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The gene expression programming method for estimating compressive strength of rocks

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Abstract. Uniaxial compressive strength (UCS) is a critical geomechanical parameter that plays a significant role in the evaluation of rocks. The practice of indirectly estimating said characteristics is widespread due to the challenges associated with obtaining high-quality core samples. The primary aim of this study is to investigate the feasibility of utilizing the gene expression programming (GEP) technique for the purpose of forecasting the UCS for various rock categories, including Schist, Granite, Claystone, Travertine, Sandstone, Slate, Limestone, Marl, and Dolomite, which were sourced from a wide range of quarry sites. The present study utilized a total of 170 datasets, comprising Schmidt hammer (SH), porosity (n), point load index (Is(50)), and P-wave velocity (Vp), as the effective parameters in the model to determine their impact on the UCS. The UCS parameter was computed through the utilization of the GEP model, resulting in the generation of an equation. Subsequently, the efficacy of the GEP model and the resultant equation were assessed using various statistical evaluation metrics to determine their predictive capabilities. The outcomes indicate the prospective capacity of the GEP model and the resultant equation in forecasting the unconfined compressive strength (UCS). The significance of this study lies in its ability to enable geotechnical engineers to make estimations of the UCS of rocks, without the requirement of conducting expensive and time-consuming experimental tests. In particular, a user-friendly program was developed based on the GEP model to enable rapid and very accurate calculation of rock's UCS, doing away with the necessity for costly and time-consuming laboratory experiments.

Keywords: gene expression programming; machine learning; uniaxial compressive strength; user-friendly software

1. Introduction

Fracture mechanics provides insights into the behavior and failure mechanisms of materials under different loading conditions, which is crucial for designing safe and reliable structures (Li *et al.* 2023, Jia *et al.* 2023, Wang *et al.* 2023, Huang *et al.* 2021). Understanding fracture mechanics helps engineers and researchers assess the structural integrity of materials and predict their failure under different stress scenarios (Wang *et al*. 2024). By studying fracture mechanics, we can determine the critical stress levels at which materials start to crack and propagate, allowing us to design structures with appropriate safety factors (Liu *et al.* 2023, Zhang and Zhang 2023). Rock mechanics and rock engineering are indeed crucial fields within fracture mechanics (Yao *et al.* 2023). Understanding the mechanical properties of rocks is essential for several applications (Ren *et al*. 2023, Liu *et al*. 2021a).

The significance of uniaxial compressive strength (UCS) in rock and geotechnical engineering cannot be overstated (Yu *et al*. 2021, Ren *et al*. 2022a, b, Xu *et al*. 2022). Its role in preliminary and final design stages is vital for ensuring the stability, safety, and success of various engineering projects. Direct methods for determining the UCS in the laboratory are not known to be efficient in terms of time and money (Mahdiyar *et al*. 2019). Further, it is difficult to provide the necessary exposure to a sufficient number of well-formed samples in rocks that are either readily broken or severely worn (Asheghi *et al*. 2019).

Soft computing methods such as machine learning and deep learning have revolutionized various engineering applications and have proven to be powerful tools for solving complex problems (Shahani *et al*. 2021, Kidega *et al*. 2022, Shi *et al*. 2023, Tie *et al*. 2023, Long *et al*. 2023).

These methodologies wield the prowess to sift through vast troves of data, discern intricate patterns, and render precise prognostications or determinations (Liu *et al.*

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2021b, Su *et al*. 2023).

After comparing the UCS estimation accuracy of the fuzzy model with the multiple regression analysis method, Alvarez Grima and Babuska (1999) found that the UCS is more accurately predicted by the fuzzy model. Many scientists use various regression models and artificial neural networks (ANN) to estimate the UCS of clay-bearing rocks, like Travertine, Carbonate, Schistose, and Sandstones. They discovered that the ANN-based models provide more accurate predictions than the standard statistical methods. Gultekin *et al.* (2013) calculated UCS using multiple regression (MR), ANN, and adaptive neuro fuzzy inference system (ANFIS) techniques across three models and five datasets, and found that the ANFIS approach was the most robust model. Additional research demonstrates that when comparing the accuracy of anticipated UCS using different soft computing methods, ANFIS performs the best. Comparatively, the UCS network prediction accuracy of the generalized neural network regression models revealed by Singh et al. (2013) was much higher than that of the ANFIS model. In addition, it was shown that the AI model coupled with the metaheuristic optimization method was even more foreseeably accurate (Hosseini and Khaled 2014). UCS predictability may be improved by combining particle swarm optimization with the ANN model developed by Momeni *et al.* (2015). To better predict UCS, Asheghi et al. (2019) proposed a model that combines ICA and GFFN (ICA-GFFN) and found that their combined model was a dependable and practical option. It has been determined via sensitivity analyses that rock class and P-wave velocity (V_p) are, respectively, the least and most important factors on the UCS prediction.

