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Single Valued Neutrosophic Number Ensemble Learning Model for Stability Classification of Open Pit Mine Slopes

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Abstract: China's open pit mining industry faces the dual challenge of increasing production and preventing disasters. In order to ensure the safe exploitation of mineral resources, the stability of slopes must be assessed. In light of the fact that over 1,950 landslide accidents have occurred over the past decade, accounting for 15% of all safety incidents, the evaluation of slope stability has become a critical research focus in the fields of geo-resources and geo-engineering. Traditional slope stability evaluation methods rely on empirical tools and the expertise of professionals to assess slope stability. In contrast, machine learning (ML) methods offer a more comprehensive approach, analyzing the intricate features present in diverse sampling data. As a novel extension of ML, this paper presents a single-valued neutrosophic number-based ensemble learning (SVNN-EL) model. This model employs binary coding groups (1, 0, 0), (0, 1, 0) and (0, 0, 1) to express the learning outcomes of the slope stability, quasi-stability and instability statuses. Subsequently, a similarity measure is employed to determine the classification results of slopes. Finally, the proposed SVNN-EL model is applied to a case study in Yunnan province, China, the proposed model's four performance metrics, namely accuracy, precision, recall, and F1-score (the harmonic mean of precision and recall), are 0.915, 0.894, 0.948, and 0.921, respectively. A comparison with the k-nearest neighbor, support vector machine and random forest methods reveals that the performance metrics of the proposed SVNN-EL model are superior to those of existing methods.

Keywords: single-valued neutrosophic number; ensemble learning; slope stability classification; similarity measure

1. Introduction

As the predominant method of mineral resource development in China, open-pit mining faces two significant challenges: enhancing production and ensuring disaster prevention. It is of the utmost importance to assess the stability of slopes in open-pit mines (OPMs) in order to guarantee the security of the mining process. During the past decade, there have been more than 1,950 landslide accidents in OPMs in China, representing 15% of the total number of safety production accidents [1]. Furthermore, the total number of fatalities resulting from these accidents is the highest among all safety production incidents. The stability of OPM slopes is typically influenced by a range of structural surfaces and features, including those developed at different scales within the slopes themselves. A substantial proportion of slope destabilization incidents is associated with internal slip surfaces and the geometric characteristics of slopes [2]. The evaluation of slope stability in OPMs is of great importance for ensuring the safe and efficient mining of these facilities. Furthermore, it represents a significant research area and a major frontier topic in the field of international geo-resources and geo-engineering.

A slope is a common structure made of solid and rock in the field, and its stability is affected by many factors. As we all know, there is a lot of uncertainty and ambiguity in human nature. Traditional techniques for calculating slope stability factors are common evaluation methods; these methods, including the limit equilibrium method (LEM) [3], the finite element method (FEM) [4] and the discrete element method (DEM) [5], require experienced engineers to spend a significant amount of time to modelling, calculating and testing. In contrast, engineers have developed a number of methods such as rock mass rating (RMR) [6], slope mass rating (SMR) [7], geological strength index (GSI) [8] and Q-classification systems [9, 10] to assess slope stability.

When collecting data on slope features, it is not uncommon to encounter a considerable amount of uncertain, vague, and imprecise information. Consequently, some soft computing methods based on fuzzy theory have been applied to improve the assessment of slope stability. Zhen and Zu [11] first applied the uncertainty of rock mechanical parameters to the Q classification system. Liu and Wang [12] introduced fuzzy mathematics into the neural network (NN) and obtained a comprehensive evaluation for each series of weighted numbers and engineering classification of rocks. A practical and efficient approach using NN and fuzzy clustering systems was applied to the Saeen landslide to estimate the date range of the next probable landslide [13]. An efficiency coefficient method based on fuzzy analytic hierarchy process (FAHP) has been proposed to classify rock slides [14]. Azarafza et al. [15] introduced a fuzzy logical decision making algorithm (DMA) based on block theory to assess the reliability of discontinuous rock slopes under different slip scenarios. Nanehkaran et al. [16] used a fuzzy logic based DMA method and geographical information system (GIS) to evaluate landslide hazard zoning in the Tabriz region. Azarafza et al. [17] used a fuzzy logic DMA to rapidly evaluate block failure instability in discontinuous rock slopes through kinematic analysis.

The application of machine learning (ML) methods has become increasingly common in recent research on slope stability prediction/evaluation. Lin [18] evaluated the effectiveness of four supervised learning methods in slope stability prediction and proposed the gravity search algorithm (GSA), the random forest (RF) algorithm, the support vector machine (SVM) algorithm, and the Naïve Bayesian (NB) algorithm for use in classifier construction. The GSA and RF models demonstrated satisfactory classification results. Ahangari Nanehkaran et al. [19] investigated the efficacy of five machine learning models, namely multilayer perceptron (MLP), SVM, k-nearest neighbor (k-NN), decision tree (DT), and RF, in predicting slope safety factors. The objective of developing these models was to evaluate and optimize them for the calculation of safety factors (FSs) and the selection of slope reinforcement methods. In the ML models, the input parameters included geotechnical indices such as slope height, total slope angle, dry density, cohesion, and internal friction angle, which were used for the estimation of 70 slopes in the South Pars region of Iran. Huang [20] employed a deep learning (DL) algorithm based on a long short-term memory network (LSTM) to predict slope stability. This addressed the limitations of conventional ML models with respect to nonlinear performance, local optimality, and incomplete feature extraction. In his study, RF, a traditional ensemble learning (EL) method, was included in the comparison experiment with more complex deep learning (DL) algorithms, such as a convolutional neural network (CNN). The results demonstrated that RF achieved superior performance on certain programs.

