Universidad Nacional de Trujillo

Journal of Advanced Mining Modeling (JAMM)

Journal website: https://revistas.unitru.edu.pe/index.php/jamm/index
Vol. 2, Nº 1, pp. 24-41, January – June 2026

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Implementation of the K-Nearest Neighbors algorithm for the prediction of open-pit mine slope failures

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Received: December 13, 2025 Revised: December 18, 2025 Accepted: December 31, 2025 Published online: January 3, 2026

Abstract

The purpose of this study was to analyze the use of the K-Nearest Neighbors (KNN) method to anticipate slope failures in open-pit mining, using the geotechnical parameters of each slope. The assessment of landslide hazards in open-pit mine slopes can be described as the evaluation of the potential collapse risk of these structures, which is essential to ensure operational safety. To achieve this, continuous monitoring of the slopes and the evaluation of all variables that may influence their stability are imperative. A quantitative approach was applied, evaluating the factor of safety classified as stable (ST), moderately stable (OF), and unstable (FSB), considering a distance of K = 11 nearest neighbors. The geomechanical relationships among the slope parameters significantly contributed to improving the prediction of slope stability conditions. With the implementation of the KNN algorithm, highly effective results were obtained for slope stability prediction, achieving a precision of 0.90, sensitivity (recall) of 0.90, and F1-score of 0.90 for stable slopes (ST), as well as an overall accuracy of 83.33%. Finally, the KNN method is a reliable alternative for predicting stable slope conditions in open-pit mining. The selected k-value demonstrated a prediction efficiency of 73.73%, facilitating technical decision-making and contributing to the reduction of slope failure risks through a systematic analysis of slope variables.

Keywords: K-Nearest Neighbors (KNN), Slope stability, Open-pit mining, Slope failure prediction, Geotechnics.

1. Introduction

Data mining constitutes a process that employs various analysis tools in order to identify patterns, models, and relationships within large sets of information, which can later be used to make reliable predictions.

In the mining field, multiple disciplines intervene to ensure that operations are carried out safely and efficiently. One of the essential areas is geotechnics, whose purpose is to study, interpret, and anticipate the behavior of soils and rocks, so that mining works and activities can be executed without landslides or structural failures [1].

Within this discipline, slope stability in surface mining operations is a fundamental aspect, as it is linked to the analysis of the geotechnical characteristics of the materials that make up the pit, considering its three scales: bench, inter-ramp, and global. A slope is considered to have failed when it reaches a displacement that compromises its operational safety or when it no longer adequately fulfills the function for which it was designed. In such situations, it is necessary to modify the initial configuration and design established by engineering.

One of the most used algorithms in the field of machine learning for the generation of predictive models is (KNN). This method learns by identifying similarities between a new data point and other nearby data points

within the multidimensional space. The KNN algorithm is part of the classification techniques commonly used in data mining processes [2].
The problem faced by miners is the construction of slopes with good stability, which motivates the formulation of the following question: How is the (KNN) algorithm applied to predict collapse in open-pit mine slopes?
The general objective of this article is to examine the application of K-Nearest Neighbor (KNN) to anticipate slope failure in surface mining. As specific objectives, the following are proposed: Analyze the relationship between various geotechnical characteristics through KNN to anticipate landslides; evaluate the effectiveness of the KNN model using classification accuracy measures and the confusion matrix; analyze how data is distributed in relation to the training and testing datasets using K-Nearest Neighbor to anticipate slope failures.
This research article contributes to the knowledge about the prediction of mining events, specifically slope failures, through the application of an algorithmic method based on data collected in the field and processed using the Python programming language.

2. Materials and methodology

The purpose of this research is to demonstrate the reality of the information with due scientific rigor, which will allow obtaining valid and efficient results through the application of the (KNN) algorithm for predicting slope collapse in surface mining. Mining operations must be carried out based on geotechnical studies of the rock mass, in order to determine the condition of the soils and rocks. In open-pit operations, knowing the physical properties of the rocks is always an essential requirement [3].