Previous research has consistently demonstrated that soft computing methods yield more accurate predictions of UCS compared to traditional methods. Nevertheless, a notable constraint of these methodologies lies in the fact that the correlation between input variables and output outcomes frequently lacks a deterministic mathematical structure. Consequently, these techniques are deemed less intuitive and graspable when juxtaposed with regression-based models and empirical formulas. This lack of transparency and interpretability has led to the term "black box" being used to describe these approaches.

While numerous computational approaches have been studied for forecasting the UCS parameter, some of these methods have not been employed at all or are only used rarely. Therefore, the predictability of other computational approaches should be carefully considered in order to anticipate the UCS parameter. In this work, 170 separate datasets representing various kinds of rock are used in conjunction with the gene expression programming (GEP) technique to make predictions for the UCS parameter. The most influential factors on the UCS are taken into account, as determined by prior research and current knowledge. Using the available data, the GEP model's hyperparameters are tuned during training to provide the most accurate predictions. The UCS estimation equation based on ML techniques is another target of this research. The GEP technique may compute the equation for the trained model.

This is the first time an equation using the GEP approach has been produced to estimate the UCS parameter, as far as the reader is aware.

2. GEP

The GEP method, inspired by natural selection and evolution, is a technique for developing computational and mathematical models. It utilizes a dataset described in Ferreira's work (2006) to generate tree-like solutions. The GEP technique aims to improve upon previous approaches, such as genetic algorithms (GA) and genetic programming (GP), in determining how to pass on features. Unlike the GP algorithm, the GEP algorithm ensures the long-term health of child chromosomes through various genetic operators (Ferreira, 2006), successfully surpassing both the Replicator and Phenotype thresholds in natural evolution processes. In this method, a function represents a relation between multiple variables and can be effectively expressed using algebraic operators (*, -, /, +) and other functions. The connections between different factors are crucial. The GEP technique starts by generating a population of linear chromosomes and then establishes a connection between variables a, b, and y. Each gene on these chromosomes may include one of the variables. The fitness of each chromosome is evaluated using an expression tree (ET) that represents the chromosomes, similar to how a protein functions in a normal cell (Ferreira 2006). Utilizing Ferreira's Karva language, each chromosome yields a mathematical equation (program), thereby birthing extraterrestrials (ETs). By subtracting and recording the values of y for different values of a and b, the fitness of the equation is assessed. The goal is to minimize the gap between the calculated value of y and the true values. In the inaugural generation, the fitness of every chromosome undergoes assessment, dictating the subsequent generation's value based on the fitness it contributes to the population at large. The most fit individuals from each generation are passed on to the next (Ferreira 2006). The succeeding generation inherits chromosomes from the present one, encompassing both functional and nonfunctional variants. Mutations can activate previously inactive regions of genes, leading to changes in the offspring. The development of a GEP algorithm involves defining the fitness function, establishing terminology and operational descriptions, examining the genetic makeup of the chromosomes, and setting the goal of establishing connections. Once the characteristics of the operators are determined, the algorithm can be built (Ferreira 2006). The progression toward the next generation entails employing the Roulette Wheel method, wherein a chromosome is randomly selected on each iteration. This selection process favors better-rated chromosomes, mimicking nature's random selection process.

The genes of the current generation are passed on to the next, maintaining a constant average number of chromosomes. Restructuring can then take place, determining the order in which genetic operators are applied to the chromosomes. By generating and evaluating new generations of chromosomes, the algorithm approaches the optimal equation of interest. If there is no improvement after a certain period, the number of

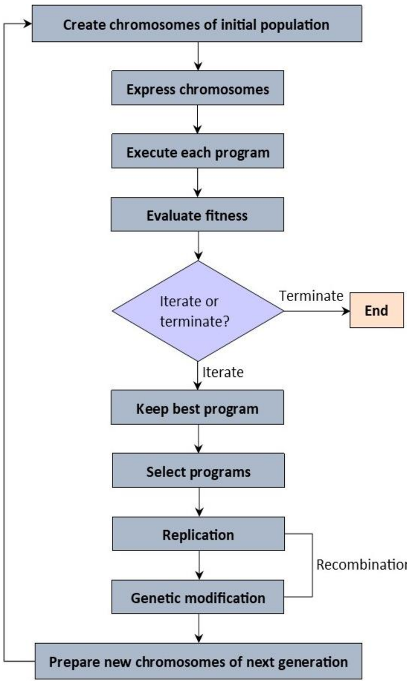

Fig. 1 The flowchart of a GEP algorithm (Ferreira 2006).

iterations can be limited. The GEP process is summarized in Fig. 1.

