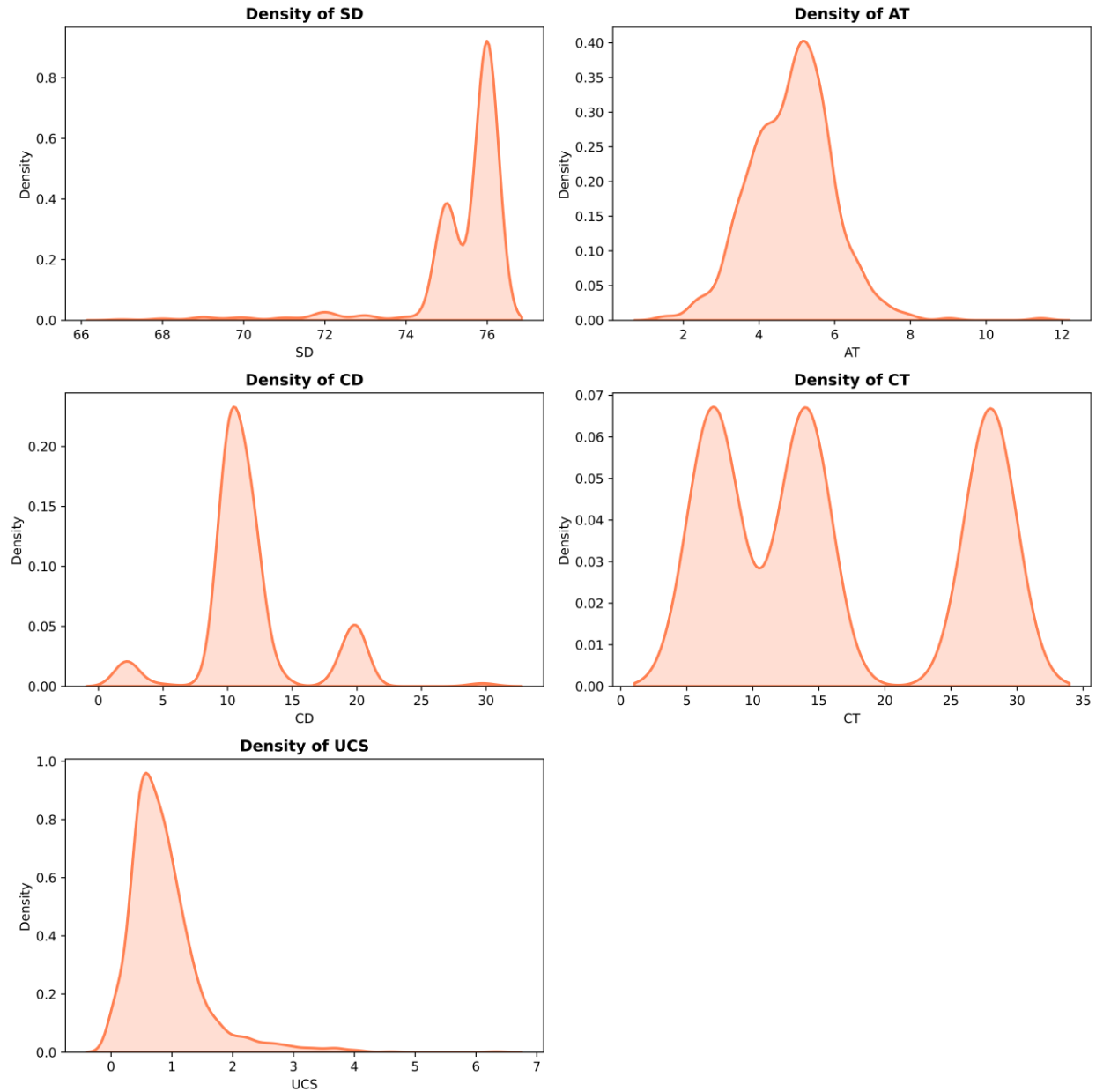


Figure 1. Density distributions of inputs (SD, AT, CD, CT) and the output UCS used in this study.

Figure 2 shows the correlation heatmap, which expresses the interactions between the inputs (SD, AT, CD, and CT) and the output UCS. It illustrates that a robust positive relationship is detected between CT and UCS (0.47), signifying that greater CT values are related to greater UCS. A

moderate positive correlation is also found between SD and AT (0.45), indicating a significant direct relationship between these two variables. In contrast, CD and AT show a moderate negative correlation (-0.35), indicating that increases in AT are related with decreases in CD. UCS shows a weak negative correlation with AT = -0.20, while its relationship with SD is very weak and positive (0.09). The most remote residual correlations are close to zero, mainly for individuals, including CT with SD, AT, and CD, indicating negligible linear dependence among these variables. Figure 2 proposes narrow multicollinearity in the construction of the dataset, with only a few moderate relations. This supports the use of these variables in subsequent statistical modeling and predictive analysis.

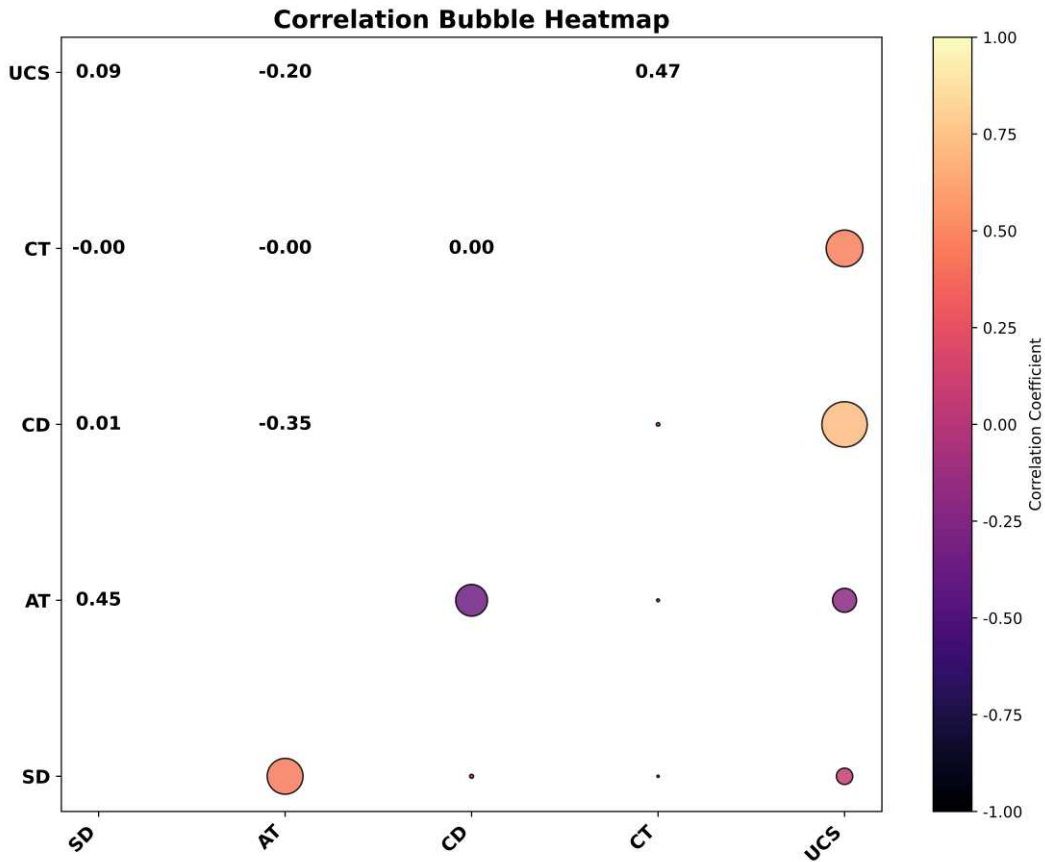


Figure 2. Correlation heatmap within input parameters and output UCS of the given dataset

### 3. Methods

To predict UCS of CHB, initially, the gradient boosting models were employed in this study, followed by the data preparation, model training, and evaluation procedures. The models, such as LightGBM, CatBoost, AdaBoost, and GBM, were selected due to their proven effectiveness in nonlinear regression problems [27,32,46,47]. The approach adopted to optimize model hyperparameters and improve generalization performance. The models were implemented in Python, employing scikit-learn for AdaBoost, the LightGBM basis for gradient boosting, and the CatBoost library for categorical boosting, to ensure the transparency and reproducibility of the study. Fig. 3 shows the systematic flowchart of the proposed methodology in this study.