Qin [21] developed the single-valued neutrosophic number (SVNN) based ANFIS to assess slope stability. Subsequently, Qin [22] proposed a Gaussian progress regression (GPR) to predict slope stability in a SVNN scenario, demonstrating its efficacy through the analysis of 167 slope cases. Moreover, a neutrosophic genetic algorithm (NGA) was proposed and used for the clustering of rock discontinuities, demonstrating the capacity to perform optimal clustering analysis of slope sampling data in actual applications.

However, existing ML research relies heavily on the provided FSs as the basis for supervised learning. As a matter of fact, the FSs already indicate the safety information of slope stability, and there is no need to use ML methods to evaluate slope stability. In order to overcome this problem, this paper proposes a training method for obtaining binary coding-based ML results that reflect the stability, quasi-stability and instability statuses of slopes. Consequently, this study develops a SVNN-based ensemble learning (SVNN-EL) model that utilizes binary coding groups (1, 0, 0), (0, 1, 0), and (0, 0, 1) to express the learning results of the slope stability, quasi-stability and instability statuses. Thereafter, a similarity measure is employed to determine the classification results of slopes. The SVNN-EL model has the potential to enhance its generalizability and applicability in the evaluation and classification process of practical slope stability. Finally, the practical engineering cases of the Lanping OPM are presented to verify the efficiency of the developed model. Based on the accuracy, precision, recall, and F-1 score (the harmonic mean of precision and recall) metrics, the superiority of the proposed SVNN-EL model is demonstrated by a comparison with the existing ML methods. The following section presents a summary of the key findings of this study.

(1) The truth, indeterminacy and falsity degrees in SVNN are capable of comprehensively expressing the hybrid information of uncertainty, inconsistency and incompleteness contained in the raw field slope data. Consequently, the raw data obtained from field investigation and measurement can be transformed into SVNNs by the truth, indeterminacy and falsity membership functions, which are able to capture the comprehensive information in the slope data for ML.

(2) The binary coding groups (1, 0, 0), (0, 1, 0) and (0, 0, 1) are employed to represent the three stability states (stability, quasi-stability, and instability) for slopes and to establish a ML method between the input data (SVNNs) and the output coding groups. Then, the similarity measure value between the ML result and the binary coding groups is used to determine the final classification result for each slope.

(3) A comprehensive comparison of the classification performance of the proposed SVNN-EL model and existing ML methods is performed based on the accuracy, precision, recall, and F-1 score metrics. The results demonstrate that the proposed model outperforms the existing methods in all four-performance metrics.

The remainder of this paper is presented in the following sections. Section 2 provides an overview of the preliminary concepts related to single-valued neutrosophic set (SVNS), SVNN, and EL. Section 3 presents the general framework of a SVNN-EL model to address the slope stability classification problem. In Section 4, the proposed model is applied to the Lanping OPM slopes of Yunnan Province in China as a case study to demonstrate the reasonableness and efficiency of the slope stability classification results in the SVNN scenario. In Section 5, the conclusions derived from the study are presented, accompanied by an analysis of the limitations of the study and suggestions for future research.

2. Preliminaries

2.1 Relative Concepts of Single-Valued Neutrosophic Set (SVNS) and SVNN

From a philosophical perspective, the neutrosophic set (NS) [23] can represent indeterminate and inconsistent information in objects by the use of independent truth, indeterminacy, and falsity membership functions (MFs). As these MFs of NS are situated within a real standard interval [0, 1] or a non-standard interval $]^{-}0, 1^{+}[$, they are difficult to use in the expression and analysis of real-life problems. Consequently, the concept of SVNN was proposed as a subclass of NS based on the standard interval [0, 1] for easy engineering applications [24, 25].

Definition 1 [24, 25]. Let Ψ be a finite set of objects, and let ψ be a common element in Ψ. Then, a SVNS P in Ψ can be defined as

$$P = \left\{ \left\langle \psi, T_p(\psi), U_p(\psi), F_p(\psi) \right\rangle \mid \psi \in \Psi \right\}, \quad (1)$$

where $T_P(\psi)$, $I_P(\psi)$, and $F_P(\psi)$ represents the truth, indeterminacy, and falsity MFs, respectively. For convenience, we use $p_\psi = \langle T_\psi, U_\psi, F_\psi \rangle$ to represent SVNN as an element in SVNS.

The similarity measure is a critical mathematical tool in clustering analysis and pattern recognition. In this paper, we introduce the cosine similarity measure of SVNNs [26].