In terms of generality, GEP can be considered a general-purpose machine learning method. GEP is capable of solving a wide range of problems, including regression, classification, time series prediction, and optimization. This versatility is due to its ability to evolve programs in the form of symbolic expressions, which can represent complex relationships and decision-making processes. Compared to other machine learning paradigms, such as neural networks or support vector machines, GEP has the advantage of being able to automatically discover the structure of the models it evolves. This means that GEP can handle problems where the underlying relationships are not well understood or difficult to model explicitly. Additionally, GEP can handle both numerical and symbolic data, making it suitable for problems involving both continuous and discrete variables. This flexibility allows GEP to be applied to a wide range of domains and problem types. However, it's worth noting that the generality of GEP does not imply that it will always outperform other machine learning methods. The effectiveness of GEP depends on the specific problem and dataset at hand. As with any machine learning technique, it is important to carefully select and tune the parameters of GEP to achieve optimal performance.

While GEP is generally more effective for larger datasets, it can still be applied to smaller datasets. However, careful consideration of data quality, overfitting, and generalization issues is necessary for achieving reliable results.

3. Evaluation of the results

In order to better understand and anticipate the behavior of complex environmental processes and systems, mathematical models are required. However, testing and evaluating these predictions in real-world contexts is crucial. Statistical measures and indices are used to compare expected and actual values in order to assess the accuracy of prediction models.

Numerous statistical measures have been proposed in the literature to evaluate the similarity between observed and predicted time series data. The predictive capacities of the models were assessed using the coefficient of determination (R^2), mean absolute error (MAE), mean squared error (MSE), and variance accounted for (VAF) metrics.

R^2 measures how much of the variation in the observed data can be accounted for by the projected values. The R2 number is a measure of how well the anticipated and observed data match up.

MAE quantifies how off the model has been, on average, while making predictions. Better prediction accuracy is indicated by a smaller MAE number.

MSE measures how far off the mark a prediction is from the actual results. It's helpful for evaluating the model's overall prediction performance since it gives greater weight to higher mistakes.

VAF measures how much of the overall variation in the observed data can be explained by the expected values. The model's capacity to account for observed variability increases as the value of the VAF rises.

Researchers may assess the accuracy of various models in making predictions about the outcomes of complex environmental processes and systems by using these statistical criteria. These metrics allow for educated decision-making and enhanced predictive skills by providing vital insights into the models' accuracy and dependability.

$$R^2 = 1 - \frac{sum\ squared\ regression\ (SSR)}{sum\ of\ squares\ total\ (SST)} \tag{1}$$

$$\mathrm{MAE} = \left(\frac{1}{n}\right)\sum_{i=1}^{n}|y_i - y_i'| \tag{2}$$

$$\mathrm{MSE} = \left(\frac{1}{n}\right)\sum_{i=1}^{n}(y_i - y_i')^2 \tag{3}$$

$$\mathrm{VAF} = 1 - \left[\frac{var(y_i - y_i')}{var(y_i)}\right] \times 100\% \tag{4}$$

where y_i is the actual value and y_i' is the predicted value, and n is the number of datasets.

4. Database

In this article, the impact of four rock parameters on the UCS is thoroughly examined. Porosity (n), Schmidt hammer number (SHR), P-wave velocity (Vp), and point load index (Is(50)) are all examples of such variables. These parameters were selected based on their proven effectiveness in predicting UCS using advanced intelligent methodologies in previous studies.

A total of 170 datasets were gathered from different quarries to make sure the research was accurate and thorough. Samples of various rocks such as granite, claystone, schist, travertine, sandstone, limestone, dolomite, marl, and slate were analyzed in the lab to compile these datasets. The goal of using such a broad variety of rocks was to better represent the spectrum of geological differences and to offer a solid basis for the research.

Two subsets, one for training and one for testing, were created from the acquired data. Eighty percent of the datasets (136) were utilized for model training, while the remaining datasets (20%) were used for model evaluation. This section made sure the models were tested with hidden information, providing a fair evaluation of their predicting ability.