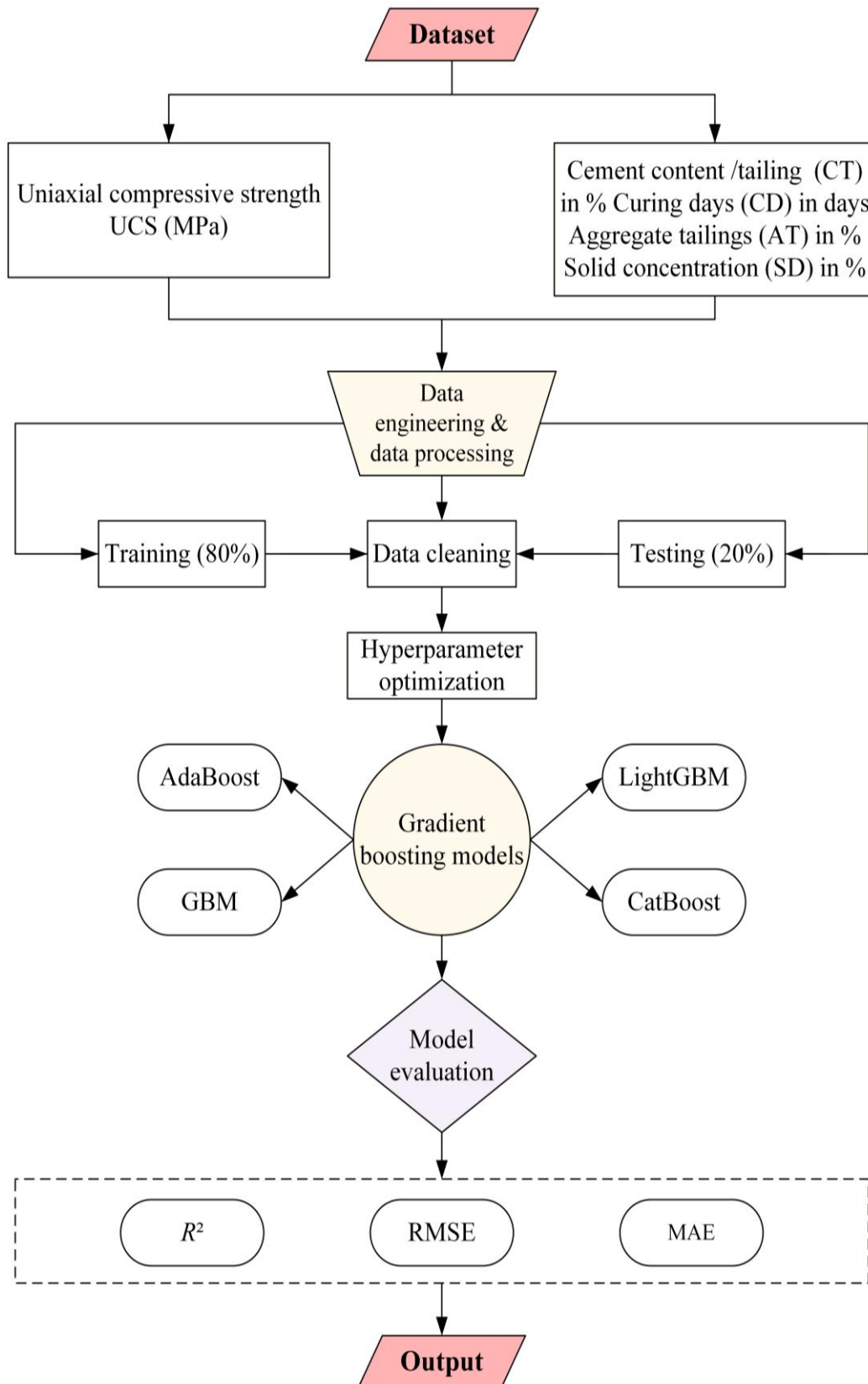


Figure 3. Flowchart of the methodology used in this work

## 2.1 Light Gradient Boosting Machine

LightGBM is a fast and efficient machine learning model based on the gradient boosting decision tree (GBDT). LightGBM is an ensemble learning implementation based on the gradient boosting framework, as presented in prior studies [30,31]. The model is based on the histogram-based DT approach, which is efficient in both computation and prediction accuracy, using the leaf-wise growth policy. It is based on the GBDT model, focusing on the ensemble learning of multiple models, where each model is trained based on the residuals of the previous model, leading to the convergence of the ensemble model to the optimal solution, as represented in Figure 4.

The model is built in stages, with one regression tree at a time, by optimizing a second-order approximation of the objective, with the best leaf weights obtained in closed form at each iteration, with greedy selection of the splits according to the gain provided.

$$F_M(x) = \sum_{m=1}^M f_m(x), f_m \in F \quad (1)$$

$f_m(x)$  is the  $m$ -th regression tree,  $F$  is the space of regression trees, and  $M$  is the number of boosting iterations.

At iteration  $m$ , LightGBM minimizes a regularized.

$$L^{(m)} = \sum_{i=1}^n L(y_i, F_{m-1}(x_i) + f_m(x_i)) + \Omega(f_m) \quad (2)$$

$L(\cdot)$ : differentiable loss (e.g., MSE, log-loss),  $\Omega(f)$ : tree complexity penalty

LightGBM uses:

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

$T$ : number of leaves,  $w_j$ : leaf weight,  $\gamma, \lambda$ : regularization parameters.

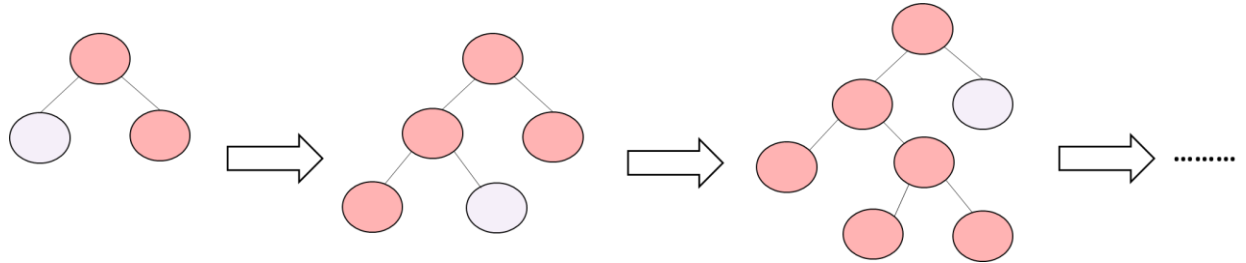


Figure 4. Demonstrates the performance of leaf-wise lightGBM

## 2.2 Adaptive Boosting

AdaBoost, also known as Adaptive Boosting, is an ensemble ML model that combines multiple weak learning models, such as decision stumps, into a powerful predictive model. The process is carried out sequentially, with each model focusing on misclassified instances identified by previous models by increasing the corresponding weights. The final prediction is made by summing the outputs of all the weak models. As illustrated in Figure 5, this technique was initially used to substantially improve the performance of weak classifiers, such as DTs [32]. This technique is used for classification and regression issues. One of the major advantages of using

this technique is that it is highly adaptable, allowing compatibility with a wide range of models. However, to obtain the best performance, several parameters and characteristics need to be tuned [33].

Let  $h_M(x) \in \{-1, +1\}$  be the  $m$ -th weak learner and  $\alpha_m$  its weight. The ensemble prediction after  $M$  rounds is.

$$F_M(x) = \text{sign}(\sum_{m=1}^M \alpha_m h_m(x)) \quad (4)$$

Training modernizes weights  $w_i^{(m)}$  so that misclassified points get more weight;  $\alpha_m$  depends on the weak learner's weighted error  $\varepsilon_m$ :

$$\alpha_m = \frac{1}{2} \ln \left( \frac{1-\varepsilon_m}{\varepsilon_m} \right), \quad w_i^{(m+1)} \propto w_i^{(m)} \exp(-\alpha_m y_i h_m(x_i)) \quad (5)$$

AdaBoost can be seen as minimizing the exponential loss  $L(y, F) = \exp(-yF)$  in a stage-wise manner.

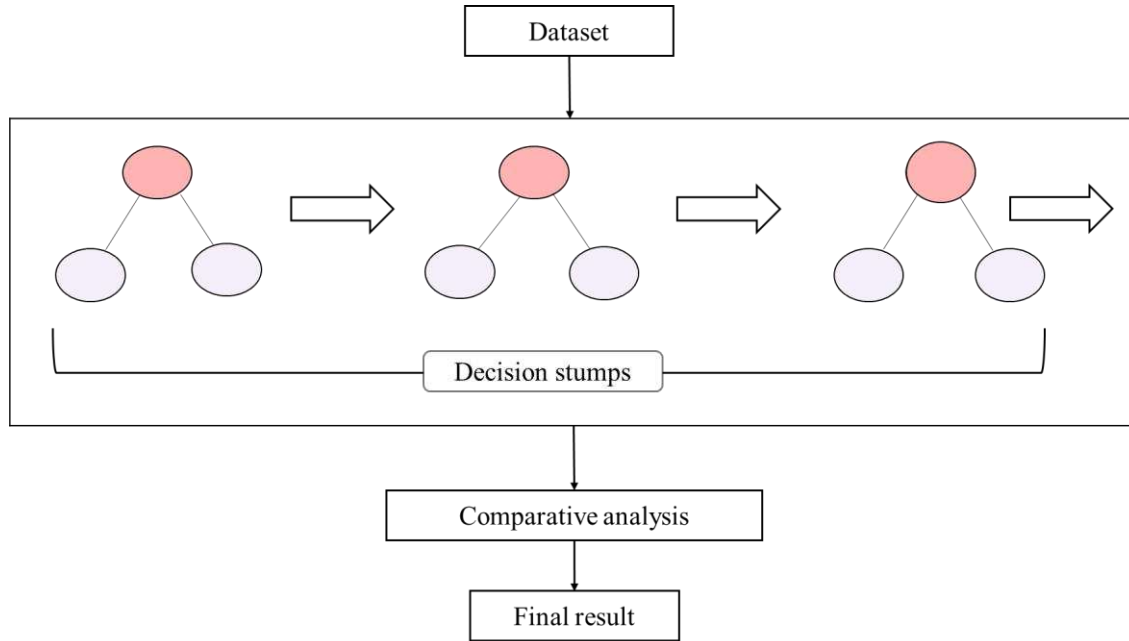


Figure 5. Graphical representation of the AdaBoost model

## 2.3 CatBoost

CatBoost is a sophisticated ML model developed by Yandex, a Russian firm, in 2017. CatBoost is considered to be an advanced version of the GBDT model [34]. Generally, GBDT models are trained on the residuals of the current model ensemble to produce each DT. This results in strong inter-tree correlations and overfitting. CatBoost abstracts this problem using the ordered boosting technique along with a new weight scheme. This technique reorders the training set and uses identical leaf nodes to store similar feature values. This improves the accuracy and reliability of the gradients while reducing their variance to tackle the overfitting problem.

