

Gaussian process regression model to predict factor of safety of slope stability

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(Received June 28, 2021, Revised November 5, 2022, Accepted November 15, 2022)

Abstract. . It is essential for geotechnical engineers to conduct studies and make predictions about the stability of slopes, since collapse of a slope may result in catastrophic events. The Gaussian process regression (GPR) approach was carried out for the purpose of predicting the factor of safety (FOS) of the slopes in the study that was presented here. The model makes use of a total of 327 slope cases from Iran, each of which has a unique combination of geometric and shear strength parameters that were analyzed by PLAXIS software in order to determine their FOS. The K-fold (K = 5) technique of cross-validation (CV) was used in order to conduct an analysis of the accuracy of the models' predictions. In conclusion, the GPR model showed excellent ability in the prediction of FOS of slope stability, with an R² value of 0.8355, RMSE value of 0.1372, and MAPE value of 6.6389%, respectively. According to the results of the sensitivity analysis, the characteristics (friction angle) and (unit weight) are, in descending order, the most effective, the next most effective, and the least effective parameters for determining slope stability.

Keywords: factor of safety; feature selection; Gaussian process regression; machine learning; slope stability

1. Introduction

Studying and researching natural hazards or hazards related to human manipulations such as roads (Xu *et al.* 2022), tunnels, dams, and buildings is of particular importance. For example, we can refer to the dangers caused by landslides or earth and rock slopes that are created naturally or as a result of human manipulations. To prevent these risks, different solutions have been used until now. For example, the use of construction materials such as concrete, shotcrete, reinforcement, etc. have been used to prevent such risks from occurring. Even the study on increasing the quality of construction materials including

reinforced concrete (RC) is developing and progressing day by day (Zhang and Abedini 2021, Huang *et al.* 2022).

The evaluation of a slope's capacity to remain stable is an essential part of geotechnical engineering (Xu *et al.* 2022, Wang *et al.* 2022a, Li *et al.* 2022). Over the course of history, economics has advanced, and along with that progression, the number of slopes has increased. As a consequence of this, landslides brought on by unstable slopes have been among the top three most disastrous natural catastrophes that have occurred anywhere in the globe, alongside earthquakes and volcanoes (Xie *et al.* 2021a, b). As a clear example of slope failure, we can refer to the second parameter. Kennecott Utah copper's Bingham Canyon Mine in the United States of America is shown in Fig. 1. This open-pit mine is considered to be the largest man-made excavation in the world, and its dimensions are 1 kilometer in depth and 4 kilometers in width. The massive movement of the upper half of the northern pit wall was caused by the landslide that occurred in Bingham Canyon on April 10, 2013. The landslide took place in the Canyon's open-pit copper mines. As can be seen in Fig. 1, the slide buried the floor of the mine in a layer of thick debris. Prior to the incident, the geotechnical surveillance teams as well as the mine operators were fully aware of the instability and had evacuated the mine workers as well as the equipment from the unstable zones. As a result, there were no reported casualties or injuries. Several minor earthquakes were responsible for setting off the landslide. Six days after the event that caused the landslide, a total of sixteen additional seismic events were detected in the mine area (Kolapo *et al.*

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Fig. 1 A massive slope failure occurred at the open pit of the Bingham Canyon Mine in Utah (Kolapo et al. 2022)

Significant study has been carried out in many different regions of the globe. Despite the fact that there is still a great deal of work to be done, slope stability can now be predicted and evaluated. Previous studies have made use of a variety of helpful models developed by various scholars in order to investigate and make predictions about the collapse of slopes (Lin et al. 2018). These methods may be broken down into four distinct categories, which are referred to as the qualitative analysis, the quantitative analysis, the physical simulation, and the field monitoring analysis. These experts have accomplished a significant amount of work in the field of slope stability. On the other hand, the strategies that they developed aren't the most effective and can only provide answers that are tailored to certain slopes. Due to the following limitations (Lin et al. 2018) of these models, they are not appropriate for use in solving all slope stability issues in their entirety:

- Due to the deficiencies, the approaches that were taken should not be considered suitable. For instance, the limit equilibrium approach is unable to take into account the constitutive connection of the soil, therefore it must look for the sliding surface that presents the most risk. In addition, the study is made more difficult by the presence of many layers in the soil. Therefore, the correct safety and dependability cannot be properly elucidated using this method during the stability slopes study.
- The safety factor has not been specified in a very clear way. In general, slopes are considered to be safe if they have a factor of safety (FOS) that is more than 1.20. In spite of this, there have been instances of failed slopes in actual engineering that had FOS values that were more than 1.2.
- These techniques are susceptible to the influence of human subjective variables.

