Research Article

Predicting Tunnel Squeezing Using Multiclass Support Vector Machines

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Tunnel squeezing is one of the major geological disasters that often occur during the construction of tunnels in weak rock masses subjected to high in situ stresses. It could cause shield jamming, budget overruns, and construction delays and could even lead to tunnel instability and casualties. Therefore, accurate prediction or identification of tunnel squeezing is extremely important in the design and construction of tunnels. This study presents a modified application of a multiclass support vector machine (SVM) to predict tunnel squeezing based on four parameters, that is, diameter (D), buried depth (H), support stiffness (K), and rock tunneling quality index (Q). We compiled a database from the literature, including 117 case histories obtained from different countries such as India, Nepal, and Bhutan, to train the multiclass SVM model. The proposed model was validated using 8-fold cross validation, and the average error percentage was approximately 11.87%. Compared with existing approaches, the proposed multiclass SVM model yields a better performance in predictive accuracy. More importantly, one could estimate the severity of potential squeezing problems based on the predicted squeezing categories/classes.

1. Introduction

Redistributed stresses owing to tunnel excavation may exceed rock strength, and this could cause large plastic deformations, a phenomenon often referred to as tunnel squeezing [1]. Tunnel squeezing often occurs in soft/weak rock masses (such as shales and schists) subjected to high in situ stresses and constitutes one of the main geological disasters for rock underground engineering [2]. It could cause shield jamming, budget overruns, and construction delays and could even lead to tunnel instability and casualties. Therefore, accurate prediction or identification of tunnel squeezing is extremely important in the design and construction of tunnels. Many researchers have been studying the prediction or identification of tunnel squeezing since the 1980s. A summary of these studies for predicting tunnel squeezing is listed in Table 1. Overall, these approaches can be divided into three categories: (i) those based on the relationship between rock mass strength and in situ stress, (ii) those based on the correlations between overburden and the rock mass classification (such as Q), and (iii) those based on the prediction of deformation ε . Note that

the deformation ε used herein refers to the percentage strain (or is alternatively referred to as “normalized convergence”) and is defined as 100x the ratio of the tunnel closure to tunnel diameter [3]. The commonly accepted threshold for squeezing occurrence is $\varepsilon = 1\%$ [4–6]; that is, the tunnels with strains larger than 1% will likely encounter construction problems.

In addition, numerical simulation has also been used as an important tool in squeezing prediction or tunnel support design, by considering, among others, the three-dimensional (3D) stress conditions and the time-dependent response. Numerical studies and solutions to time-dependent (or creep) deformations (e.g., [7–9]) are not reviewed herein because they are beyond the scope of this study.

Recently, soft computational methods, such as artificial neural networks (ANNs) and support vector machines (SVMs), have been proposed to predict tunnel squeezing (or convergence) [1, 17–20] because ANN and SVM do not require prior knowledge of a particular model form and possess a flexible nonlinear modeling capability [21]. For instance, Shafiei et al. [1] proposed an SVM classifier, which yields a higher accuracy than the commonly used empirical

TABLE 1: Summary of previously published empirical correlations for predicting tunnel squeezing.

Proposed by	Correlations	Required parameters	Sources	Type
Jethwa et al. [10]	$N_c = \sigma_{cm}/\gamma H \leq 2.0$; $\sigma_{cm} = 2c_p \cos \phi_p / (1 - \sin \phi_p)$	σ_{cm} , γ , and H	—	Semiempirical
Singh et al. [11]	$H \geq 350Q^{1/3}$	H and Q	Thirty-nine case histories	Empirical
Aydan et al. [12]	$\alpha = \sigma_c/\gamma H \leq 2.0$	σ_c , γ , and H	Cases from Japan tunnels	Semiempirical
Barla [13]	$\sigma_{cm}/\gamma H \leq 1.0$	σ_{cm} , γ , and H	—	Semiempirical
Bhasin and Grimstad [14]	$\sigma_\theta/\sigma_{cm} \geq 1.0$ with $\sigma_{cm} = 0.7\gamma Q^{1/3}$	σ_{cm} and σ_θ	Tunnel case histories	Semiempirical
Hoek [15]	$\varepsilon\% = 0.15(1 - p_i/p_0) \cdot (\sigma_{cm}/p_0)^{-(3p_i/p_0+1)/(3.8p_i/p_0+0.54)} \geq 1$ (%)	p_i , p_0 , and σ_{cm}	Finite element models	Semiempirical
Jimenez and Recio [6]	$H \geq 424.4Q^{0.32}$	H and Q	Sixty-two case histories	Empirical
Dwivedi et al. [16]	$\varepsilon = (0.0191\sigma_v Q^{-0.2})/(K+1) + 0.0025 \geq 1\%$ with $\sigma_v = 0.027H$	σ_v , Q , and K	Sixty-three case histories	Empirical

N_c (or α): competency factor (also called “strength stress ratio (SSR)”), σ_{cm} : rock mass uniaxial compressive strength (MPa), γ : rock mass specific weight (MN/m³), H : overburden or depth of tunnel (m), c_p : rock mass peak cohesion (MPa), ϕ_p : rock mass peak friction angle (degree), Q : rock tunneling quality index, σ_c : uniaxial compressive strength of intact rock (MPa), σ_θ : tangential stress (MPa), ε : percentage strain (ratio of tunnel closure to tunnel diameter), p_0 : in situ vertical stress at tunnel depth (MPa), p_i : internal support pressure (MPa), σ_v : vertical in situ stress (MPa), and K : support stiffness (MPa).

method to predict tunnel squeezing based on the Q tunneling index and the buried depth of the tunnel (H). However, the proposed SVM classifier is a binary classifier, which means it can only classify each tunnel case as squeezing or non-squeezing, but cannot estimate the severity of tunnel squeezing. In addition, the input parameters for the proposed SVM classifier are only Q and H , indicating that the influence of the support systems cannot be properly considered.