Definition 2 [26]. Given two SVNNs $p_{\psi1}$ = <$T_{\psi1}$, $U_{\psi1}$, $F_{\psi1}$> and $p_{\psi2}$ = <$T_{\psi2}$, $U_{\psi2}$, $F_{\psi2}$>, the cosine similarity measure between $p_{\psi1}$ and $p_{\psi2}$ is represented as

$$S_c(p_{\psi1}, p_{\psi2}) = \frac{T_{\psi1}T_{\psi2} + U_{\psi1}U_{\psi2} + F_{\psi1}F_{\psi2}}{\sqrt{T_{\psi1}^2 + U_{\psi1}^2 + F_{\psi1}^2} \cdot \sqrt{T_{\psi2}^2 + U_{\psi2}^2 + F_{\psi2}^2}}, \quad S_c(p_{\psi1}, p_{\psi2}) \in [0,1]. \tag{2}$$

2.2 Ensemble Machine Learning Models

2.2.1 Bagging

Bagging, or bootstrap aggregating (BA), is an ensemble learning (EL) technique in ML. Its objective is to reduce the variance of a model by generating multiple independent samples of the training data and training a base model on each sample. The final prediction is then obtained by aggregating the predictions of all the base models. Bagging can be applied to a variety of models, including decision trees, NNs, and SVMs. One of the most popular bagging algorithms is the random forest. RF is a modified version of bagging, in which the classification and regression tree technique is often used as the individual learner. RF uses subsamples of the original data to construct decision trees and randomly selects a subset of variables to determine each split in the tree. RF excludes approximately 30% of training samples from the modeling process due to the use of bootstrapping and random subspace techniques and then it is often used to compute the out-of-bag (OOB) prediction error. The benefits of bagging include improvements in predictive performance, reductions in variance, and increases in model stability. However, bagging can also result in increases in computation time and memory requirements due to the necessity of training and storing multiple models. Overall, bagging is a powerful technique for improving the accuracy and stability of ML models, particularly in situations where the data are noisy or high-dimensional [29, 30]. The diagram of the bagging method is shown in Figure 1.

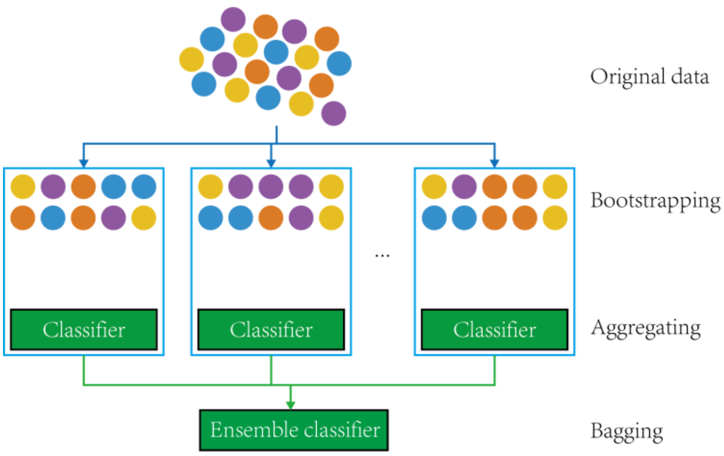


Figure 1. Diagram of the bagging method

2.2.2 Voting

Voting regressor is a EL technique that combines the predictions of multiple base regression models to produce a final prediction. Each base regressor provides its prediction, and the voting regressor aggregates these predictions, often by taking the average, to produce the final output. This approach can be beneficial when different regression models capture different aspects of the underlying data, leading to improved predictive performance compared to using a single model. The weights of the individual regressors can be uniform or customized based on their performance on the training data. The voting regressor is a versatile tool that can be used to exploit the strengths of various regression algorithms, such as linear regression, decision trees, SVMs and others, to create a robust and accurate predictive model [31].

3. SVNN-EL Model

The section proposes a SVNN-EL model, which is composed of the true bagging method, the indeterminate bagging method, and the false voting method and the cosine similarity measure. Then, its classification process is described as follows.

Step1: Data preparation. Assume that there is a collection of n slopes $D = (d_1, d_2, \ldots, d_n)$, then every slope contains q influence factors $d_i = (a_{i1}, a_{i2}, \ldots, a_{iq})$ ($i = 1, 2, \ldots, n$) sampled from the field investigation. These slopes imply the three kinds of stability status, which are denoted as three coding groups $y_1 = (y_{t1}, y_{u1}, y_{f1}) = (1, 0, 0)$, $y_2 = (y_{t2}, y_{u2}, y_{f2}) = (0, 1, 0)$, and $y_3 = (y_{t3}, y_{u3}, y_{f3}) = (0, 0, 1)$, corresponding to stable slopes, quasi-stable slopes and unstable slopes.

Step 2: Data neutrosophication. The original data $D = (d_1,d_2, \ldots, d_n)$ are then processed by the truth, indeterminacy and falsity MFs to transform the original data into SVNNs, which are represented as the data sets of the truth, indeterminacy and falsity degrees $D_t = \{d_{t1},d_{t2}, \ldots, d_{tn}, y_{tj}\}$, $D_u = \{d_{u1},d_{u2}, \ldots, d_{un}, y_{ui}\}$, and $D_f = \{d_{f1},d_{f2}, \ldots, d_{fn}, y_{fj}\}$ containing the coding values.