In general, the metrics of the test model offer a superior gauge of a model's performance and its ability to generalize, surpassing the training metrics in accuracy. Here's why:

- Evaluation on unseen data: During model training, the model learns from the training data to minimize its error or loss. Training metrics gauge the model's adequacy in fitting or predicting the training data. Nonetheless, this doesn't ensure equivalent performance on unfamiliar data. Test metrics, conversely, evaluate the model's efficacy on a distinct set of unfamiliar data, furnishing a more authentic assessment of its generalization capability.
- Mitigation of overfitting: Overfitting transpires when a model excels excessively on the training data yet falters to generalize to novel data. Training metrics may not reflect overfitting issues because the model optimizes its parameters specifically for the training set. In contrast, test metrics can reveal if the model is overfitting by showing a significant drop in performance when evaluated on the test data.
- Dependence on model complexity: Models with higher complexity can easily memorize the training data, resulting in excellent training metrics. However, this propensity can result in subpar generalization and elevated error rates on unseen data. Test metrics help assess if the model's complexity is appropriate, as they provide a more objective measure of how well the model performs on new data.
- Performance comparison and model selection: Test model metrics allow for fair comparisons between different models or variations in model settings. By evaluating multiple models on the same test data, it becomes easier to determine which model performs better and select the most suitable one for deployment.

Table 1 includes a brief summary of the datasets that were used in the research. The properties of the dataset may be better grasped with the help of the information provided in this table, which presumably contains the rock type, the number of samples, and other important parameters.

Fig. 2 is a correlation matrix showing the links between the four input factors and the end score, UCS, providing more insight into the database utilized in the research. The strength of these correlations is quantified using Pearson's correlation coefficient (R), a standard measure of correlation that ranges from -1 to 1. A correlation of -1 indicates a highly negative relationship, whereas a correlation of 1 signifies an exceedingly positive correlation. The values of the correlations between the input parameters and UCS are shown in Fig. 2.

Table 1 A brief review of the datasets used.

Datasets		n [%]	SHR	V_p [m/s]	$I_{s(50)}$ [Mpa]	UCS [MPa]
Training	count	136	136	136	136	136
	mean	2.67	42.71	5057.46	3.73	95.33
	std	3.82	13.66	1438.66	1.83	52.18
	min	0.06	11.00	1211.00	0.86	12.01
	25%	0.30	31.61	4319.25	2.43	38.93
	50%	0.47	45.18	5260.00	3.34	95.60
	75%	3.95	53.00	6146.25	4.97	138.57
	max	14.75	67.07	7485.00	9.00	215.21
Testing	count	34	34	34	34	34
	mean	2.44	45.53	5157.30	3.91	94.796
	std	3.60	10.44	1215.04	2.15	45.174
	min	0.11	22.00	1500.00	0.20	25.120
	25%	0.31	38.77	4650.00	2.12	50.055
	50%	0.46	48.50	5419.00	3.66	105.00
	75%	3.31	52.48	6017.50	5.42	131.98
	max	10.94	64.43	6790.00	9.00	181.00

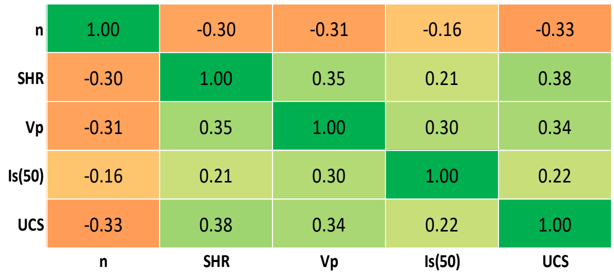

Fig. 2 The correlation matrix for variables

The correlation between the SHR and UCS variables is particularly strong at 0.38. This association is suggestive of a weakly positive connection between SHR (the input variable) and UCS (the output variable). It's worth noting, nevertheless, that a value of 0.38 for a correlation implies a moderate rather than a high or very significant link.

There are no significant correlations (greater than 0.38) between the other input parameters and UCS. This indicates that their associations with UCS are not as robust as those with SHR. When assessing the impact of these input factors on the UCS, it is essential to account for these lower correlation values.

5. Model implementation

The GEP procedure in this study was implemented using the Jupyter Notebook environment, which is a popular tool included in Anaconda Navigator 3.7. Anaconda is a free and open-source program that simplifies package management and execution for scientific computing in Python. By utilizing Anaconda, researchers benefit from a streamlined workflow and easy access to a wide range of scientific libraries and tools.

The calculations for the GEP modeling were performed

Table 2 Configuration settings for the GEP model

	Parameter	Description
General	Length of head	10
	No. of genes within a chromosome	2
	RNC array length	6
	Linking function	addition
	Function of fitness	MSE
	Function set	-, +, *, /, Sqrt (x), Pow (x,y), x^2, x^3, 1/x, $x^{1/3}$, Exp, sin, cos, tan, MSE, R^2
Genetic operators	Rate of IS transposition	0.10
	Rate of inversion	1.0
	Rate of mutation	1.0
	Rate of one-point recombination	0.30
	Rate of gene recombination	0.10
	Rate of two-point recombination	0.20
	Rate of RIS transposition	0.10
	Gene transposition	0.10
Numerical constants	Upper bound	+10
	Lower bound	-10
	Constants per gene	2
	Data type	Floating – Point

on a system equipped with an Intel Core i7-10750H processor running at a frequency of 2.60 GHz and 32 GB of RAM. This powerful hardware configuration ensures efficient and reliable execution of the GEP procedure, allowing for the analysis of large datasets and complex models.