To overcome these problems, we propose a multiclass SVM classifier to predict the severity of tunnel squeezing based on four parameters, that is, diameter (D), buried depth (H), support stiffness (K), and rock tunneling quality index (Q). The main advantages of the proposed multiclass SVM classifier with respect to previous approaches, such as those listed in Table 1, are that (a) multiclass SVM can carry out a multiclassification prediction (in other words, the severity of potential squeezing problems could be estimated based on the predicted squeezing classes), (b) the influences of support systems can be properly accounted for through the input of support stiffness, and (c) the predicted results are expected to be more accurate. To this end, an extensive database, including 117 case histories from different countries, was compiled to train the multiclass SVM classifier with LibSVM, which is a simple, easy-to-use, fast, and effective software package, for the construction of SVM models, developed by Chang and Lin [22]. Finally, the predictions of the proposed multiclass SVM classifier have been validated using 8-fold cross validation.

2. Database Description

We compiled a database based on an extensive literature review, including a total of 117 datasets obtained from different countries, such as India, Nepal, Bhutan, Venezuela, China, Austria, and Greece. All the datasets contained the values of diameter (D), buried depth (H), support stiffness (K), rock tunneling quality index (Q), normalized convergence (%), and squeezing classes (1/2/3). Based on the five categories of squeezing problems in rock tunnels proposed by Hoek and

Marinos [3], the squeezing problems are divided into three classes associated with different levels of normalized convergence in this study, that is, nonsqueezing problems (with $\varepsilon < 1\%$), minor squeezing problems (with $1\% \leq \varepsilon < 2.5\%$), and severe to extreme squeezing problems (with $\varepsilon \geq 2.5\%$), as shown in Figure 1 (Figure 1 is reproduced from Hoek and Marinos [3], under the Creative Commons Attribution License/Public Domain). The squeezing class labels are defined as 1 = nonsqueezing problems, 2 = minor squeezing problems, and 3 = severe to extreme squeezing problems.

Figure 2 shows the histograms, cumulative distributions, and additional statistics, including the number of data (N), minimum and maximum values (Min and Max), means (Mean), and standard deviations (Std. Dev.) of D , H , Q , K , and ε . According to Figure 2(f), among the total 117 case histories, 33 cases are nonsqueezing tunnels with $\varepsilon < 1\%$, 24 cases are minor squeezing tunnels with $1\% \leq \varepsilon < 2.5\%$, and the remaining 60 cases are severe to extreme squeezing tunnels with $\varepsilon \geq 2.5\%$.

Note that only 56 case histories in our database reported specific values of K and the remaining provided information allowing us to compute the values of K using the methods described below [20]:

(a) Stiffness of concrete or shotcrete linings

Assuming that a closed ring of concrete or shotcrete is installed in a circular tunnel, its elastic stiffness, K_c , can be expressed as [23]

$$K_c = \frac{E_c [R^2 - (R - t_c)^2]}{1 + \nu_c [(1 - 2\nu_c)R^2 + (R - t_c)^2]}, \quad (1)$$

where E_c = elastic modulus of concrete or shotcrete, ν_c = Poisson's ratio of concrete or shotcrete, R = radius of tunnel, and t_c = thickness of concrete or shotcrete ring.

(b) Stiffness of steel sets

The effective stiffness of a steel set with backfill, K_{sb} , can be estimated as [16]

FIGURE 1: Multiclass squeezing problems with different levels of normalized convergence (modified from Hoek and Marinos [3]).

$$K_{sb} = p \frac{R}{u}, \quad (2)$$

where p = monitored radial support pressure and u = measured radial deformation.

(c) Stiffness of ungrouted rock bolts and cables

The stiffness of an ungrouted rock bolt or cable, K_b , can be computed as [23]:

$$\frac{1}{K_{sb}} = \frac{s_c s_l}{R} \left[\frac{4l}{\pi d_b E_b} + Q_{ld} \right], \quad (3)$$

where s_c = circumferential spacing of rock bolts or cables, s_l = longitudinal spacing of rock bolts or cables, l = free length of rock bolts or cables, d_b = diameter of rock bolts or cables, E_b = elastic modulus of rock bolts or cables, and Q_{ld} = a load-displacement constant (in units of displacement/force).

(d) Stiffness of combined support systems

Assuming that several support systems are installed together at the same time, their combined stiffness can be computed as the summation of their individual support stiffness [23].

3. Multiclass Support Vector Machine (SVM) Method

3.1. Classic SVM Method. The support vector machine (SVM) is a type of the machine learning method developed based on statistical learning theory (SLT) [24, 25] and is extensively used as one of the most robust binary classifiers [1]. SVMs do not require prior knowledge of a particular model form, possess a flexible nonlinear modeling capability, and have high generalization performance. Therefore, they have become popular in various fields, such as mechanical engineering [26], biomedical engineering [27, 28], information and communication engineering [29], and agriculture [30]. They have also been employed in geotechnical engineering [31–35].