In the GBDT model, the node split criterion is based on the mean values of the data labels. The formula for this is given as:

$$\hat{x}_k^i = \frac{\sum_{j=1}^N I_{\{x_j^i = x_k^i\}} y_j}{\sum_{j=1}^N I_{\{x_j^i = x_k^i\}}} \quad (6)$$

where  $x_k^i$  denotes the  $i^{\text{th}}$  feature of the  $k^{\text{th}}$  training sample;  $\hat{x}_k^i$  represents the mean value;  $I$  is an indicator function that indicates whether a specific condition holds; and  $y_i$  refers to the label value of the  $j^{\text{th}}$  sample.

Unlike the GBDT method, the CatBoost algorithm uses an adaptive learning rate. This helps to improve the accuracy of the model by precisely controlling the impact of weak learning at each step. The process of implementing an adaptive learning rate in the CatBoost algorithm for neural networks can be described as follows:

$$\begin{cases} \eta_t = \frac{1}{\sqrt{k+1}} \\ \alpha_t = \frac{\sum_{i=1}^t \eta_i}{k} \end{cases} \quad (7)$$

where  $t$  denotes the iteration number,  $\eta_t$  signifies the learning rate for the  $t^{\text{th}}$  round of iteration, and  $\alpha_t$  signifies the average learning rate over the first  $t$  iterations.

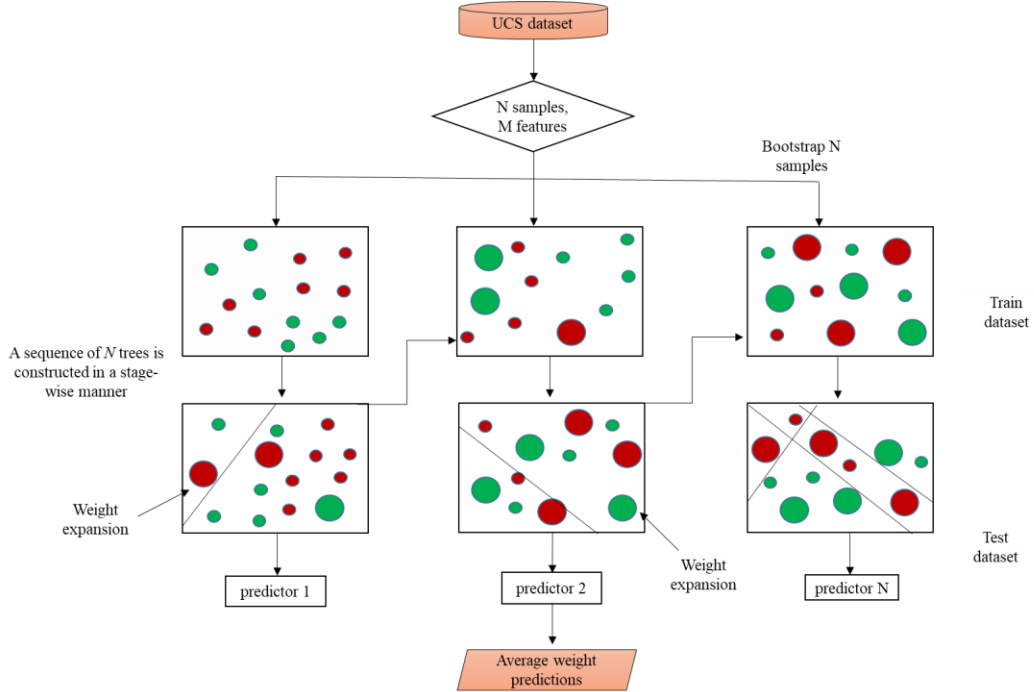


Figure 6. Graphical representation of the CatBoost model

Unlike conventional neural network models, which require a huge dataset to train and deliver accurate results, the CatBoost model is a decision tree-based model. This model does not require a huge dataset to deliver accurate results. In addition, the CatBoost model can be trained efficiently

to deliver accurate results. This characteristic of the CatBoost model makes it unique in comparison to other conventional neural network models in terms of training and prediction speeds [35]. Figure 6 shows the performance of the CatBoost model.

## 2.4 Gradient Boosting Machine

Ensemble learning, where Figure 7 represents a set of weak learners that are combined to produce a strong learner, is one of the promising paradigms of ML and is implemented using Boosting or DT [36]. In the Boosting paradigm, a set of input objects is evaluated one by one, and successive models are built to correct the errors of the previous model. More specifically, for each object, a weak learner  $f_i$  is applied to produce an output  $y_i$ , where  $f_i$  produces a hypothesis  $h_m(x)$  aiming to reduce the error of the current model.

However, unlike AdaBoost, GB is a more general approach for ensemble learning. This approach can be viewed as an optimization process with appropriate cost functions, and it is based on GB [37]. In this framework, GB is implemented as an ensemble learning algorithm following the Boosting approach and utilizing multiple DT [38]. In other words, it is an iterative process for optimizing a cost function over weak hypotheses, following the negative gradient direction (as described in Eq. 3). More specifically,

$$F_m(x) = F_{m-1}(x) + \rho_m h_m(x) \quad (8)$$

Where the hypothesis  $h_m(x)$  is multiplied by the weight function,  $\rho_m$ . In contrast with RF, GB computes the loss function from the previous step and compensates for the loss of the  $m^{\text{th}}$  iteration at the  $(m + 1)^{\text{th}}$  step.

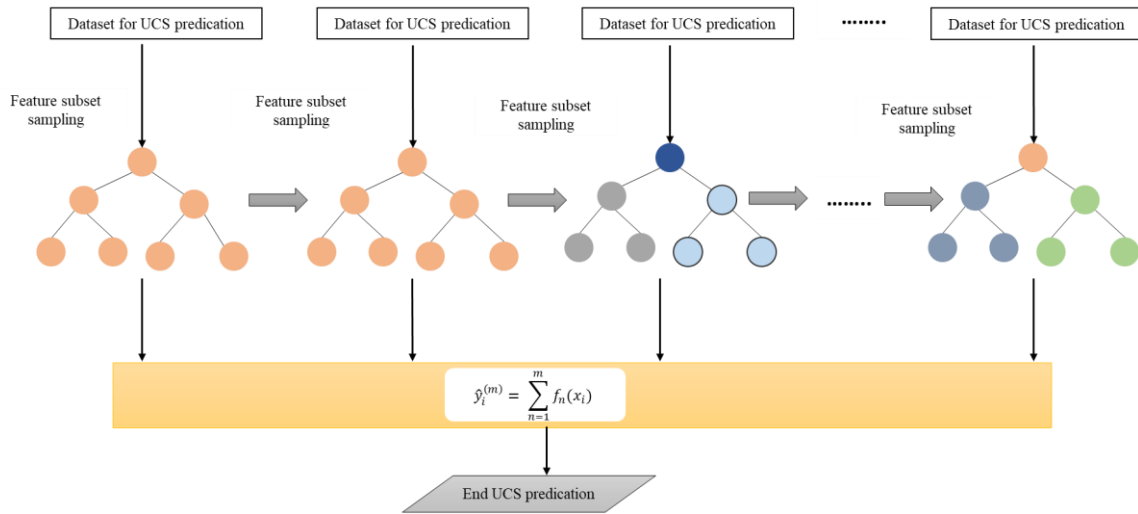


Figure 7. Graphical representation of the gradient boosting model

## 2.5 Cross-Validation Method

The use of a systematic optimization approach is evident, which incorporates grid search and K-fold cross-validation. The best predictor parameter combination is achieved based on evaluation parameters, including the  $R^2$ , RMSE, and MAE. The GridSearchCV framework, using Python's

scikit-learn library, sequentially evaluates and scores all available hyperparameter combinations within the distinct search space. In order to ensure the reliability of the generalization performance, a 5-fold cross-validation approach is used, as shown in Figure 8. The choice of the fold is based on a balance between the need for statistical reliability and the availability of data. With the large number of available data sets, increasing the folds will result in reducing the size of the available data set for each fold, thus increasing the variance. Sensitivity analyses were conducted with different fold numbers, and it was found that there were no significant improvements in the strength of the prediction, thus supporting the use of a 5-fold cross-validation approach. The GridSearchCV framework not only evaluates the model's performance but also aids in the prediction of the hyperparameters.

