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Rock sample strength evaluation using a series of machine learning methods

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Abstract:

Rock engineering tasks including tunneling, dam building, and ensuring rock slope stability rely heavily on the uniaxial compressive strength (UCS) as a key geomechanical metric. The primary goal of this research was to compare the accuracy of the random forest (RF), k-nearest neighbors (kNN), the decision tree (DT), and the Adaboost in predicting the various rock UCS samples. The approaches were applied to 170 data sets, including point load index (Is(50)), porosity (n), Schmidt hammer (SH), and P-wave velocity (Vp). Initially, the 4 outlier data techniqes were implemented to improve the effectiveness of the used approaches. Then, using the selected data, 4 different machine learning models were developed to predict UCS. Based on different criteria, the 4 models were compared with each other, among which the Adaboost model provided the best response. This model provided R^2 values of 0.9631, RMSE of 9.781 and an MAE of 3.684

for the training part and R^2 values of 0.9326, RMSE of 13.234 and an MAE of 9.656 for the testing part. Finally, two parameters porosity (n) and Schmidt hammer (SH) were introduced as the most influential parameters in these models.

Keywords:

Uniaxial compressive strength; Rock; Machine learning; Random forest; Adaboost.

1. Introduction

The The UCS of intact rock is a major factor in the success of rock mass slope stability, excavation, tunneling, dam construction, and even the creation of infrastructures (Lawal and Kwon 2023). Laboratory checks of specimens are the primary method for assessing UCS and E, with protocols developed by organizations like the ASTM and ISRM (Ying et al. 2020), respectively. Nevertheless, it is well-known that direct approaches to determining tensile strength in the laboratory are not time- and cost-efficient. Fragile or extensively weathered rocks make it difficult to provide the necessary exposure to a sufficient number of high-quality formed samples. It is common practice to use simple and multiple regression techniques in statistics (Danial Jahed Armaghani et al. 2024) when developing empirical equations. Some of the more prominent equations developed in recent years for predicting UCS are shown in Table 1.

The engineering community now recognizes the promise of soft computational approaches (Danial J Armaghani et al. 2021; Fakharian et al. 2024; P. Kumar et al. 2025; Nouri, Ghanbari, et al. 2025; Nouri, Ghanizadeh, et al. 2025; Skentou et al. 2023). The human brain's extraordinary ability to reason and learn in an environment of uncertainty and imprecision (Tan et al. 2020) inspired a new computer paradigm called "soft computing". Modern prediction methods have attracted researchers' attention in the past due to their focus on probabilistic and soft computation strategies (Bardhan, Kumar Suman, et al. 2024; Bardhan, Tunar Ozcan, et al. 2024; Zeyad et al. 2024). Evidence from Alvarez Grima and Babuska (Grima and Babuška 1999) indicates that the UCS is better estimated using the fuzzy model than through conventional methods of multiple regression analysis. Numerous researchers, including Dehghan et al. (2010) use various regression models and ANN to predict the UCS of clay-bearing rocks, travertine, schistose, carbonate, and sandstones. Their research revealed that the models used ANN outperformed more traditional statistical methods in terms of forecast accuracy. Gultekin et al. (2013) calculated UCS with MR, ANN, and an ANFIS technique across three models and five datasets, and found that the ANFIS approach was the most predictive. In addition, a study compares the projected UCS from other soft computing methods and finds that ANFIS is the most effective (Mishra et al. 2015). Singh et al. (2001) presented the ANFIS and generalized models of neural network regression with significantly higher accuracy in the prediction network of the UCS than ANFIS. It was also established that the AI model that included the metaheuristic optimization algorithm was even more reliable in its predictions. Combining PSO along with an ANN model, as done by Momeni et al. (2015), can improve the UCS's predictability. As demonstrated by Jahed Armaghani et al. (2016), hybrid ICA-ANNs are more accurate and predictive than traditional ANNs. ANN itself was also proposed by several researchers in this field to find an easier way to predict UCS of rock. A model developed by Ferentinou and Fakir (2017) was shown to be reliable and could be used as a substitute indirect estimate of UCS for sedimentary and igneous rocks. A non-linear parameters and a non-parametric predictive modelcan be used as a robust and accurate UCS evaluation and estimation technique, as noted by Matin et al. (2018), who used the RF method to predict the UCS. In order to foretell UCS, Asheghi et al. (2019) developed ICA and GFFN (ICAGFFN) models. They concluded that their approach was a good and reliable way to forecast UCS. In sensitivity analysis performed on the UCS forecast, rock type was determined to have the least impact, whereas P-wave velocity (Vp) had the greatest impact (Rezaei et al. 2024). These results show that utilizing soft computing methods to predict UCS is more accurate than using typical statistical models. The lack of a consistent mathematical pattern between inputs and outputs is a fundamental drawback of these approaches. Thus, the term "black box" is used to indicate that these techniques are not as open and straightforward to comprehend as regression-based models and empirical formulas (Le et al. 2022; Parsajoo et al. 2021; Zhou et al. 2021). The UCS parameter has been predicted using a number of computational methods, although other methods have not been employed or are rarely used. This necessitates giving special attention to additional predictability factors relating to computational methods if the UCS parameter is to be predicted.

This research uses 170 data sets of different rock types, each with their own porosity (n), Schmidt hammer (SH), P-wave velocity (Vp), and point load index (Is(50)), to make predictions about the UCS parameter. To reduce discrepancies between input and output parameters, we standardized them all before modeling. To measure the efficacy of the methods, the outlier data was examined. At last, we compared each model's prediction accuracy using several metrics. The next step was to compare each model's output to that of the others, to the actual mode, and to established literature. Last but not least, a recommendation was made for future research on the best intelligent model for UCS prediction. Here is how the rest of the paper is laid out: Part 2 of this article reviewed about the research database that was employed. In the third section, we cover the approaches that may be taken to deconstruct the outcomes produced by the intelligent models. In section 4, the machine learning models used in this research are explained in depth, and the outcomes of the predictions are discussed, and we compare the predictive accuracy of the various intelligent models.

Table 1. Regression equations to predict UCS.

Type	Equation	Variable (s)	Reference	Description
Linear equations	UCS = 183 – 16.55n	n	Tugrul and Zarif (1999)	n: Porosity; EH: Equotip hardness; ρ: Density; SH: Schmidt hammer number; Vp: P-wave velocity; PLS: Point load strength; Is(50): Point load index; TS: Tensile strength; CI: Cone indenter hardness; WC: Water content; SD: Slake durability index; BPI: Block punch index; PR: Poisson's ratio; BPI: Block punch index; CPI: Cylinder punch index; UW: Unit weight; SHR: Schmidt hardness rebound number; L: Cubic sample sizes.
	UCS = 0.386EH + 39.268ρ – 1.307n – 246.804	EH – ρ – n	Alvarez Grima and Babuska (1999),	
	UCS = 0.0065Vp + 1.468PI + 4.094PLS + 2.418TS – 225	Vp – Pl – PLS - TS	Gokceoglu and Zorlu (2004)	
	UCS = 29.63SD – 28.58	SD	Yagiz (2011)	
	UCS = -2.572n + 23.665PLS + 41.654PR + 12.197ρ – 0.001Vp – 11.813	N – PLS – PR – ρ - Vp	Madhubabu et al. (2016)	
	UCS = -153.61n + 0.010Vp + 7.111(Is(50))	n – Vp - Is(50)	Jahed Armaghani et al. (2016)	
	UCS = -120.912 – 2.036Vp + 31.064(Is(50))	Vp - Is(50)	Matin et al. (2018)	
	UCS = 1.277SHN + 2.186BPI + 16.41(Is(50)) + 0.011Vp – 82.436	SHN – BPI - Is(50) – Vp	Heidari et al. (2018)	
	UCS = -6.479 + 3.425BPI + 0.639CPI + 7.889(Is(50))	BPI – CPl - Is(50)	Mahdiabadi & Khanlari (2019)	
	UCS = 29.3UW + 0.4Vp – 687.43 UCS = 15.14UW + 2.88SHR – 446.3 UCS = -6.53L + 3.63Vp + 3.45SHR – 50.68	UW – VP – SHR – L	Çelik (2019)	
Non-linear equations	UCS = 74.4 exp(-0.04n)	n	Palchik (1999)	
	UCS = 7.3 PLS1.71	PLS	Tsiambaos and Sabatakakis (2004)	
	UCS = 0.88 $\rho^{2.24}$ $SH^{0.22}$ $CI^{0.89}$	ρ – SH - Cl	Tiryaki (2008)	
	UCS = $0.0028^{2.584\ SH}$	SH	Yagiz (2009)	
	UCS = 165.05 exp (-4.452/Vp)	Vp	Moradian and Behnia (2009)	
	UCS = -595.303 – 442.363Vp + 45.338V^2p – 6.1n + 0.52n^2 + 28.314(Is(50) – 4.06$(Is(50))^2$ + 115.822SH – 2.007SH^2	Vp – n - Is(50 - SH	Dehghan et al. (2010)	
	UCS = 0.458 exp (1.504Vp)	Vp	Nefeslioglu (2013)	
	UCS = exp (0.011BPI + 0.065PLS + 0.029SH + 0.000012Vp + 2.157)	BPI – PLS – SH - Vp	Mishra and Basu (2013)	
	UCS = 0.047 exp (0.065SD)	SD	Kahraman et al. (2017)	

