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Simplified and Rapid Modeling of Road Embankments Slope Safety Factor Using Regularized Regression Techniques

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Abstract

The primary objective of this research is to examine the viability of simplified regularized regression models in predicting the slope safety factor of road embankments. The methodology involves developing and comparing several regularized linear regressions against conventional methods. A total of 276 data points are collected from the literature, and 70% of these are utilized for model training, while 30% are employed for testing. The findings indicate that these models yield results better than established approaches, with Stochastic Gradient Descent and Bayesian Ridge achieving strong performances. This study provides an alternative technique that offers rapid and manually solvable equations, thus enhancing practical adaptability for routine professional tasks. The novelty lies in bridging the gap between traditional finite element-based investigations and emerging data-driven methods, demonstrating that regularized regression can be both simple and sufficiently accurate. Overall, the study outcomes emphasize the significance of these advanced yet computationally light models for road embankment stability assessments, presenting a valuable and time-efficient tool for practitioners.

Keywords: Road Embankments; Slope Safety Factor; Regularized Regression Models; Simplified Modeling; Rapid Estimation.

1. Introduction

Landslides can cause serious hazards, particularly on mountainous roads where embankments are placed and cut slopes are created [1]. Even small misjudgments in the design of these slopes sometimes lead to major losses [2]. A standard way to check the stability is by calculating the slope safety factor, which indicates if the slope is secure or might fail [3]. Currently, traditional calculation techniques include the limit equilibrium method, finite element modeling, and empirical approaches, all intended to find the minimal safety factor [4, 5]. However, there is persistent research on new solutions to embankment stability because engineers look for simpler, less time-demanding procedures [6-8]. For instance, some studies focused on stabilizing soil with special additives [9], others employed new fill materials [10], and several investigations analyzed embankment performance under thermal or environmental factors [11, 12]. Additional works investigated how machine learning might predict or classify slope reliability with data-driven methods [13-15].

Some research also included real-world validations or examined the economic feasibility of alternative embankment solutions [16-18]. Data science approaches like artificial neural networks or ensemble learning have grown popular for slope stability [19-22]. Nonetheless, certain machine learning models are not suitable for routine professional tasks because engineers cannot solve them manually, and complicated codes or long run-times might result. The problem is how to balance advanced predictive accuracy and quick, practical analysis, especially for

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large embankment projects that require multiple design iterations. Past research investigated ways to predict the safety factor with methods such as differential evolution neural networks, particle swarm optimization, and multi-linear regressions [21, 23]. These are promising but sometimes yield complex equations. A major motivation for the present work is offering an alternative that stays close to simpler linear regression forms while incorporating modern "regularization" concepts. This category of regression (Ridge, Lasso, ElasticNet, etc.) controls problems like overfitting or highly correlated inputs while still being easy to implement. The aim of this study is to determine if such regularized regression models can accurately predict road embankment slope stability. The research uses a dataset of 276 data points from Mesa-Lavista et al. [24] to build and test these models. The training ratio is 70%, and the remaining 30% is for testing. In general, the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and maximum error are taken as evaluation metrics. Then, the models are compared to common limit equilibrium approaches to see if they can compete in accuracy. Machine learning can indeed produce better results (e.g., ensemble methods), but this investigation focuses on simpler, direct formulas that engineers can adopt without specialized software. This is why more advanced machine learning, such as neural networks, is not considered herein since the guiding principle is to produce simple, rapid, and adequately precise solutions for slope stability in road embankment design. The study also uses a wide dataset and cross-validation to confirm the ability of the final regression to generalize across different embankment types.

2. Estimation of Slope Safety Factor

The safety factor for road embankment slopes shows whether they remain stable or might fail. It is derived from the ratio between the forces that resist failure and the forces that drive failure. Engineers use it as a straightforward measure that helps avoid unwelcome slope collapses. A value of 1 implies that the slope stands at the limit of safety, and higher values indicate more stability against sliding. Several approaches have been offered over the years for its calculation. Empirical methods were first used by experienced engineers to base judgments on basic field observations. Over time, more systematic strategies emerged, including the strength reduction method and the limit equilibrium method. Both of these rely on specific equilibrium equations to check if the slope is near failure or still safe.

The example in Figure 1 (Fellenius approach) shows one of the limit equilibrium procedures, where the slope can be split into slices, and each slice is examined under equilibrium assumptions. The idea here is to find the smallest possible factor of safety that satisfies equilibrium. This approach sometimes requires some iterative calculations, but engineers still prefer it for its transparency. Figure 2 demonstrates how modern computer-based analysis, such as finite element programs, has brought more detailed checks. These methods can represent various soil layers, boundary conditions, and loading aspects to better estimate deformation and stability margins.

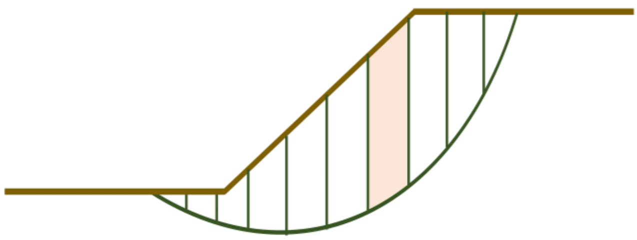


Figure 1. An example of the limit equilibrium method using the Fellenius approach

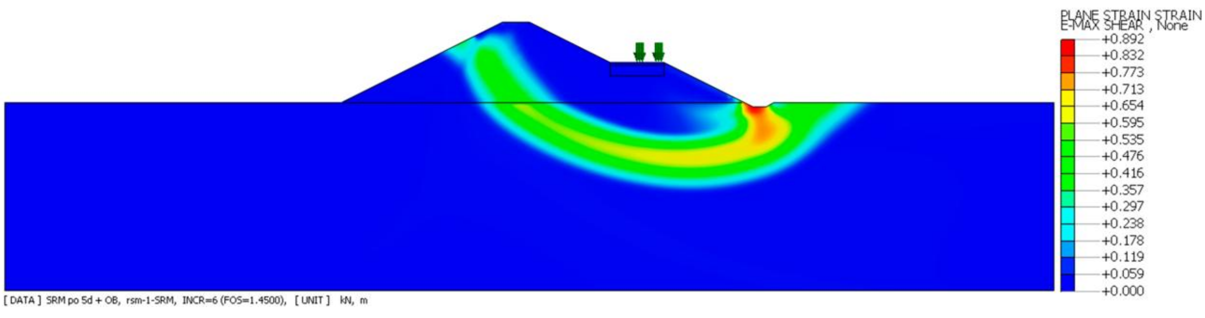


Figure 2. An example of finite element simulation of road embankments from Morman-Wątor & Pilecka [25]

Table 1 lists different ways to estimate the slope safety factor. Many engineering projects rely on finite element methods because they can represent complicated terrain shapes and soil properties in more realistic detail. However, the high computational requirements of such methods might be impractical in some day-to-day projects. Traditional limit equilibrium approaches often demand fewer inputs. Field methods, on the other hand, allow direct measurements and can capture actual ground conditions. For simpler tasks, empirical approaches might be good enough. That is why the final selection of the best approach may depend on schedule, budget, and available equipment.