2.1. Parts of a slope

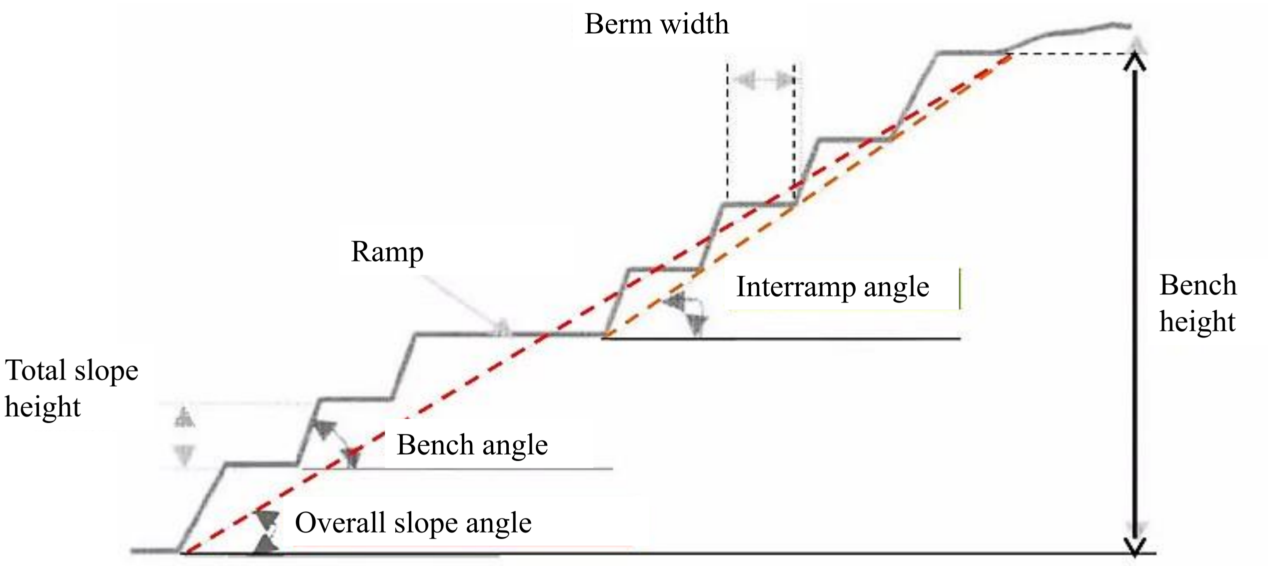

Figure 1. Slope components

In Figure 1, the slope and its corresponding parts can be observed, showing how a slope occurs in surface mining. There are two different variables classified on the x and y axes, and there is an unknown in the middle for which the safety factor must be: $FS \geq 1.5$ stable, $1.20 \leq FS < 1.5$ marginally stable, $FS \leq 1.20$ unstable.
At the beginning, the separation between this unknown location and the other points is determined by the value of K, which limits the number of data points examined. This indicates how many nearby neighbors should be considered when analyzing according to the established parameters [4].
The safety, functional efficiency, and profitability of mining activities largely depend on the stability of slopes in open-pit mines. Over time, various strategies have been developed and implemented to measure and ensure the stability of these slopes. One of the most common approaches is the limit equilibrium method, known for its ease of use and effectiveness in various geotechnical situations [5].

2.2. Rock quality designation (RQD)

This analysis examined the consistency of such slopes using geomechanical techniques based on RQD. The strategy included field investigations for geological and geotechnical identification [6].

Table 1. Rock quality (RQD)

Rock quality	RQD (%)
Poor	<25
Low	25 – 50
Fair	50 – 75
Good	75 – 90
Excellent	90 - 100

2.3. Barton's Q index

The Barton Q Index helps to predict the support and stress in rock-excavated slopes by providing guidelines on a safe slope angle. The Q value is calculated using the following parameters: rock quality (RQD), number of joint sets (Jn), joint roughness index (Jr), joint alteration index (Ja), geological condition factor (Jwice), and the slope-strength reduction factor [7].

Table 2. Barton's Q index

Rock quality (Q)	Rating
0.01 – 0.01	Critically poor
0.01 – 0.1	Very poor
0.1 – 1	Extremely poor
1 – 4	Poor
4 – 10	Fair
10 – 40	Good
40 – 100	Very Good
100 – 400	Excellent
400 - 1000	Exceptionally good

2.4. Geological strength index (GSI)

The simplicity of the GSI system proves to be its main disadvantage, as it only measures the fracturing level of the rock mass and the condition of discontinuity surfaces [8].

2.5. K-Nearest Neighbors (KNN)

KNN is described as a prediction technique in the field of supervised learning that is based on the distance between the current sample and the nearest neighbors, which are determined by a value of k. This determines the outcome of the prediction made [9].