By examining the previous works, it can be acquainted with the application of different predictive models for data analysis. However, this research introduces a new approach for data analysis according to the selection of data set features. This study used the outlier data technique, which is one of the data selection techniques based on closely related features, to provide a system for solving the more accurate analysis and evaluation of problems. The above-mentioned machine learning models can be trained and validated using a dataset with 170 experimental data samples from the existing previous works. There are 4 features (inputs) in the dataset, including Schmidt hammer number (SHN), P-wave velocity (Vp), porosity (n), and point load index (Is(50)) for assessment of the the UCS. The research introduces this methodology, compares it with different machine learning models, and finally, shows their performance.

2. Dataset

As shown in Table 1, Schmidt hammer number (SHN), P-wave velocity (Vp), porosity (n), and point load index (Is(50)) were selected as four effective rock features on the UCS based on prior studies done on predicting UCS (Asteris et al. 2024). The 170 samples of limestone, slate, dolomite, claystone, granite, schist, sandstone, travertine, and marl were subjected to a battery of laboratory tests to compile the database (Mahmoodzadeh et al. 2021). Table 2 provides a brief overview of the data source that was queried. The scope of this study is far wider than that of many similar sorts of earlier studies since a larger portion of the database was used. Table 3 provides some of the data used in this study that was used to develop the ML models.

Table 2. Statistical information of input and output datasets.

Parameter	n (%)	SHR	Vp (m/s)	Is(50) (Mpa)	UCS (Mpa)
Min	0.06	25.46	2725	0.86	12.01
Average	2.79	44.40	5368.48	4.26	96.03
Max	16.8	67.07	7943	14.13	215.21

Table 3. Some of the data used to develop the models

No	n (%)	SHR	Vp (m/s)	Is(50) (Mpa)	UCS (Mpa)
1	0.4	56	5020	3.01	77.3
2	0.15	57	7002	4.97	163.3
3	0.4	53	6080	3.23	149.05
4	0.4	48	4568	2.45	81.05
5	0.39	46	4432	2.89	83.95
6	0.45	50	4922	2.44	84.09
7	0.43	54	5380	3.49	95
8	0.44	42	4955	3.21	120.02
9	0.3	53	6125	2.25	176.4
10	0.36	48	4615	3.34	92.1
11	0.18	58	6895	5.29	154.3
12	0.19	56	6615	5.38	148
13	0.12	61	7943	6.54	154.3
14	0.51	40	2823	1.02	35
15	0.14	61.8	5729	9.23	144.2
16	0.54	43	4635	1.39	113.9
17	0.52	38	3268	0.89	48.08
18	0.25	56.7	5491	6.93	125
19	3.48	27.63	5670	2.98	24.32
20	0.87	32.4	6112	7.23	50.34
21	6.1	31.47	5521	7.79	44.78
22	0.5	31.66	5685	2.45	100.09
23	0.37	52	6503	3.12	170.94
24	4.52	54.18	4522	9.59	89.54
25	0.46	46.3	5445	3.48	125
26	0.25	45	5950	3.12	175.43

27	3.49	27.38	5790	3.02	25.37
28	1.54	34.96	5980	0.86	69.7
29	0.39	47	5506	2.31	155
30	8.39	51.22	3935	5.8	69.2

3. Materials and Methods

3.1. Principles of the Used Models and Research Process

3.1.1. Decision Tree

To break down a set of independent variables into progressively more homogeneous regions, a decision tree (DT) with decision rules (Teimouri and Ghatee 2020). The primary goal of DT is to investigate decision rules for predicting a result given a group of inputs. Regression trees and classification trees are the names given to DT depending on whether the target variables are continuous or discrete. Many studies have shown that DT can be utilized successfully for prediction and/or classification in a variety of real-world settings.

The greatest strength of DT is its ability to model intricate connections between preexisting variables. By taking the data distribution into account, DT models can accommodate both continuous and categorical variables without imposing any restrictions. A DT may be constructed quickly and easily, and the resulting models are clear and easy to comprehend. Additionally, DT is able to supply all-inclusive, perfect data on the relative importance of input parameters. However, DT has two drawbacks: the lack of output qualities and the susceptibility to noisy inputs (Teimouri and Ghatee 2020).

ID3, CART, C4.5, and Chi-squared Automatic Interaction Detection (CHAID) decision tree are only a few of the many methods developed by various researchers to build DT models. One can find both internal and external nodes in a tree structure, in addition to the obvious root node. The former is made up of everything that will be fed into the system. Each decision node within the network can hold two or more internal branches. The result of one given input vector is displayed at the level of each leaf node.

DT modeling entails two phases: tree construction and pruning. The first stage involves locating the input variable to use as the DT root node with the highest gain ratio. The training dataset is then partitioned using the root values as a criterion for creating sub-nodes. All possible values for a discrete input variable are represented by a child node in the tree. whereas the threshold finding procedure creates two sub-nodes based on a threshold in the case of continuous input variables. After that, the gain ratio is calculated for each child node, and this process is carried out one level at a time until all instances included within a given node are of the same type. Leaf nodes are nodes that are assigned the label "class value" and are considered to be at the top of the classification hierarchy.

It is often necessary to trim a tree that has been constructed in order to improve its classification accuracy for fresh data if it has too many branches due to an over-fitting problem. There are two distinct types of tree pruning: pre- and post-pruning. The previous type of algorithm stops growing the tree after a certain criterion is fulfilled, while the latter type forms the entire tree first and then replaces the ending subtrees with leaves based on an error comparison between the tree's state before and after replacing subtrees. Figure 1 illustrates a view of DT process for this research.