In fact, the SVM is a classifier dividing the data into two groups by devising a hyperplane as a decision surface. In other words, the dataset is separated by the “optimal” hyperplane, as illustrated by the linearly separable case of Figure 3. Additionally, the reference used herein to “optimal” indicates that the distance between the nearest points to the hyperplane is maximized. As described below, the optimal decision plane could be determined by maximizing the margin of separation between the members of the two classes, that is, maximizing the classification margin between the decision boundary lines H_1 and H_2 , which are parallel to the optimal classification line (or hyperplane).

Assume that the dataset $\{(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_N, y_N)\}$, $y \in \{-1, 1\}$, can be optimally separated by the hyperplane determined by the weight vector $\mathbf{w}$ and the bias b , that is, $\mathbf{w}^T \mathbf{x} + b = 0$. The problem is equivalent to determining the parameters $\mathbf{w}$ and b which minimize the cost function [1]:

$$f(\mathbf{w}) = \frac{1}{2} \mathbf{w}^T \mathbf{w}, \quad (4)$$

subject to the constraints

$$y_i(\mathbf{w}^T \mathbf{x} + b) \geq 1 \quad \text{for } i = 1, 2, \dots, N. \quad (5)$$

For the maximal margin hyperplane, the solution to the above optimization problem is given by Vapnik [25] as follows:

$$\mathbf{w} = \sum_{i=1}^N \alpha_i y_i \mathbf{x}_i, \quad (6)$$

$$b = -\frac{1}{2} (\mathbf{w}^T (\mathbf{x}_r + \mathbf{x}_s)), \quad (7)$$

where α represents the Lagrange multipliers and $\mathbf{x}_r$ and $\mathbf{x}_s$ are the support vectors satisfying the equations

$$\begin{aligned} \alpha_r, \alpha_s &> 0, \\ y_r &= -1, \\ y_s &= 1. \end{aligned} \quad (8)$$

It is easy to prove that the Lagrange multipliers are positive real numbers that maximize

FIGURE 2: Histograms, cumulative distributions, and statistical evaluations of the experimental data.

FIGURE 3: Schematic diagram of optimal hyperplane.

$$\sum_{i=1}^N \alpha_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j \mathbf{x}_i^T \mathbf{x}_j, \quad (9)$$

subject to

$$\sum_{i=1}^N \alpha_i y_i = 0, \quad \alpha_i > 0. \quad (10)$$

For nonlinear separable cases, the kernel function is often used to map the training data into a higher dimensional space where the data can be separated in an easier manner. The solutions for the kernel SVM could be similarly obtained by replacing the term $\mathbf{x}_i^T \mathbf{x}_j$ in (17) with $K(\mathbf{x}_i, \mathbf{x}_j)$. In addition, the corresponding hyperplane could be expressed as

$$\sum_{i=1}^N \alpha_i K(\mathbf{x}_i, \mathbf{x}_j) + b = 0. \quad (11)$$

The four basic kernel functions are as follows: (1) linear kernel function: $K(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i^T \mathbf{x}_j$, (2) n th order polynomial kernel function: $K(\mathbf{x}_i, \mathbf{x}_j) = (\mathbf{x}_i^T \mathbf{x}_j + 1)^n$, (3) radial basis function (RBF): $K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-(\|\mathbf{x}_i - \mathbf{x}_j\|/2\sigma^2))$, and (4) sigmoid-kernel functions with parameters k and θ : $K(\mathbf{x}_i, \mathbf{x}_j) = \tanh(k(\mathbf{x}_i^T \mathbf{x}_j) + \theta)$. In this study, the most commonly used RBF kernel has been adopted because it has been reported that the RBF kernel could result in higher classification accuracy than the other kernels [22].

3.2. Multiclass SVM. As previously discussed, the classical SVM classifiers were originally designed for binary classifications. However, there are more than two classes in some practical classification problems. For instance, one has to divide the potential squeezing effect into several classes according to the magnitude of the normalized convergence so that the severity of the squeezing could be adequately

FIGURE 4: The structure of DAG-SVM used for three-class classification problems.

assessed or predicted. This constitutes a typical multiclass classification problem.

Two commonly used strategies for constructing multiclass SVM are the “one-against-one” and “one-against-all” approaches. In the “one-against-one” approach, we build one SVM for each pair of classes, which means that if there are k classes, then $k(k-1)/2$ binary SVM classifiers are constructed to distinguish the samples of one class from the samples of another class. In the classification, we use a voting strategy, that is, each binary classification is considered to be a voting, whereby votes can be cast for all the samples. In the end, a point is designated to be part of a class with the maximum number of votes. However, in the one-against-all approach, we build as many binary classifiers as there are classes, and each trained classifier is used to separate one class from the rest. To predict a new instance, we choose the classifier with the largest decision function value.

In this study, we used the directed acyclic graph SVM (DAG-SVM) approach that combines the SVM and the decision tree. The training process is the same as the “one-against-one” method, which also constructs $k(k-1)/2$ binary SVM classifiers. However, the method uses a binary acyclic graph in the process of detection.