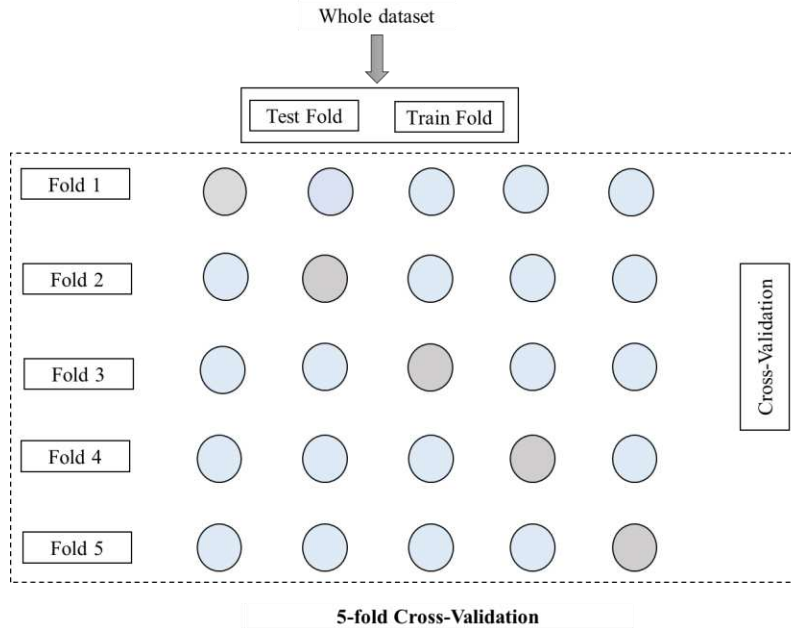


Figure 8. Standardized five-fold cross-validation method used in this work

## 2.6 Models' performance evaluation

To estimate the performance of the suggested optimization gradient boosting models, such as LightGBM, CatBoost, AdaBoost, and GBM, the  $R^2$ , RMSE, and MAE are used. The performance criteria are calculated using Eq. (8-10).

$$R^2 = 1 - \frac{\sum_{n=1}^n (y_i - \hat{y}_i)^2}{\sum_{n=1}^n (y_i - \bar{y}_i)^2} \quad (8)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{n=1}^n (y_i - \hat{y}_i)^2} \quad (9)$$

$$\text{MAE} = \frac{1}{n} \sum_{n=1}^n |y_i - \hat{y}_i| \quad (10)$$

Where  $y_i$  and  $\hat{y}_i$  are the actual and predicted UCS values, respectively.  $\bar{y}_i$  is the mean of the actual UCS values.  $n$  is the overall quantity of datasets.

### 3. Results and Discussion

The results illustrate that employing gradient boosting models is operational for the prediction of UCS of CHB. It signifies that, among all models, the GBM model has good execution because of its ability to decrease the errors of the models [26, 27, 39]. The uniformity of the results of the train data set and the test data set shows that the models are well systematized and are not experiencing significant overfitting. Moreover, the results of the factor analysis have shown that the input variables are not equally contributing to the output of the models. A few of the input variables are playing a vital role in the output of the models. At the same time, the influence of the models indicates significant insights into the changes of the input variables. Overall, the results have shown that the ensemble learning models are highly effective for the predictive purposes of the UCS of CHB.

#### 3.1 Hyperparameter Optimization

Table 2 highlights the optimization configuration and hyperparameters of the LightGBM, CatBoost, AdaBoost, and GBM used in this study. For LightGBM, we considered varying learning rates between 0.01 and 0.1, maximum depth between -1 and 10, and estimators between 100 and 300 to achieve a fair balance between model complexity and overall generalization ability. For instance, low learning rates paired with high estimators often result in improved model performance. For CatBoost, we considered varying numbers of iterations between 200 and 300, learning rates between 0.01 and 0.05, and maximum depth between 4 and 8 due to CatBoost's tendency to favor moderate numbers of iterations and low learning rates due to their symmetric tree structure. For AdaBoost, we considered varying numbers of estimators, 100 and 200, and learning rates, 0.01 and 1, as learning rates are critical for controlling each weak learner's contribution to overall model performance. Likewise, we considered varying numbers of estimators between 100 and 200, learning rates between 0.01 and 0.1, and maximum depth between 3 and 5 for GBM models, as low depth is often preferred to allow for better generalization through sequential minimization of residuals. Overall, the hyperparameters considered are informed by common practices in prior studies [33, 38, 46-49]

Table 2. Optimization Configuration and hyperparameters of the developed models.

|                      | Hyperparameter | value     |
|----------------------|----------------|-----------|
| Optimization setting |                |           |
| LightGBM             | learning_rate  | 0.01-0.1  |
|                      | max_depth      | -1-10     |
|                      | n_estimators   | 100-300   |
| CatBoost             | iterations     | 200-300   |
|                      | learning_rate  | 0.01-0.05 |
|                      | max_depth      | 4-8       |
| AdaBoost             | n_estimators   | 100-200   |
|                      | learning_rate  | 0.01-1    |
| GBM                  | n_estimators   | 100-200   |
|                      | learning_rate  | 0.01-0.1  |
|                      | max_depth      | 3-5       |

### 3.2 Analysis of Models' Predictive Performance

In this study, Figure 9 represents a comparative evaluation of the predicted values and actual values of UCS based on the performance of the four gradient boosting-based robust ML models, namely LightGBM, CatBoost, AdaBoost, and GBM. It is observed from the graph that the dashed 45° line represents the ideal prediction, where the predicted values of UCS are closer to the actual values. It is evident from Figures 9(a) and (b) that the performance of LightGBM and CatBoost is quite high, where the data points are densely clustered closer to the reference line. This specifies the high accuracy of the prediction results. However, the performance of AdaBoost in Figure 9(c) is relatively poor when the data points are scattered. It can be observed from Figure 9(d) that the GBM performs well in terms of the high correlation coefficient, where the data points are moderately scattered. Thus, in Figure 9, it can be observed that the GBM performs robustly in the UCS of CHB.