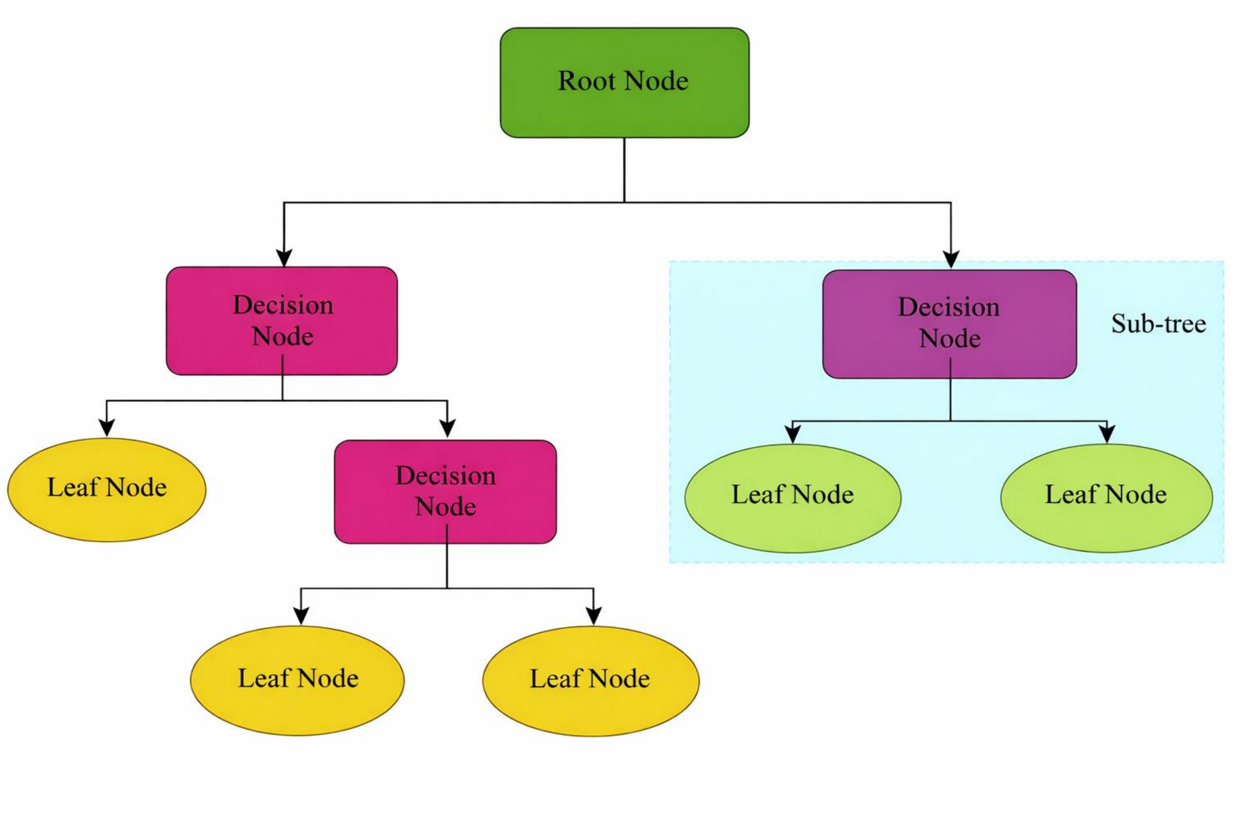

Figure 1. Flowchart of DT.

3.1.2. AdaBoost

By adaptively allocating weights across the training data, AdaBoost picks a set of classifier instances in an iterative fashion, making it an efficient method for ensemble learning. In order to create an ensemble, this algorithm linearly integrates the chosen classifier samples. AdaBoost-based ensembles rarely exhibit over-fitting even when multiple base classifier instances are used in the model. These ensembles minimize a loss function that increases exponentially by fitting a series of additive models. Minimizing classification error implies optimizing a non-differentiable, non-smooth cost function, which can be best approximated by an exponential loss. This means that AdaBoost is effective in solving a wide variety of classification issues.

AdaBoost modifies the normality of the training set. Let εt denote misclassifying rate on trial t; under these circumstances, the misclassified sample weights in the training set are adjusted by a factor $\beta t = (1 - \varepsilon t)/\varepsilon t$.

The aggregate of the recalculated weights is then normalized to 1. Based on the weighted voting, a combination of the classifiers C1,...,Ct is generated, with Ct weighted by log (βt). If εtN0.5 is less than 0.5, the trials will stop and trial T will be set to t1. If, however, εt =0 (representing perfect accuracy), then the T trial is renamed to t. AdaBoost ensures that the freshly generated ensemble classifiers give their full attention to the 'harder' cases during this procedure. Each classifier's performance is taken into account when determining the final labels. This work use DT to build AdaBoost, with trees built using the entropy gain ratio. Figure 2 gives an overarching overview of the AdaBoost algorithm.

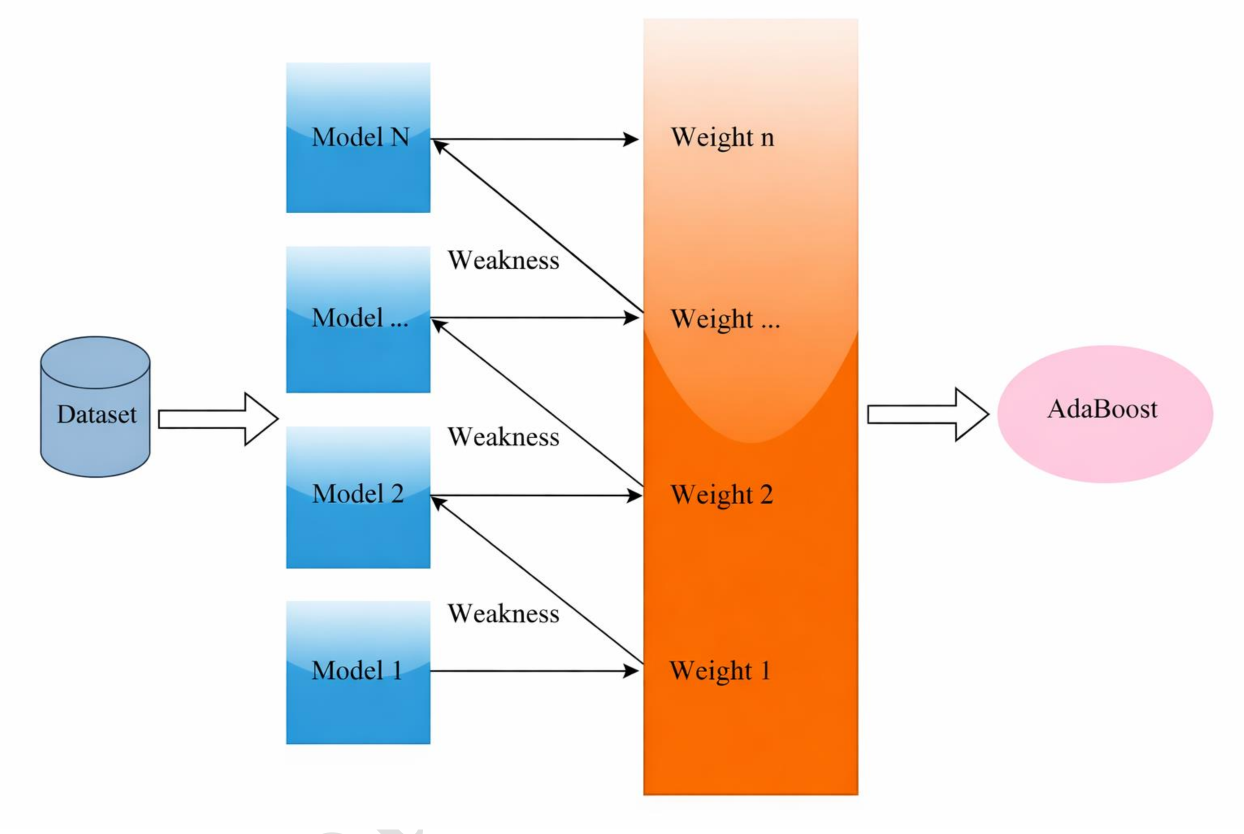

Figure 2. Flowchart of AdaBoost.

3.1.3. Random Forest

Random forests (RFs) are created by a collection of classifiers learned from a varying training set via the bagging technique (Asteris et al. 2021; Mohammed et al. 2021; Yang et al. 2025). In order to generate new training sets, this method randomly resamples the original data set n times with replacement. That is to say, the freshly selected sample will remain a part of the pool for the subsequent draw. This results in certain training samples being chosen multiple times, while others aren't chosen at all for a new set. To put it another way, bagging taps on a classifier instability to increase classification accuracy by decreasing the standard deviation of mistakes. Un this context, "instability" suggests that significant shifts in accuracy might result from even a small change in the training samples. When combining classifiers, a majority vote is used, with each classifier's vote being given equal consideration. In the event of a deadlock, a resolution is reached in accordance with established procedures or at random. Using the impurity Gini index, RF constructs several trees at once (Matin et al. 2018). Despite the fact that at each forking point RF randomly selects a portion of the input features (bands), the tree can expand without any intervention. Keep in mind that RF requires no trimming and only uses a subset of the input data, making it computationally lightweight. The computation time grows exponentially with $T\sqrt{M}N\log(N)$ (T, N, and M are the number of trees, training samples, and bands used in each split, respectively). Also, an out-of-bag technique can be used if a dedicated test set is unavailable. Three-and-a-half percent (33%) of samples from a freshly generated training set are arbitrarily removed, becoming the out-of-bag (OOB) samples. The remaining ones, known as in-the-bag samples, are applied during the tree procedure. Votes are tallied whenever a sample is classified as one of the out-of-bounds (OOB) types for the purpose of accuracy prediction. The majority vote decides the ultimate classification. When a decision needs to be made, just 33% of the artificial trees can cast a ballot. Predictions of OOB errors have been shown to be impartial in a number of experiments. The method has little to no bearing on the features used in each split. The ensemble classifiers' combined verdicts are arrived at using the majority vote method. Breiman's research provides a thorough description of the RF. A similar summary is provided by Gislason et al. (Figure 3).