Table 1. A brief discussion of various approaches to calculate the safety factor of road embankment

Estimation Approach	Description
Limit Equilibrium Method	This method assumes that the slope is in a state of equilibrium and that the forces acting on the slope are in balance. The method involves calculating the minimum safety factor by determining the forces acting on the slope and comparing them to the resisting forces. Additionally, they are widely used for the stability analysis of slopes with non-circular slip surfaces and are regarded as being more accurate than simpler methods.
Finite Element Method	This method involves using computer software to simulate the slope behavior under different loads and conditions.
Slope Mass Rating Method	This method involves determining the available factor of safety of a slope by assessing the quality and quantity of the materials making up the slope.
Empirical Method	This method uses data and information from past slope failures to estimate a slope's minimum safety factor.
Field Investigation Method	This method includes conducting a field investigation of the slope, such as a visual inspection, soil testing, and other measurements to determine the slope's safety conditions.

Another emerging trend is machine learning, which forecasts slope safety factors based on prior data. This can cut calculation times if a dataset is available. Recent studies reported that neural networks or other learning algorithms can reach excellent levels of accuracy with less modeling work. Still, many professional engineers want straightforward solutions that can be performed with fewer computational resources or that can be quickly checked by hand. In every case, the slope safety factor remains an important design requirement, as unstable embankments risk major harm to vehicles and people. That underlines why engineers pay strong attention to stable slope design.

3. Materials and Methods

The evaluation of slope safety factors is crucial in building highway embankments. Various approaches, such as finite element modeling and neural networks, were previously employed [26, 27]. However, the current analysis aims to generate simpler mathematical forms that permit prompt slope stability estimates under diverse conditions. Figure 3 presents a newly updated flowchart reflecting the revised research methodology. It begins with data acquisition for embankments and then moves to perform model validation and performance assessment.

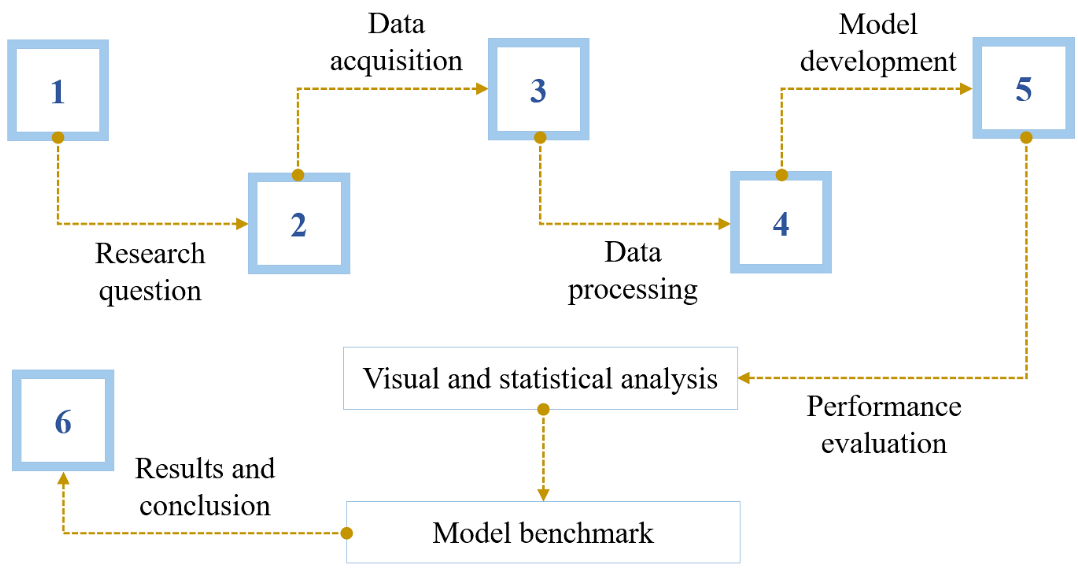


Figure 3. Research methodology used in this study

3.1. Utilized Database

For this research, a dataset with 276 points representing a wide range of cases from an open-source repository has been sourced [24]. It will serve as the foundation for both training and evaluating the regularized regression models. This dataset encompasses a wide range of parametric studies focusing on different embankment safety factors calculated using the finite element method. Details of the dataset and its ranges are given in Table 2.

Table 2. Descriptive statistics of the adopted database

Variable	Sample Size	Mean	Standard Deviation	Variance	Coefficient of Variation	Minimum	Q1	Median	Q3	Maximum
Height of Slope Embankments	276	12.26	6.01	36.1	49	6	6	12	18	24
Slope Angle	276	58.2	6.1	37.4	10.5	45	56.3	56.3	63.4	63.4
CBR	276	7.87	5.28	27.9	67.1	3.00	3.00	5.00	15	15
Specific Weight	276	21	1.489	2.216	7.09	18	20	20.75	22.75	23
Moisture Content	276	13.3	4.0	15.7	29.9	7	9.25	13.5	17.25	20
Deformation Modulus	276	30	11.9	142.2	39.8	10	20	30	40	50
Cohesion	276	10	10.8	116.3	107.8	2	4	6	9.5	40
Friction Angle	276	33.75	4.63	21.432	13.72	25	30	35	38.75	40
Poisson's Ratio	276	0.28	0.03	6.30E-04	9.11	0.25	0.25	0.28	0.3	0.30
Dilatancy Angle	276	5.06	0.69	0.4822	13.72	3.75	4.5	5.25	5.81	6
Factor of Safety	276	2.19	0.52	0.2653	23.51	0.92	1.81	2.22	2.54	3.67

3.2. Regression Techniques

Previous research has proposed various regularized regression models over the years. Extensive studies have been conducted to evaluate these models' efficiency. However, there is a notable scarcity of information comparing the performance of these models in the specific context of slope safety factor estimation. This study, therefore, aims to compare the performance of different regularized regression techniques in accurately predicting slope safety factors.

