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Utilization of a least square support vector machine (LSSVM) for slope stability analysis

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Abstract This paper examines the capability of a least square support vector machine (LSSVM) model for slope stability analysis. LSSVM is firmly based on the theory of statistical learning, using regression and classification techniques. The Factor of Safety (FS) of the slope has been modelled as a regression problem, whereas the stability status (s) of the slope has been modelled as a classification problem. Input parameters of LSSSVM are: unit weight (γ), cohesion (c), angle of internal friction (ϕ), slope angle (β), height (H) and pore water pressure coefficient (r_u). The developed LSSVM also gives a probabilistic output. Equations have also been developed for the slope stability analysis. A comparative study has been carried out between the developed LSSVM and an artificial neural network (ANN). This study shows that the developed LSSVM is a robust model for slope stability analysis.

1. Introduction

The analysis of slope stability is an imperative task in the design and construction of different civil engineering structures, such as highways, open pits, earth dams etc. Geotechnical engineers use different methods for slope stability analysis, such as limit equilibrium [1–4], upper bound limit analysis [5–12], finite element [13,14], maximum likelihood [15], genetic programming [16] etc. The artificial neural network (ANN) has been successfully adopted in the slope stability problem [17,18]. However, ANN has some limitations, such as arriving at local minima, a low convergence speed, a black box approach and a lesser generalization performance [19,20].

This study employs the least square support vector machine (LSSVM) for prediction of the Factor of Safety (*FS*), which has been modeled as a regression problem, and the stability status (s) of the slope, which has been modeled as a classification problem. LSSVM is a statistical learning theory that adopts a least squares linear system as a loss function [21]. LSSVM is closely related to regularization networks [22]. With the quadratic cost function, the optimization problem reduces to find the solution of a set of linear equations. The data have been taken from the work of Sakellatiou and Ferentinou [17]. The dataset contains information about unit weight (d), cohesion (c), angle of internal friction (ϕ), slope angle (β), height (H), pore water pressure coefficient (r_u), *FS* and *s*. The paper has the following aims:

1. To examine the feasibility of LSSVM for slope stability analysis;
2. To determine probabilistic output;
3. To develop equations for slope stability analysis;
4. To make a comparative study between the developed LSSVM model and the ANN model developed by Sakellatiou and Ferentinou [17].

2. LSSVM for classification

This section of the paper serves as an introduction to LSSVM. Details of this method can be found in Suykens et al. [23]. A binary classification problem is considered, having a set of training vectors (D) belonging to two separate classes.

$$D = \left\{(x^1, y^1), \ldots, (x^l, y^l)\right\}, \quad x \in R^n, y \in \{-1, +1\}, \qquad (1)$$

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where $x \in R^n$ is an n-dimensional data vector, with each sample belonging to either of two classes labelled $y \in \{-1, +1\}$, and l is the number of training data. This study uses d, c, ϕ, β, H and r_u as input parameters. So $x = [d, c, \beta, \phi, r_u, H]$. In the current context of classifying the status of the slope, the two classes labeled $+1$ and -1 may mean stable slope and failed slope. The Support Vector Machine (SVM) approach aims at constructing a classifier of the form:

$$y(x) = \text{sign}\left[\sum_{k=1}^{N} \alpha_k y_k k(x, x_k) + b\right], \quad (2)$$

where α_k are positive real constants, b is the scalar threshold, N is the number of the dataset and $k(x, x_k)$ is the Kernel function. For the case of two classes, one assumes:

$$w^T\varphi(x_k) + b \geq 1, \quad \text{if } y_k = +1 \text{ (stable slope)},$$
$$w^T\varphi(x_k) + b \leq 1, \quad \text{if } y_k = -1 \text{ (failed slope)}, \quad (3)$$

where w is an adjustable weight vector, T is the transpose and $\varphi(.)$ is the feature map that maps the input space into a higher dimensional space, which is equivalent to:

$$y_k\left[w^T\varphi(x_k) + b\right] \geq 1, \quad k = 1, \ldots, N. \quad (4)$$