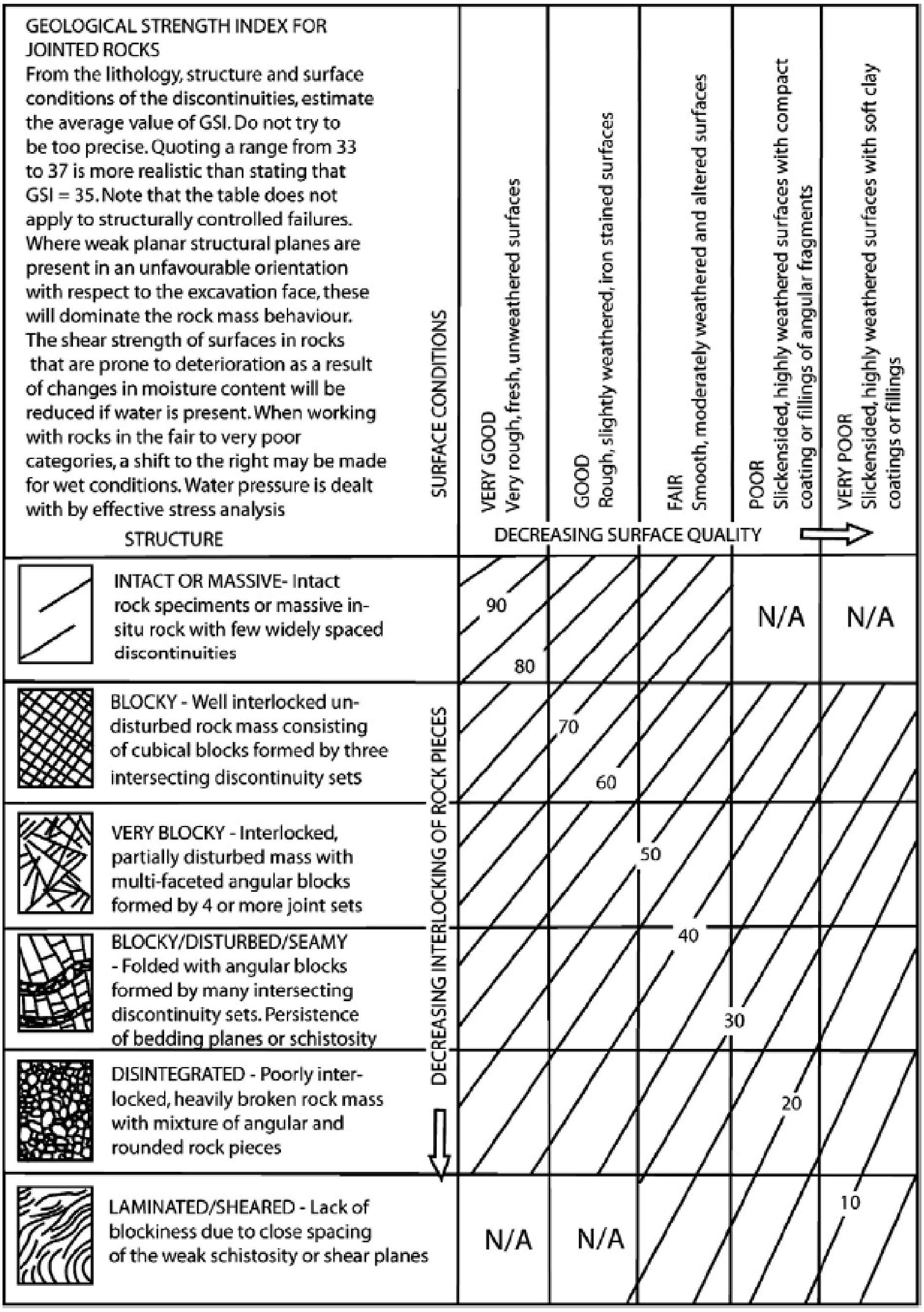

Figure 2. Geological strength index (GSI)

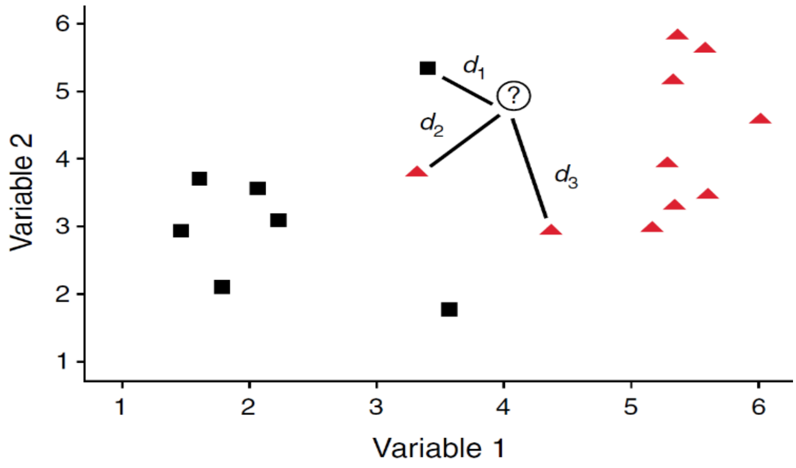

Figure 3. K-Nearest Neighbors (KNN)

In Figure 3, it is shown that K equals 3. Taking the dataset into account, it is possible to identify the category of a particular data point by measuring its closeness to other samples. There are several approaches to calculate this closeness, with Euclidean distance being the most used method to evaluate the separation between two locations [10].

$$D(x,y) = \sqrt{(x1-y1)^2 + (x2-y2)^2 + .. + (xn-yn)^2} \quad (1)$$

Where
$D(x,y)$ - metric distance between 2 points
x, y – specific variables,
n – number of dimensions.
After the value of k was established and the KNN model was trained, this method was used to predict the risk of slope collapse with varying characteristics, by comparing the attributes of the new data point only with those in the training dataset [11].