Multiple Linear Regression (MLR) is a statistical technique that creates a linear relationship between a single dependent variable and multiple independent variables. The mathematical formula of MLR is given in Equation 1.

$$Y = \beta X + \varepsilon \tag{1}$$

where $Y = [y_1, \dots, y_n]^T$ indicate the vector of the dependent variable; $X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,k} \\ \vdots & \ddots & \vdots \\ x_{n,k} & \cdots & x_{n,k} \end{bmatrix}$ represents the matrix of the independent variables; $\beta = [\beta_1, \dots, \beta_k]^T$ represents the coefficients of the model; $\varepsilon = [\varepsilon_1, \dots, \varepsilon_k]^T$ represents the residuals.

Ridge Regression, on the other hand, calculates coefficients in multi-variable regression models, particularly useful when the input variables are highly correlated. This method is anticipated to yield more precise safety factor predictions than MLR models. For example, in a regression model with a single dependent variable Y, as shown in Equation 1, the β coefficients are typically calculated using the ordinary least squares approach, as depicted in Equation 2.

$$\hat{\beta} = (X^T X)^{-1} X^T Y \tag{2}$$

where $\hat{\beta}$ represents the best unbiased linear estimate of β.

Alternatively, Hoerl & Kennard (1980) [28] introduced Ridge Regression to tackle multicollinearity issues in scenarios where independent variables are closely interrelated. This technique employs Equation 3 for β computation.

$$\hat{\beta}^* = \left(X^T X + \alpha I_p\right)^{-1} X^T Y \tag{3}$$

where $\hat{\beta}^*$ is the ridge estimator, $\alpha > 0$ is the complexity parameter that controls the amount of shrinkage and ensures that $E\left[(\hat{\beta}^* - \beta)^T (\hat{\beta}^* - \beta)\right] < E\left[(\hat{\beta} - \beta)^T (\hat{\beta} - \beta)\right]$, and I_p is the identity matrix.

Moreover, Ridge Regression enhances the ordinary least squares method by incorporating a penalty on coefficient magnitudes. This method determines ridge coefficients by minimizing a residual sum of squares, including the penalty component.

$$\min_{\beta} = \|\beta X - y\|_2^2 + \alpha \|\beta\|_2^2 \tag{4}$$

As a result, Ridge Regression employs the ℓ_2 regularization technique, which is based on the squared Euclidean norm, to impose a penalty on the coefficient vector.

The Lasso is a linear model that predicts coefficients approximating zero, which is advantageous in scenarios necessitating solutions with fewer non-zero coefficients, thus simplifying the feature set. It incorporates a regularization term and aims to minimize the following function:

$$\min_{\beta} = \frac{1}{2n_{samples}} \|\beta X - y\|_2^2 + \alpha \|\beta\|_1 \tag{5}$$

The Lasso estimate is obtained by solving the minimization problem of the least-squares penalty with the addition of $\alpha||\beta||_1$, where α is a constant and $||\beta||_1$ is the ℓ_1 norm of the coefficient vector.

ElasticNet is a hybrid linear regression model that employs both ℓ_1 and ℓ_2 norm regularizations for its coefficients. This dual approach yields a model that possesses the sparsity of Lasso and the regularization strength of Ridge. ElasticNet is particularly effective in scenarios with correlated predictors. Unlike Lasso, which tends to select one feature from a group of correlated ones, ElasticNet tends to include multiple correlated features. Moreover, ElasticNet benefits from Ridge's stability under feature rotation. The goal is to minimize a specific equation, as outlined in the model.

$$\min_{\beta} = \frac{1}{2n_{samples}}||\beta X - y||_2^2 + \alpha\rho||\beta||_1 + \frac{\alpha(1-\rho)}{2}||\beta||_2^2 \tag{6}$$

where ρ represents a parameter that controls the convex combination of ℓ_1 and ℓ_2.

Bayesian regression, a variant of linear regression (referenced as Equation 1), applies Bayesian inference for statistical analysis. This method presumes that errors are independent, identically distributed normal variables, with each error term $\varepsilon_i \sim N(0, \Sigma_\varepsilon)$ distribution for every observation i. Fundamentally, Bayesian Regression combines a prior probability distribution of parameters with a likelihood function to derive the posterior probability distribution, depicted in Equation 7 [29].

$$P(\beta, \Sigma_\varepsilon|Y, X) \propto P(Y|X, \beta, \Sigma_\varepsilon)P(\beta, \Sigma_\varepsilon) \tag{8}$$

where α is the priors over the parameter and λ is the precision selected to be gamma distributions and is estimated jointly with β during model fitting.

Stochastic Gradient Descent (SGD) is a simple yet effective technique for fitting linear models and machine learning algorithms. Essentially an optimization method, SGD is not tied to a specific model but is invaluable when dealing with numerous features. SGD has been a staple in machine learning for a long time but has recently garnered more attention for its use in large-scale learning. SGD calculates the gradient of the loss for each sample individually and updates the model progressively with a diminishing learning rate. The loss function includes a regularizer that penalizes the model parameters towards zero, using the squared Euclidean norm (ℓ_2), the absolute norm (ℓ_1), or a blend of both, as in ElasticNet. This study applies ElasticNet for estimation purposes.

Huber regression is a type of linear regression model designed to be less sensitive to outliers. It combines squared loss and absolute loss in its optimization process, depending on each sample's deviation from predicted values. For errors within a predefined threshold, squared loss is used; for larger errors, absolute loss is applied. This method reduces the influence of outliers on the loss function while considering their presence. Unlike Ridge regression, Huber regression employs a linear loss function for outlier data points.