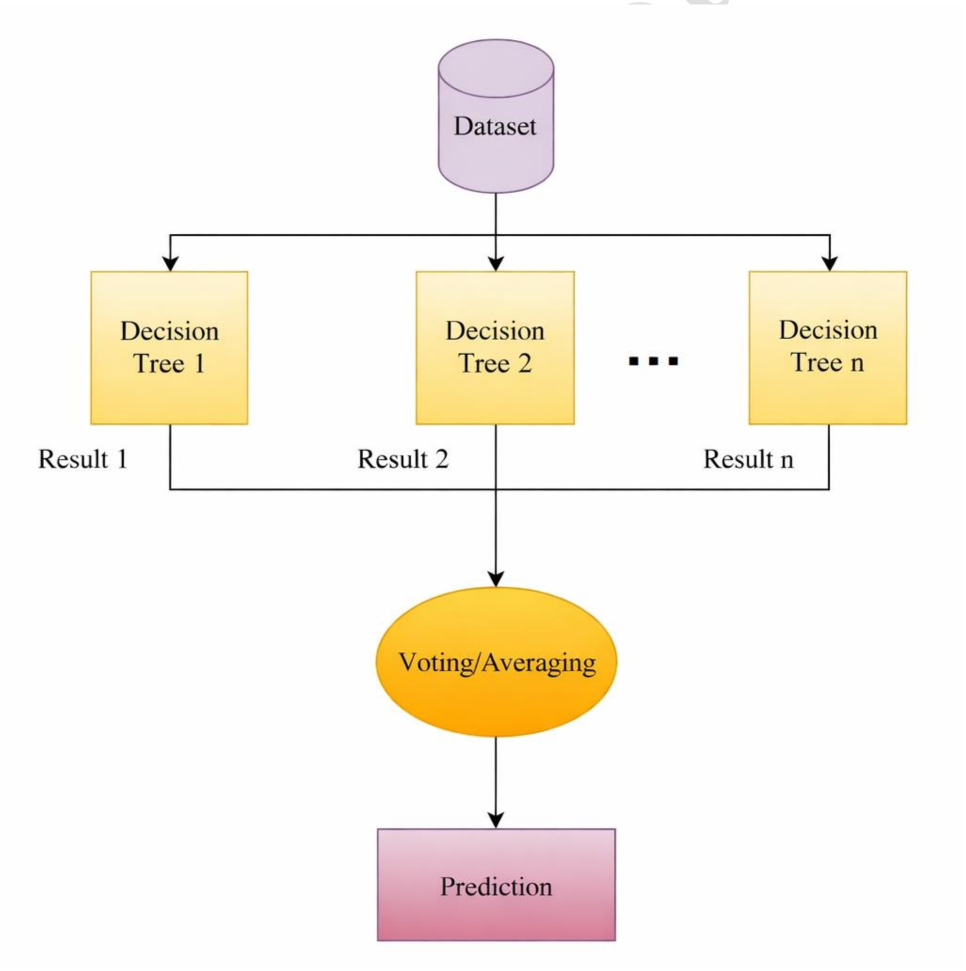

Figure 3. The RF process.

3.1.4. The k-Nearest Neighbors

Most machine learning experts agree that k-nearest neighbors (kNN) is a slack algorithm. First, the kNN algorithm stores all of the data it has read, and then, using distance functions, it makes predictions about new data. The primary goal of kNN is to compute a numerical target by averaging the values of k's nearest neighbors (Zhang et al. 2023) . On top of that, the inverse distance weighted average is used for this distance calculation. kNN uses the following three distance functions to calculate neighbor distances for regression-related tasks:

$$\text{Euclidean function: } \sqrt{\sum_{i=1}^{f}(x_i - y_i)^2} \quad (1)$$

$$\text{Manhattan function: } \sum_{i=1}^{f}|x_i - y_i| \quad (2)$$

$$\text{Minkowski function: } \left(\sum_{i=1}^{f}(|x_i - y_i|)^q\right)^{1/q} \quad (3)$$

where q presents the order between x and y points, and xi and yi donate the ith dimensions of x and y points, respectively. The whole process of KNN for this study was shown in Figure 4.

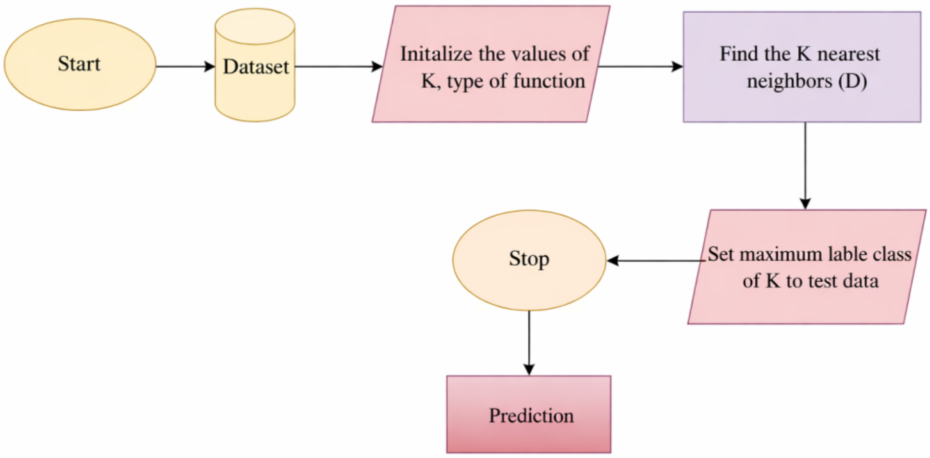

Figure 4. KNN process of current research.

3.2. Research Process

In order to create accurate models for predicting the compressive strength of cement-based mortars, the current work amassed 170 laboratory data from the previous studies (Mahmoodzadeh et al. 2021). The significance of each parameter was evaluated, and their interplay was established, once the data was analyzed. The data was arbitrarily separated into testing and training sets. The smart models were created with the help of the training data (which accounted for 80% of the total data), and their performance was assessed with the help of the testing data (which accounted for 20% of the total data). Five different ML models were developed in this study to predict UCS of rock samples. Parametric analysis is ideal for achieving the unique characteristics of each AI model. Finally, the proposed models were compared, and the model's efficacy, practicality, and ease of use as a predictive tool for UCS were demonstrated (Figure 5).