In recent years, artificial intelligence (AI) and soft computing techniques have been broadly applied in Engineering (Glowacz 2021a,b, Khishe and Mosavi 2020, Khishe and Mosavi 2019). Coding based on these methods are also continuously being developed and optimized in different engineering fields with different programming languages (Xi et al. 2022, Wang et al. 2022b). In a nutshell, learning more about these strategies can cut down on wasted time and money when undertaking large-scale projects. This means it has a lot of potential uses and is

highly relevant in the real world (Lu et al. 2022). Day by day, these models are being developed in the field of geotechnical engineering for various applications including tunnel resources (Lu et al. 2020, Liu et al. 2021a, Xiang et al. 2021, Liu et al. 2021b, Bai et al. 2021), landslide displacement (Liu et al. 2021), rock bursts (Zhou et al. 2016). There are now a number of supervised learning methods that may be used to predict how stable a slope is. The outcomes of using these techniques have been astounding (Lin et al. 2018). Slope stability analysis may be improved by combining the gray system technique with artificial neural networks, as shown by Lu and Rosenbaum (2003), for example. In order to conduct slope stability evaluations, Das et al. (2011) employed artificial neural networks (ANN). The relevance vector machine was used by Zhao et al. (2012) to study the relationship between slope stability and its impact characteristics. Slope stability was examined in 97 examples by Liu et al. (2014) using the extreme learning machine approach. Metaheuristic least squares support vector regression for slope analysis has been developed by Hoang and Pham (2016) via 168 instances. Using a genetic algorithm created by Manouchehrian et al. (2014), they were able to predict the FOS for slopes. For the support vector machine (SVM) model, particle swarm optimization (PSO) was recommended by Xue et al. (2014). Li et al. (2013) and Samui (2008) both used SVM to examine slope stability, and both came up with useful results. Li et al. (2013) and Samui (2008), for example, both used SVM to predict slope stability and came up with excellent results. Khajehzadeh et al. (2012) studied slope stability and applied a gravitational search algorithm (GSA) to solve global optimization issues and minimize the FOS.

Despite progress in quantitative ML methods, many steps in creating an ML-based model still call for human judgment. Dataset selection, cleaning and labeling of the training set data, and the parameters used to develop the model all necessitate the expertise of the ML practitioner. While the numerical methods are clearly laid out, these evaluations call for serious consideration and comparison. Algorithms that aren't properly cross-validated may do well in one setting but tank in another. Second, the reliability of the model relies on how closely the input data and labels match the target domain. In order to encourage critical thinking, generate ideas, and question presuppositions, ML should return to the traditional Socratic style of questioning and replying. Developers should be aware that this scrutiny and reformulation helps them clean detected biases from their training data, run continuous simulations based on empirical evidence, and tune their algorithms appropriately. People would have more faith in AI if it had been subjected to such a human audit, which would increase its dependability and accountability.

The intelligent models that were previously proposed by other researchers to predict the FOS of slopes, can explain the failings of slopes, but they are not enough to completely solve the problems. It is possible for one method to be acceptable for one set of circumstances while being inappropriate for another set of circumstances. However, in the prediction of slope stability, no difference amongst the

Table 1 Earlier studies on the slope stability predictions using soft computing approaches