The objective function that this method tries to minimize is as follows:

$$\min_{\beta,\sigma} = \sum_{i=1}^{n}\left(\sigma + H_\epsilon\left(\frac{|\beta X_i - y_i|}{\sigma}\right)\sigma\right) + \alpha||\beta||_2{}^2 \tag{9}$$

where H_ϵ is defined as:

$$H_\epsilon(z) = \begin{cases} z^2, & \text{if } |z| < \epsilon, \\ 2\epsilon|z| - \epsilon^2, & otherwise \end{cases} \tag{10}$$

Quantile regression focuses on estimating the median or other quantiles of the dependent variable (y) in relation to the independent variable (X), in contrast to the traditional least squares approach that predicts the expected value of y based on X. This model offers linear predictions for different quantiles (q ranging from 0 to 1) of the dependent variable. The coefficients or weights are determined by minimizing a specific problem.

$$\min_{\beta} = \frac{1}{n_{samples}}\sum_i PB_q(\beta X_i - y_i) + \alpha||\beta||_1 \tag{11}$$

where PB_q is the pinball loss (also known as linear loss) given in the following equation:

$$PB_q(t) = qmax(t, 0) + (1-q)\max(-t, 0) = \begin{cases} qt, & t > 0, \\ 0, & t = 0, \\ (1-q)t, & t < 0 \end{cases} \tag{12}$$

The linear nature of the pinball loss, evident only in residuals, renders quantile regression substantially more robust against outliers than mean estimation using squared error. This approach proves particularly advantageous when the goal is to predict a range rather than a single point. Commonly, prediction intervals are derived assuming the prediction error adheres to a normal distribution with a zero mean and constant variance. Nonetheless, quantile regression remains effective in generating meaningful prediction intervals even when errors exhibit variable (yet predictable) variance or deviate from a normal distribution.

3.3. Model Development and Hyperparameters Tunning

The performance of regression models is critical impacted by the selection of hyperparameters, which necessitates careful tuning [30-35]. This research employed the grid search technique combined with k-fold cross-validation during the training phase to fine-tune the hyperparameters of these methods [36-40]. In similar to existing literature, the proposed framework for developing the regression algorithms, as depicted in Figure 4, involves splitting the dataset into two segments: 70% for training and 30% for testing. It conducted a 10-fold repeated cross-validation process to identify the most suitable hyperparameters. After finalizing the hyperparameters for each method, it evaluated the ultimate, optimized model performance by comparing outcomes from various scoring criteria on the test dataset.

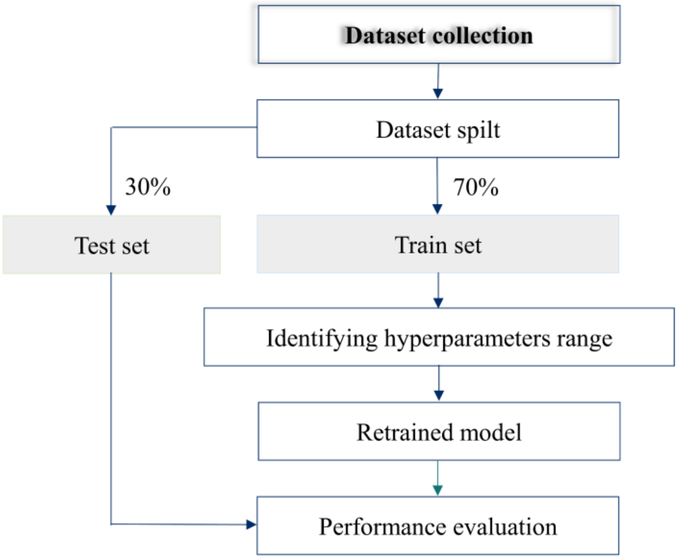


Figure 4. Methodology utilized in developing the regularized regression models

3.4. Models Performance Evaluation

This study analyzed the performance of the formulated models using statistical metrics and graphical representations. The models' fit was assessed using the coefficient of determination, as illustrated in Equation 13. Error analysis involved the application of the root mean square error (RMSE), as shown in Equation 14, and the mean absolute error (MAE), outlined in Equation 15.

$$R^2 = 1 - \frac{\sum(x_i - y_i)^2}{\sum(x_i - \bar{x}_i)^2} \tag{13}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}} \tag{14}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \bar{y}_i| \tag{15}$$

where x_i is the measured value, $\bar{x}_i$ is the mean of the measured values, y_i is the predicted value, $\bar{y}_i$ is the mean of the predicted values, and n is the number of observations.

4. Results Analysis

As highlighted earlier, the factor of safety is a pivotal metric in assessing the stability and reliability of road embankments, necessitating precise predictions. This analysis explored various models for this prediction, including MLR, SGD, and Lasso. Indeed, selecting a good model relies on the accuracy of the predicted outcomes. Figure 5 displays the performance of the investigated models in estimating the factor of safety within the training dataset. Generally, it appears that the SGD and Bayesian Ridge models emerge as superior, offering reliable predictions of the factor of safety in comparison to finite element results. Additionally, Figure 6 shows the outcomes of the testing dataset, indicating a consistent pattern and a robust correlation between the measured and predicted data across most models. The SGD and Bayesian Ridge models maintained their effectiveness in predicting the factor of safety on the testing dataset, reinforcing their appropriateness for this purpose.