Step3: SVNN-EL model training. In this process, three independent ensemble machine learning methods are established based on the true, false and indeterminate information. Then we use the truth set $D_t = \{d_{t1},d_{t2}, \ldots, d_{tn}, y_{tj}\}$ for the true decision tree-based bagging method, the indeterminacy set $D_u = \{d_{u1},d_{u2}, \ldots, d_{un}, y_{uj}\}$ for the indeterminate decision tree-based bagging method, and the falsity set $D_f = \{d_{f1},d_{f2}, \ldots, d_{fn}, y_{fj}\}$ for the false voting method, where the base algorithms are linear regression (LR), RF and support vector regression (SVR). Their outputs $y_{t,pred}$, $y_{u,pred}$ and $y_{f,pred}$ are constructed as a prediction group $y_{pred} = (y_{t,pred}, y_{u,pred}, y_{f,pred})$.

Step4: Similarity measure. Using Eq. (2), we calculate the similarity measures of $S_c(y_{pred}, y_j)$ ($j = 1, 2, 3$) for each slop sample.

Step5: Classification result. According to $j^* = \arg\max_{1\le j\le 3}\{S_C(y_{pred}, y_j)\}$, the slope sample with the largest measure value belongs to the corresponding classification y_{j^*}.

In general, the proposed SVNN-EL model is constructed as the flowchart in Figure 2.

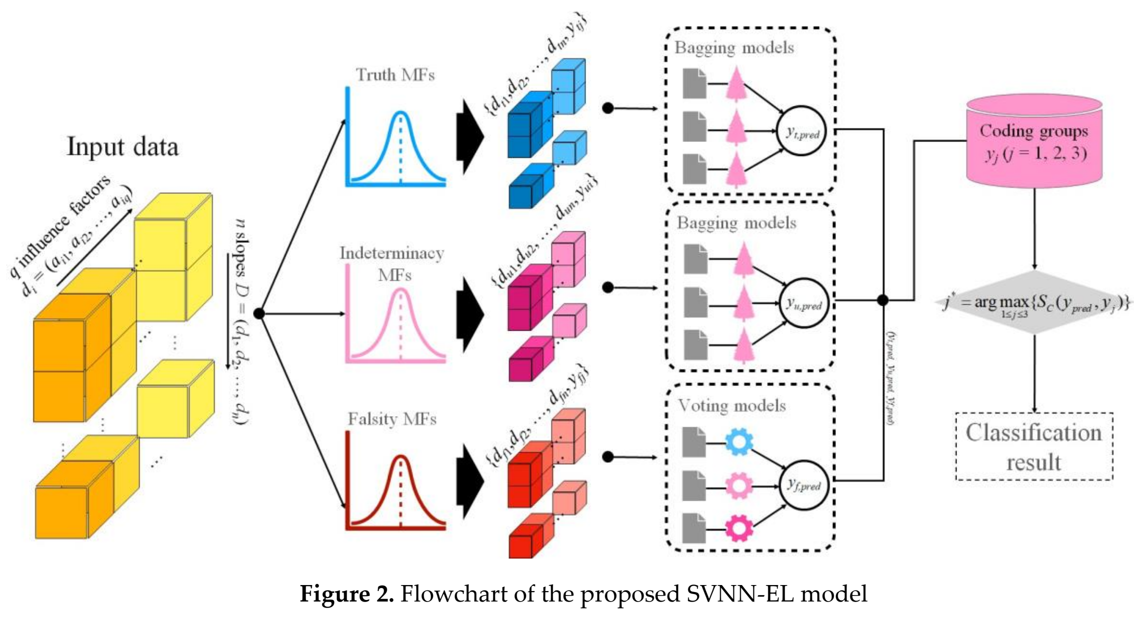


Figure 2. Flowchart of the proposed SVNN-EL model

4. Case Study

4.1 Raw Data Processing of the Lanping OPM Slopes

To validate the effectiveness and suitability of the proposed slope stability classification model, this section applies the proposed SVNN-EL model to classify the stability status of 215 slope samples in Yunnan Province, China. The Lanping OPM is situated in Yunnan Province, China, with geographic coordinates at 99°25′39.47′′E and 26°24′13.30″ N. The highest elevation within the mining area is 2885m, while the lowest elevation is 2475m, resulting in a relative height difference of 410m and characterizing it as a low mountainous terrain. Over years of mining activities, the OPM has taken on an inverted "C" shape; numerous small landslides and failures have occurred within its boundaries. The general conditions and location of this OPM are shown in Figure 3. Hence, it is necessary to provide a classification analysis of slope stability in the Lanping OPM. According to the actual engineering statuses and experts' experience, we consider slope height (a_1), slope angle (a_2), cohesion (a_3), internal friction angle (a_4), and rock density (a_5) as the main factors affecting slope stability. Then, 215 slope samples d_i (i = 1, 2, …, 215) were collected in situ from different areas as a classification case. Figure 3 shows the actual study area of the Lanping OPM.