To obtain the best possible outcomes, multiple iterations of the GEP modeling process were conducted. The specific settings used for each iteration are outlined in Table 2, which likely includes details such as the values for the n_pop and n_gen parameters. These parameters were adjusted at each step of the model's execution, enabling the exploration of different combinations to optimize the model's performance. To control overfitting in the GEP model, the following techniques were employed:

- Train-Test Split: The authors partition the dataset into distinct training and test sets, guaranteeing the evaluation of the model on previously unseen data. This helps in determining if the model is overfitting by checking its performance on data it has not been trained on.
- Early Stopping: Employing early stopping allows to monitor the model's performance on a validation set during training. If the performance on the validation set starts to decline, the training can be stopped early to prevent further overfitting. This technique helps in finding the optimal point to stop training and avoid overfitting the model to the training data.
- Data Standardization: Data standardization was applied to the input features before feeding them into the model. This technique involves scaling the data to have a mean of zero and a standard deviation of one. Standardization helps in normalizing the input data, which can prevent the model from being overly sensitive to features with larger scales. It can also improve the model's ability to generalize to unseen data.

Following the execution of the GEP modeling, the obtained findings were thoroughly analyzed. The accuracy of the models was evaluated using various statistical criteria, which were likely mentioned earlier in the text.

Based on the comprehensive assessment of the models' accuracy using these statistical criteria, the top-performing models were selected. This selection process ensures that the final models chosen for analysis and interpretation provide the most accurate predictions and reliable insights into the investigated phenomenon.

6. Results and discussion

6.1 Analysis of results

In this investigation, the GEP model was executed 35 times to ensure the most accurate findings. The parameters "n_pop" and "n_gen" were varied in each run, ranging from a minimum value of 16 for "n_pop" to an upper limit of 220, and from a minimum value of 8 for "n_gen" to an upper limit of 200. This variation in parameters allowed for a comprehensive exploration of the model's performance across a wide range of settings.

After implementing the 35 different models, the most accurate one was selected based on the evaluation criteria. The specifications of the chosen model, including the optimal values for the parameters and other relevant details are presented in Table 3. This information provides transparency and allows for reproducibility in future studies.

Fig. 3 visually presents the expression tree for the proposed GEP model. This graph illustrates how different variables interact with each other using the GEP method. The ability to capture and represent these interactions is one of the strengths of the GEP algorithm, setting it apart from other ML techniques. This capability contributes to the superior results generated by the GEP algorithm in this investigation.

For the selected model, an equation was derived through the best fit on the predicted results. This equation, presented in Table 3 as Eq. 5, was carefully chosen to include all the input parameters considered in the datasets used in this study. This approach ensures that the equation provides a comprehensive representation of the relationship between the input parameters and the predicted UCS values for different rock samples.

To gauge the accuracy of the derived equation, it underwent testing with input parameters sourced from both the training and testing datasets. The accuracy was assessed using an array of statistical measures (Eqs. (1)-(4))

Figs. 4 and 5 further illustrate the performance of the proposed equation by comparing the projected UCS values for both the testing and training datasets with the true values. These figures demonstrate that the observed and