According to the structural risk minimization principle, the risk bound is minimized by formulating the following optimization problem [24]:

$$\text{Minimize: } \frac{1}{2}w^T w + \frac{\gamma}{2}\sum_{k=1}^{l} e_k^2,$$

$$\text{Subjected to: } y_k\left[w^T\varphi(x_k) + b\right] = 1 - e_k, \quad k = 1, \ldots, N, \quad (5)$$

where γ is the regularization parameter, determining the trade-off between the fitting error minimization and smoothness, and e_k is error variable. This optimization problem (Eq. (5)) is solved by Lagrange multipliers [21], and its solution is given by:

$$y(x) = \text{sign}\left[\sum_{k=1}^{N} \alpha_k y_k K(x, x_k) + b\right], \quad (6)$$

where sign () is the signum function. It gives $+1$ (stable slope) if the element is greater than or equal to zero, and -1 (failed slope) if it is less than zero.

This study adopts the above methodology for prediction of 's' of the slope. The dataset consists of 46 case studies of slopes. To use these data for classification purposes, a value of 1 is assigned to the stable condition of the slope, while a value of -1 is assigned to the failure condition of the slope so as to make this a two-class classification problem. In this model, d, c, ϕ, β, H, and r_u are used as input parameters. The data are normalized between 0 to 1. In carrying out the formulation, the data have been divided into two sub-sets, such as:

(a) A training dataset: This is required to construct the model. In this study, 32 out of 46 data are considered for the training dataset.
(b) A testing dataset: This is required to estimate the model performance. In this study, the remaining 14 data are considered as a testing dataset. To train the LSSVM model, a radial basis function has been used as a Kernel function.

The program of the classification problem is constructed using MATLAB.

3. LSSVM for regression

LSSVM models are an alternate formulation of SVM regression [25], proposed by Suykens et al. [23]. Consider a given training set of N data points, $\{x_k, y_k\}_{k=1}^N$, with input data $x_k \in R^N$, and output $y_k \in r$, where R^N is the N-dimensional vector space and r is the one-dimensional vector space. For a regression problem, the same input variables are employed as used in the classification problem. The output of the LSSVM model is FS. So, in this study $x = [d, c, \beta, \varphi, r_u, H]$ and $y = FS$. In feature space, LSSVM models take the form:

$$y(x) = w^T\varphi(x) + b, \quad (7)$$

where the feature map $\varphi(.)$ maps the input data into a higher dimensional feature space; $w \in R^n$; $b \in r$; w = an adjustable weight vector; and b = the scalar threshold. In LSSVM, for function estimation, the following optimization problem is formulated:

$$\text{Minimize: } \frac{1}{2}w^T w + \frac{1}{2}\sum_{k=1}^{N} e_k^2,$$

$$\text{Subject to: } y(x) = w^T\varphi(x_k) + b + e_k, \quad k = 1, \ldots, N, \quad (8)$$

where N is the number of data.

The following equation for FS prediction has been obtained by solving the above optimization problem [26,27]:

$$FS = y(x) = \sum_{k=1}^{N} \alpha_k K(x, x_k) + b. \quad (9)$$

The radial basis function has been used in this analysis, and is given by:

$$K(x_k, x_l) = \exp\left\{-\frac{(x_k - x_l)^T(x_k - x_l)}{2\sigma^2}\right\}, \quad k, l = 1, \ldots, N, \quad (10)$$

where σ is the width of the radial basis function.

This study examines the capability of the above methodology for prediction of FS. The same training dataset, testing dataset and normalization technique have been adopted as used in the classification problem. The program of the classification problem is constructed using MATLAB.

4. Results and discussion

The design values of γ and σ have been determined by a trial and error approach. The training and testing performance has been calculated using the following formula:

Training performance (%) or
Testing performance (%)

$$= \left(\frac{\text{No of data predicted accurately by LSSVM}}{\text{Total data}} \times 100\right). \quad (11)$$

The design values of γ and σ are 80 and 30, respectively. The training performance has been determined by using the design values of γ and σ and is 100%. Therefore, the developed LSSVM models have successfully captured the input and output relationship. Now, the developed LSSVM model has been used to determine the performance of the testing dataset. Only one data has been misclassified for testing the dataset. Therefore, the testing performance is 92.85%. The developed LSSVM model

Table 1: Performance of training dataset for prediction of s of slope.