2.5.1. Confusion matrix

The confusion matrix was used to assess the specific performance of each model in relation to different rock classes. This table compiles the correct predictions versus incorrect ones, facilitating the detection of classification bias, confusion between similar lithologies, and systematic recurring errors [12].

2.5.2. Performance metrics

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (2)$$

Where:
TP – True positives
TN – True negatives
FP – False positives
FN – False negatives

$$\text{Positive precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (3)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (4)$$

$$\text{F1} - \text{Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (5)$$

2.6. Description of the data and how it will be processed in KNN

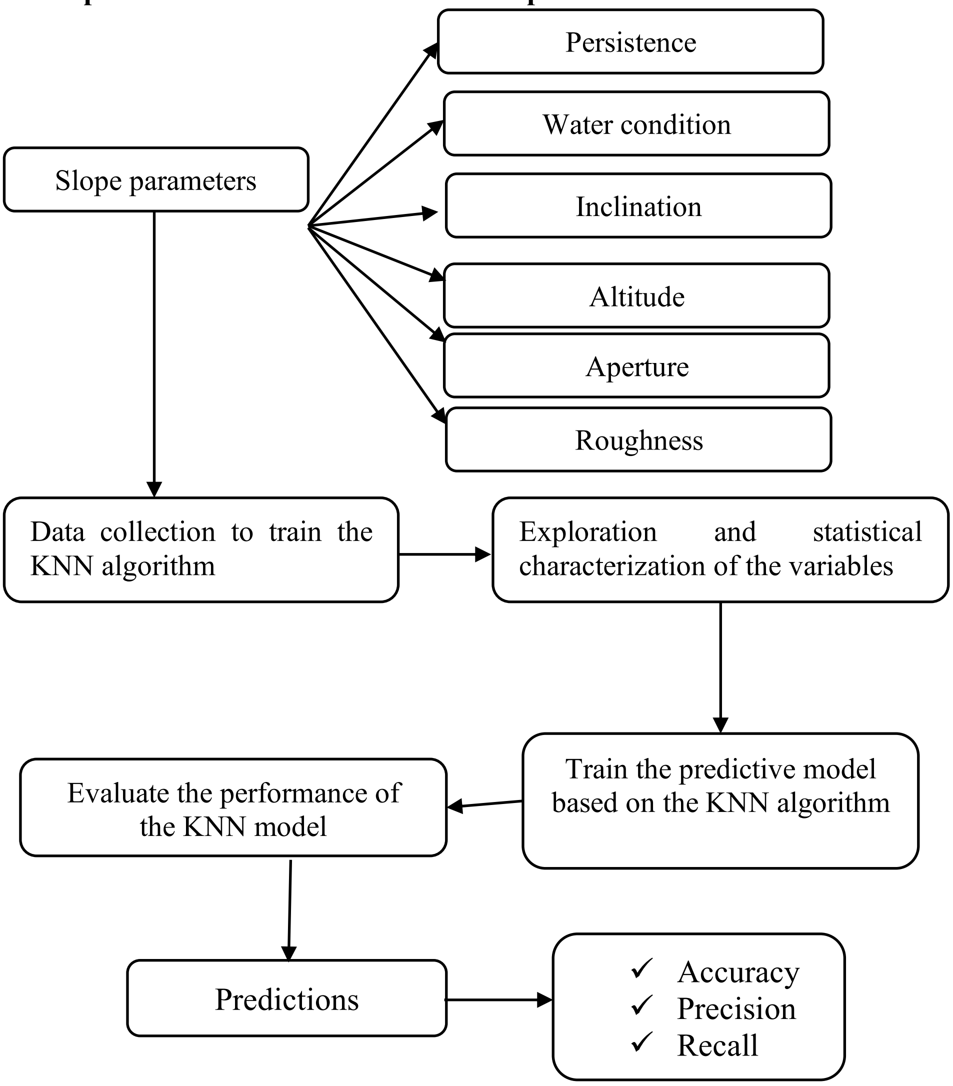

Figure 4. Data flowchart

2.7. Instrumentation and data collection techniques

The instruments used for handling data from the open-pit mine were: compass, clinometer, hammer, and geotechnical forms, which were analyzed in tables containing authentic information that helps to detail the properties of slopes across various rock samples. The applied methodologies are based on technical references and multiple documents related to slope failure analysis [2]. The variables used for the database are:

H0: Discontinuity persistence length (m)
H1: Discontinuity spacing (mm)
H2: Discontinuity roughness grade
H3: Discontinuity orientation
H4: Weathered rock
H5: Groundwater presence
H6: Total slope elevation (m)
H7: Global slope inclination (°)

Table 3. Slopes with FSB Status – 0 (Inter-ramp failure)

H0	H1	H2	H3	H4	H5	H6	H7	STATUS
12.86	3.08	3.91	3.18	1.99	4.01	193	38.81	FSB
11.54	2.9	4.29	3.8	2.78	3.8	241.16	41.83	FSB
18.11	3.03	3.24	3.21	3.83	4.29	590.74	36.38	FSB
17.49	2.9	3.17	4.2	3.98	4.12	803.71	34.94	FSB
14.74	3.03	3.94	3.05	2.11	4.02	482.7	35.37	FSB
1.26	3.06	3.81	3.99	2.09	2.84	182.52	40.18	FSB
0.42	0.51	3.07	3.81	3.21	2.82	179.47	51.73	FSB
2.6	2.91	2.88	3.16	2.08	2.98	323.14	52.85	FSB
2.4	0.55	2.9	3.12	2	2.81	285.79	67.09	FSB
8.37	3.14	4.14	5.17	4.26	5.04	725.92	41.43	FSB
23.55	2.97	2.79	4.65	3.93	2.94	317.19	53.42	FSB
26.49	3.21	2.8	4.84	3.18	1.85	308.54	57.82	FSB
12.82	2.81	1.86	4.17	3.18	2.78	346.12	59.06	FSB
21.32	2.97	3.15	3.77	3.9	3.04	337.51	53.24	FSB
21.28	2.92	3.96	2.96	2.85	4.16	314.9	47.19	FSB
5.18	2.93	3.14	3.74	3.23	2.87	530.77	49.1	FSB
10.02	3.16	2.9	4.27	3.17	3.84	232.53	44.92	FSB
5.07	3.02	4.32	4.24	3.95	4.22	154.29	57.67	FSB
6.79	0.53	3.73	3.08	3.2	4.07	637.25	38.06	FSB
6.83	0.54	2.09	5.39	2.81	3.09	770.32	31.25	FSB
8.1	0.56	3.14	3	3.85	4.21	222.46	29.68	FSB
6.46	3.07	3.96	4.13	2.97	4.77	156.37	44.53	FSB
9.95	4.89	4.13	3.17	2.95	3.89	327.55	52.81	FSB
5.52	3.03	3.16	2.1	4.25	3.97	452.57	25.92	FSB
6.21	0.52	2.09	3.14	0.93	3.91	48.18	44.24	FSB
11.13	0.31	1.89	1.91	4.26	4	19.21	49.94	FSB
9.34	2.15	1.85	1.92	2.09	4.16	20.18	48.64	FSB

Table 4. Slopes with OF Status – 1 (Global failure)

H0	H1	H2	H3	H4	H5	H6	H7	STATUS
11.97	3.06	2.1	3.93	2.12	5.13	173.24	31.7	OF
25.91	6.58	3.23	5.06	2.08	3.81	199.4	39.51	OF
0.86	3.03	2.78	4.64	2.94	3.03	92.41	54.78	OF
0.66	2.84	2.94	5.22	1.91	2.05	169.17	46.29	OF
6.83	2.82	2.79	4.16	2.15	2.9	226.22	35.36	OF
7.05	3.19	2	3.75	2.03	1.93	18.82	44.45	OF
6.15	2.76	3.09	5.36	2.97	3.87	757.8	32.62	OF
6.17	2.84	1.97	5.01	3.09	3.12	730.55	40.94	OF
7.79	3.01	2.98	5.21	2.79	2.89	733.17	34.51	OF
10.47	3.09	3.08	3.76	2.88	2.96	209.34	32.69	OF
9.77	3.1	2.93	4.76	3.73	2.98	193.93	34.96	OF
14.41	3.15	2.03	3.69	3.07	3.88	194.94	31.43	OF
16.14	3.04	3.9	2.9	1.89	2.06	272.11	45.46	OF
18.54	3.01	3.03	3.06	2.8	3.05	454.51	29.89	OF

17.09	4.8	3.11	5.28	2.08	2.02	272.47	36.32	OF
18.02	4.76	2.84	4.07	2.15	3.1	593.75	35.22	OF
19.68	2.76	3.22	4.01	4.21	4.06	95.7	42.91	OF
5.46	3.09	3	4.26	3.14	3.01	267.51	32.94	OF
11.68	0.49	2.05	3.88	1.05	3.96	53.99	51.74	OF