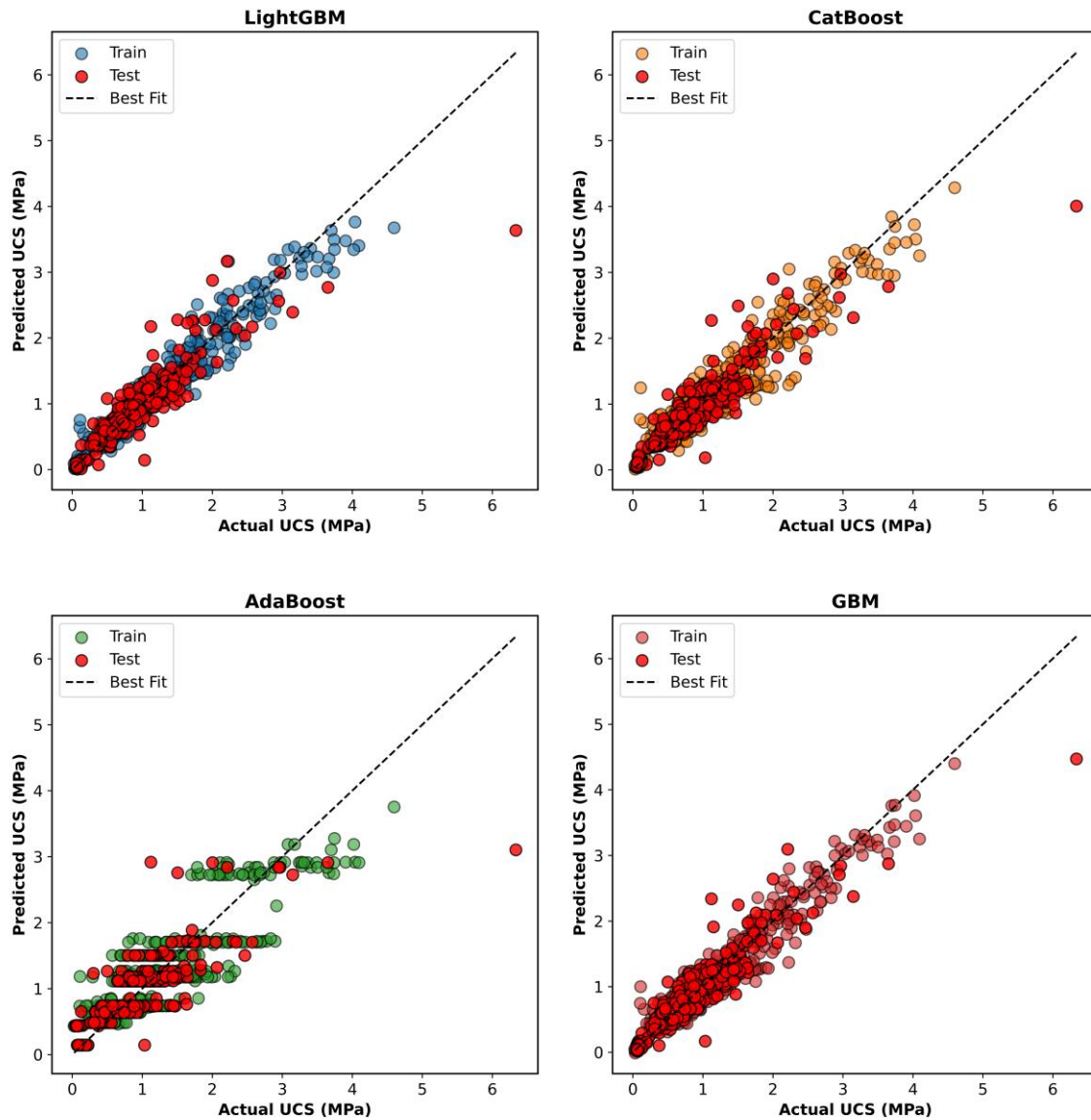


Figure 9. Scatter plot of actual versus predicted UCS values

The statistical performance metrics of the developed models are presented in Table 3. In Table 3, it is clear that the performance of the models was evaluated using the  $R^2$ , RMSE, and MAE on both the training and testing sets. The GBM model is the best performer in terms of simplification among all the studied models, achieving the highest  $R^2$  value of 0.86, with the lowest RMSE and MAE values of 0.2289 and 0.1395, respectively, on the test data. This indicates that the GBM model is the most accurate and consistent in its predictions on unseen data. Although the LightGBM model also shows the best performance in terms of accuracy on the training set with an  $R^2$  of 0.95 and low error, at the test set, the  $R^2$  value is significantly lower at 0.82, suggesting that there is some level of overfitting in this model compared to the GBM model. On the other hand, the performance of the CatBoost model is good, as its  $R^2$  value is 0.83 at the test set with medium error, signifying that this model has good predictive potential. However, the performance of the AdaBoost model is the worst among all the models, as its test  $R^2$  value is the lowest at 0.68 with the highest error, suggesting that this model had poor predictive potential in terms of estimating the nonlinear relationship in CHB strength development. In summary, the ensemble gradient boosting models, particularly the GBM model, show robust predictive accuracy in predicting the UCS of CHB.

Table 3. Performance metrics of the developed ensemble prediction models.

| Model    | Train |        |        | Test  |        |        |
|----------|-------|--------|--------|-------|--------|--------|
|          | $R^2$ | RMSE   | MAE    | $R^2$ | RMSE   | MAE    |
| LightGBM | 0.95  | 0.1401 | 0.0934 | 0.82  | 0.2597 | 0.1465 |
| CatBoost | 0.91  | 0.1824 | 0.1280 | 0.83  | 0.2492 | 0.1470 |
| AdaBoost | 0.79  | 0.2798 | 0.1997 | 0.68  | 0.3447 | 0.2161 |
| GBM      | 0.93  | 0.1590 | 0.1130 | 0.86  | 0.2289 | 0.1395 |

Figure 10 illustrates the comparison of the predictive performance of LightGBM, CatBoost, AdaBoost, and GBM models using  $R^2$ , RMSE, and MAE on the training and testing datasets. As represented in Figure 10, the GB models have good learning and predictive performance on the training dataset, with LightGBM and GBM models performing better in terms of  $R^2$ , RMSE, and MAE compared to the CatBoost and AdaBoost. In particular, AdaBoost performs worse than the other three models, with higher RMSE and MAE and lower  $R^2$ . More importantly, the models' performance on the test set indicates differences in their oversimplification performance. In particular, the performance of the GBM model is the best among all the models, with the highest  $R^2$ , lowest RMSE, and MAE, signifying that this model achieves the best in terms of predictive performance on unseen data. In contrast, the performance of the LightGBM and CatBoost models on the test dataset shows a moderate drop in  $R^2$  compared to show on the train dataset, suggesting that there is some level of model flexibility and learning ability. In particular, the performance of the AdaBoost model on the test dataset demonstrates the lowest  $R^2$ , highest RMSE, and MAE, signifying that this model is not good at modeling the nonlinear relationship between variables in the framework of CHB. The above comparative analysis of the exhibition of the models on the test and train datasets shows that the GBM model is more reliable in terms of predictive performance

from the perspective of UCS prediction. At the same time, it specifies that more recent gradient boosting models can efficiently capture the composite relationships among variables in the prediction of the UCS of CHB.

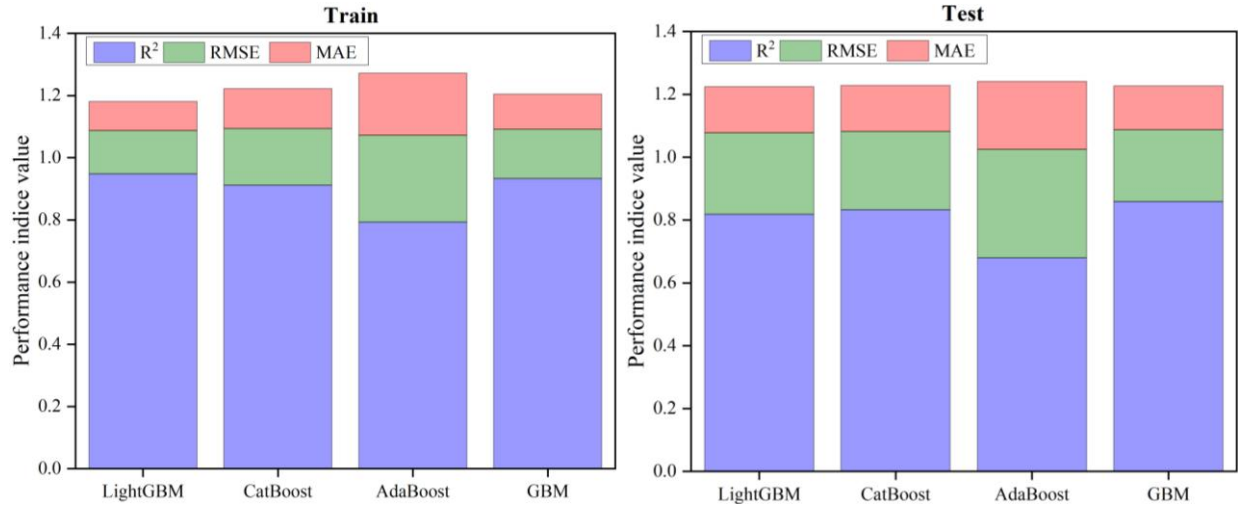


Fig. 10 Column chart plots of the performance metrics for O-LightBoost, O-CatBoost, and O-AdaBoost and GBM

### 3.3 Taylor Diagram Representation

Figure 11 illustrates the Taylor diagram for both the training and testing datasets, showing a comprehensive comparison between the predictive performance of gradient boosting models and observed UCS values for CHB. The diagram allows for the simultaneous evaluation of three statistical parameters, such as  $R^2$ , RMSE, and Standard deviation. This enables an integrated evaluation and assessment of the predictive accuracy and reliability of each gradient boosting model [39]. The Taylor diagram refers to a concise statistical explanation of how well the contexts match their standard deviation and correlation. Taylor diagram can be expressed as in Eq. (11) [40]:

$$R = \frac{\frac{1}{P} \sum_P (r_n - \bar{r})(f_n - \bar{f})}{\sigma_r \sigma_f} \quad (11)$$

Where  $R$  highlights a correlation,  $P$  is the discrete point number,  $r_n$  and  $f_n$  are both vectors,  $\sigma_r$  and  $\sigma_f$  illustrate the standard deviation of  $r$  and  $f$ , and  $\bar{r}$  and  $\bar{f}$  describe the mean value of vectors  $r_n$  and  $f_n$ , respectively.

The Figure 11 analysis indicates that all models achieved strong agreement with observed values during training; however, GBM consistently outperformed others by exhibiting higher  $R^2$  and lower RMSE. LightGBM and CatBoost also delivered reliable predictions, whereas AdaBoost showed comparatively larger standard deviations, reflecting reduced accuracy. A similar pattern was observed in testing, where GBM maintained superior generalization with standard deviations closely matching measured data. The closeness of model outputs to the reference point confirms improved predictive capability and reduced errors. Thus, boosting-based ensemble methods,

particularly GBM, demonstrate enhanced effectiveness in modeling nonlinear relationships for UCS prediction, consistent with prior relevant studies [38,41].