References	Parameters	Soft computing method	Datasets no.
Feng (2000)	$r_u, H, \alpha, \gamma, \phi, c$	FFNN	82
Lu and Rosenbaum (2003)	$H, \alpha, \gamma, \phi, c, r_u$	BPNN	32
Li (2004)	$H, \alpha, \gamma, \phi, c$	ANN and ANFIS	59
Huang <i>et al.</i> (2004)	$H, \alpha, \gamma, \phi, c, r_u$	CNN	64
Samui (2008)	$H, \alpha, \gamma, \phi, c, r_u$	SVM	46
Zhao (2008)	γ, ϕ, c	SVM	10
Choobbasti <i>et al.</i> (2009)	$a_h, X, \phi, \alpha, a_v, c, Y, S_r$	ANN	36
Das <i>et al.</i> (2011)	$r_u, H, \alpha, \gamma, \phi, c$	ANN	46
Erzin and Cetin (2013)	$\gamma, c, \phi, \alpha, H$	ANN	675
Liu <i>et al.</i> (2014)	$r_u, H, \alpha, \gamma, \phi, c$	ELM	97
Gordan <i>et al.</i> (2016)	$H, \alpha, \gamma, \phi, c, \text{PGA}$	PSO-ANN	699
Hoang and Pham (2016)	$r_u, H, \alpha, \gamma, \phi, c$	LS-SVC	168
Suman <i>et al.</i> (2016)	$r_u, H, \alpha, \gamma, \phi, c$	FNs, MARS, MGGP	103
Verma <i>et al.</i> (2016)	pp, c, α, ϕ	ANN	100
Rukhaiyar <i>et al.</i> (2017)	$r_u, H, \alpha, \gamma, \phi, c$	PSO-ANN	83
Xue (2017)	$r_u, H, \alpha, \gamma, \phi, c$	PSO-LSSVM	46
Feng <i>et al.</i> (2018)	$r_u, H, \alpha, \gamma, \phi, c$	NBC	82
Zhou <i>et al.</i> (2019)	$r_u, H, \alpha, \gamma, \phi, c$	GBM	221
Ray <i>et al.</i> (2020)	$H, c_r, \phi_j, c_s, \phi_s, c_j, D, E_r, \phi_r, \alpha$	ANN	400

proposed intelligent modeling techniques has been seen. As a result, the trustworthiness and accuracy of the models cannot be said to be firmly established. In addition, cross-validation (CV) is a method that may check the prediction performance of the models in a way that is both efficient and accurate (Lin *et al.* 2018). For the purpose of ensuring that optimized models provide accurate results, it is essential to suggest using CV.

In this study, the Gaussian process regression (GPR) approach is used in order to anticipate the FOS of the slopes. In order to determine the FOS of 327 different slope situations in Iran, the PLAXIS program is used to analyze the input parameters, which include unit weight (γ), cohesion (c), friction angle (ϕ), slope angle (α), slope height (H), and pore pressure ratio (r_u). These datasets are used in the development of the prediction models. The K-fold ($K=5$) CV procedure is used in order to conduct the evaluation of the model's prediction output. The PLAXIS program is used to evaluate the FOSs, and then the results are compared to the predicted values produced by the GPR model. At long last, the most accurate prediction model has been determined. Additionally, the backward selection approach is utilized in order to demonstrate how each of the input parameters influences the FOS of a slope. This is done so that the results may be more clearly understood. By doing so, the characteristics that have the most significant impact on the steadiness of slopes may be determined.

2. Database and statistical analysis

The results of many studies that attempted to forecast the circular mode of slope stability using gentle computational approaches are reported in Table 1. Six factors $\gamma, H, \phi, c, \alpha$, and r_u have been found to be significant

Table 2 Statistical features of the remained slope cases

	γ [kg/ m ³]	c [kPa]	Φ [°]	α [°]	H [m]	r_u	FOS
count	327	327	327	327	327.0	327	327
mean	20.5	16.1	27.7	34.8	78.90	0.19	1.25
std	4.09	15.8	10.4	10.3	114.9	0.17	0.37
min	12.0	0.00	0.00	16.0	3.60	0.00	0.23
25%	18.5	3.40	22.0	28.0	10.0	0.00	1.02
50%	20.0	11.7	30.0	35.0	32.0	0.25	1.20
75%	22.4	24.9	35.0	45.0	88.0	0.32	1.45
max	31.3	70.0	45.0	65.0	565	0.64	2.31

for slope stability in these analyses. Therefore, these six characteristics are taken into account in this study based on previous research and available data.

A database consisting of 327 different slope instances that were investigated for cyclic failure mechanisms was used so that the accuracy of the GPR model utilized in this study for the stability of slopes could be evaluated. Table 2 shows the outcomes of the simple descriptive statistical analysis achieved for the datasets. A common kind of slope failure that occurs in places with soil and rock that is more fragmented is called a circular failure. In order to calculate the value of FOS, the finite element software known as PLAXIS was used to do studies on each of the slopes. When contrasted with the results of the GPR predictions, several analytical outputs are considered.

To measure the general efficiency of soft computing issues, fresh datasets must be used to test prediction models. In this way, the dataset might be separated into two sets: one for training, and another for testing. The hyper-parameters of the prediction model are tweaked using training data. Separate testing datasets are used for

evaluating the overall predictive model efficacy.