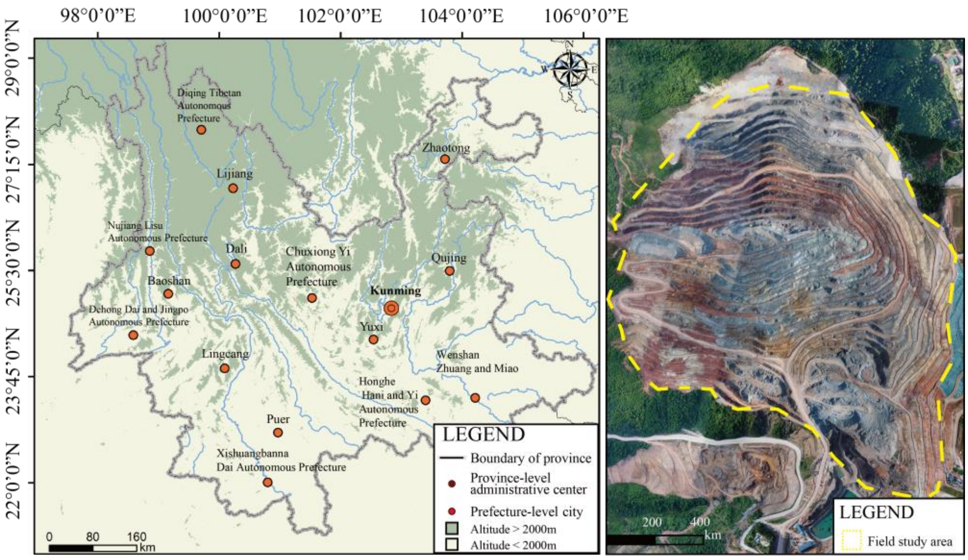


Figure 3. The top view of the actual study area in the Lanping OPM.

Regarding the Lanping OPM, the 215 slopes D = (d_1, d_2, …, d_{215}) were collected from the field study area, including the five influence factors: slope angle (a_1), slope height (a_2), cohesion (a_3), friction angle of the rock (a_4) and rock density (a_5). Subsequently, the original data can be divided into the true, indeterminate and false data sets.

First, the original data are neutrosophicated into SVNNs by utilizing truth, indeterminacy and falsity Gaussian membership functions based on the following Gaussian membership function:

$$f(x,\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}}, \tag{3}$$

where σ stands for standard deviation and c stands for mean. The three Gaussian membership functions used in this study are listed in Table 1.

After data neutrosophication, the true, indeterminate and false values in SVNNs and the coding values in y_j (j = 1, 2, 3) are constructed as the true, indeterminate and false data sets D_t = {d_{t1},d_{t2}, …, d_{tn}, y_{tj}}, D_u = {d_{u1},d_{u2}, …, d_{un}, y_{uj}}, and D_f = {d_{f1},d_{f2}, …, d_{fn}, y_{fj}}.

Table 1. Specified truth, indeterminacy, and falsity MFs d_{tk}, d_{uk}, and d_{fk}, (k = 1, 2, 3, 4, 5) for the five affecting factors.

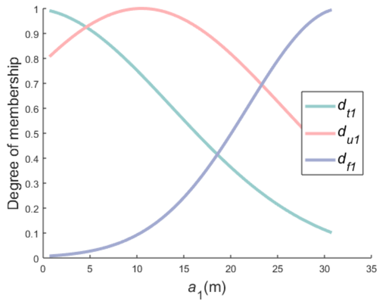
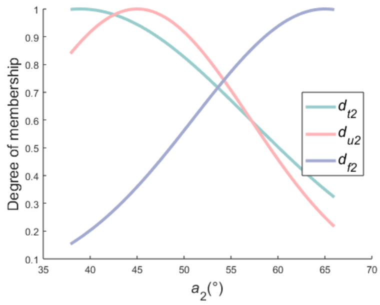
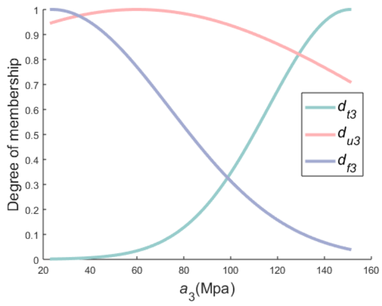
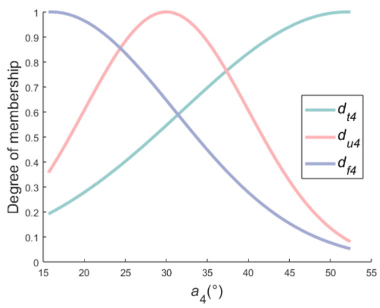
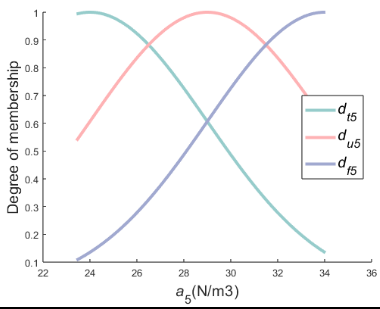
Influence factor	**Parameter of Gaussian MFs**			**Gaussian membership curve**
	Truth	**Indeterminacy**	**Falsity**	
a_1(m)	σ_{t1}=15.00 c_{t1}=-2.67	σ_{u1}=15.00 c_{u1}=10.50	σ_{f1}=10.00 c_{f1}=31.84	
a_2(°)	σ_{t2}=18.00 c_{t2}=38.90	σ_{u2}=12.00 c_{u2}=45.00	σ_{f2}=14.00 c_{f2}=65.02	
a_3(MPa)	σ_{t3}=35.00 c_{t3}=150.00	σ_{u3}=110.00 c_{u3}=60.00	σ_{f3}=30.00 c_{f3}=23.84	
a_4(°)	σ_{t4}=20.00 c_{t4}=52.00	σ_{u4}=10.00 c_{u4}=30.00	σ_{f4}=15.00 c_{f4}=16.00	
a_5(N/m³)	σ_{t5}=5.00 c_{t5}=24.00	σ_{u5}=5.00 c_{u5}=29.00	σ_{f5}=5.00 c_{f5}=34.00	