If a binary decision tree is constructed for the k -class data samples, each leaf node of the tree corresponds to a class, and each nonleaf node corresponds to a sub-SVM classifier. Therefore, the decision tree has $k(k-1)/2$ nonleaf nodes (i.e., the number of sub-SVM classifiers is $k(k-1)/2$) and k leaf nodes (the number of classes is k). There are different schemes for constructing a strict DAG with k leaf nodes. For instance, the structure of a DAG-SVM for three-class classification problems is shown in Figure 4, where $\bar{k}$ indicates that $\mathbf{x}$ does not belong to class k . Starting at the root node (i.e., node “sub-SVM₂₃”) for an input data sample $\mathbf{x}$, we determine whether the left or right sub-SVM classifier (i.e., the nodes “sub-SVM₂₁” or “sub-SVM₁₃”) would be used depending on the output value. Subsequently, the class of the input data sample would be finally determined based on the output value of node “sub-SVM₂₁” or “sub-SVM₁₃”.

TABLE 2: Resultant accuracy and confusion matrices of 8-fold CV.

Validation groups	Accuracy (%)	Error rates (%)	Confusion matrices			
No. 1	93.33	6.67	Actual			
			1	2	3	Predicted
			8	0	0	1
			0	1	0	2
No. 2	86.67	13.33	Actual			
			1	2	3	Predicted
			12	0	0	1
			0	0	0	2
No. 3	80.00	20.00	Actual			
			1	2	3	Predicted
			8	1	0	1
			0	0	2	2
No. 4	93.33	6.67	Actual			
			1	2	3	Predicted
			0	0	0	1
			0	3	0	2
No. 5	80.00	20.00	Actual			
			1	2	3	Predicted
			0	0	0	1
			0	4	2	2
No. 6	100.00	0.00	Actual			
			1	2	3	Predicted
			0	0	0	1
			0	2	0	2
No. 7	80.00	20.00	Actual			
			1	2	3	Predicted
			0	0	0	1
			0	9	3	2
No. 8	91.67	8.33	Actual			
			1	2	3	Predicted
			3	0	0	1
			0	0	0	2
Average	88.13	11.87	0	1	8	3

4. Results and Discussion

4.1. K-Fold Cross Validation. The aim of our proposed multiclass SVM classifier is to predict the severity of tunnel squeezing, and 8-fold cross validation is performed to estimate its validity in practice. Firstly, the original 117 datasets are equally divided into eight groups. Secondly, seven out of eight groups are used to train the multiclass SVM classifier with LibSVM [22], and the remaining group is left for validation purposes. Finally, the above process will be repeated eight times so that each case is predicted once in the entire database, and the cross validation accuracy is the percentage of data which are correctly classified. The corresponding classification accuracy and confusion matrices are listed in Table 2, and the average classification accuracy is

FIGURE 5: Actual and predicted classification results of group No. 1.

approximately 88.1%. The confusion matrix could clearly show whether the class is misclassified (i.e., if a class is classified erroneously as another class) and describe the difference between the predicted and the actual classes. Furthermore, the sum of the elements on the principal diagonal represents the number of cases which are correctly classified. In addition, the sum of the elements off the principal diagonal represents the number of cases that are misclassified.

When group No. 1 is used for model validation, the resultant classification results are shown in Figure 5. The horizontal axis represents the cases of the validation dataset (group No. 1). There are fifteen cases in total. The vertical axis represents the class of the cases. Only case No. 14 was misclassified as class 3 (i.e., $\varepsilon > 2.5\%$ with severe to extreme squeezing problems) since the actual class of case No. 14 is class 2 (i.e., $1\% \leq \varepsilon < 2.5\%$ with minor squeezing problems), thereby indicating that the predicted result is conservative and safe. The classification accuracy is approximately 93.3%.

4.2. Comparison with Traditional Methods. In order to compare the performance of the proposed multiclass SVM classifier with that of the traditional methods, we have employed both the proposed multiclass SVM classifier and the empirical formula proposed by Singh [11] (i.e., $H > 350Q^{1/3}$) to predict the squeezing class using all 117 datasets, and the results are listed in Table 3. Note that the accuracy for squeezing ground can be computed as the number of squeezing cases correctly classified divided by the total number of squeezing tunnels tested, the accuracy for nonsqueezing ground can be computed as the number of nonsqueezing cases correctly classified divided by the total number of nonsqueezing tunnels tested, and the overall accuracy can be computed as the number of tunnels correctly classified divided by total number of tunnels tested.

From the total number of datasets, 94 cases were correctly classified using the empirical approach, and the

TABLE 3: Performance of the proposed approach, the empirical formula, and the two-class SVMs used to determine the squeezing.

Method	Number of classes	Accuracy for squeezing ground (%)	Accuracy for nonsqueezing ground (%)	Overall accuracy (%)
Empirical formula	2	82.1	78.8	80.3
Binary SVM	2	79.4	88.1	84.1
Multiclass SVM	3	86.9	93.9	88.1

TABLE 4: Accuracy elicited using 8-fold CV with all parameters, without parameter K , and without parameter D .

	No. 1	No. 2	No. 3	No. 4	No. 5	No. 6	No. 7	No. 8	Average
Accuracy with all four parameters (%)	93.33	86.67	80.00	93.33	80.00	100.00	80.00	91.67	88.13
Accuracy without K (%)	80.00	60.00	60.00	80.00	73.33	73.33	73.33	91.67	73.96
Accuracy without D (%)	93.33	86.67	86.67	73.33	86.67	86.67	66.67	91.67	83.96

predicted accuracy was approximately 80.3% (i.e., 94/117). One probable reason for this relatively worse performance of the empirical formula proposed by Singh et al. [11] is that we have extended the original database employed in their work and constructed the multiclass SVM model based on the extended database.