d (kN/m^3)	c (kPa)	φ (°)	β (°)	H (m)	r_u	Actual class	Predicted class	Values of α for classification	Values of α for regression
18.68	26.34	15	35	8.23	0	−1	−1	0.78	−4.33
16.5	11.49	0	30	3.66	0	−1	−1	−8.30	6.71
18.84	14.36	25	20	30.5	0	1	1	9.72	3.35
28.44	29.42	35	35	100	0	1	1	17.82	0.63
28.44	39.23	38	35	100	0	1	1	−6.43	6.06
14.8	0	17	20	50	0	−1	−1	39.00	−6.91
14	11.97	26	30	88	0	−1	−1	−5.35	−2.16
25	120	45	53	120	0	1	1	4.07	−1.15
26	150.05	45	50	200	0	1	1	−3.37	−5.75
18.5	12	0	30	6	0	−1	−1	−4.23	5.49
22.4	10	35	30	10	0	1	1	−22.52	−0.17
21.1	10	30.34	30	20	0	1	1	29.54	−9.11
22	0	36	45	50	0	−1	−1	14.38	−2.32
12	0	30	35	4	0	1	1	26.99	0.61
12	0	30	35	4	0	1	1	26.99	0.88
12	0	30	45	8	0	−1	−1	36.44	1.57
23.47	0	32	37	214	0	−1	−1	0.95	4.44
19.63	11.97	20	22	12.19	0.405	−1	−1	14.69	−11.98
21.82	8.62	32	28	12.8	0.49	−1	−1	52.76	6.54
18.84	0	20	20	7.62	0.45	−1	−1	28.29	−5.97
21.43	0	20	20	61	0.5	−1	−1	−19.47	2.39
19.06	11.71	28	35	21	0.11	−1	−1	41.37	−10.97
21.51	6.94	30	31	76.81	0.38	−1	−1	4.02	−3.27
18	24	30.15	45	20	0.12	−1	−1	−13.88	3.72
23	0	20	20	100	0.3	−1	−1	7.15	0.15
22.4	10	35	45	10	0.4	−1	−1	0.73	2.2
20	20	36	45	50	0.25	−1	−1	3.57	−1.74
20	20	36	45	50	0.5	−1	−1	−9.96	2.27
20	0	36	45	50	0.5	−1	−1	−8.18	−2.71
22	0	40	33	8	0.35	1	1	24.32	1.06
20	0	24.5	20	8	0.35	1	1	65.52	1.64
18	5	30	20	8	0.3	1	1	2.12	18.75

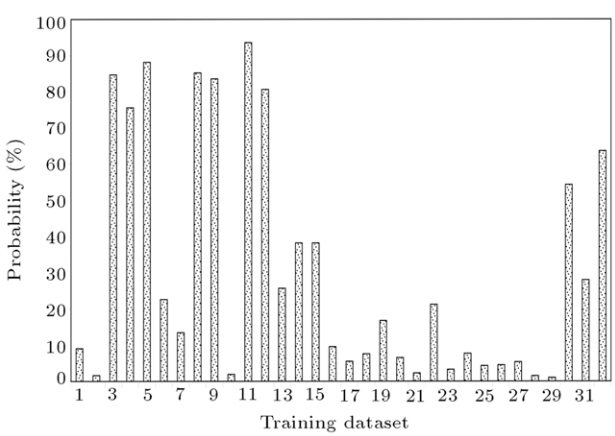

Figure 1: Probability of training dataset.

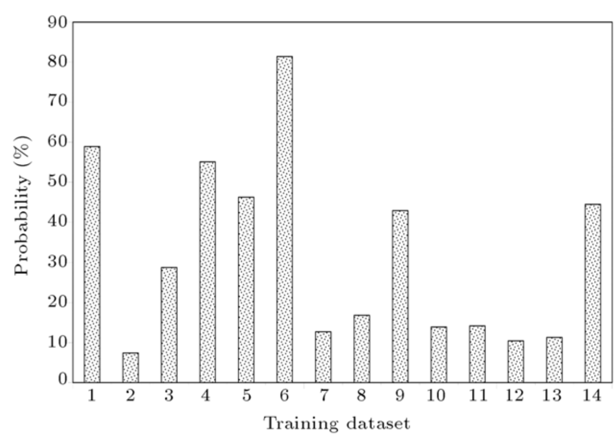

Figure 2: Probability of testing dataset.