Model selection can be achieved through a number of cross-validation (CV) approaches, including the hold-out method, K-fold CV, leave-one-out CV, and the bootstrap method. To verify the accuracy of the predictions, we use a K-fold CV (K = 5) analysis. The K-fold CV technique involves randomly sampling from the original training set a fixed number of times, resulting in K equal-sized folds. Every model is trained K times, with K-1 folds used for training and the remaining fold (fold 1) used for validation. Take the mean of the K individual errors to get the prediction error. The robustness of the model may be evaluated by calculating the error variance. The benefit of this approach is that the partitioning of the data is less critical. Selection bias is less likely to occur in this model. This method is superior to repeatedly using a random sampling procedure for confirmation because each observation is only used once for the process.

Understanding, modeling, and predicting complex environmental processes and systems necessitates the use of mathematical models. Whatever the application, an evaluation of these forecasting results is required. With the use of statistical measures, usually known as indices, it is possible to compare anticipated and measured values of the important parameters in every assessment.

Several measures in the literature look at how well the observed and expected time series match up from a statistical point of view. Some statistical indices, including the coefficient of determination (R²), mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE), are included in this research to assess the prediction models' accuracy (Eqs. (1)-(4)).

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

$$\text{MAE} = \left(\frac{1}{n}\right) \sum_{i=1}^n |y_i - y'_i| \quad (2)$$

$$\text{RMSE} = \sqrt{\left(\frac{1}{n}\right) \sum_{i=1}^n (y_i - y'_i)^2} \quad (3)$$

$$\text{MAPE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_i - y'_i}{y_i} \right| \times 100\% \quad (4)$$

where y_i is the real value, y'_i is the forecasted value, \bar{y}_i is the mean of y_i , \bar{y}'_i is the mean of y'_i , and n is the number of test datasets.

3. GPR prediction model of slope stability and results analysis

Despite the merits of various ML approaches, according to the No-Free-Lunch (NFL) theorem, there is no ML model to solve all engineering problems as the best method successfully. Therefore, researchers have tried to evaluate the efficiency of various ML approaches for solving various optimization. In this study, the GPR model is used as the NFL theorem. However, the key features of the GPR model,

which motivate us to use it, is as follows:

- Model uncertainty is captured directly by the GPR. Rather than providing a single prediction value, GPR gives a distribution for regression. There is ambiguity in neural networks, but it is not explicitly accounted for.
- We may incorporate previous information and requirements regarding the model's structure when utilizing the GPR by selecting alternative kernel functions. We may, for example, pick a different prior depending on the responses to the following questions. Is the model slick? Is it lacking in content? Is it appropriate for it to be able to evolve so dramatically? Is it possible to differentiate it? Researchers now have the capacity to create models that can be applied to a wide range of datasets.

3.1 GPR

In the field of ML, GPR is making waves as a nonparametric, Bayesian method to regression. Rather of learning single, fixed values for each parameter of a function, as is the case with many common supervised ML algorithms, the Bayesian method infers a probability distribution across those values. To illustrate, consider the linear function $y = wx + \epsilon$. The Bayesian method involves setting a prior distribution, $p(w)$, on the parameter w , and then shifting probability in light of evidence (i.e. observed data) using Bayes' Rule (Eq. (1)).

$$p(w|y, X) = \frac{p(y|X, w)p(w)}{p(y|X)} \quad (5)$$

$$\text{posterior} = \frac{\text{likelihood} \times \text{prior}}{\text{marginal likelihood}}$$

Accordingly, the prior distribution and the dataset are both included into the updated distribution $p(w|y, X)$, which is known as the posterior distribution. Forecasts may be obtained for unknown sites of interest (x^*) by weighing the various predictions according to their posterior distribution. In order to make the integration manageable, it is common practice to assume a Gaussian distribution for the prior and likelihood.

$$p(f^*|x^*, y, X) = \int_w p(f^*|x^*, w) p(w|y, X) dw \quad (6)$$

Assuming this and solving for the predictive distribution yields a Gaussian distribution, from which we can derive a point prediction using its mean and a measurement of uncertainty using its variance.