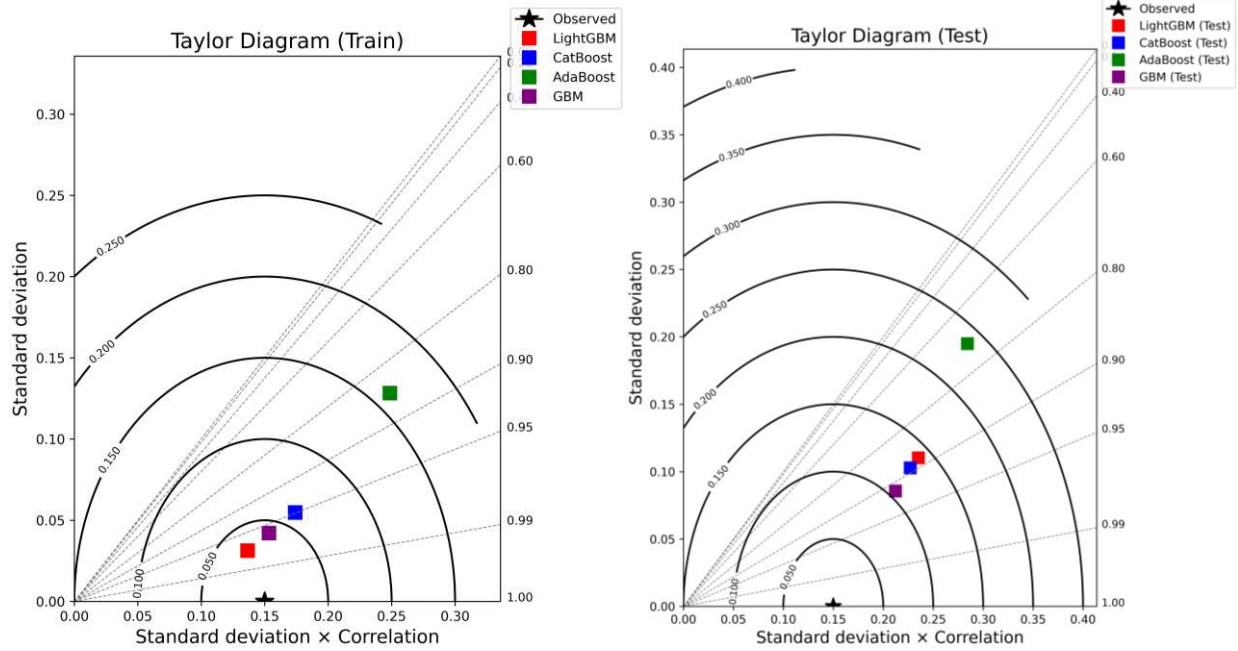


Figure 11. Graphical representation of the Taylor diagram

### 3.4 SHAP Analysis

SHAP analysis boosts the prediction of UCS of CHB, quantifying the impact and collaboration of input parameters such as CT, CD, SD, and AT, so refining model interpretability and supporting optimized mix design and decision-making in geomechanical engineering applications. Figure 12 shows SHAP summary plots for the gradient boosting models for both training and testing datasets, showing that the feature contributes to the prediction of the UCS for CHB. SHAP values measure how each feature affects the prediction, with positive SHAP values showing an increase in UCS, while negative SHAP values represent a decrease in UCS [48,49].

From Figure 12, it is evident that the feature with the most significant effect on UCS prediction is the CD, as shown by the wide range of SHAP values for the feature in both plots. The SHAP values for feature range from negative to positive, with higher CD in red showing higher SHAP value magnitudes, thus indicating that this feature has a significant positive effect on UCS prediction, while lower CD in blue have lower SHAP value magnitudes, showing that this feature has a small effect on UCS prediction, thus validating the fact that longer durations in the curing process improve CHB strength through hydration reactions. In the study by Li et al. [42], CD and the CT ratio were identified as the dominant factors determining the strength of the backfill material. While CD was found to be more important than CR in this analysis, the literature [43] and the GBM model results are consistent: in both cases, the greater the cement content and the longer the curing time, the higher the UCS value. Other factors, such as AT and SD, had very little influence on the model's results, in alignment with the results seen in this analysis when the values for CD and cement are held constant.

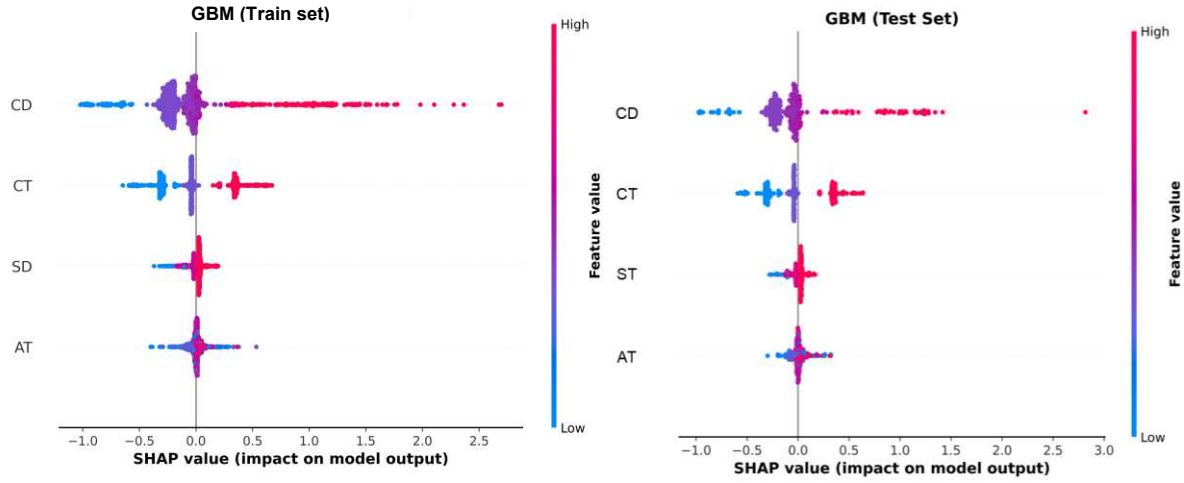


Figure 12. The SHAP analysis plot shows feature significance and the influence of each variable on the prediction output.

### 3.5 Sensitivity Analysis

The cosine amplitude method (CAM) was employed for sensitivity analysis. Since only the GBM model demonstrated ideal UCS prediction, sensitivity analysis was conducted exclusively on this model. The sensitivity between an input variable  $x_i$  and output  $y$  using CAM is represented in equation (12) [50].

$$r_i = \frac{\sum_{k=1}^n x_{ik} y_k}{\sqrt{\sum_{k=1}^n x_{ik}^2} \sqrt{\sum_{k=1}^n y_k^2}} \quad (12)$$

Where,  $r_i$  is the sensitivity (cosine amplitude value) of variable  $i$ ,  $x_{ik}$  is the value of input variable  $i$  at data point  $k$ ,  $y_k$  is the output value at data point  $k$ , and  $n$  is the number of data points.

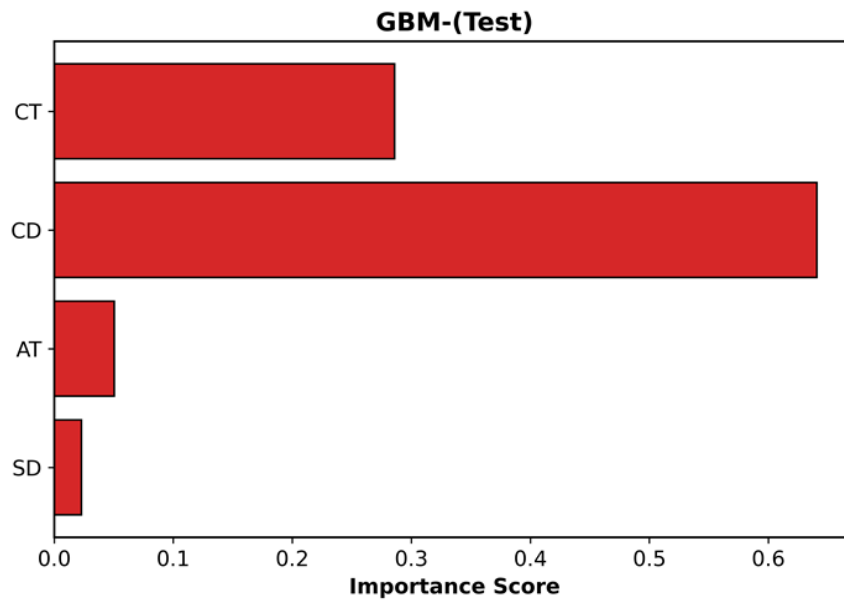


Figure 13. Sensitivity analysis of the GBM Model

Figure 13 illustrates the important features based on the GBM prediction model applied to the test set for the prediction of the UCS of the CHB. The vertical axis represents the parameters, which are enumerated based on their limitations: CT, CD, AT, and SD. The horizontal axis represents the significance of the parameter; it is observed that the CD has the highest importance score of about 0.65, indicating that the prediction is highly sensitive to the CD. It is observed that the CT has the second-highest importance score of about 0.26. In distinction, the standing scores of the last two factors, AT and SD, are almost zero. The result shows that the CD is the most prevailing factor in the prediction outcomes. In contrast, the influence of the cement ratio is not as significant as the CD but is still significant. In comparison, the influence of the AT of the backfill is very low. This is consistent with the fact that the UCS gained by the backfill is mostly a purpose of the CD. It is widely understood that the backfill gains strength mostly during the time from 7 days to 28+ days [29,42].