has been also used to determine the probability. Figures 1 and 2 depict the probability of training and testing the dataset, respectively. These figures can be also used to predict the corresponding risk. The developed LSSVM model also gives the following equation (by putting $K(x, x_k) = \exp\left\{-\frac{(x_k-x)^T(x_k-x)}{2\sigma^2}\right\}$, $N = 32$, $\sigma = 30$ and $b = 1.1432$ in Eq. (6)) for determination of 's' of the slope:

$$s = \text{sign}\left[\sum_{k=1}^{32} \alpha_k y_k \exp\left\{-\frac{(x_k-x)^T(x_k-x)}{1800}\right\} + 1.1432\right]. \quad (12)$$

The values of α have been given in Figure 3 and Table 1 for the classification problem. Table 2 shows the performance of the testing dataset.

For a regression problem, the design values of γ and σ are 20 and 30, respectively. The performance of the training dataset has been determined using the design values of γ and σ. Figure 4 illustrates the performance of the training dataset. The value of R ($R = 0.961$) is close to one for the training dataset. For a good model, the value of R should be close to one. Therefore, the developed LSSVM model has successfully captured the input and output relations for the training dataset. Now, the performance of the developed LSSVM model has been examined for the testing dataset. Figure 5 depicts the performance of the testing dataset. Figure 5 also confirms that the developed LSSVM model has the capability of predicting FS. Figures 6 and 7 show a 95% error bar for training and testing the dataset, respectively. The obtained error bar can be

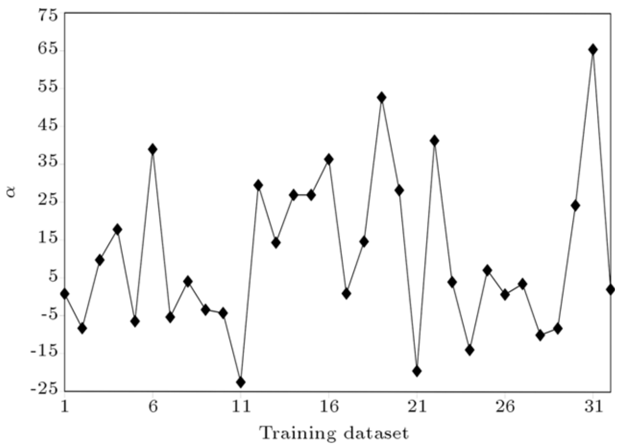

Figure 3: Values of α for classification problem.

Table 2: Performance of testing dataset for prediction of s of slope.

d (kN/m^3)	c (kPa)	φ (°)	β (°)	H (m)	r_u	Actual class	Predicted class
24	0	40	33	8	0.3	1	1
16	70	20	40	115	0	−1	−1
20.41	33.52	11	16	45.72	0.2	−1	−1
18.84	15.32	30	25	10.67	0.38	1	1
18.84	14.36	25	20	30.5	0.45	−1	−1
22.4	100	45	45	15	0.25	1	1
20	0	36	45	50	0.25	−1	−1
20.6	16.28	26.5	30	40	0	−1	−1
18.84	57.46	20	20	30.5	0	1	1
18.5	25	0	30	6	0	−1	−1
22	20	36	45	50	0	−1	−1
12	0	30	45	8	0	−1	−1
14	11.97	26	30	88	0.45	−1	−1
20.41	24.9	13	22	10.67	0.35	1	−1

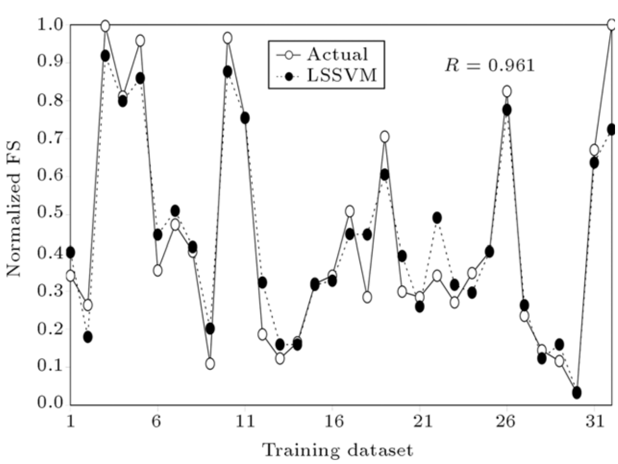

Figure 4: Performance of training dataset.