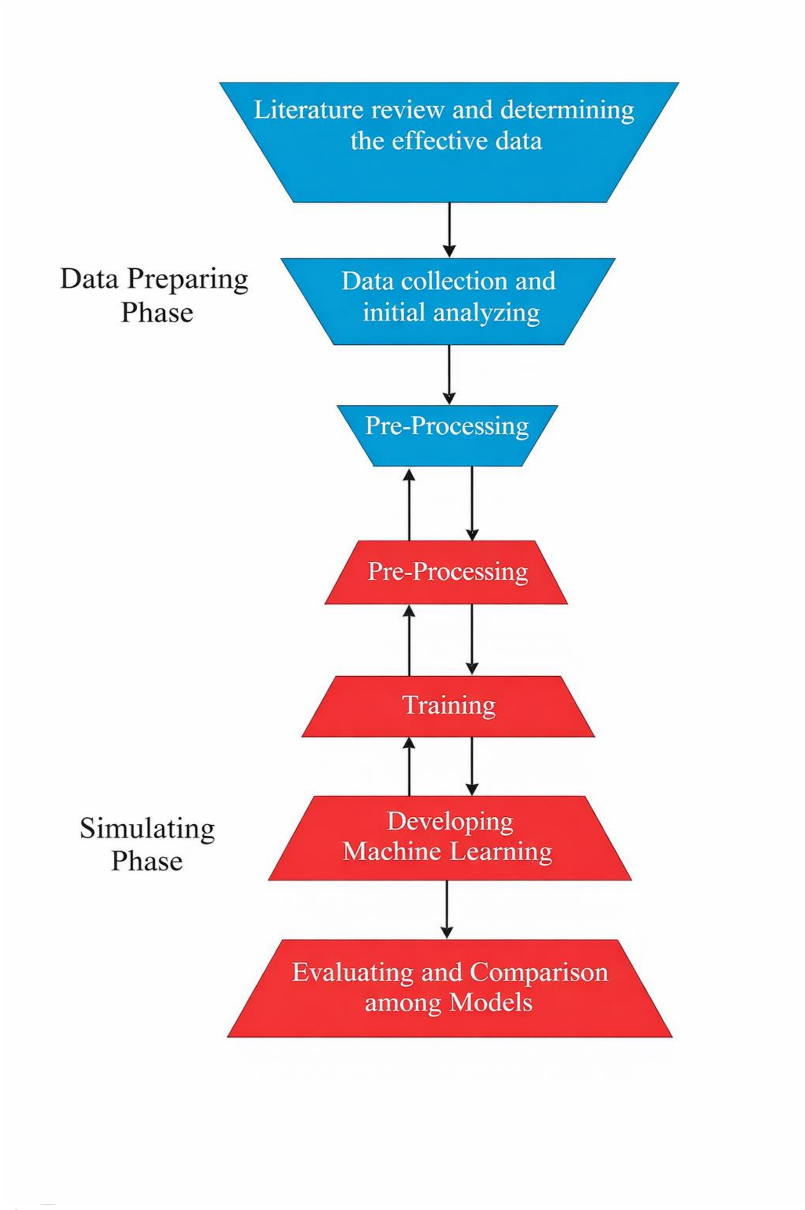

Figure 5. The general process of current research.

4. Methodology and results

4.1. Performance Indices

For both the created model and the equations from the literature, evaluation statistics such as the root mean square error (RMSE), mean absolute percentage error (MAE), and coefficient of determination were utilized (R^2). Better prediction outcomes are indicated by smaller RMSE and MAE values and a higher R^2 value, which shows a tighter fit between the analytical and forecasted values (a unit value indicates a perfect fit) (M. Kumar et al. 2024). The following formulas (Fakharian et al. 2025; Fattahi et al. 2025; Ziaie et al. 2026) have been used to derive the aforementioned statistical parameters:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \quad (7)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - y_i| \quad (8)$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}\right) \quad (9)$$

where x_i and y_i show the predicted and target values, respectively, and n indicates the total number of datasets.

4.2. Preparing data

One of the primary and important steps that has a significant impact on the performance of machine learning models is data preparation. Considering that the collected data has different distributions, with the preliminary analysis, the data that do not have favorable conditions can be excluded from the data set in order to obtain better results. Here, the data of this research is divided in the first stage by four different methods to find inlier and outlier data. Considering that each method has a specific criterion for finding outlier data, it has been tried to select the best conditions and then examine their performance by linear regression. The results of these four methods have been analyzed using cross validation and the number of folds 10. As seen in Table 4, the results of the isolation forest model have provided better performance. For this reason, the data of this method is further used by machine learning models to predict UCS parameters.

Table 4. Performance of linear regression model with different methods of determining outlier data.

Method	Number		Linear regression	
	Outliers	Inliers	R^2	RMSE
One class SVM	17	153	0.668	28.213
Covariance Estimator	17	153	0.66	28.655
Local Outlier Factor	7	163	0.685	28.293
Isolation Forest	17	153	0.728	26.07

4.3. Methodology Adopted

Our objective here is to employ cutting-edge methods in order to address difficult, nonlinear issues. Artificial intelligence (AI) based computing approaches have been regarded as a replacement for traditional statistical methods due to their greater adaptability and fewer restrictions. KNN, RF, DT, and AdaBoost models were among those used in this study. Because of their unique foundations, the various AI approaches now provide a wide variety of problem-solving capabilities. Since this research aimed to obtain prediction models for UCS of rock samples, a number of structures were built. Analyzing the models' structures and determining their parameters helps improve their performance. The results were compared using four different statistical indices: mean absolute error (MAE), root mean squared error (RMSE), and correlation coefficient (R^2). Model quality can be evaluated and compared using these metrics with reasonable precision.

Next, we'll look at the structural design of each model and analyze its attributes. When building SC and AI models, we first assess the data we'll be using, and then we exclude everything that isn't highly connected to other data we've already used. The best quality of each model is obtained by iterative training and data rectification in order to forecast the UCS of rock samples. If the necessary requirements are met, the test data is delivered to the models so that they can evaluate how well they function in the new setting.

4.4. Results and Discussion

According to the claims, five AI models were created to foretell the UCS of rock samples. A total of 153 datasets were gathered and used for simulation based on the information presented above. To create the models, we used around 80% of the data, and we used the other 20% to test how well the models worked. Table 5 summarizes the best aspects of each created model and presents them after a random data split and parametric analysis.

Table 5. Developed models for predicting UCS values in rock samples.

Models	Parameters	Optimum Parameters
KNN	Number of Neighbor	2
	Function Type	Minkowski
Random Forest	Number of Trees	6
	Split subset limit	> 5
Decision Tree	Min. number of instances in leaves	2
	Split subset limit	>8
	Max. tree depth	5
AdaBoost	Base estimator	Tree
	Number of estimator	10

We employed statistical indicators to compare the accuracy of predictions made by four different AI models. The model findings for UCS of rock samples are shown in Table 6. Each model's results are indicative of its abilities. Tree-based models (including RF and AdaBoost models) typically perform better than other models in terms of accuracy. R^2 values of 0.9546 and 0. 9631 for the RF and AdaBoost models on the training data are achieved. Evaluations using test data reveal that these models continue to perform at the highest levels, with R^2 values of 0.9271 for the RF model and 0.9326 for the AdaBoost model. The simulation appears to be reasonably accurate and adaptable to fresh data. Figures (6–13) show the results of using the four AI models to estimate the UCS of rock samples for training and testing data, respectively.

Table 6. The results of developed models.

Section	Model	MAE	RMSE	R^2
Training	KNN	8.366	13.077	0.9328
	RF	6.338	10.653	0.9546
	DT	8.656	11.699	0.9461
	AdaBoost	3.684	9.781	0.9631
Testing	KNN	10.469	16.864	0.8913
	RF	9.769	13.842	0.9271
	DT	12.493	16.346	0.9028
	AdaBoost	9.656	13.234	0.9326

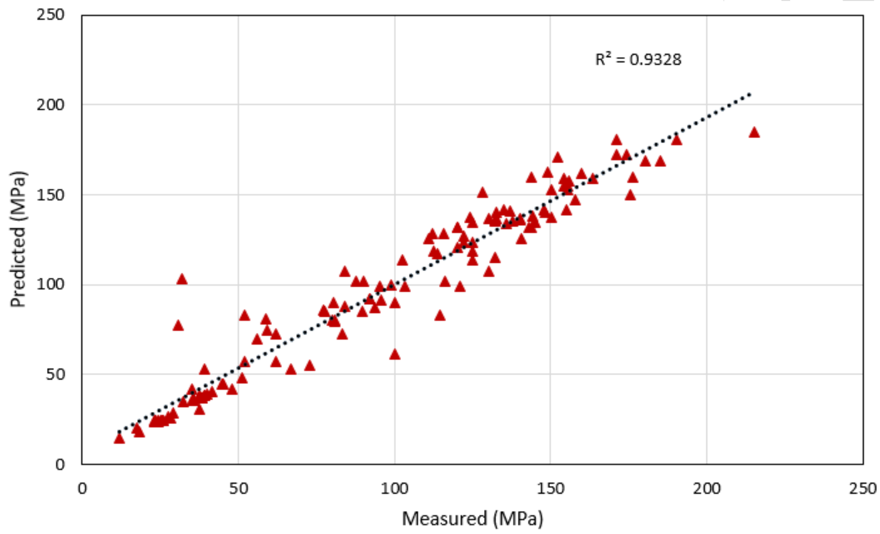

Figure 6. The of training data for KNN model.