Table 2. Specified parameters of the proposed EL methods

EL method	Parameter	Setting
Bagging method	Base model	Decision tree
	Number of estimators	15
	Max samples	1.0
	Max features	1.0
	Warm start	True
Voting method	Estimator 1	Linear regressor
	Estimator 2	SVM regressor
	Estimator 3	RF regressor
	Weights	None

Since the true, indeterminate, and false EL methods are contained in the proposed SVNN-EL model, their specific parameters are given in Table 2. In order to eliminate the potential influence of randomness in the experimental setup, a fixed random statement (random state = 12) is specified. the true and indeterminate data sets are used for the bagging tree models, comprising multiple decision trees. Then, the false data set is used for the voting tree models, which are also based on a multitude of weak decision trees.

According to the actual slope stability status, the slopes are categorized into the binary coding groups: y_1 = (1, 0, 0), y_2 = (0, 1, 0) and y_3 = (0, 0, 1), which mean stability, quasi-stability, and instability for the slopes. The training and testing data sets are generated using the Python package Scikit-learn, incorporating a constant random statement. The actual stability states and training/testing data sets are presented in Table 3.

4.2 SVNN-EL Classification Results and Discussion

The confusion matrix [32] is a valuable tool to evaluate the performance of a classification model. It provides an overview of the predictions of the model by comparing them with the actual values. The predicted results are listed in the confusion matrix. As shown in Figure 4, the elements c_{ij} in the confusion matrix represent the number of instances, where an observation belonging to the actual class *i* is predicted to be the class *j*. The diagonal elements (c_{ii}) represent true positives for each class. Non-diagonal elements (c_{ij}) denote false positives or false negatives.

Actual \ Predicted	Predicted 1	Predicted 2	…	Predicted *n*
Actual 1	c_{11}	c_{12}	…	c_{1n}
Actual 2	c_{21}	c_{22}	…	c_{2n}
…	…	…	…	…
Actual *n*	c_{n1}	c_{n2}	…	c_{nn}

Note: Since each class has an individual performance metric, we take their average values for comparative convenience.

Figure 4. Confusion matrix for multi-class classification.

Table 3. Similarity measure values and classification results of the testing data sets.

$y_{t,pred}$	$y_{u,pred}$	$y_{f,pred}$	$S_C(y_{pred}, y_1)$	$S_C(y_{pred}, y_2)$	$S_C(y_{pred}, y_3)$	Result	Real
0.8651	0.0000	0.0927	0.9943	0.0000	0.1066	(1,0,0)	(1,0,0)
0.8379	0.0000	0.0354	0.9991	0.0000	0.0422	(1,0,0)	(1,0,0)
0.3481	0.0914	0.6213	0.4847	0.1273	0.8653	(0,0,1)	(0,0,1)
0.3536	0.0017	0.7857	0.4104	0.0019	0.9119	(0,0,1)	(0,0,1)
0.7556	0.0671	0.0232	0.9956	0.0885	0.0305	(1,0,0)	(1,0,0)
0.3495	0.0081	0.3335	0.7233	0.0167	0.6903	(1,0,0)	(1,0,0)
0.2701	0.5086	0.0000	0.4690	0.8832	0.0000	(0,1,0)	(0,1,0)
0.3645	0.0036	0.7966	0.4161	0.0041	0.9093	(0,0,1)	(0,0,1)
0.3844	0.0236	0.7503	0.4558	0.0280	0.8896	(0,0,1)	(0,0,1)
0.4894	0.4629	0.0817	0.7212	0.6822	0.1204	(1,0,0)	(1,0,0)
0.3401	0.0300	0.7504	0.4125	0.0364	0.9102	(0,0,1)	(0,0,1)
0.4590	0.4610	0.0000	0.7056	0.7087	0.0000	(0,1,0)	(0,1,0)
0.9046	0.0000	0.0419	0.9989	0.0000	0.0462	(1,0,0)	(1,0,0)
0.4987	0.4829	0.0588	0.7158	0.6932	0.0844	(1,0,0)	(1,0,0)
0.3978	0.0671	0.6506	0.5196	0.0877	0.8499	(0,0,1)	(0,0,1)
0.3227	0.4837	0.0746	0.5504	0.8251	0.1272	(0,1,0)	(0,1,0)
0.3757	0.0359	0.2882	0.7912	0.0755	0.6069	(1,0,0)	(1,0,0)
0.4334	0.4749	0.0000	0.6741	0.7386	0.0000	(0,1,0)	(0,1,0)
0.4425	0.0295	0.8035	0.4822	0.0321	0.8755	(0,0,1)	(0,0,1)
0.6833	0.0833	0.0000	0.9926	0.1211	0.0000	(1,0,0)	(1,0,0)
0.5423	0.4888	0.0000	0.7428	0.6695	0.0000	(1,0,0)	(0,1,0)
0.3294	0.0711	0.0000	0.9775	0.2111	0.0000	(0,0,1)	(0,0,1)
0.6667	0.0833	0.0000	0.9923	0.1240	0.0000	(1,0,0)	(1,0,0)
0.3378	0.0000	0.6204	0.4782	0.0000	0.8783	(0,0,1)	(0,0,1)
0.4657	0.0295	0.8642	0.4742	0.0300	0.8799	(0,0,1)	(0,0,1)
0.7119	0.0594	0.0626	0.9927	0.0829	0.0873	(1,0,0)	(1,0,0)
0.3201	0.5027	0.0000	0.5371	0.8435	0.0000	(0,1,0)	(0,1,0)
0.3308	0.0100	0.7187	0.4181	0.0126	0.9083	(0,0,1)	(0,0,1)
0.4219	0.1081	0.4364	0.6844	0.1753	0.7077	(0,0,1)	(1,0,0)
0.4068	0.0300	0.2971	0.8061	0.0595	0.5888	(1,0,0)	(1,0,0)
0.7530	0.0278	0.0505	0.9971	0.0368	0.0669	(1,0,0)	(1,0,0)
0.7814	0.0019	0.1013	0.9917	0.0024	0.1285	(1,0,0)	(1,0,0)
0.4511	0.1278	0.7096	0.5303	0.1502	0.8344	(0,0,1)	(1,0,0)
0.5401	0.0300	0.5007	0.7328	0.0407	0.6792	(1,0,0)	(0,0,1)
0.7556	0.0278	0.0000	0.9993	0.0367	0.0000	(1,0,0)	(1,0,0)
0.3747	0.0914	0.4748	0.6125	0.1494	0.7762	(0,0,1)	(0,0,1)
0.7333	0.1042	0.0000	0.9901	0.1406	0.0000	(1,0,0)	(1,0,0)
0.4536	0.0017	0.8119	0.4877	0.0018	0.8730	(0,0,1)	(0,0,1)
0.8493	0.0019	0.0714	0.9965	0.0022	0.0838	(1,0,0)	(1,0,0)