Table 5. Slopes with ST Status – 2 (Stable)

H0	H1	H2	H3	H4	H5	H6	H7	STATUS
29.62	3.01	3.07	3.75	3.86	4.63	195.21	52.33	ST
21.19	2.99	3.81	0.98	3.04	5.22	206.07	34.99	ST
10.63	0.98	3.02	3.85	4.63	4.92	195.69	57.68	ST
9.9	1.11	3.17	4	4.87	4.95	216.99	59.08	ST
24.05	3.23	2.79	4.22	4.24	5.07	214.5	46.83	ST
22.75	0.98	3.98	2.82	3.76	5.37	202.68	45.29	ST
7.78	2.91	2.78	4.04	2.8	5.02	164.43	48.5	ST
2.38	1.26	3	2.93	4.16	4.64	185.61	47.66	ST
1.62	0.75	4.08	2.14	3.05	5.23	157.6	39.21	ST
1.66	1.52	3.85	3.19	3.03	5.01	166.75	42.59	ST
2.08	1.16	3.15	2.84	4.22	4.84	174.93	42.61	ST
6.74	3.06	4.07	2.14	3.94	5.18	427.23	34.56	ST
11.52	2.91	3.83	3.72	4.07	4.84	595.05	36.03	ST
13.81	3.08	3.21	1.94	3.17	5.17	443.64	37.58	ST
6.61	5.56	3.83	3.04	4.01	3.88	299.53	36.26	ST
12.76	2.82	3.86	3.19	2.82	3.7	361.48	32.25	ST
0.51	3.13	4.01	1.98	3.15	4.32	193.16	52.73	ST
0.71	0.56	3.73	3.21	2.84	3.98	95.51	51.89	ST
0.98	3.04	3.2	2.82	3.76	3.94	93.21	59.81	ST
6.48	2.77	4.18	2.95	2.87	4.14	237.66	38.5	ST
5.62	0.54	2.91	2.78	4.23	4.8	719.54	28.95	ST
4.16	0.56	1.84	3.82	2.99	4.85	715.32	33.95	ST
2.6	0.51	3.92	2.88	3.22	5.32	730.02	32.08	ST
1.84	0.52	3.71	1.94	3.94	4.86	309.78	51.53	ST
6.21	0.56	4.23	2.92	3.84	4.9	517.86	54.63	ST
3.09	2.83	5.1	2.08	4.09	4.08	464.84	57.3	ST
4.68	0.59	4.21	4.1	3.94	5.27	491.75	42.77	ST
4.48	3.01	4.14	3.02	3.75	4.8	509.84	58.35	ST
3.09	0.56	3.92	3.01	5.38	5.28	249.34	52.99	ST
3.29	0.57	3.97	3.22	4.14	4.9	331.28	52.83	ST
2.3	0.09	3.86	2.09	3.74	5.21	321.66	45.17	ST
2.24	0.52	3.17	1.93	4.26	3.89	118.05	41.86	ST
3.76	0.59	4.27	1.94	4.17	4.05	721.38	40.66	ST
3.32	0.58	3.88	2.05	3.2	3.98	713.13	37.76	ST
3.77	0.52	3.16	2.84	3.72	3.95	725.57	43.15	ST
2.97	0.1	4.21	1.84	4.02	4.69	237.7	33.74	ST
4.24	0.53	3.96	2.05	3.8	3.82	251.93	25.06	ST

3.71	3.01	4.05	2.82	3.98	4.72	104.27	41.82	ST
7.63	0.57	4.17	3.06	3.74	4.17	282.6	52.78	ST

2.7.1. Data handling method

The information collected and evaluated regarding slopes in open-pit mining will be analyzed through the application of the KNN method.

2.7.2. Procedure

To use the KNN approach in predicting slope collapse, a dataset was employed that incorporates details about the geotechnical properties of the slope and the terrain. With this information, the KNN method was trained with the objective of assessing the risk of landslides, taking into account the characteristics of the ground and the type of failure that could occur on the slope [13].

3. Results

Persistence refers to the increase in the dimensions of the discontinuity, and aperture is the measurement of the distance between them.