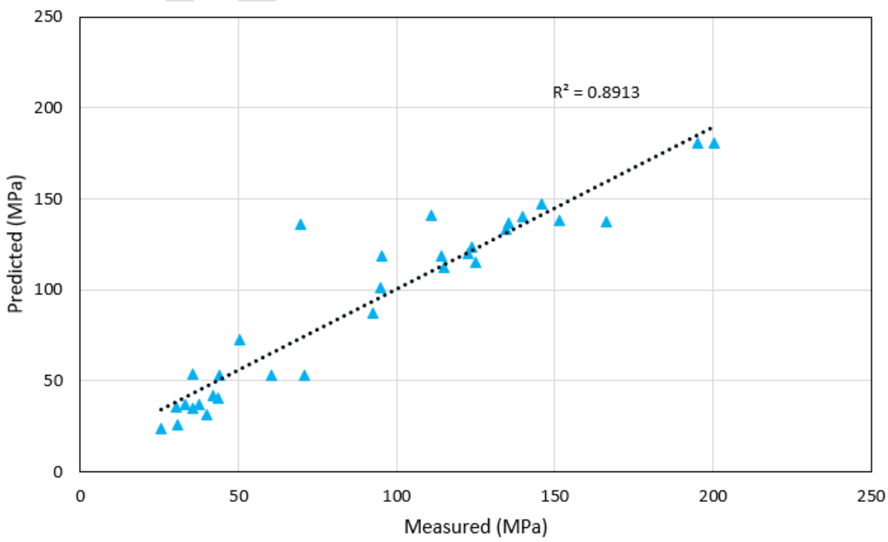

Figure 7. The testing data for KNN model.

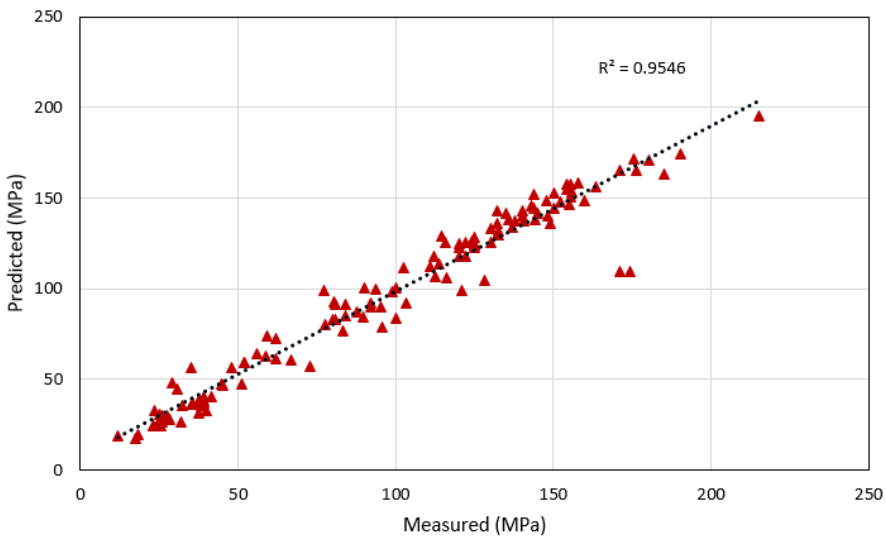

Figure 8. The training data for RF model.

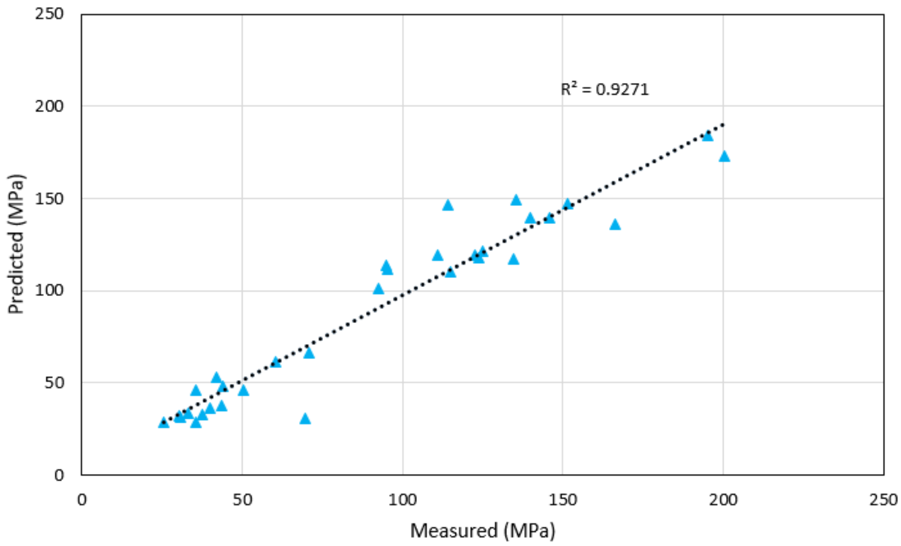

Figure 9. The testing data for RF model.

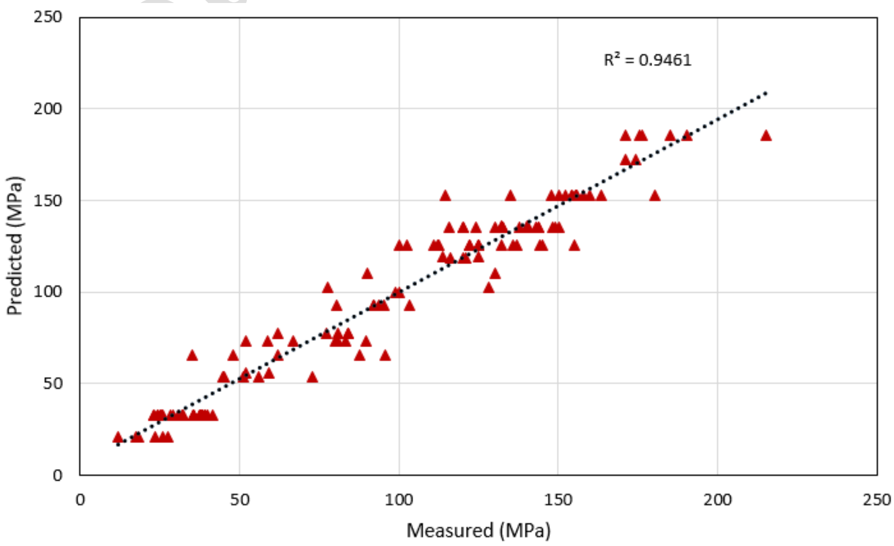

Figure 10. The training data for DT model.

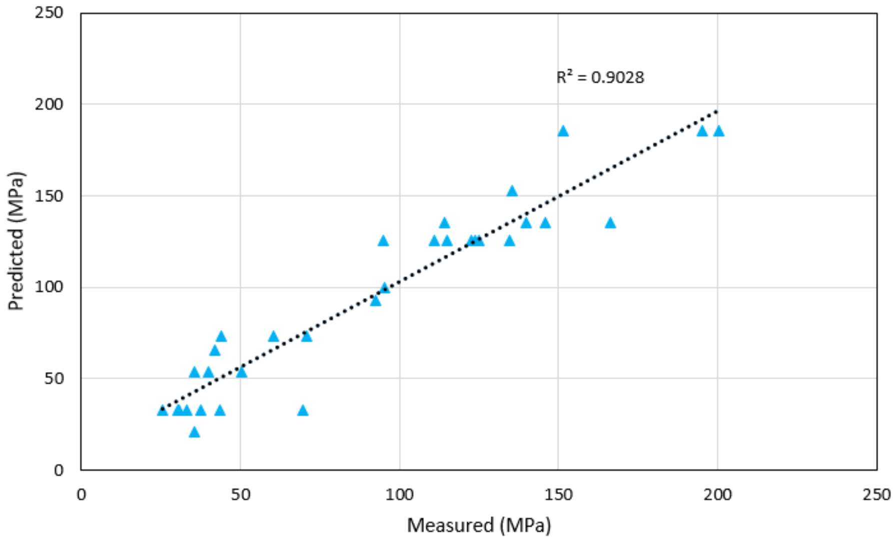

Figure 11. The testing data for DT model.

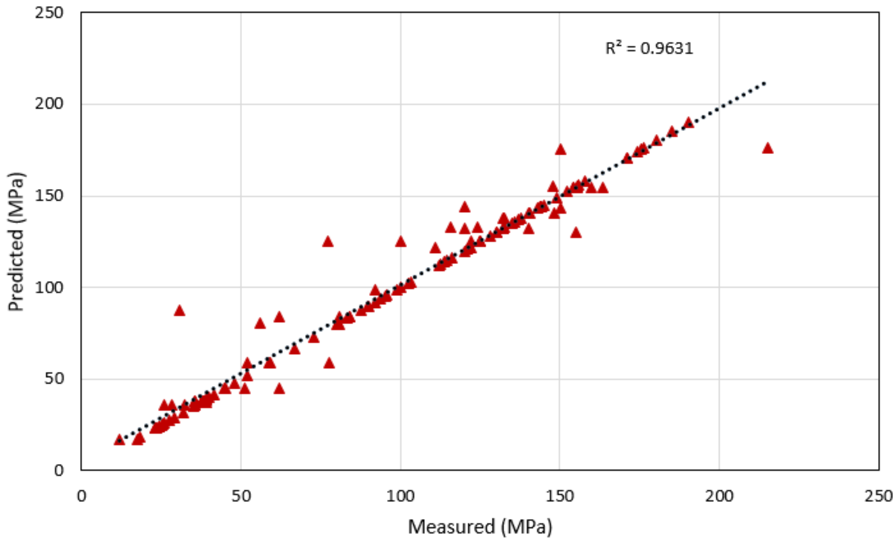

Figure 12. The training data for AdaBoost model.