used for determination of the confidence interval. The following equation (by putting $K(x, x_k) = \exp\left\{-\frac{(x_k-x)^T(x_k-x)}{2\sigma^2}\right\}$, $N = 32$, $\sigma = 30$ and $b = -0.4386$ in Eq. (9)) has been developed for the prediction of FS:

$$FS = \sum_{k=1}^{32} \alpha_k \exp\left\{-\frac{(x_k - x)^T(x_k - x)}{1800}\right\} - 0.4386. \tag{13}$$

Figure 8 and Table 1 show the values of α for FS prediction.

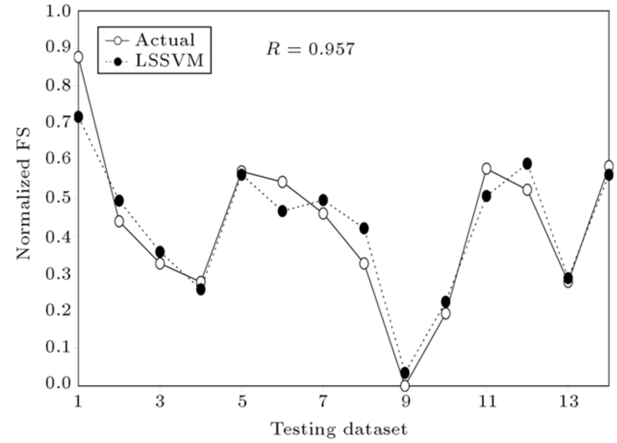

Figure 5: Performance of testing dataset.

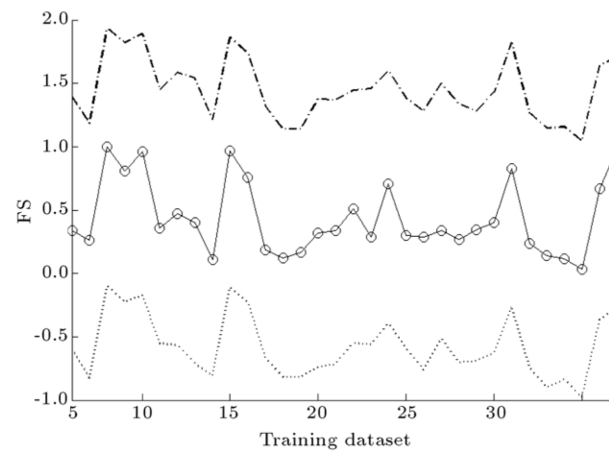

Figure 6: 95% error bar for training dataset.

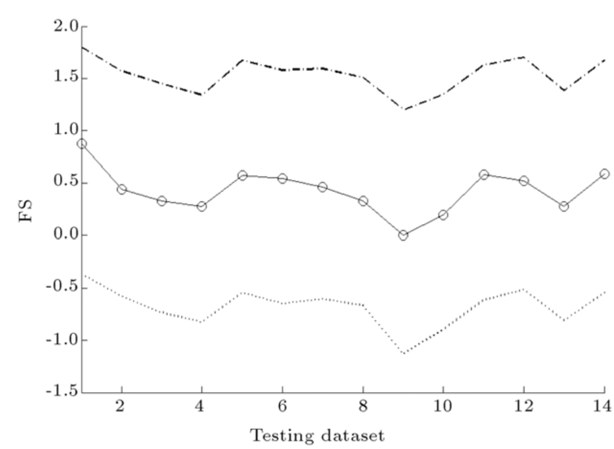

Figure 7: 95% error bar for testing dataset.

A comparative study has been carried out between the developed LSSVM for FS prediction and the ANN model [17]. The ANN model consists of one input layer, one hidden layer with six neurons and one output layer. The learning rate and error goal of the ANN model are 0.02 and 0.03, respectively. The data have been collected from the chart given by Hoek and Bray [28], Lin et al. [29], Madzie [30]and Hudson [31]; Table 3 presents the dataset. Comparison has been done in terms of Root Mean Square Error (RMSE) and Mean Absolute

Table 3: Data from different literatures.