0.3324	0.0771	0.7875	0.3873	0.0898	0.9176	(0,0,1)	(0,0,1)
0.3349	0.1748	0.6848	0.4282	0.2234	0.8756	(0,0,1)	(0,0,1)
0.3452	0.0850	0.5786	0.5084	0.1252	0.8520	(0,0,1)	(0,0,1)
0.3012	0.4996	0.1254	0.5047	0.8373	0.2102	(0,1,0)	(0,1,0)
0.3844	0.0236	0.7095	0.4761	0.0292	0.8789	(0,0,1)	(0,0,1)
0.3082	0.0833	0.6719	0.4143	0.1120	0.9032	(0,0,1)	(0,0,1)
0.5415	0.0220	0.2306	0.9194	0.0373	0.3915	(1,0,0)	(1,0,0)
0.3479	0.5281	0.0232	0.5497	0.8346	0.0367	(0,1,0)	(0,1,0)

Table 4. Classification results for the proposed SVNN-EL model.

	Stable	**Quasi-stable**	**Unstable**
Actual	19	1	1
Actual	0	7	0
Actual	2	0	17

All the results of the testing data are presented in Table 3. Here, the similarity measure values between the EL results $y_{t,pred}$, $y_{u,pred}$, $y_{f,pred}$ and the three coding groups (1, 0, 0), (0, 1, 0) and (0, 0, 1) are obtained by Eq. (2). Subsequently, each slope is classified in terms of the classification method of Step 5. The total classification results of the 47 testing slopes are presented in Table 4. The classification results can be visualized in a three-dimensional scatter plot (Figure 5), which is enabled to show a more detailed representation of the distance between the classified points and the target coding groups.

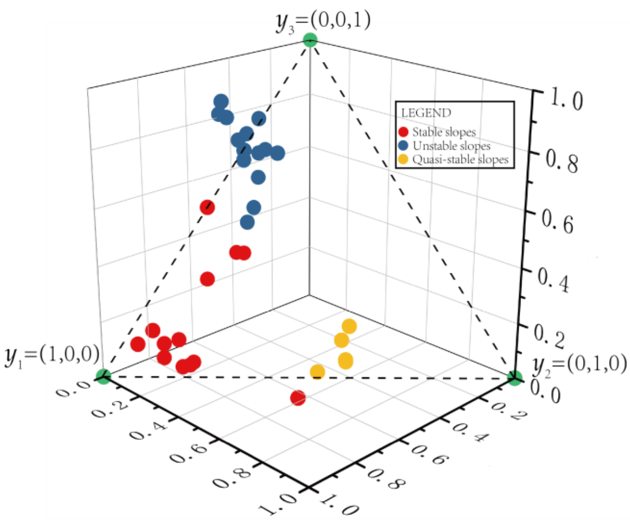


Figure 5. Classification result of the 47 testing slopes.

To show the effectiveness of the proposed SVNN-EL model, the four-performance metrics of the Acc, precision, recall and F1-score are considered below.