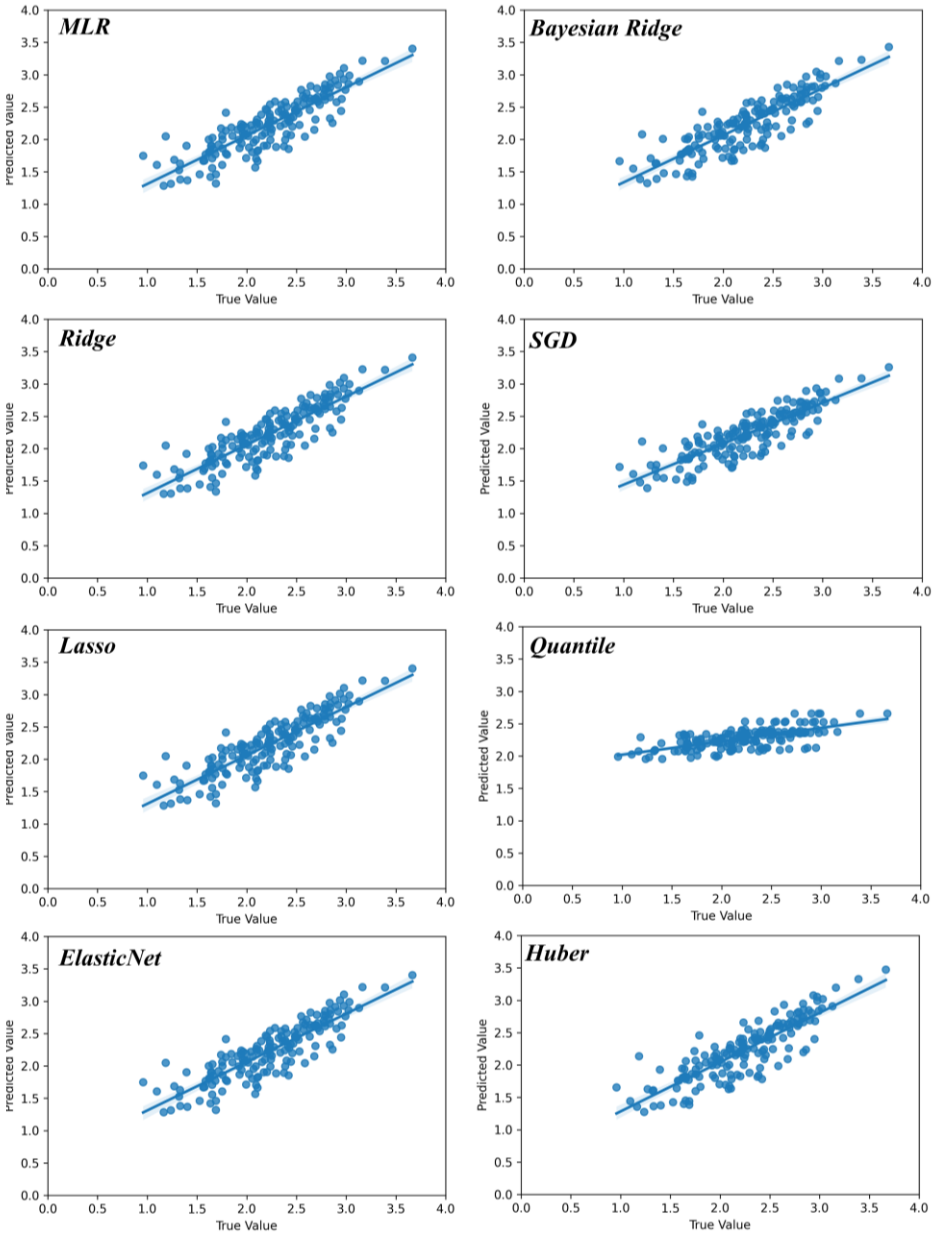
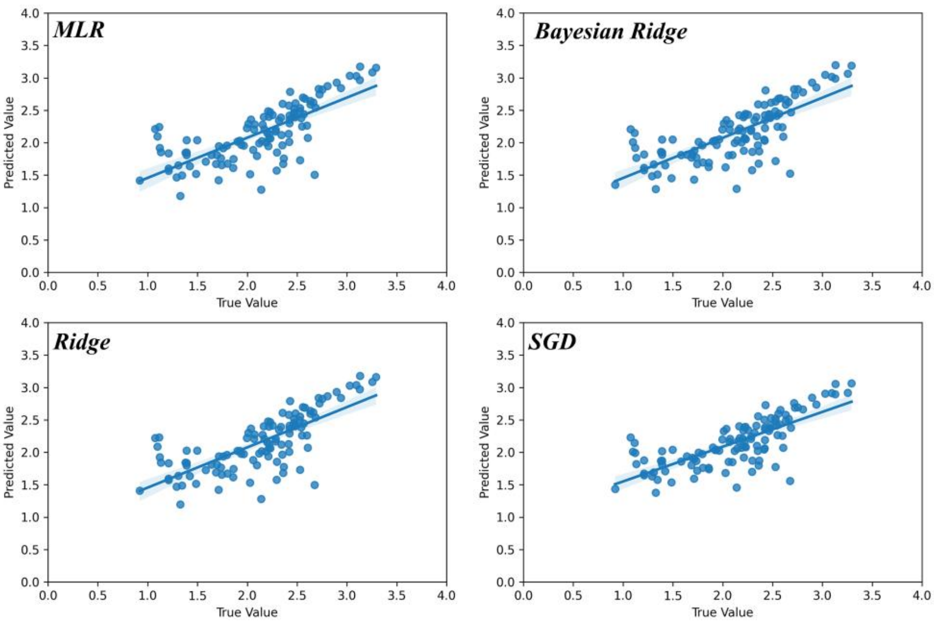


Figure 5. Results of the regression models for the training dataset



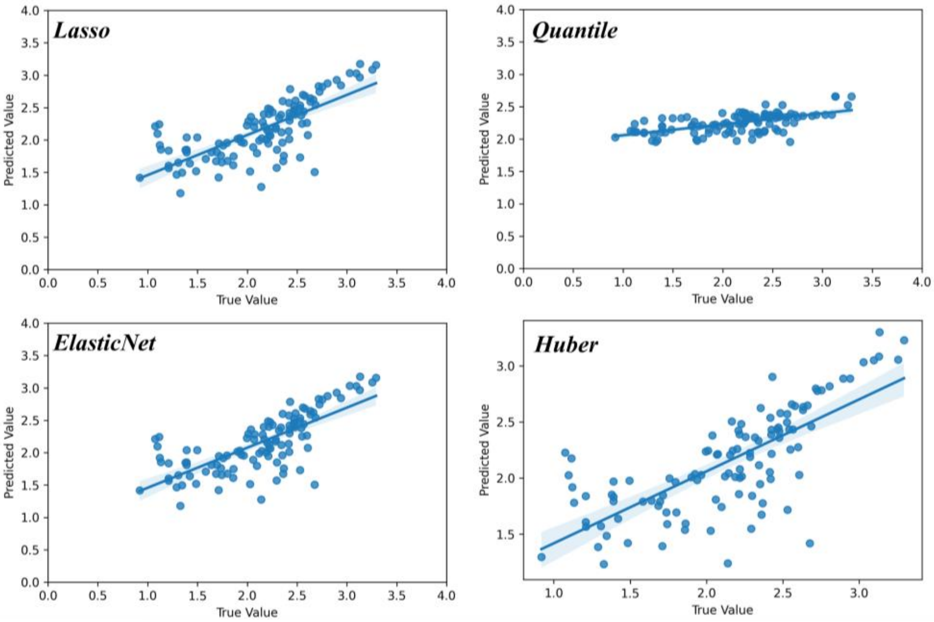


Figure 6. Results of the regression models for the testing dataset

Table 3 provides the coefficients and intercepts of nine distinct regularized regression models, each designed to predict the safety factors of road embankments. An aspect highlighted in the table is the variance in the weights assigned by each model. These weights represent the significance of each input variable in predicting the safety factor of road embankments. A consistent observation across most models is their varied weighting of input factors, yet a unanimous agreement on the importance of slope height underscoring its uniform impact on the outcome. Contrarily, the Quantile regression model, with numerous input factors assigned a zero weight, suggests a potential reason for its lower predictive accuracy, as it implies these factors' negligible effect on the predicted safety factor.