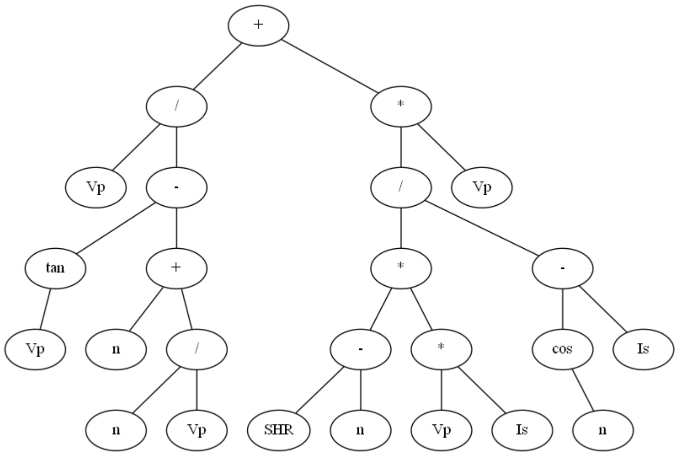

Fig. 3 Expression tree for forecasting UCS

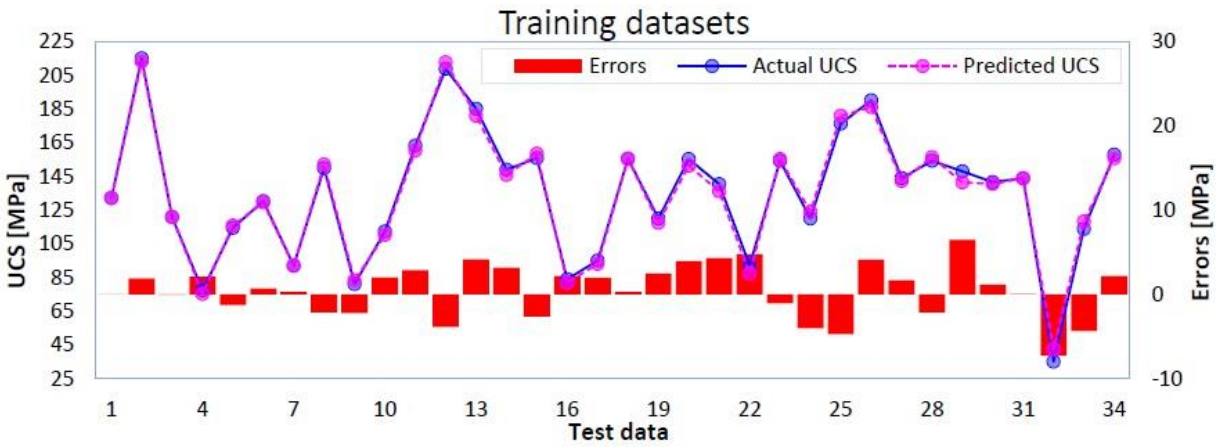

Fig. 4 Comparison of the average equation's results with the actual measured ones for the training datasets

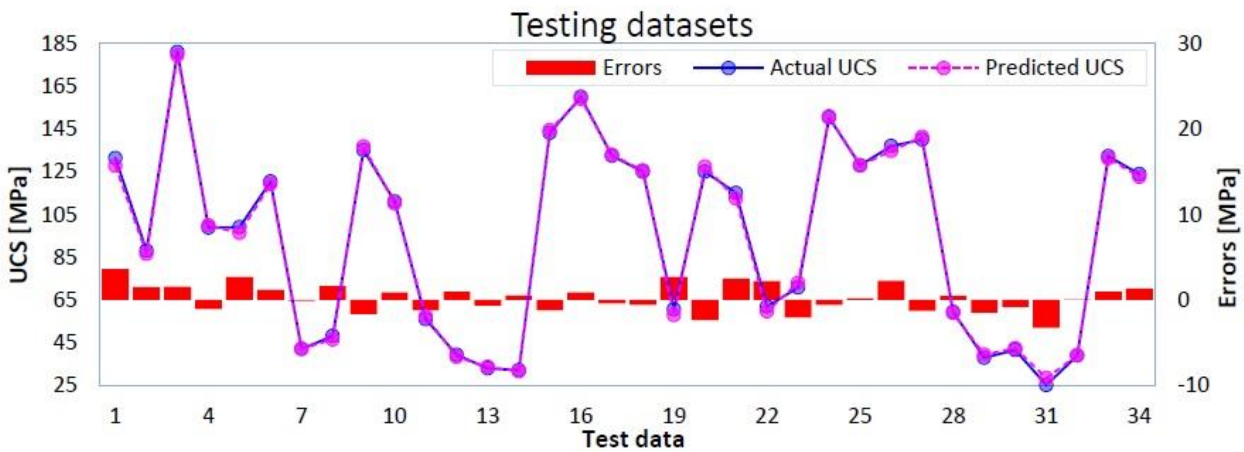

Fig. 5 Comparison of the average equation's results with the measured ones for the testing datasets

Table 3 The best model's specifications selected to predict UCS.

Parameters	n_pop = 50 n_gen = 35
Run time	6.20s
Generated equation	$UCS = -\frac{3.83872126684879 \times 10^{-8} \times Vp^2(-Is(50)(SHR-n)(Vp(n-\tan(Vp))+n)-Is(50)+\cos(n))}{(Is(50)-co(n))(Vp(n-\tan(Vp))+n)}$ $+26.8364353967831$ MPa (5)

Table 4 The value of statistical metrics obtained for the suggested model

Datasets	R^2	MAE [MPa]	MSE [$(MPa)^2$]	VAF [%]
Training	0.9934	3.53	18.38	99.76
Testing	0.9987	1.37	2.68	99.96

predicted UCS values are closely aligned, with minimal differences. This strong agreement between the observed and predicted values confirms the outstanding performance and high accuracy of the forecasting model in predicting UCS.