In addition, Shafiei et al. [1] used a more comprehensive database, including 198 tunnel cases, to construct their binary SVM classifier to predict the tunnel squeezing. Unfortunately, this comprehensive database cannot be directly used because their database contains only two input parameters, that is, H and Q , and does not provide any information about the other two parameters (i.e., K and D) considered in this study. The overall accuracy was reported to be equal to 84.1%, and the accuracy for squeezing ground was reported to be 79.4%. For multiclass SVM model, the overall accuracy and the accuracy for squeezing ground are 88.1% and 86.9% (Table 3), respectively, showing that the multiclass SVM model performs slightly better than the binary SVM classifier. As shown in Table 3, for the multiclass SVM model, the accuracy for nonsqueezing ground is higher than that for the squeezing ground, indicating a relatively “conservative” (and safe) model.

Instead of predicting the class, many applications require posterior class probability which can be approximated by a sigmoid function (see Platt [36] for detailed descriptions) and such posterior probabilities can be used to assess the acceptability of the prediction [1]. For instance, let us imagine a new tunnel whose design is considered with $K = 20$ MPa, $H = 200$ m, $Q = 0.4$, and $D = 6.0$ m. The posterior probability $P(y = 1|\mathbf{x})$ can be estimated as 78.3%, indicating that there is probably nonsqueezing problems for this tunnel, and this prediction is accepted with high confidence. And the posterior probability could be useful in tunnel risk analyses.

In general, our approach performs slightly better than the empirical approach and the classical binary SVM in terms of the classification accuracy. Additionally, the empirical approach and the binary SVM classifier can only make a binary classification; that is, it can only predict whether squeezing occurs but cannot predict the severity of squeezing. Finally, it is important to mention that, as discussed by Jimenez and Recio [6, 37], the proposed multiclass SVM model should not be considered as a “final solution” and it should be expected to

be further updated and improved as more tunnel squeezing cases are included in the training database.

4.3. Influence of Support Stiffness and Tunnel Diameter. Tunnel deformation may be effectively controlled by installing appropriate support systems at a proper time. In other words, the squeezing condition could be influenced by the support stiffness applied to the tunnel. However, few studies have employed support stiffness as one of the input parameters to predict tunnel squeezing [16]. In order to assess the influence of support stiffness on tunnel squeezing, the support stiffness (K) is removed from the four input parameters (i.e., diameter (D), depth (H), support stiffness (K), and rock tunneling quality index (Q)); that is, the tunnel squeezing is predicted based on the remaining three parameters, that is, Q , H , and D . The 8-fold CV method is used again to validate the trained multiclass SVM using only three input parameters. The results are listed in Table 4. If the support stiffness is removed, the average accuracy obtained is reduced from 88.1% to 74.0%, showing that support stiffness has a significant influence on the classification accuracy of tunnel squeezing.

Similarly, the influence of tunnel diameter can be assessed, and the results are also listed in Table 4. The resultant average accuracy is slightly reduced from 88.1% to 84.0%, indicating that tunnel diameter does not seem to have a significant influence on the predictive capabilities of the proposed model. This observation is coincident with the study by Jimenez and Recio [37].

In addition, we performed analysis of variance (ANOVA) to demonstrate the significance of these two parameters, namely, K and D , and the significance values for K and D are 0.046 and 0.004, respectively, indicating that the influence of K and D on tunnel squeezing is significant.

5. Conclusions

A multiclass SVM classifier was developed to predict the tunnel squeezing based on four input parameters: diameter (D), depth (H), support stiffness (K), and rock tunneling quality index (Q). An “one-against-one” approach was employed to train the classifier from 117 available training datasets obtained from previous studies (Table 5). The 8-fold