Table 3. Coefficients of the proposed regularized regression models

	MLR	Ridge	Lasso	ElasticNet	Bayesian Ridge	SGD	Quantile	Huber
Height	-0.06266	-0.06237	-0.06266	-0.06266	-0.06032	-0.05927	0.02038	-0.06547
Slope	0.03306	0.03305	0.03306	0.03306	0.03273	0.02595	0.00000	0.03179
CBR	0.02157	0.02128	0.02157	0.02157	0.02135	0.02118	0.00000	0.01670
Specific weight	-0.31644	-0.08995	-0.31642	-0.31642	-0.03446	0.00238	0.00000	-0.03750
Moisture	-0.03245	0.00290	-0.03245	-0.03245	0.00607	0.01231	0.00000	0.01006
Deformation modulus	0.00804	0.00935	0.00804	0.00804	-0.00034	0.00379	0.00000	0.00253
Cohesion	0.04051	0.02410	0.04051	0.04051	0.01779	0.01769	0.00470	0.02105
Friction angle	0.05461	0.02959	0.06973	0.06973	0.03757	0.01969	0.00000	0.03973
Poisson's ratio	-8.36241	-0.02728	-8.36167	-8.36167	0.00082	0.00023	0.00000	0.00198
Dilatancy angle	0.00819	0.00444	-0.09259	-0.09259	0.00564	0.00295	0.00000	0.00596
Constant	7.71206	1.18510	7.71144	7.71144	0.04100	0.00026	2.44149	0.00295

Figure 7 illustrates the performance indicators of different regression models during both the training and testing phases. Typically, most models exhibit an R^2 value around 0.85 for training and 0.75 for testing datasets, an exception being the Quantile model, which shows significantly lower performance, scoring approximately 0.27 and 0.17, respectively. Moreover, the RMSE values for most models hover around 0.25 and 0.35 for training and testing, whereas the Quantile model presents higher RMSEs of 0.45 and 0.53, respectively. This trend is similarly reflected in the MAE values.

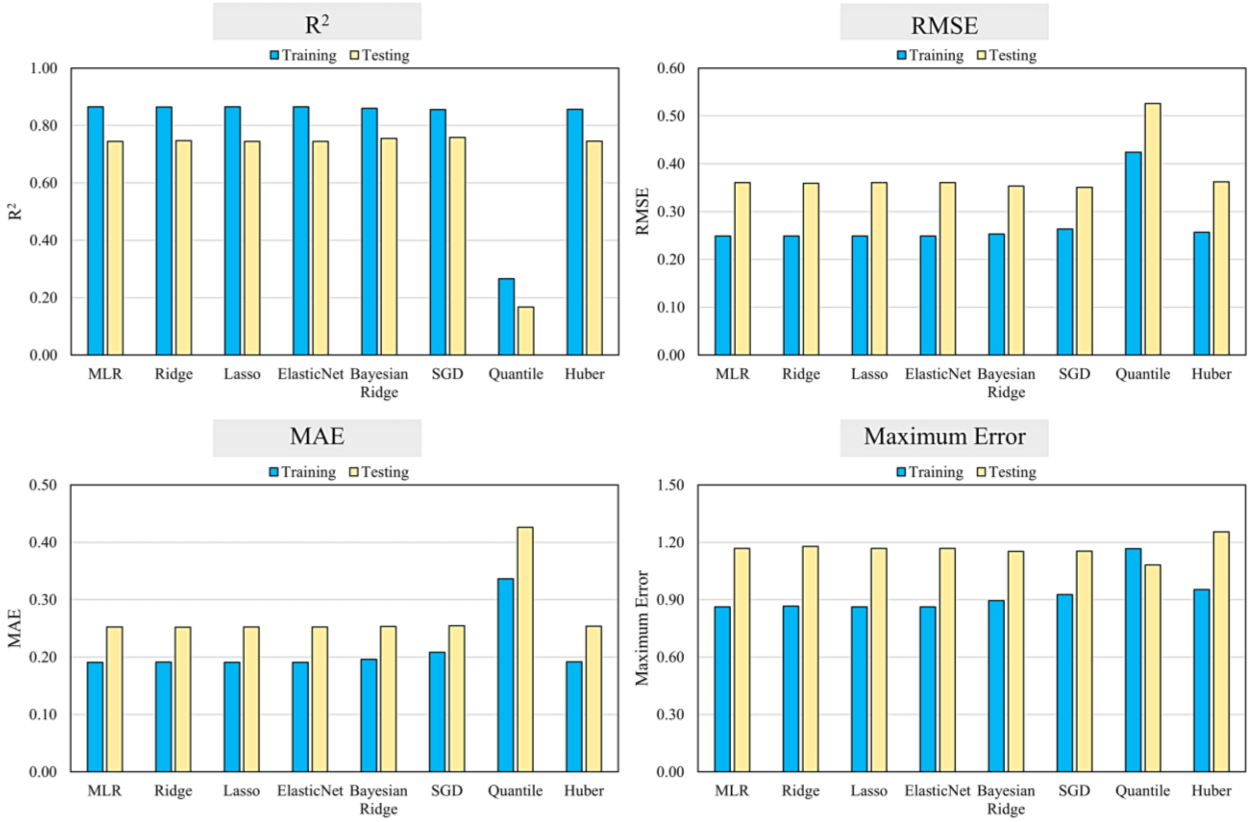


Figure 7. Performance of the developed regression models

5. Comparison with Traditional Methods

The study results are discussed herein focusing on comparing the new regularized regression approaches against traditional methods' outcomes. The comparative analysis, depicted in Table 4 and Figure 8, reveals that while most regularized models demonstrate comparable performance, the SGD and Bayesian Ridge models stand out with the lowest error rates. Conversely, the Quantile regression model records the highest error figures, reinforcing the earlier observation of its inferior predictive prowess. Among the traditional methods, the Bishop method exhibits the lowest RMSE value of 0.33, closely followed by the Morgenstern-Price method with an RMSE of 0.33. The Janbu and Fellenius methods, however, show higher RMSEs of 0.45 and 0.42, respectively, surpassing most of the new models.