Reference	d (kN/m^3)	c (kPa)	φ (°)	β (°)	H (m)	r_u	FS
Hoek and Bray [28]	21	20	40	40	12	0	1.84
	21	45	25	49	12	0.3	1.53
	21	30	35	40	12	0.4	1.49
	21	35	28	40	12	0.5	1.43
	20	10	29	34	6	0.3	1.34
	20	40	30	30	15	0.3	1.84
	18	45	25	25	14	0.3	2.09
	19	30	35	35	11	0.2	2
	20	40	40	40	10	0.2	2.3
Hudson [31]	18.85	24.8	21.3	29.2	37	0.5	1.07
	18.85	10.34	21.3	34	37	0.3	1.29
Lin et al. [29]	18.8	30	10	25	50	0.1	1.4
	18.8	25	10	25	50	0.2	1.18
	18.8	20	10	25	50	0.3	0.97
	19.1	10	10	25	50	0.4	0.65
	18.8	30	20	30	50	0.1	1.46
	18.8	25	20	30	50	0.2	1.21
	18.8	20	20	30	50	0.3	1
	19.1	10	20	30	50	0.4	0.65
Madzie [30]	22	20	22	20	180	0	1.12
	22	20	22	20	180	0.1	0.99

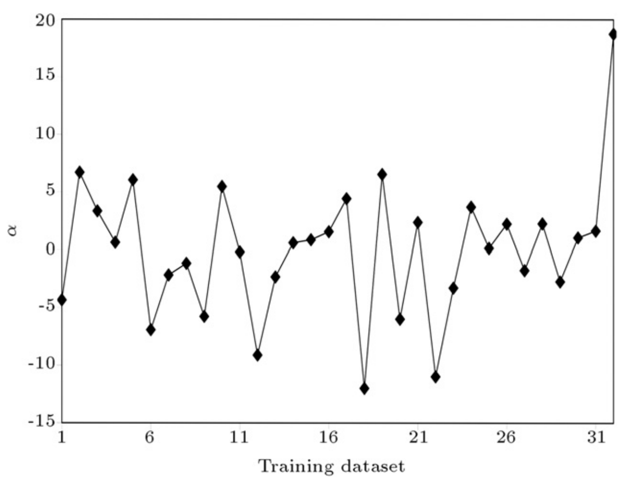

Figure 8: Values of α for FS prediction.

Table 4: Comparison between ANN and LSSVM models.

Model	RMSE	MAE
ANN	0.3743	0.3134
LSSVM	0.2840	0.2325

Error (MAE). Table 4 shows the values of RMSE and MAE for ANN and LSSVM models. From Table 4, it is clear that the developed LSSVM model outperforms the ANN model. The LSSVM model uses only two parameters (γ and σ), whereas ANN uses a number of hidden layers, a number of hidden nodes, a learning rate, a momentum term, a number of training epochs, transfer functions, and weight initialization methods. Obtaining an optimal combination of these parameters is also a difficult task.

The results from the LSSVM model have been also compared with the SVM and the Relevance Vector Machine (RVM) developed by Samui [32] and Samui et al. [33]. For the classification problem, the performance of the LSSVM model is better than the SVM model. The performances of LSSVM and RVM models are the same for the classification problem. The developed SVM model gives the values of RMSE $= 0.27$ and MAE $= 0.24$ for literature data. Therefore, for the regression problem, the performances of LSSVM and SVM are comparable. Equations have not been developed for SVM and RVM models. This study gives equations for both classification and regression problems. The developed RVM model has some limitations, such as a highly nonlinear optimization process and difficulties in finding an optimum solution for the large data set. The developed SVM model is solved using quadratic programming methods. However, these methods are often time consuming and are difficult to implement adaptively. The developed SVM did not give the error bar (FS prediction) and probability (stability status prediction) of the predicted output, whereas the developed LSSVM does.

5. Conclusion

The LSSVM for slope stability analysis has been described in this paper. Forty six data have been employed to construct the LSSVM model. The developed LSSVM has given encouraging results for prediction of the stability status of the slope, as well as the factor of safety. It also gives a probabilistic output. The performance of the developed LSSVM is found to be better than that of the ANN. The developed LSSVM model can be used as a quick tool for slope stability analysis without using any table or chart. The user can employ the developed equations for slope stability analysis. The developed LSSVM model can be used as a powerful tool for slope stability analysis.

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