TABLE 5

No.	<i>D</i> (m)	<i>H</i> (m)	<i>Q</i>	<i>K</i> (MPa)	ϵ (%)	Class	Tunnel	Location	Rock type	Reference
1	6.0	150.0	0.400	26.19	0.42	1	Khara hydroproject	India	Clay conglomerate	[38, 39]
2	6.0	200.0	0.400	20.00	0.75	1	Khara hydroproject	India	Clay conglomerate	[38, 39]
3	5.8	350.0	0.500	2.53	7.90	3	Maneri stage I	India	—	[38]
4	4.8	225.0	3.600	1000.00	0.06	1	Maneri-Bhali hydroproject	India	Fractured quartzite	[39, 40]
5	4.8	340.0	1.800	500.00	0.40	1	Maneri-Uttarkashi power	India	Sheared metabasics	[40]
6	4.8	550.0	5.100	1600.00	0.05	1	Maneri-Uttarkashi power	India	Foliated metabasics	[40]
7	12.0	220.0	0.800	32.89	0.38	1	Tehri dam project	India	Argillaceous phyllite	[38, 39]
8	13.0	52.0	15.000	16.67	0.18	1	Upper Krishna project	India	Banded schists	[38, 39]
9	3.0	280.0	0.050	9.80	2.80	3	Chibro-Khodri tunnel	India	Crushed red shales	[15, 38]
10	3.0	280.0	0.022	5.96	4.50	3	Chibro-Khodri tunnel	India	Soft and plastic black clays	[38]
11	9.0	680.0	0.050	9.90	6.00	3	Chibro-Khodri tunnel	India	Seamy crushed red	[38]
12	9.0	280.0	0.022	48.56	2.00	2	Chibro-Khodri tunnel	India	Soft and plastic black clays	[38]
13	4.2	100.0	0.005	88.96	2.62	3	Khimti 1 hydroproject A1 ch515	Nepal	Sheared schists	[41]
14	4.0	112.0	0.006	71.28	1.19	2	Khimti 1 hydroproject A4 ch1013	Nepal	Sericite schists	[41]
15	4.3	111.0	0.008	1936.00	0.75	1	Khimti 1 hydroproject A1 ch580	Nepal	Sheared schists	[41]
16	4.0	112.0	0.008	936.00	0.20	1	Khimti 1 hydroproject A4 ch974	Nepal	Gneiss	[41]
17	4.0	112.0	0.008	651.00	0.10	1	Khimti 1 hydroproject A4 ch1045	Nepal	Clay-filled sheared gneiss	[41]
18	4.0	140.0	0.009	430.00	0.80	1	Khimti 1 hydroproject A3 ch220	Nepal	Schists	[41]
19	4.2	100.0	0.010	31.72	3.81	3	Khimti 1 hydroproject A1 ch500	Nepal	Sheared schists	[41]
20	4.0	138.0	0.013	1934.00	0.19	1	Khimti 1 hydroproject A2 ch601	Nepal	Sericite schists	[41]
21	4.4	212.0	0.040	5324.00	0.02	1	Khimti 1 hydroproject A2 ch1283	Nepal	Gneiss and sericite schists	[41]
22	5.0	300.0	0.050	1430.00	0.18	1	Khimti 1 hydroproject A3 ch345	Nepal	Gneiss and sericite schists	[41]
23	4.0	112.0	0.060	458.00	0.30	1	Khimti 1 hydroproject A1 ch665	Nepal	Gneiss and schists	[41]
24	4.0	95.0	0.065	933.00	0.29	1	Khimti 1 hydroproject A2 ch1730	Nepal	Gneiss	[41]
25	4.0	218.0	0.070	739.00	0.14	1	Khimti 1 hydroproject A4 ch550	Nepal	Chlorite sericite gneiss	[41]
26	4.0	98.0	0.080	933.00	0.77	1	Khimti 1 hydroproject A1 ch475	Nepal	Gneiss and sericite schists	[41]
27	5.0	284.0	0.090	68.55	1.24	2	Khimti 1 hydroproject A3 ch235	Nepal	Gneiss	[41]
28	5.0	300.0	0.090	664.29	0.28	1	Khimti 1 hydroproject A3 ch340	Nepal	Gneiss and sericite schists	[41]
29	4.0	261.0	0.095	931.00	0.15	1	Khimti 1 hydroproject A2 ch1357	Nepal	Banded gneiss and chlorite schists	[41]
30	4.0	198.0	0.140	934.00	0.29	1	Khimti 1 hydroproject A2 ch895	Nepal	Gneiss and chlorite schists	[41]
31	4.0	225.0	0.140	1430.00	0.24	1	Khimti 1 hydroproject A4 ch503	Nepal	Gneiss and sericite schists	[41]
32	5.0	130.0	0.200	936.00	0.34	1	Khimti 1 hydroproject A3 ch15	Nepal	Gneiss and schists	[41]
33	4.1	158.0	0.230	650.00	0.32	1	Khimti 1 hydroproject A3 ch59	Nepal	Gneiss and schists	[41]
34	5.0	276.0	0.250	940.00	0.77	1	Khimti 1 hydroproject A3 ch200	Nepal	Gneiss and schists	[41]
35	5.0	276.0	0.280	652.00	0.56	1	Khimti 1 hydroproject A3 ch210	Nepal	Gneiss and schists	[41]
36	4.0	126.0	0.300	461.00	0.03	1	Khimti 1 hydroproject A2 ch441	Nepal	Gneiss	[41]
37	4.0	114.0	0.470	648.00	0.03	1	Khimti 1 hydroproject A4 ch852	Nepal	Banded gneiss	[41]
38	4.0	114.0	0.600	556.00	0.24	1	Khimti 1 hydroproject A4 ch876	Nepal	Banded gneiss	[41]
39	4.6	300.0	0.023	7.71	7.00	3	Loktak hydro	India	—	[38]
40	4.8	350.0	0.500	25.32	7.90	3	Maneri-Bhali stage I	India	Fractured quartzite	[15, 40]
41	4.8	800.0	2.500	48.99	8.90	3	Maneri-Uttarkashi power	India	Laminated metabasics	[15, 40]
42	7.0	285.0	0.100	9.79	2.87	3	Maneri stage II tunnel	India	Sheared metabasics	[42, 43]
43	7.0	410.0	0.300	9.79	2.80	3	Maneri stage II tunnel	India	Sheared metabasics	[42, 43]
44	7.0	415.0	0.880	9.79	2.19	2	Maneri stage II tunnel	India	Metavolcanic	[42, 43]
45	2.5	480.0	0.800	9.84	2.88	3	Maneri stage II tunnel	India	Metavolcanic	[42, 43]
46	7.0	500.0	1.000	9.79	2.64	3	Maneri stage II tunnel	India	Metavolcanic	[42, 43]
47	2.5	510.0	0.880	9.84	2.42	2	Maneri stage II tunnel	India	Metavolcanic	[42, 43]
48	4.6	240.0	0.120	3.97	4.50	3	Giri-Bata tunnel	India	Crushed phyllites	[42–44]

TABLE 5: Continued.