The results can be related to the findings of current studies conducted in this area. It has been found that the UCS of CHB is mainly related to the CT, SD, curing temperature, and CD the outcomes of the present model are consistent with the findings of Li et al. [42], as the variable of CD has been identified as the highest factor in the present study, as it has been shown in the previous study, with the variable of CT ranking second in the present study, as opposed to ranking first in the aforementioned. Qi et al. [43] identified the cement ratio (CR) as the top factor in the DNN model based on the global CPB dataset. Xiong et al. [44], the variable of binder proportion (tailings percentage) has been identified as the topmost factor, with the variable of curing ranking second in importance in this study. These findings can be clarified in light of the fact that the amount of cement in the mixes is already sufficient; thus, the addition of more cement will only have a marginal effect on the strength of the mixes, with the variable of CD ranking first in importance in the present study. Min et al. [45], it was found that binder content and slurry attraction are important variables in determining the UCS of the CPB. In conclusion, it can be believed that previous studies have shown that the strength of the CHB is determined by variables such as CR and CD, and the sensitivity analysis of the present model has shown that the variable of CD is the predominant factor in determining the strength of the CHB.

#### 4. Conclusion

This study proposes a novel explainable GBM model in forecasting the UCS of CHB, which addresses the major limitations of conventional and black-box ML techniques. The study yielded the following important conclusions:

- 1) This study presents LightGBM, CatBoost, AdaBoost, and GBM to predict UCS based on input variables, such as CD in days, CT in %, AT, and SD in %. To avoid overfitting, the dataset of 1,641 samples was distributed into 80% for training and 20% for testing. The results illustrate that the GBM model gives the highest accuracy in predicting UCS than the other studied models, achieving an  $R^2 = 0.93$ , MAE = 0.1130, RMSE = 0.1590, during training; and  $R^2 = 0.86$ , MAE = 0.1395, RMSE = 0.2289, during testing.
- 2) Taylor diagram representation for both the train and test datasets, illustrating an inclusive evaluation between the predictive performance of gradient boosting models and detected

UCS values for CHB. The diagram allows for the immediate evaluation of three statistical parameters, such as  $R^2$ , RMSE, and Standard deviation. In addition, SHAP provides a clear understanding of the effect and influence of each parameter in predicting outcomes by incorporating SHAP analysis results, which reveal that CT in % and CD in days have a significant positive impact on UCS prediction, while variations in SD in % and AT have a significant impact on UCS prediction.

- 3) Sensitivity analysis using CAM was employed, since only the GBM model validated the robust UCS prediction. In comparison to previous studies that mainly emphasized predictive results in this area, this study places more emphasis on model transparency and interpretability, which are more applicable and helpful for engineers in practice.
- 4) In summary, this study contributes to explainable AI in mining or geotechnical engineering and proposes a reliable predictive model, particularly GBM, for safe and efficient underground mining operations.

To develop model simplicity, it is recommended to expand the number of datasets in demand to include a variety of actual circumstances, such as binders, tailings, and environmental assessment criteria. To develop prediction performance, hybrid models integrating gradient boosting with metaheuristic optimization models, including genetic algorithms (GA), particle swarm optimization (PSO), or whale optimization (WO), may be investigated. Future work may also look at merging physics-informed ML models with deep learning techniques to enhance the capture of key material performance. Furthermore, confirming the developed models through actual field measurements will increase their real-world efficiency. The implementation of these models in real-time predicting applications or smart decision-assistance stages could considerably enhance engineering workflows for CHB design and optimization.

### **Author Contributions**

**Santosh Kumar** and **Niaz Muhammad Shahani** completed the conception and design of the study. **Arzoo Batool** and **Xin Wei** handled material preparation, data collection, and analysis. The first draft of the manuscript was written by **Santosh Kumar** and **Niaz Muhammad Shahani**. **Xigui Zheng** and **Tarek Salem Abdennaji**, **Aymen Flah** proofread the manuscript. All authors provided comments on previous versions and read and approved the final manuscript.

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### **Data availability**

The datasets used and/or analyzed during the study are available from the corresponding author upon reasonable request.

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## Conflict of Interest

Authors declare no potential conflict of interest.

## 5. References

1. Aydogmus, H.Y.; Erdal, H.I.; Karakurt, O.; Namli, E.; Turkan, Y.S.; Erdal, H. A comparative assessment of bagging ensemble models for modeling concrete slump flow. *Comput. Concr.* 2015, 16, 741–757.
2. Unlu, R. An assessment of machine learning models for slump flow and examining redundant features. *Comput. Concr.* 2020, 25, 565–574.
3. Namli, E.; Erdal, H.I.; Erdal, H. Dalgacık dönüşü, sumu ile beton basınç dayanım tahmininin iyileştirilmesi (Turkish) (Improving Prediction Accuracy of Concrete Compressive Strength via Wavelet Transform). *J. Polytech.* 2016, 19, 471–480.
4. Shariati, M.; Mafipour, M.S.; Ghahremani, B.; Azarhomayun, F.; Ahmadi, M.; Trung, N.T.; Shariati, A. A novel hybrid extreme learning machine–grey wolf optimizer (ELM-GWO) model to predict compressive strength of concrete with partial replacements for cement. *Eng. Comput.* 2022, 38, 757–779.
5. Hematibahar, M.; Kharun, M. Prediction of concrete mixture design and compressive strength through data analysis and machine learning. *J. Mech. Cont. Math. Sci.* 2024, 19, 1–21.
6. Prakash, S.; Kumar, S.; Rai, B. A new technique based on the gorilla troop optimization coupled with an artificial neural network for predicting the compressive strength of ultrahigh-performance concrete. *Asian J. Civ. Eng.* 2024, 25, 923–938.
7. Nguyen, N.H.; Nguyen, T.H.T.; Bui, L.G.; Ly, H.B. Enhancing concrete structure maintenance through automated crack detection: A computer vision approach. *J. Sci. Technol.* 2024, 4, 11–23
8. Shahani NM, Xiaowei Q, Wei X, Jun L, Aizitiliwumaier T, Xiaohu M, Shigui Q, Weikang C and Longhe L. Hybrid PSO with tree-based models for predicting uniaxial compressive strength and elastic modulus of rock samples. *Front. Earth Sci.* 2024, 12:1337823. doi: 10.3389/feart.2024.1337823
9. Wadhawan, S.; Bassi, A.; Singh, R.; Patel, M. Prediction of compressive strength for fly ash-based concrete: Critical comparison of machine learning algorithms. *J. Soft. Comput. Civ. Eng.* 2023, 7, 68–110.

10. Fattahi, H.; Ghaedi, H.; Armaghani, D.J. Optimizing fracture toughness estimation for rock structures: A soft computing approach with GWO and IWO algorithms. *Measurement*, 2024, 238, 115306.
11. He, Y.; Cheng, Y.; Ma, M.; Li, F.; Song, Y.; Liu, L.; Wang, X.; Huang, J. A novel design concept of cemented paste backfill (CPB) materials: Biobjective optimization approach by applying an evolved random forest model. *Materials* 2022, 15, 8298
12. Mishra, K.; Paul, P.S.; Ghosh, C.N.; Singh, P.; Behera, S.K.; Mandal, P.K. Predicting and optimising the strength of cemented paste fills through bayesian network model. *Min. Metall. Explor.* 2022, 39, 2095–2120
13. Qi, C.; Zheng, J.; Yang, X.; Chen, Q.; Wu, M. Application of deep neural network in the strength prediction of cemented paste backfill based on a global dataset. *Constr. Build. Mater.* 2023, 391, 131827.
14. Hu, Y.; Li, K.; Zhang, B.; Han, B. Strength investigation and prediction of superfine tailings cemented paste backfill based on experiments and intelligent methods. *Materials* 2023, 16, 3995.
15. Tran, V.Q. Using artificial intelligence approach for investigating and predicting yield stress of cemented paste backfill. *Sustainability* 2023, 15, 2892.
16. Pang H, Qi W, Song H, Pang H, Liu X, Chen J, Chen Z. Predictive Modelling of Alkali-Slag Cemented Tailings Backfill Using a Novel Machine Learning Approach. *Materials (Basel)*. 2025 Mar 11;18(6):1236. doi: 10.3390/ma18061236. PMID: 40141519; PMCID: PMC11943603.
17. Kurniati, E.O.; Zeng, H.; Latypov, M.I.; Kim, H.J. Machine learning for predicting compressive strength of sustainable cement paste incorporating copper mine tailings as supplementary cementitious materials. *Case Stud. Constr. Mater.* 2024, 21, e03373.
18. Zhang, B., Li, K., Zhang, S., Hu, Y., Han, B. A Modeling Method for Predicting the Strength of Cemented Paste Backfill Based on a Combination of Aggregate Gradation Optimization and LSTM. *Journal of Renewable Materials*, 2022, 10(12), 3539–3558. <https://doi.org/10.32604/jrm.2022.021845>
19. Shahani, N.M., Zheng, X., Wei, X. *et al.* Predicting Elastic Modulus of Rocks Using Metaheuristic-Optimized Ensemble Regression Models. *Rock Mech Rock Eng*, 2025, 58, 8397–8413 . <https://doi.org/10.1007/s00603-025-04499-4>
20. YUAN Congxiang, LIU Zhixiang, YANG Xiacong, GUO Jinfeng, WAN Chuanchuan, XIONG Shuai, LIU Weijun. Strength Prediction of Cemented Paste Backfill Body Based on WOA-XGBoost Model [J]. *Chinese Journal of High Pressure Physics*, 2023, 37(5): 054201. doi: 10.11858/gywlxb.20230668
21. Quoc Trinh Ngo, Canh Tung Ngo, Quang Hung Nguyen, Huu Nam Nguyen, Linh Quy Nguyen, Kien Quyet Nguyen, Van Quan Tran. Data-driven approach in investigating and predicting unconfined compressive strength of cemented paste backfill, *Materials Today Communications*, Volume 37, 2023, 107065, ISSN 2352-4928, <https://doi.org/10.1016/j.mtcomm.2023.107065>.
22. Chendi Min, Shuai Xiong, Ying Shi, Zhixiang Liu, Xinyue Lu. Early-age compressive strength prediction of cemented phosphogypsum backfill using lab experiments and