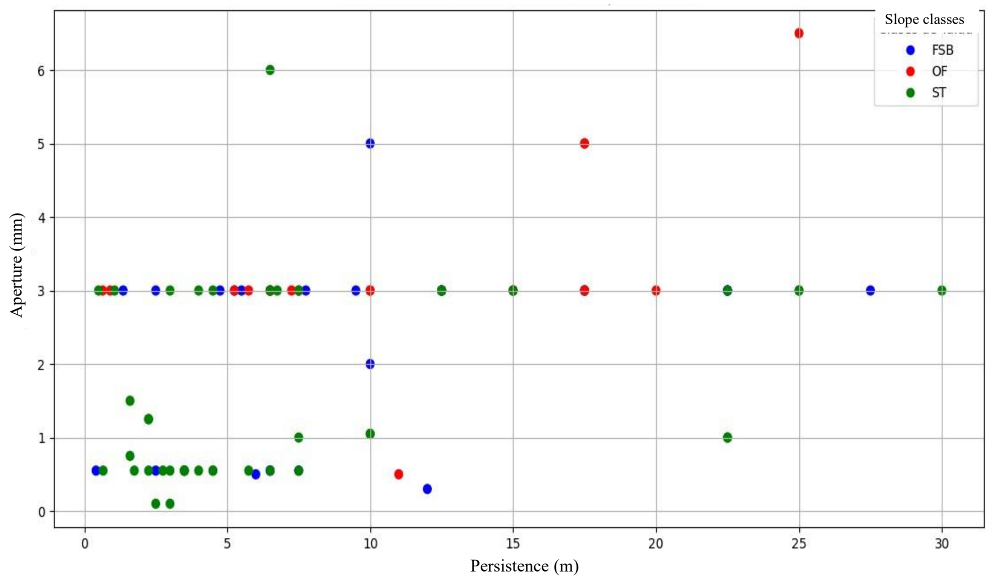

Figure 5. Relationship between aperture and persistence parameters

Selection of the optimal K using all the variables from our dataset, calculated in Python.