3.2 Results

We use MATLAB 2018's regression learner program, which takes into account optimization mode. To get the most precise forecasts, this setting takes into account the optimal parameter values or types for the MATLAB application. For the GPR technique, the regression learner app provides four model options: Matern 5/2, rational quadratic, squared exponential, and exponential. The GPR forecasts are based on the model type that provided the most reliable results. In this case, an exponential model best

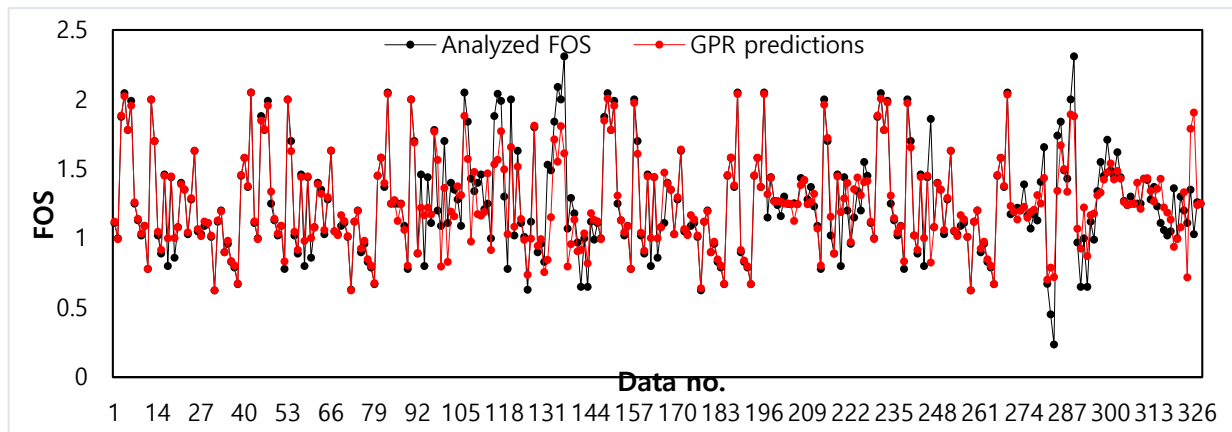


Fig. 2 Comparison of the FOS results predicted by the GPR model with the analyzed ones

captured the data. The use of an optimization technique, such as a metaheuristic algorithm, to determine the best value for the GPR parameter, however, remains an active area of study.

The GPR model's hyper-parameters, such as the number and kind of hyper-parameters, are optimized by the app's optimization mode. Table 3 displays the regression learner app's optimized GPR hyper-parameters, including their type and value.

The GPR model's anticipated 5-fold CV findings for slope stability are shown in Fig. 2. As in Fig. 2, the measured FOS values are quite near to those anticipated by the GPR model. The GPR model's ability to accurately estimate the FOS of a slope is shown by such a little mistake. A number of additional statistical assessment indices, such as R^2 , the RMSE, and the MAPE, were also found to be 0.8355, 0.1372, and 6.6389, respectively. The GPR model's great prediction accuracy is confirmed by all the results, which were included into the database used in this study.

In addition to the GPR model, the performance ability of the other ML methods such as random forest (RF), adaptive neuro fuzzy inference system (ANFIS), recurrent neural networks (RNN), gated recurrent unit (GRU), extreme gradient boosting (XGBoost) methods in the prediction of FOS of slopes stability is also investigated. In Table 4, the results produced by these techniques are compared with each other through the statistical indices results. When the values of the statistical evaluation indices for each model are compared, it becomes clear that the majority of the models have produced results that are comparable to one another and that there is little to no difference in their accuracy. The GPR model, however, yields the maximum precision. Therefore, the GPR model provides the most desirable outcomes, which are not drastically different from the studied ones.

The GPR model's superior accuracy may be attributed to two main factors: first, the Bayesian formulation allows GPs to be trained successfully from short training sets, which is especially helpful for jobs where training data is sparse in relation to the model's dimension. As a second benefit, the GPR produces a predicted distribution rather than a single projected value, allowing for a probabilistic

Table 3 The optimized parameters of the GPR model

Parameter	Type/Value
Kernel function	'Exponential'
Beta	1.2517
Fit method	Exact Gaussian process regression
Sigma	0.0845
Basis function	'Constant'

Table 4 Comparison of the statistical evaluation indices results produced by the prediction models

Method	R^2	MAE	RMSE	MAPE [%]
GPR	0.8355	0.076	0.1372	6.6389
ANFIS	0.7834	0.094	0.1183	7.8261
RF	0.7811	0.098	0.1242	7.9010
XGBoost	0.7580	0.110	0.1315	8.9421
GRU	0.7245	0.135	0.152	9.2473
RNN	0.7194	0.140	0.168	9.5590

method of gauging confidence in forecasts, which is particularly useful in contexts such as active learning. Last but not least, the GP framework's kernel parameters may be learned by maximizing the marginal probability (or evidence) of the training data. This allows more expressive kernels like compound kernels that model different trends in the data or multiple kernel learning, in which features are optimally combined by adjusting the weights on each feature's kernel function, and is typically more efficient than traditional cross-validation (which requires a grid search).