- ensemble learning models, *Case Studies in Construction Materials*, Volume 18, 2023, e02107, ISSN 2214-5095, <https://doi.org/10.1016/j.cscm.2023.e02107>.
23. Chen X, Wang Y, Miao S, Zhang S, Yu Z, Du L. Evaluation of Multiple Influences on the Unconfined Compressive Strength of Fibre-Reinforced Backfill Using a GWO-LGBM Model. *Materials (Basel)*. 2026 Jan 5;19(1):200. doi: 10.3390/ma19010200. PMID: 41515864; PMCID: PMC12787078.
  24. Fan, T.; Zhang, S.; Ni, W. Predicting the Strength of Fly Ash–Slag–Gypsum-Based Backfill Materials Using Interpretable Machine Learning Modeling. *Appl. Sci.* 2025, 15, 12035. <https://doi.org/10.3390/app152212035>
  25. Huanbao Zhang, Fengping Xu, Yu Yin, Linhai Wan, Jie Guo, Haiyang He, Qibin Lin, Shenchen Zhang, Shijiao Yang, Fulin Wang, Strength prediction of cemented paste backfill with different machine learning and SHapley Additive exPlanation (SHAP) approaches, *Results in Engineering*, Volume 28, 2025, 108269, ISSN 2590-1230, <https://doi.org/10.1016/j.rineng.2025.108269>.
  26. Zheng, X.; Batool, A.; Kumar, S.; Shahani, N.M. Grey Wolf Optimization-Optimized Ensemble Models for Predicting the Uniaxial Compressive Strength of Rocks. *Appl. Sci.* 2026, 16, 1130. <https://doi.org/10.3390/app16021130>
  27. Shahani N.M, Kamran M, Zheng X, Liu C, Guo X. Application of Gradient Boosting Machine Learning Algorithms to Predict Uniaxial Compressive Strength of Soft Sedimentary Rocks at Thar Coalfield. *Advances in Civil Engineering*, 2021, Volume, Article ID 2565488, 19 pages <https://doi.org/10.1155/2021/2565488>
  28. Zhu, Lei, Gu, Wenzhe, Liu, Zhicheng, Qiu, Fengqi, Application of Artificial Intelligence Models to Predict the Tensile Strength of Glass Fiber-Modified Cemented Backfill Materials during the Mine Backfill Process, *Geofluids*, 2022, 4100638, 8 pages, <https://doi.org/10.1155/2022/4100638>
  29. H. Basarir, H. Bin, A. Fourie, A. Karrech, M. Elchalakani. An adaptive neuro-fuzzy inference system to model the uniaxial compressive strength of cemented hydraulic backfill. *Mining of Mineral Deposits*. 2018, Volume 12 Issue 2, pp. 1-12 <https://doi.org/10.15407/mining12.02.001>
  30. Wang, R., Zhang, J., Lu, Y., and Huang, J. Towards designing durable sculptural elements: ensemble learning in predicting compressive strength of fiber-reinforced nano-silica modified concrete. *Buildings*. 2024, 14 (2), 396. doi:10.3390/buildings14020396
  31. Lu, S., Cui, M., Gao, B., Liu, J., Ni, J., Liu, J., et al. A comparative analysis of machine learning algorithms in predicting the performance of a combined radiant floor and fan coil cooling system. *Buildings*, 2024, 14 (6), 1659. doi:10.3390/buildings14061659
  32. Freund, Y.; Schapire, R.E. A decision-theoretic generalization of on-line learning and an application to boosting. *J. Comput. Syst. Sci.* 1997, 55, 119–139. <https://doi.org/10.1006/jcss.1997.1504>.
  33. Wang, G.; Chen, X.; Chen, W. Spatial Prediction of Landslide Susceptibility Based on GIS and Discriminant Functions. *ISPRS Int. J. Geo-Inf.* 2020, 9, 144. <https://doi.org/10.3390/ijgi9030144>.

34. Hancock JT, Khoshgoftaar TM. CatBoost for big data: an interdisciplinary review. *J Big Data*. 2020;7(1):94. doi: 10.1186/s40537-020-00369-8. *Epub* 2020 Nov 4. PMID: 33169094; PMCID: PMC7610170.
35. He Dasi, Zhang Ying, Boyuan Yang. Predicting the consumed heating energy at residential buildings using a combination of categorical boosting (CatBoost) and metaheuristics algorithms, *Journal of Building Engineering*, 2023, Volume 71, 106584, ISSN 2352-7102, <https://doi.org/10.1016/j.jobbe.2023.106584>.
36. Brownlee J. XGBoost with Python: gradient boosted trees with XGBoost and scikit-learn. *Machine Learning Mastery*, 2016
37. Jerome H. Friedman "Greedy function approximation: A gradient boosting machine" *The Annals of Statistics*, *Ann. Statist.* 2001, 29(5), 1189-1232,
38. Bentéjac, C., Csörgö, A. & Martínez-Muñoz, G. A comparative analysis of gradient boosting algorithms. *Artif Intell Rev.* 2021, 54, 1937–1967 <https://doi.org/10.1007/s10462-020-09896-5>
39. Xin, W., Li, J., Zheng, X. *et al.* A Data-Driven Method for Predicting Rocks' Young's Modulus: Case Study. *Rock Mech Rock Eng*, 2026. <https://doi.org/10.1007/s00603-026-05419-w>
40. Taylor, K.E. Summarizing multiple aspects of model performance in a single diagram. *Journal of Geophysical Research*. 2001, 106(D7), 7183–7192. <https://doi.org/10.1029/2000JD900719>
41. Chai, T. and Draxler, R. R.: Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature, *Geosci. Model Dev.*, 2014, 7, 1247–1250, <https://doi.org/10.5194/gmd-7-1247>
42. Li, J.; Yilmaz, E.; Cao, S. Influence of Solid Content, Cement/Tailings Ratio, and Curing Time on Rheology and Strength of Cemented Tailings Backfill. *Minerals*. 2020, 10, 922. <https://doi.org/10.3390/min10100922>
43. Liu, G.; Li, L.; Yao, M.; Landry, D.; Malek, F.; Yang, X.; Guo, L. An Investigation of the Uniaxial Compressive Strength of a Cemented Hydraulic Backfill Made of Alluvial Sand. *Minerals*, 2017, 7, 4. <https://doi.org/10.3390/min7010004>
44. Chongchong Qi, Jiashuai Zheng, Xingyu Yang, Qiusong Chen, Mengting Wu. Application of deep neural network in the strength prediction of cemented paste backfill based on a global dataset, *Construction and Building Materials*, 2023, Volume 391, 131827, ISSN 0950-0618, <https://doi.org/10.1016/j.conbuildmat.2023.131827>
45. Xiong S, Liu Z, Min C, Shi Y, Zhang S, Liu W. Compressive Strength Prediction of Cemented Backfill Containing Phosphate Tailings Using Extreme Gradient Boosting Optimized by Whale Optimization Algorithm. *Materials (Basel)*. 2022 Dec 28; 16(1):308. doi: 10.3390/ma16010308. PMID: 36614647; PMCID: PMC9821812.
46. Chendi Min, Shuai Xiong, Ying Shi, Zhixiang Liu, Xinyue Lu. Early-age compressive strength prediction of cemented phosphogypsum backfill using lab experiments and ensemble learning models, *Case Studies in Construction Materials*, 2023, Volume 18, 02107, ISSN 2214-5095, <https://doi.org/10.1016/j.cscm.2023.e02107>

47. Ke, G.; Meng, Q.; Finley, T.; Wang, T.; Chen, W.; Ma, W.; Ye, Q.; Liu, T.Y. LightGBM: A highly efficient gradient boosting decision tree. *Advances in Neural Information Processing Systems*. 2017; 30.
48. Prokhorenkova, L.; Gusev, G.; Vorobev, A.; Dorogush, A.V.; Gulin, A. CatBoost: Unbiased boosting with categorical features. *Advances in Neural Information Processing Systems*. 2018; 31. <https://doi.org/10.48550/arXiv.1706.09516>
49. Lundberg, S.M., & Lee, S.I. A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems (NeurIPS)*, 2017, 30. DOI: 10.48550/arXiv.1705.07874
50. Hosseini, S., Poormirzaee, R., Gilani, SO. *et al.* A reliability-based rock engineering system for clean blasting: risk analysis and dust emissions forecasting. *Clean Techn Environ Policy*, 2023, 25, 1903–1920 <https://doi.org/10.1007/s10098-023-02479-2>