Collectively, the comprehensive evaluation and analysis presented in this investigation validate the effectiveness of the GEP model and its resulting equation in accurately predicting UCS for different rock samples. The findings highlight the potential of the GEP algorithm as a robust tool for forecasting and understanding complex phenomena in rock mechanics.

To evaluate the dependability of the proposed model, a newly suggested engineering indicator called the a10-index (Eq. (6)) was utilized. This indicator provides a valuable assessment of the accuracy of the model by considering the *experimental value/predicted value* ratios of the samples. The M datasets consist of samples with ratios ranging from 0.90 to 1.10, indicating a range of 10% variation from the expected values. The m10 datasets represent the total number of samples.

$$a10\_index = \frac{m10}{M} \tag{6}$$

An ideal prediction model would have an a10-index of 1, implying perfect accuracy, as it would indicate that all the samples have an inaccuracy of 10% or less from their expected values. The proposed a10-index is advantageous as it is not only statistically meaningful but also relevant from a physical engineering perspective.

The proposed model, represented by Eq. (5), demonstrates accurate predictions of the UCS parameter. This assertion is bolstered by the a10-index findings illustrated in the scatter plots presented in Fig. 6. Notably, among the scatter plots, merely one sample demonstrated a deviation exceeding 10% across both the training and testing phases. This exceptional performance of the model, with minimal deviations from the expected values, further reinforces its reliability and accuracy in predicting the UCS parameter.

To assess the generalization ability of the suggested model, a 5-fold cross-validation was performed. This analysis provides a comprehensive evaluation of the model's performance by testing it on different subsets of the dataset. The results obtained from the cross-validation demonstrate the superior performance of the model in predicting the UCS parameter.

Specifically, the 5-fold cross-validation yielded an R^2 value of 0.9783, indicating a high degree of correlation between the predicted and actual UCS values. The MAE was calculated as 1.90, reflecting the average magnitude of the prediction errors. The MSE was determined to be 3.12,

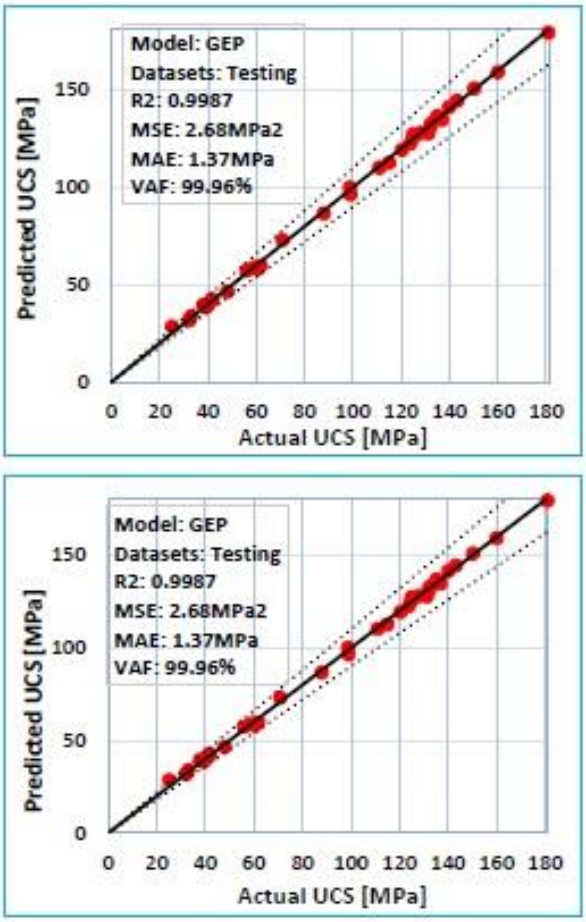

Fig. 6 Scatter plot comparing measured and estimated UCS values across validation and training datasets.

providing insight into the overall accuracy of the model's predictions. Furthermore, the VAF was determined to be 98.53%, showcasing the substantial portion of variance in the UCS parameter elucidated by the model. These exceptional results obtained from the 5-fold cross-validation further validate the superior performance and generalization ability of the suggested model. The high correlation, low prediction errors, and high explanatory power of the model affirm its reliability and accuracy in predicting the UCS parameter across different scenarios and datasets

6.2 Sensitivity analysis

It might be intimidating to look at a dataset for the first time. It's possible that many of the features will be provided to us with no explanation at all. We have no idea where to start. The degree to which a feature contributes to a goal may be quantified using a feature utility metric. This way, we'll know we're not wasting time if we want to concentrate on a subset of the most crucial capabilities.