4. Discussion

It is proposed in this research that the proposed GPR approach may be generalized. The capacity of a model to interact with and adapt to new information is described by the idea of generalization. After exercising with data not utilized during training, a model may ingest new data and make correct predictions. The capacity of a model to generalize is critical to its usefulness and success. Because

Table 5 Feature selection (first step)

	Estimate	SE	tStat	p-value	Significance code
(Intercept)	1.3518	0.078263	16.4795	4.15E-48	***
γ	0.012747	0.0048726	3.58725	0.00138462	**
c	0.03727	0.002846	15.3742	7.24E-45	***
ϕ	-0.02846	0.001926	-19.8452	3.31E-54	***
α	-0.000927845	0.00014826	-7.8463	1.21E-13	***
H	0.0092719	0.00088363	12.44984	1.20E-26	***
r_u	-0.78252	0.0683652	-11.94672	4.69E-27	***

of how successfully a model was trained on the training data, it can't be used in real-world situations. Even if the model correctly predicts the training data, it is rendered useless when new data is introduced. When a model becomes overfit, it memorizes the training data instead of 'learning' from it. Feature selection may be used to prevent the overfitting of the model. In this example, feature selection would lower the number of features, which minimizes the computational complexity of the model. The stepwise strategy for identifying an important collection of features from the data sets is applied to all the features available. There are three methods to approach stepwise regression.

The first technique (forward selection) depends on the addition of additional iterative predictors to the model, since it starts with no predictors. The process comes to an end when the gains in performance no longer have a statistically significant influence.

The second technique (backward selection), which starts with all the predictors in the model, periodically removes the lowest contributive predictors; although it ends once you acquire a model, all its predictors become statistically relevant.

Using a combination of both forward and backward procedures, **the third technique (stepwise selection)** is the most versatile. Starting with no predictors, it adds the ones that have the largest impact on the result progressively (like backward selection). In the process of introducing new variables, those that are no longer relevant should be eliminated (like forwarding selection).

This study employed the ACI [MASS Package] procedure, which determines the optimal design according to the AIC. The direction option in the model can be set to the following values: 1) Forward (to get rid of forwarding); 2) Backward (to get rid of backwarding); 3) Both.

The most polished prototype is found and brought back. One of the most well-liked feature-selection search strategies in R is called stepAIC. Constant efforts are made to reduce the values of the stepAIC model until the optimal set of features is achieved. Three asterisks (*) indicate a statistically significant value (p) in the tables below. Therefore, it has the potential to create a good relationship between two measured variables by rejecting the null hypothesis with a small p-value for the intercept and path. In most cases, a p-value of 5% or less would serve as an appropriate threshold.

First, we use all available predictors and endpoints to fit the model. Table 5 displays the outcomes of the initial feature selection step. All features have a significant impact on slope stability, as shown in Table 5. No features are removed because we have reached this point. Table 5 shows that when considering the p-values, the parameters and c have the greatest impact on the stability of the slope. The slope stability is also minimally affected by the parameter.

5. Conclusions

The GPR model was suggested in this research to estimate the FOS of slope stability. Three hundred and twenty-seven datasets were analyzed with the PLAXIS program; the models used one target of FOS and six input parameters (γ , c, ϕ , α , H, r_u). Prediction accuracy was measured using the 5-fold CV technique. The GPR outcomes were also compared to those obtained using other ML methods, including RF, ANFIS, GRU, RNN, and XGBoost. The outcomes from all the models were satisfactory and fairly close to one another. To predict slope stability, however, the GPR model with these statistics ($R^2 = 0.8355$, RMSE = 0.1372, MAPE = 6.6389%) was the most reliable.

Parameter importance in the prediction problem was evaluated using a backward selection approach. The findings demonstrated the importance of each feature in maintaining slope stability. Parameters ϕ and γ were found to have the greatest and least significant effects on slope stability, respectively.

It is recommended that the presented models be used to predict the FOS on additional slopes using recent data and a variety of input factors. Then, the best algorithms and slope stability parameters should be identified and declared.

Conflict of interest

There is no conflict of interest.

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