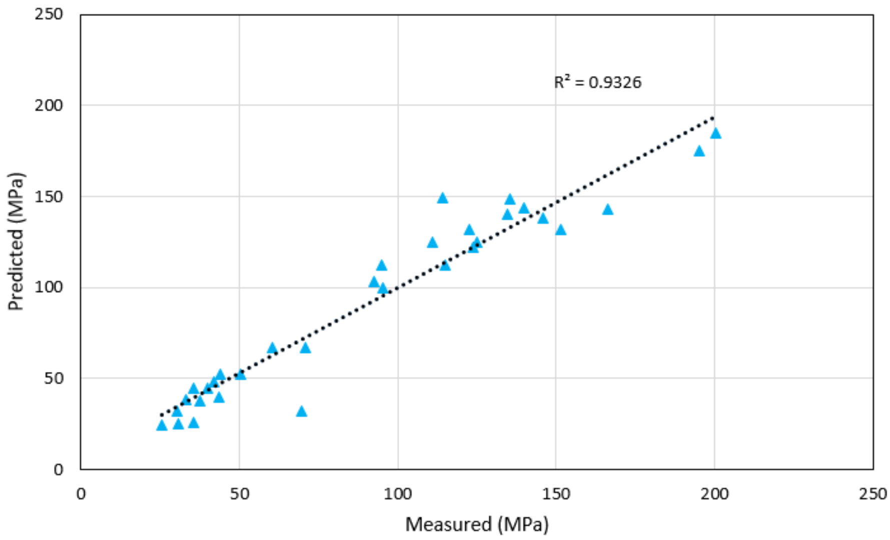

Figure 13. The testing data for AdaBoost model.

Figures 14 and 15 show the error between the actual value and the prediction of the developed models for UCS. As can be seen, between the different models, there are data with more error. However, it is possible to identify the error values and ranges where there are more error values, and analyze them more accurately for different engineering designs. In general, the data with more error values are observed in the data of the training section, while in the testing section, the data with more error occur almost for the four predictive models in the same samples. In general, Adaboost and RF models have the best performance among other models, and the difference between actual and predicted values is less, which indicates the high accuracy of the models.

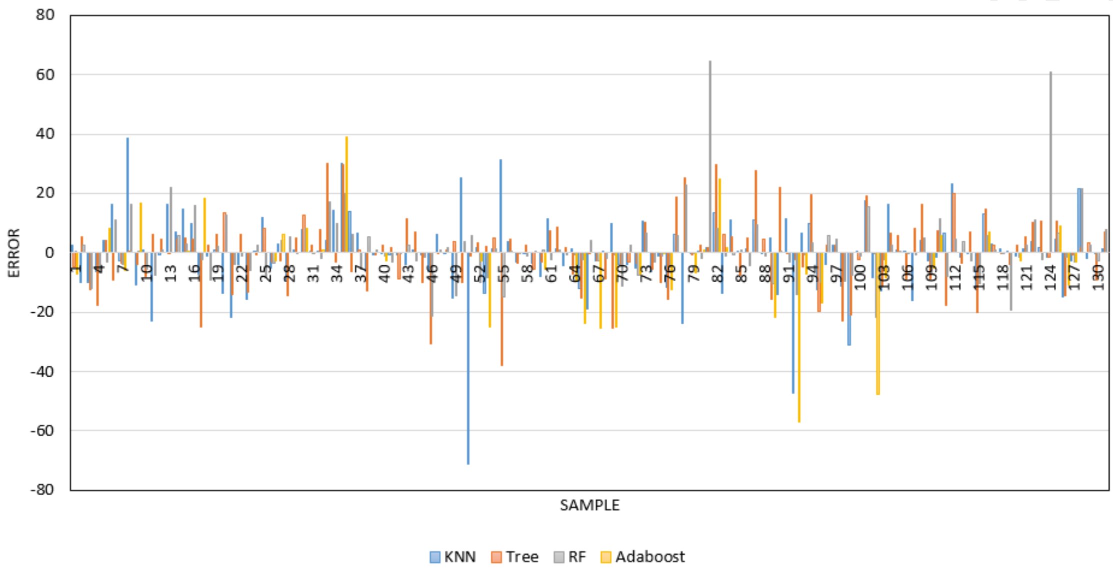

Figure 14. The error of results for the training section.

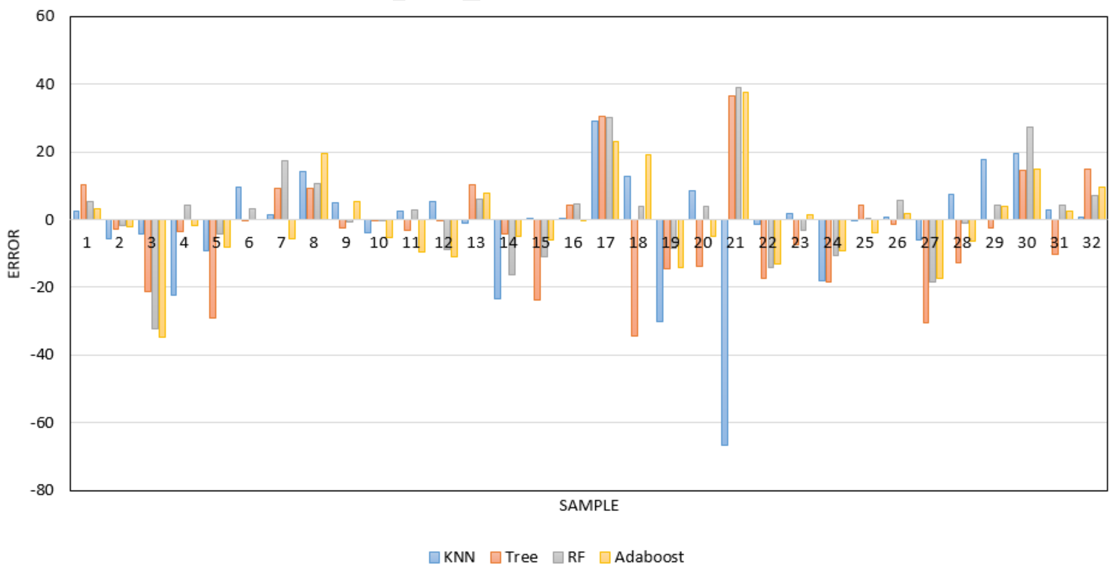

Figure 15. The error of results for the testing section.

Figures 16 and 17 present the changes of the actual and predicted values by the two top models for the training and testing data. It can be clearly seen in these figures that the two top models, Adaboost and RF, predict the trend of data changes with acceptable accuracy. In Figure 16, the Adaboost model has smoother changes than the RF model and evaluates the UCS values of rock samples from low to high strength ranges with almost significant accuracy. It should be mentioned that the RF model also has a good evaluation of the UCS trend, except for the resistances above 150 MPa, which presented irregular changes from the prediction. The models in Figure 17 were examined considering the testing data. As can be seen, they generally provide an acceptable assessment of the models, except for data numbers 14 and 20, and there is a close correlation between the actual and predicted data for the UCS values.

Finally, using two methods, Pearson and Spearman, the importance of parameters was investigated in this study. The results of this invistigation are given in Figure 18. As can be seen, in the Pearson method, parameter Schmidt hammer number (SHN) has the most influence, with a value of 0.71, then parameter porosity (n) with a value of -0.67, and parameter P-wave velocity (Vp) with a value of 0.62. While in the Speaman method, parameter porosity (n) has the most influence. However, in both models, parameter point load index (Is(50)) has the least influence on UCS prediction.