For this purpose, we will use a metric known as mutual information (MI). Both correlation and MI focus on how two variables are related. In contrast to MI, which may

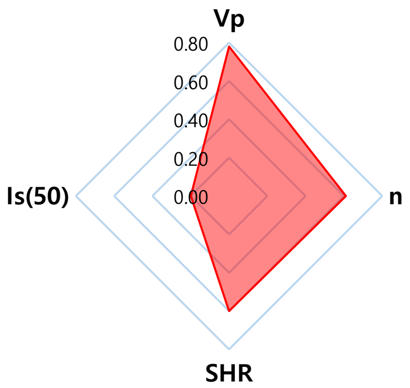

Fig. 7 The sensitivity score input parameters on the value of Eq. (5)

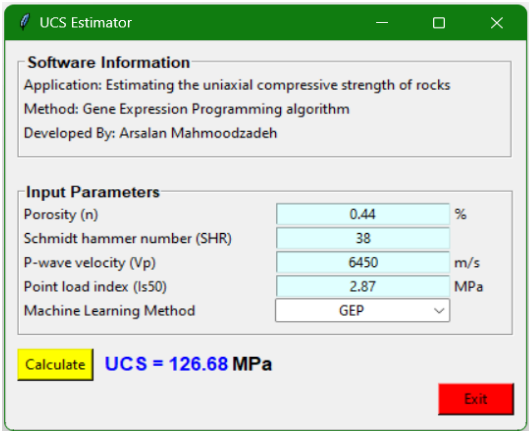

Fig. 8 A user-friendly software based on the GEP model developed in this study to estimate the UCS of rock

uncover non-linear connections, correlation can only uncover linear ones. In the early stages of feature development, when we are still unsure about the best model to use, MI may be a great general-purpose metric. It can locate links in a variety of formats, and it's easy to use. It is fast, resource-efficient, overfitting-resistant, and theoretically sound.

MI employs uncertainty as a means of defining connections. How much one piece of knowledge decreases uncertainty when applied to another is measured by the MI between the two parameters. How much more sure would we be if we knew the value of a certain trait?

Fig. 7 shows a radar plot displaying the MI method's determined sensitivity score for each input parameter. The parameter V_p clearly received the highest possible rating. In other words, the parameter V_p has a larger impact on Eq. (5). The UCS is likewise profoundly affected by the values of n and SHR. The influence of Is(50) on Eq. (5) has been shown to be negligible. Parameter Is(50), which has a major effect on the UCS, causes very little sensitivity in Eq. (5). The Sensitivity of Prediction Model Parameters is Heavily Influenced by Data Characteristics and Measurement Ranges.

6.3 User-friendly software

The most useful result of this study is a user-friendly program (Fig. 8) for measuring the UCS of rock using the suggested GEP model. This tool eliminates the need for time-consuming and expensive laboratory testing by automating the UCS computation, saving both time and money. By simply plugging the input data into the software, users may get reliable estimates of the UCS value. This eliminates the need for complex models and speeds the estimation process. The software's ability to roughly estimate a UCS value is a major plus. The new GEP algorithm used by the application removes the requirement for costly and time-consuming laboratory testing. Time and materials are saved while overall productivity in the estimation process is increased. Scientists and engineers doing their own research will find the software's ability to generate massive datasets very useful. With the software's assistance, they can efficiently generate datasets and try out several scenarios for a comprehensive look at the UCS.

6.4 Limitations and future studies

The GEP model for UCS forecasting in this research only included four interconnected parameters. Estimating the UCS also relies on other characteristics often found in the literature. More consequential factors may need to be added to the database in the future. In addition, building an intelligent UCS forecasting technique that is both precise and powerful requires a large database. Fine-tuning Hyperparameters for Estimating UCS Across Diverse Rock Types Using the Proposed Model Requires Consideration of Data Quantity and Complexity.

7. Conclusions

The following conclusions may be drawn in light of the results achieved in this study:

- One major strength of the GEP model is its ability to determine relationships between inputs and UCS estimates.
- To optimize the GEP model for various datasets, it is necessary to experiment with different values for n_pop and n_gen. In this study, the GEP procedure was executed 35 times, each time with different combinations of values for these parameters. This iterative process allowed for the identification of an optimal model that produced successful results.
- The proposed model integrates four input parameters of n, SHR, Is(50), and Vp into a single equation developed using the GEP approach, which can then be used to estimate the UCS of rocks.
- Several statistical measures were used to determine how well the resultant equation approximated UCS. Results from both the training and testing phases showed that the equation has the capacity to properly estimate the UCS of rocks (R^2 = 0.9934, MAE = 3.53 MPa, MSE = 18.38 $(MPa)^2$, VAF = 99.76%).

- To calculate the UCS of rock, a user-friendly program was developed based on the proposed GEP model. The benefit of using the program to estimate UCS values rather than doing costly and time-consuming laboratory experiments is clear. When an updated GEP model is used, the software's predictions are more precise.

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