No.	<i>D</i> (m)	<i>H</i> (m)	<i>Q</i>	<i>K</i> (MPa)	ϵ (%)	Class	Tunnel	Location	Rock type	Reference
49	4.6	440.0	0.050	3.97	10.04	3	Giri-Bata tunnel	India	Crushed phyllites	[42–44]
50	4.6	450.0	0.060	3.97	10.30	3	Giri-Bata tunnel	India	Crushed phyllites	[42–44]
51	4.6	400.0	0.030	3.98	10.43	3	Giri-Bata tunnel	India	Crushed phyllites	[42–44]
52	4.6	400.0	0.050	3.98	7.61	3	Giri-Bata tunnel	India	Crushed phyllites	[42–44]
53	4.6	200.0	0.020	2.98	6.20	3	Giri-Bata tunnel	India	Crushed phyllites	[42–44]
54	4.6	325.0	0.030	2.98	8.75	3	Giri-Bata tunnel	India	Crushed phyllites	[42–44]
55	4.6	400.0	0.512	2.98	0.67	1	Giri-Bata tunnel	India	Crushed slates	[42–44]
56	5.8	700.0	0.300	9.81	4.83	3	Maneri stage I tunnel	India	Sheared metabasics	[42, 45]
57	5.8	550.0	1.700	9.81	2.66	3	Maneri stage I tunnel	India	Siliceous phyllites	[42, 45]
58	5.8	635.0	4.000	9.81	2.33	2	Maneri stage I tunnel	India	Foliated metabasics	[42, 45]
59	5.8	650.0	4.120	9.81	2.07	2	Maneri stage I tunnel	India	Siliceous phyllites	[42, 45]
60	5.8	450.0	0.310	5.10	4.83	3	Maneri stage I tunnel	India	Sheared metabasics	[42, 45]
61	5.8	750.0	0.500	8.10	4.14	3	Maneri stage I tunnel	India	Crushed quartzite	[42, 45]
62	7.0	450.0	0.590	9.67	3.00	3	Noonidih colliery	India	Weak coal	[45]
63	6.8	337.0	0.007	44.76	2.10	2	Tala hydro-HRT, tala HRT, Bhutan	Bhutan	AGO (adverse geological occurrences):	[46]
64	6.8	337.0	0.011	16.05	3.80	3	Tala HRT, Bhutan	Bhutan	completely sheared,	[46]
65	6.8	337.0	0.006	22.58	3.10	3	Tala HRT, Bhutan	Bhutan	highly weathered	[46]
66	6.8	337.0	0.006	36.36	2.20	2	Tala HRT, Bhutan	Bhutan	biotite schist associated with banded gneiss, amphibolites, and quartzites in thin bands	[46]
67	6.8	337.0	0.080	14.09	2.20	2	Tala HRT, Bhutan	Bhutan		[46]
68	8.7	550.0	0.029	39.13	2.30	2	Kaligandaki “A” HRT	Nepal	Graphitic phyllite	[47, 48]
69	8.7	600.0	0.023	90.71	1.40	2	Kaligandaki “A” HRT	Nepal	Graphitic phyllite	[47, 48]
70	8.7	600.0	0.030	34.48	2.90	3	Kaligandaki “A” HRT	Nepal	Graphitic phyllite	[47, 48]
71	8.7	600.0	0.018	26.20	3.90	3	Kaligandaki “A” HRT	Nepal	Graphitic phyllite	[47, 48]
72	8.7	600.0	0.023	28.48	3.20	3	Kaligandaki “A” HRT	Nepal	Graphitic phyllite	[47, 48]
73	8.7	620.0	0.020	26.20	4.90	3	Kaligandaki “A” HRT	Nepal	Graphitic phyllite	[47, 48]
74	8.7	620.0	0.008	14.67	8.50	3	Kaligandaki “A” HRT	Nepal	Graphitic phyllite	[47, 48]
75	8.7	620.0	0.009	14.67	7.70	3	Kaligandaki “A” HRT	Nepal	Graphitic phyllite	[47, 48]
76	8.7	620.0	0.009	14.67	8.20	3	Kaligandaki “A” HRT	Nepal	Graphitic phyllite	[47, 48]
77	8.7	620.0	0.016	26.20	4.40	3	Kaligandaki “A” HRT	Nepal	Siliceous phyllites	[47, 48]
78	8.7	620.0	0.020	26.10	4.10	3	Kaligandaki “A” HRT	Nepal	Graphitic phyllite	[47, 48]
79	8.7	620.0	0.025	50.80	2.50	3	Kaligandaki “A” HRT	Nepal	Graphitic phyllite	[47, 48]
80	8.7	580.0	0.023	26.20	3.70	3	Kaligandaki “A” HRT	Nepal	Graphitic phyllite	[47, 48]
81	8.7	580.0	0.025	74.66	1.70	2	Kaligandaki “A” HRT	Nepal	Graphitic phyllite	[47, 48]
82	8.7	550.0	0.025	39.87	2.40	2	Kaligandaki “A” HRT	Nepal	Graphitic phyllite	[47, 48]
83	8.7	575.0	0.007	21.17	6.00	3	Kaligandaki “A” HRT	Nepal	Graphitic phyllite	[47, 48]
84	11.0	700.0	0.417	7.43	3.50	3	Nathpa Jhakri-HRT	India		[49]
85	11.0	700.0	0.333	9.14	3.50	3	Nathpa Jhakri-HRT	India		[49]
86	11.0	750.0	0.333	9.14	3.50	3	Nathpa Jhakri-HRT	India		[49]
87	11.0	600.0	0.250	9.14	3.50	3	Nathpa Jhakri-HRT	India	Quartz mica schist,	[49]
88	11.0	850.0	0.056	20.40	5.00	3	Nathpa Jhakri-HRT	India	schistose quartzites,	[49]
89	11.0	600.0	0.033	33.33	3.00	3	Nathpa Jhakri-HRT	India	and amphibolites	[49]
90	11.0	300.0	0.001	16.50	6.00	3	Nathpa Jhakri-HRT	India		[49]
91	11.0	400.0	0.003	17.00	6.00	3	Nathpa Jhakri-HRT	India		[49]
92	11.0	800.0	0.194	17.14	3.50	3	Nathpa Jhakri-HRT	India		[49]
93	6.5	300.0	0.033	10.00	3.00	3	Udhampur rail tunnel (T1)	India	Claystone, silty claystone	[49]
94	6.5	312.0	0.094	34.67	1.50	2	Udhampur rail tunnel (T1)	India	Claystone, silty claystone	[49]
95	6.5	280.0	0.083	29.33	1.50	2	Udhampur rail tunnel (T1)	India	Claystone, silty claystone	[49]
96	6.5	270.0	0.125	15.91	2.20	2	Udhampur rail tunnel (T1)	India	Claystone, silty claystone	[49]
97	6.5	285.0	0.063	12.80	2.50	3	Udhampur rail tunnel (T1)	India	Claystone, silty claystone	[49]