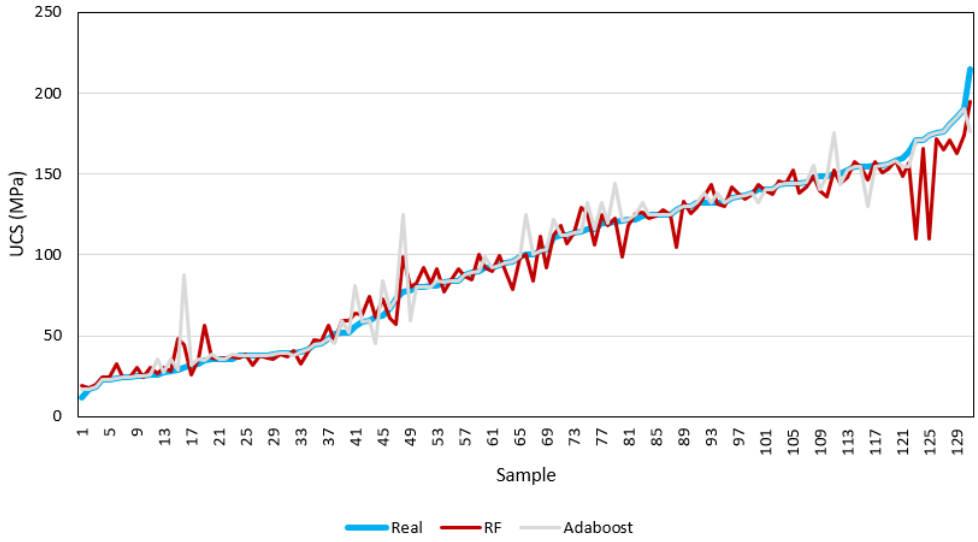

Figure 16. The UCS prediction of the selected models for the training section.

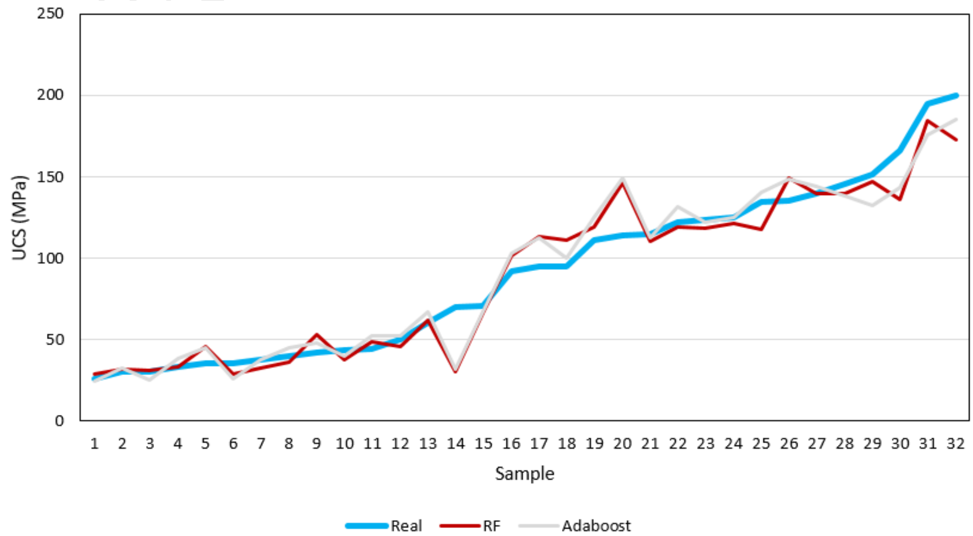

Figure 17. The UCS prediction of the selected models for the testing section.

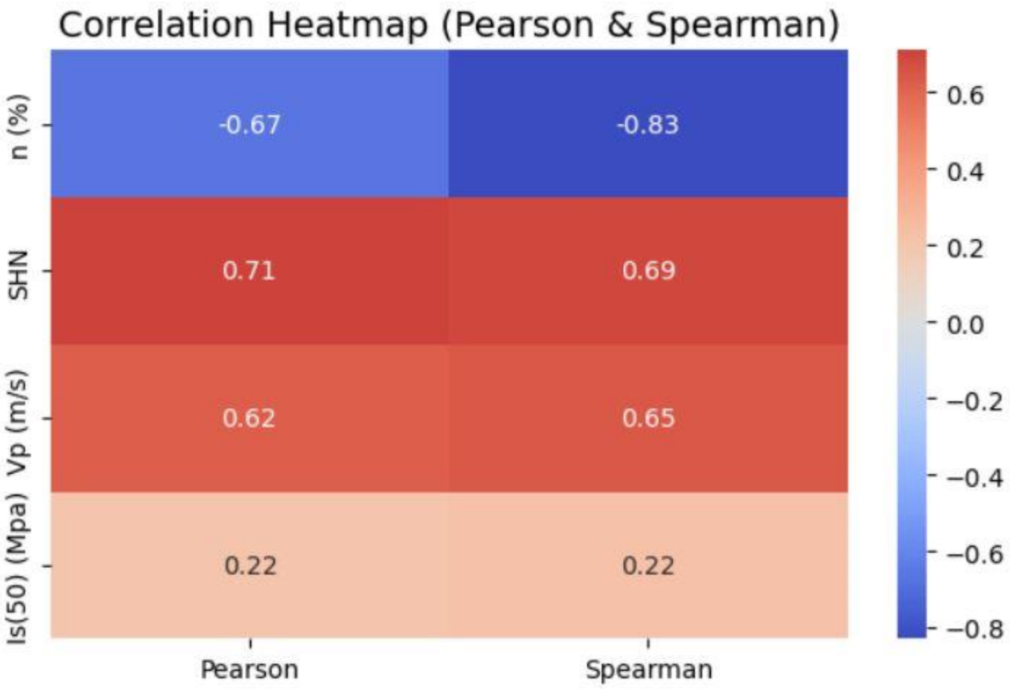

Figure 18. The importance of 4 parameters

5. Limitations and Future Works

One of the limitations in this study is related to the number of datasets. It is important to propose a model that is generalized enough to solve the same problem for different types of rocks. This needs a comprehensive database comprising of different types of rocks with other parameters of tests results available. In this way, we can cover a wider range for our inputs to predict a larger number of UCS samples. It is also possible to generate different data using different methods, such as analytical formulas, empirical formulas, and numerical model development. These methods can be useful in some cases where more detailed and sensitive investigation is required. However, each method must be implemented with high sensitivity and accuracy analysis. The models themselves can also be improved with replacing other and newer models that potentially are able to provide a higher level of accuracy and applicability.

The modeling process and results of the present work may be useful for researchers, designers, and engineers interested in assessing the UCS of rock samples and devising novel eco-efficient compositions for widespread application in civil engineering. The inability to get the optimal structure through various analyses is a major flaw in the models used in this study. It is recommended that optimization strategies be used in the future to fine-tune the model weights. In addition to lowering mistake rates, this has the potential to enhance existing models and inspire the creation of whole new ones.

6. Conclusions

This study introduces an innovative and complementary approach to determining the uniaxial compressive strength (UCS) of rock samples, one that makes use of models inspired by artificial intelligence (AI). In order to determine the UCS of rock samples, 170 datasets were culled from the aforementioned literature. The database in question includes the input parameters of Schmidt hammer number (SHN), P-wave velocity (Vp), porosity (n), and point load index (Is(50)), UCS as an output parameter.

By examining different machine learning methods, in this study, 4 different models RF, DT, KNN, and adaboost were implemented to predict the UCS parameter of rock samples. In the first step, the best conditions were obtained from the data set using the data preprocessing method and 4 different outlier data techniques. Then, these data were used to develop 4 machine learning models. Each model has effective parameters that were optimized separately for each model and the results of the models were compared with each other. The results of the best models for predicting the UCS parameter of rock samples were obtained for the two training and testing sections with R^2 values of (0.9631 and 0.9326) for the Adaboost model and (0.9546 and 0.9271) for the RF model, respectively. These models have provided high accuracy for predicting the UCS parameter. Finally, using the two Pearson and Spearman methods, the most effective parameters, which were Schmidt hammer number (SHN) and porosity (n), were identified. This research can be implemented as a new methodology that combines the impact of data preprocessing and new machine learning models for other engineering problems.

Conflict of interest

The authors declare no competing interests.

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