Table 4. Comparison between the traditional and proposed safety factor estimation

Model	R^2	RMSE	MAE	Max Error
MLR	0.74	0.36	0.25	1.17
Ridge	0.75	0.36	0.25	1.18
Lasso	0.74	0.36	0.25	1.17
ElasticNet	0.74	0.36	0.25	1.17
Bayesian Ridge	0.75	0.35	0.25	1.15
SGD	0.76	0.35	0.25	1.15
Quantile	0.17	0.53	0.43	1.08
Huber	0.75	0.36	0.25	1.26
Fellenius Method	0.46	0.42	0.38	1.19
Bishop Method	0.66	0.33	0.22	1.02
Janbu Method	0.40	0.45	0.40	1.21
Morgensten-Price Method	0.66	0.33	0.23	1.03

High Performance
Low Performance

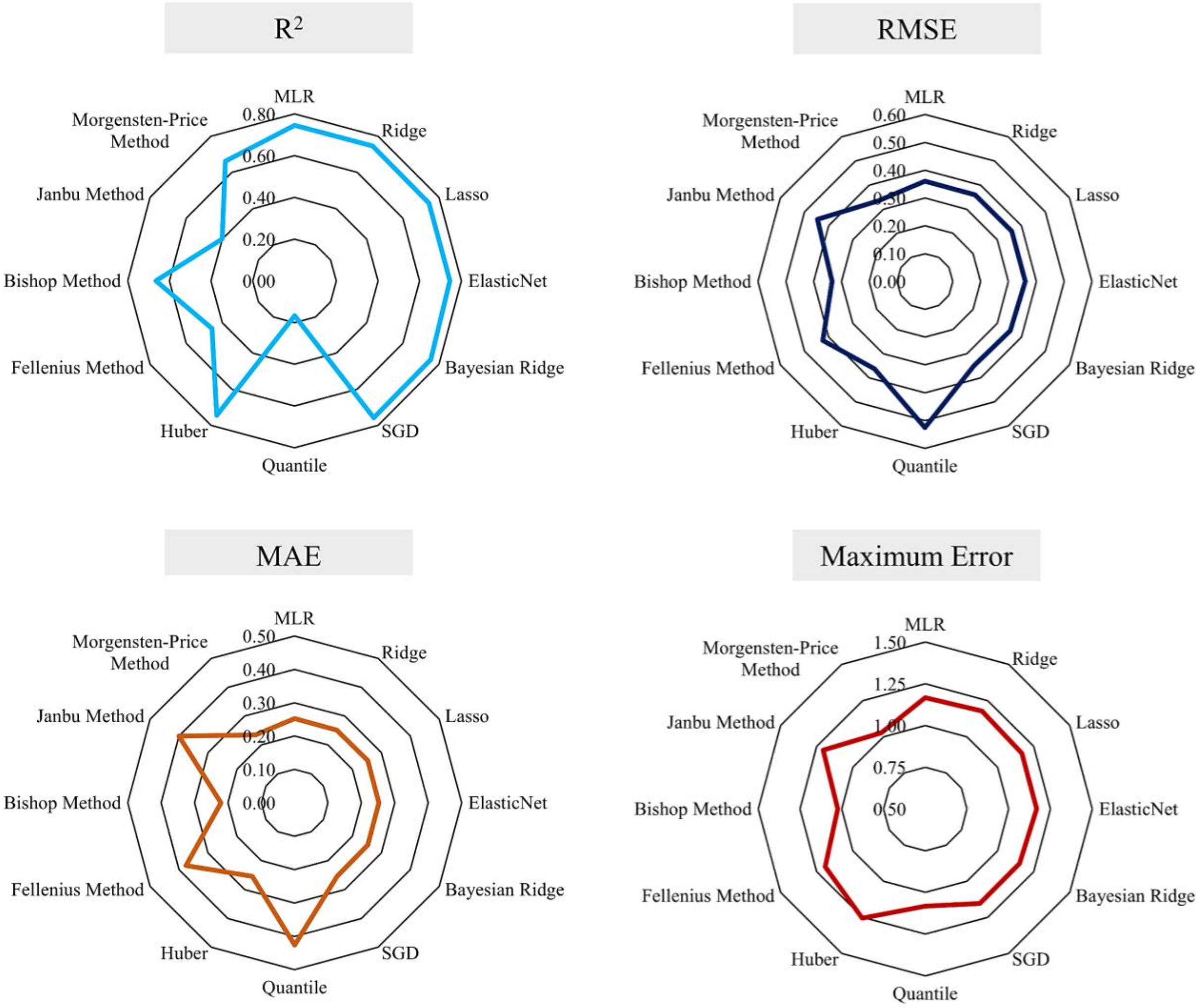


Figure 8. Benchmarking the proposed regularized regression models

Despite the slightly better accuracy of the Bishop and Morgenstern-Price methods compared to the SGD and Bayesian Ridge models, the latter are significantly simpler and faster, offering a reasonable compromise in performance. Overall, the findings suggest that regularized regression models are adept at delivering dependable predictions for the safety factor of road embankments. Those findings highlight that regularized regression can deliver proper estimates of the slope safety factor, provided that suitable hyperparameters are chosen. The superior results of SGD and Bayesian Ridge might originate from their balanced control of model complexity, with Bayesian Ridge introducing a Bayesian view that guards against extreme coefficient values and SGD benefiting from iterative gradient updates and flexible penalty terms. The best-performing models reached good predictions, which suggests they can be practical alternatives to the more time-consuming finite element methods, at least for routine tasks that aim to check slope stability at early design stages.

6. Alternative Advanced Machine Learning Models

This section aims to provide further exploration of ways to improve the accuracy of estimating the safety factor by investigating the use of advanced machine learning models. In this regard, 5 commonly used machine learning techniques were used. These techniques include Supported Vector Machine (SVM), Artificial Neural Networks (ANN), K-Nearest Neighbor (KNN), Extra Trees (ERT), and Gradient Boosting (GB). These techniques have been used a lot in the past and proved efficient in the field of civil engineering and hence their use for this problem holds good potential. These models were developed and optimized using the methodology outlined in Section 3.3 and their performance was calculated using the procedure detailed in Section 3.4. The results of these models are given in Figures 9 and 10 and Table 5.