TABLE 5: Continued.

No.	D (m)	H (m)	Q	K (MPa)	ϵ (%)	Class	Tunnel	Location	Rock type	Reference
98	6.5	280.0	0.031	11.54	2.60	3	Udhampur rail tunnel (T1)	India	Claystone, silty claystone	[49]
99	6.5	280.0	0.042	12.50	2.40	2	Udhampur rail tunnel (T1)	India	Claystone, silty claystone	[49]
100	6.0	727.0	2.287	5.88	1.70	2	Chenani–Nashri escape tunnel	India	Siltstone, silty claystone	[49]
101	6.0	736.0	2.426	7.69	1.30	2	Chenani–Nashri escape tunnel	India	Siltstone, silty claystone	[49]
102	6.0	733.0	2.903	6.25	1.60	2	Chenani–Nashri escape tunnel	India	Siltstone, silty claystone	[49]
103	6.0	690.0	1.650	9.38	1.60	2	Chenani–Nashri escape tunnel	India	Siltstone, silty claystone	[49]
104	13.0	577.0	1.517	11.11	1.80	2	Chenani–Nashri escape tunnel	India	Siltstone	[49]
105	5.4	199.7	0.020	1217.16	4.58	3	Chameliya hydroelectric project headrace tunnel 3 + 172	Nepal	Dolomite	[50]
106	5.4	217.5	0.013	1217.16	25.54	3	Chameliya hydroelectric project headrace tunnel 3 + 190	Nepal	Dolomite	[50]
107	5.4	252.2	0.010	1523.07	12.50	3	Chameliya hydroelectric project headrace tunnel 3 + 296	Nepal	Brownish	[50]
108	5.4	246.3	0.010	1523.07	3.80	3	Chameliya hydroelectric project headrace tunnel 3 + 314	Nepal	Foliated phyllite	[50]
109	5.4	283.9	0.008	1645.38	36.73	3	Chameliya hydroelectric project headrace tunnel 3 + 404	Nepal	Talcose phyllite	[50]
110	5.4	284.5	0.008	1828.98	30.19	3	Chameliya hydroelectric project headrace tunnel 3 + 420	Nepal	Talcose phyllite	[50]
111	5.4	210.8	0.010	1575.72	18.30	3	Chameliya hydroelectric project headrace tunnel 3 + 681	Nepal	Talcose phyllite	[50]
112	5.4	237.7	0.010	1575.72	10.96	3	Chameliya hydroelectric project headrace tunnel 3 + 733	Nepal	Talcose phyllite	[50]
113	5.4	230.0	0.015	1217.16	9.80	3	Chameliya hydroelectric project headrace tunnel 3 + 764	Nepal	Foliated phyllite	[50]
114	5.4	222.6	0.015	1217.16	1.20	2	Chameliya hydroelectric project headrace tunnel 3 + 795	Nepal	Foliated phyllite	[50]
115	5.4	80.0	93.500	0.00	0.00	1	Austria (Oetscher unit)	Austria	—	[51]
116	5.4	190.0	7.450	0.00	0.00	1	Austria (Oetscher unit)	Austria	—	[51]
117	5.4	130.0	1.530	0.00	0.00	1	Austria (Oetscher unit)	Austria	—	[51]

cross validation method was used to validate the constructed multiclass SVM classifier, and the results showed that the average error percentage was approximately 11.87%, which is considered acceptable for practical engineering applications. The proposed multiclass SVM classifier elicited some improvements compared to the traditional empirical formula proposed by Singh et al. [11] and the binary SVM classifier proposed by Shafiei [1], as it yielded higher accuracy and allowed the prediction of the squeezing severity. The proposed multiclass SVM classifier can be used for the preliminary classification of tunnel squeezing. However, it is not a substitute for more sophisticated methods, such as numerical simulation, wherein many other factors can be considered, such as the time effect of rock masses. The proposed approach can be further updated and improved as additional tunnel squeezing cases become available for training.

Additional Points

Data Availability. The detailed data, including 117 tunnel cases, associated with this article are listed in Table 5.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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