Accuracy (Acc) measures how well the model predicts both positive and negative classes by

$$Acc = \frac{\sum_{i=0}^{n-1} C_{ii}}{\sum_{i=0}^{n-1}\sum_{j=0}^{n-1} C_{ij}}. \tag{4}$$

Precision quantifies how many of the positively classified instances are actually correct by

$$Precision_i = \frac{C_{ii}}{\sum_{j=0}^{n-1} C_{ji}}. \tag{5}$$

Recall or sensitivity estimates how well the model identifies all real positives by

$$Recall_i = \frac{C_{ii}}{\sum_{j=0}^{n-1} C_{ij}}. \tag{6}$$

F1-score combines precision and recall into one metric using their harmonic mean value by

$$F1-score_i = \frac{2Precision \cdot Recall}{Precision + Recall}. \tag{7}$$

By Eqs. (4)–(7), the performance metrics of the Acc, precision, recall and F1-score are 0.915, 0.894, 0.948, 0.921, respectively. To show the effectiveness of the proposed SVNN-EL model, we chose the classical ML methods of KNN, SVM, RF for comparison, the specific experiment settings are shown in the Table 2. The training and testing data sets also keep the same with the proposed SVNN-EL model. The comparison results are shown in Figure 6.

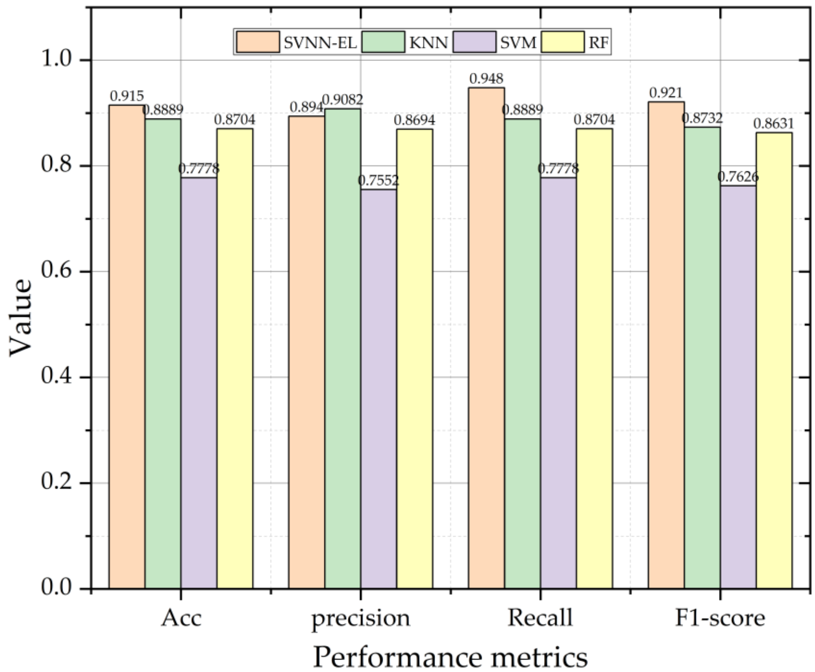


Figure 6. Performance comparison of KNN, SVM, RF and the proposed method.

As illustrated in Figure 6, the proposed SVNN-EL model exhibits the optimal accuracy, recall, and F1-score. Our findings indicate that the proposed SVNN-EL model outperforms the traditional methods in scenarios where the features are not readily discernible. Additionally, the proposed model offers the flexibility to be adapted to specific engineering conditions, a distinctive superiority over the traditional ML methods.

5. Conclusions

Based on the hybrid form of SVNN and the EL method, the SVNN-EL model was proposed as a method of classifying the stability of OPM slopes. Subsequently, the efficacy of the proposed model was validated by using a dataset comprising 215 slope samples sourced from Yunnan province, China. Then, the proposed model can reach better classification precision of the slopes. The comparative outcomes demonstrated that the proposed SVNN-EL model was superior to the existing ML methods of KNN, SVM, RF in the performance metrics of the Acc, precision, recall and F1-score. This approach offered a valuable way for mining engineers. In general, the proposed SVNN-EL model includes the following main highlights.

(1) The truth, indeterminacy and falsity degrees in SVNN can comprehensively express the hybrid information of uncertainty, imprecision and incompleteness in the raw field slope data, which provide the necessary information for the proposed SVNN-EL model.

(2) The coding groups were used to represent the stability status of each slope. Then a relationship between the coding groups and the slope stability status can be established in the ML process. Furthermore, a classification method based on the similarity measure was developed to determine the final classification result.

(3) The proposed SVNN-EL model demonstrated better performance in terms of the Acc, precision, recall and F-1 score metrics, along with the metric values of 0.915, 0.894, 0.948 and 0.921, respectively. The comparative results demonstrated that the proposed model exhibits superiority over the existing ML methods of KNN, SVM, RF in all four-performance metrics.

It should be noted that the proposed model has a limitation in that it exclusively considers the fundamental engineering conditions and plane failure modes of OPM slopes. In the future, the proposed model will be extended to encompass more complex engineering conditions, such as those associated with earthquakes and blasting loads. Furthermore, it will be applied to slopes where circular and wedge-shaped failure modes may occur. The novel technique presented in this study has the potential to be extended to other applications, including rock burst risk assessment, galaxy identification, and medical diagnosis in the presence of uncertain or inconsistent data.

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Conflicts of Interest: The authors declare that they have no conflicts of interest.

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