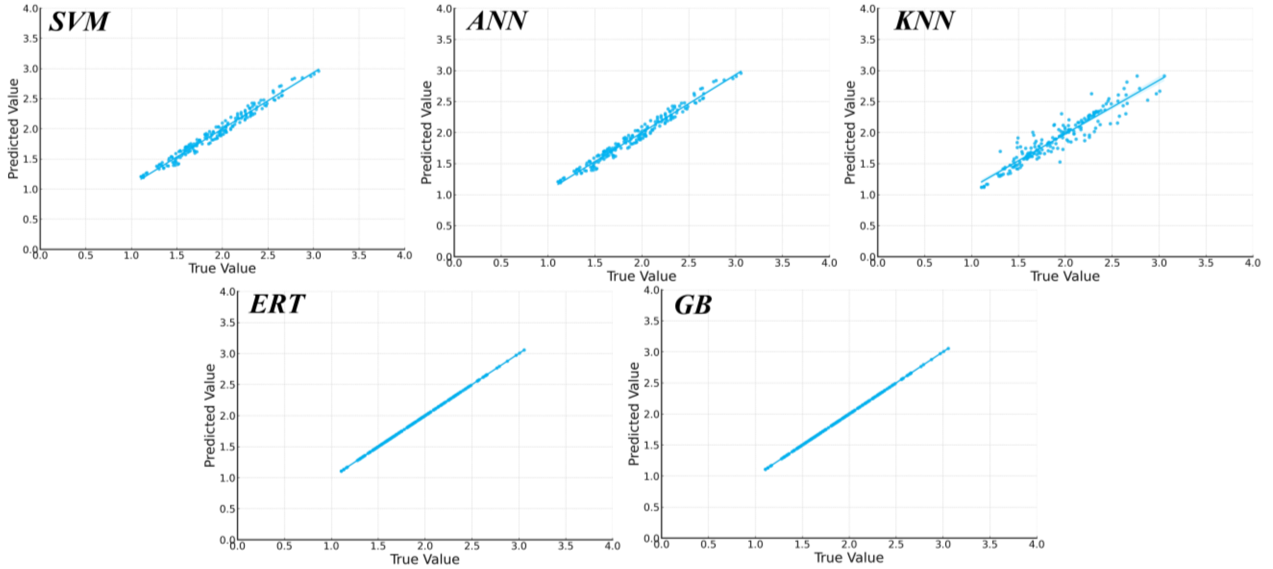


Figure 9. Performance of the developed machine learning models for the training dataset

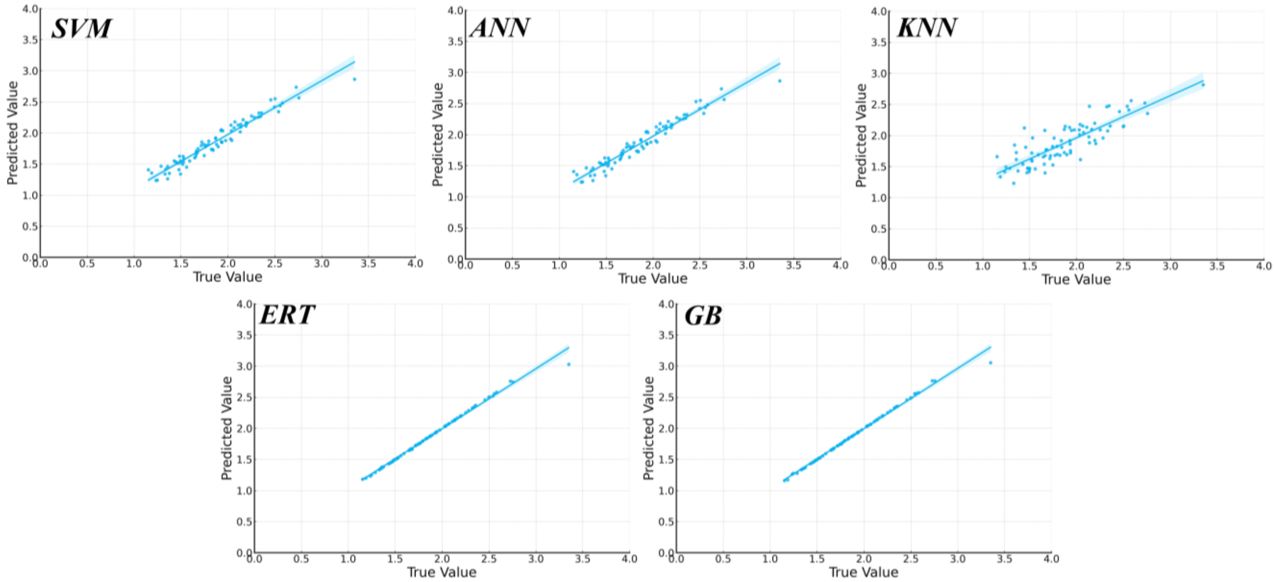


Figure 10. Performance of the developed machine learning models for the testing dataset

Table 5. Comparison between the developed machine learning models for safety factor estimation

Model	Training Dataset				Testing Dataset			
	R^2	RMSE	MAE	Max Error	R^2	RMSE	MAE	Max Error
SVM	0.97	0.07	0.06	0.10	0.94	0.10	0.08	0.49
KNN	0.89	0.14	0.09	0.10	0.71	0.22	0.17	0.49
ANN	0.97	0.07	0.06	0.42	0.94	0.10	0.08	0.68
ERT	1.00	0.00	0.00	0.00	0.99	0.04	0.01	0.32
GB	1.00	0.00	0.00	0.00	0.99	0.03	0.01	0.30

In general, it can be seen that the proposed machine learning models significantly surpasses the regularized linear regression ones as expected at the cost of more complexity. In this context, the GB model reached the best results in both training and testing cases followed by the ERT then the SVM and ANN, whereas the worst results in terms of advanced models, while again better than the regularized linear regression case, were reported in the KNN case. Accordingly, this study concludes that both the simplified and advanced models provides acceptable results; however, when higher accuracy is required the GB model can be used for the prediction.

7. Conclusion

Finally, this study evaluated the effectiveness of various regularized regression methods in predicting the safety characteristics of road embankments, benchmarking them against four conventional techniques and the finite element method. The findings highlight the potential of these regularized approaches for accurate prediction, with the SGD and Bayesian Ridge models emerging as the most effective simpler methods in minimizing maximum error. Most of the proposed models significantly outperformed traditional methods like Fellenius and Janbu, offering simpler and faster alternatives without compromising much on accuracy. Although both SGD and Bayesian Ridge models demonstrated a favorable trade-off between accuracy and computational efficiency, the quantile regression model lagged behind due to its relatively higher error rates. Additionally, advanced machine learning models achieved greater predictive accuracy than regularized linear regressions but at the expense of increased complexity. Overall, both regularized linear regression and advanced machine learning models delivered acceptable performance in estimating safety factors, supporting their viability for practical applications. However, the study is limited by the relatively small size of the dataset used, which may constrain the generalizability of the findings. Future research should consider expanding the dataset and exploring a wider variety of machine learning algorithms to further enhance model robustness and predictive accuracy.

8. Declarations

8.1. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

8.2. Funding

The author received no financial support for the research, authorship, and/or publication of this article.

8.3. Conflicts of Interest

The author declares no conflict of interest.

9. References

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