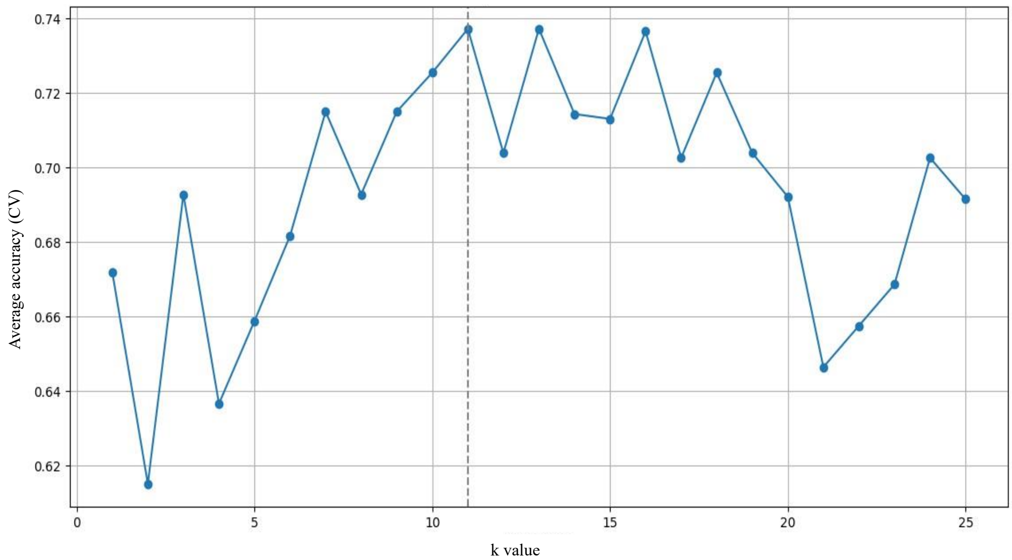

Figure 6. Value of K = 11, Average Accuracy = 73.73%

3.1. Examine the relationship between various geotechnical characteristics using KNN to anticipate landslides

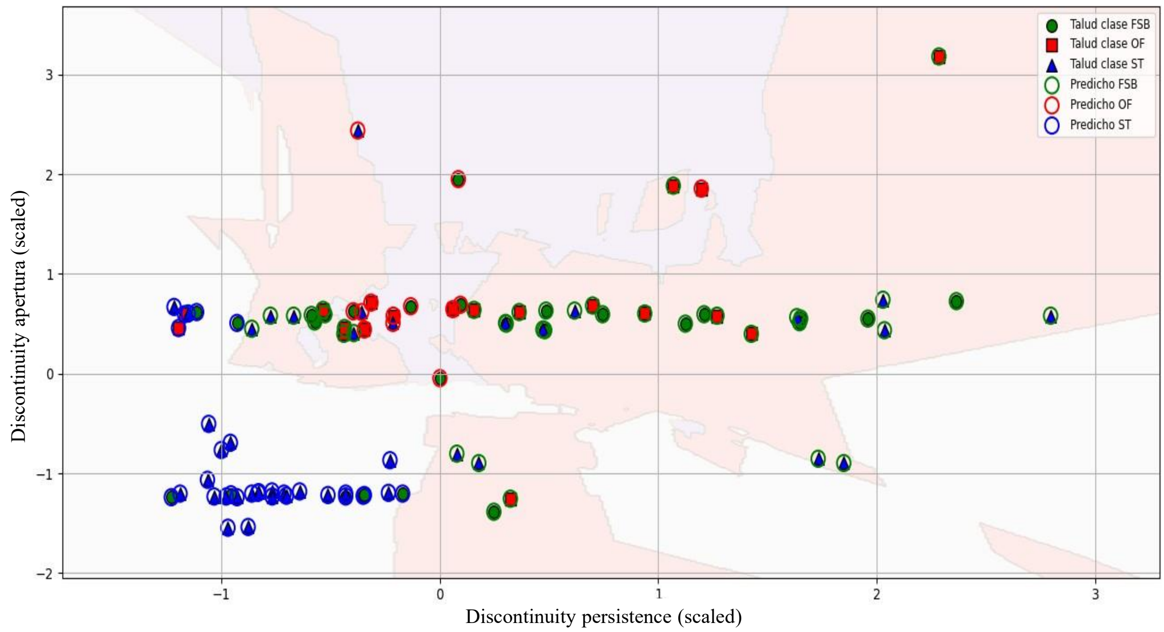

Figure 7. Aperture vs persistence and their predictions

In Figure 7, it is shown that stable slopes (ST) tend to cluster in areas with lower aperture and moderate persistence, while unstable slopes (FSB) are distributed at higher persistence levels or in critical combinations of aperture. Moderately stable slopes (OF) are positioned between these two groups, which explains their intermediate location on the model's boundary.

These areas are generated by the algorithm, which is based on the proximity of points, considering the 11 nearest neighbors in a two-dimensional space.

Empty blue circle = Predicted ST

Empty red circle = Predicted OF

Empty green circle = Predicted FSB

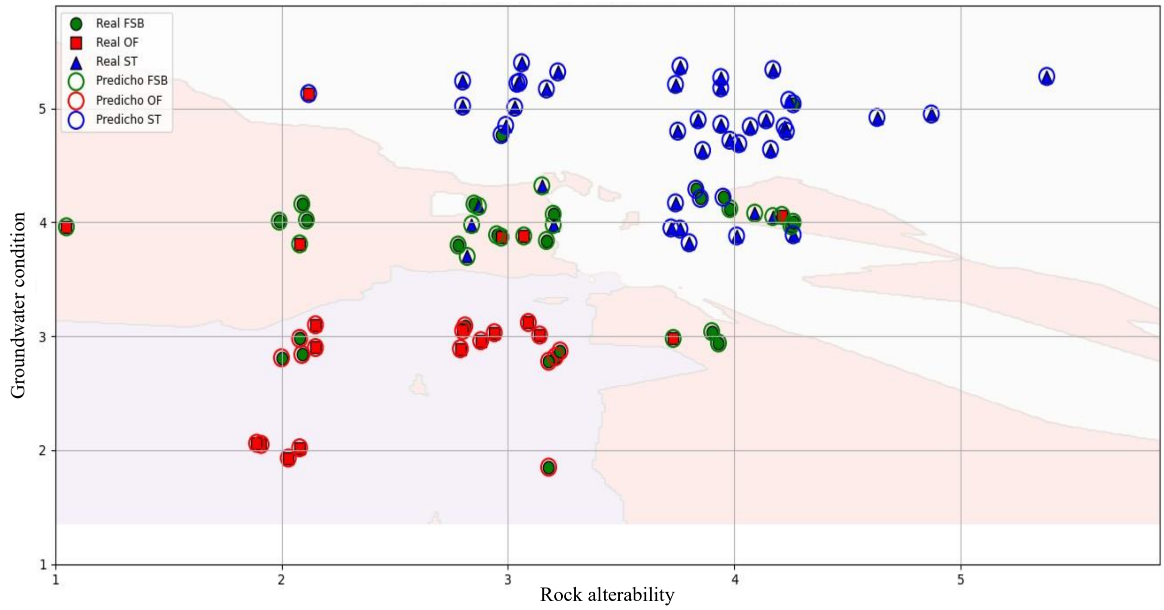

Figure 8. Water condition vs weathered rock

In general, Figure 8 shows that the KNN model correctly identifies the areas where slopes are stable, partially stable, or unstable, effectively distinguishing between categories based on the combination of rock weatherability and groundwater condition. The relationship between actual and estimated data indicates that the model performs well in classifying these two variables.
Upper right (low weatherability and low groundwater level): ST (stable)
Central area (high weatherability and medium groundwater levels): FSB (unstable), OF (intermediate stability)

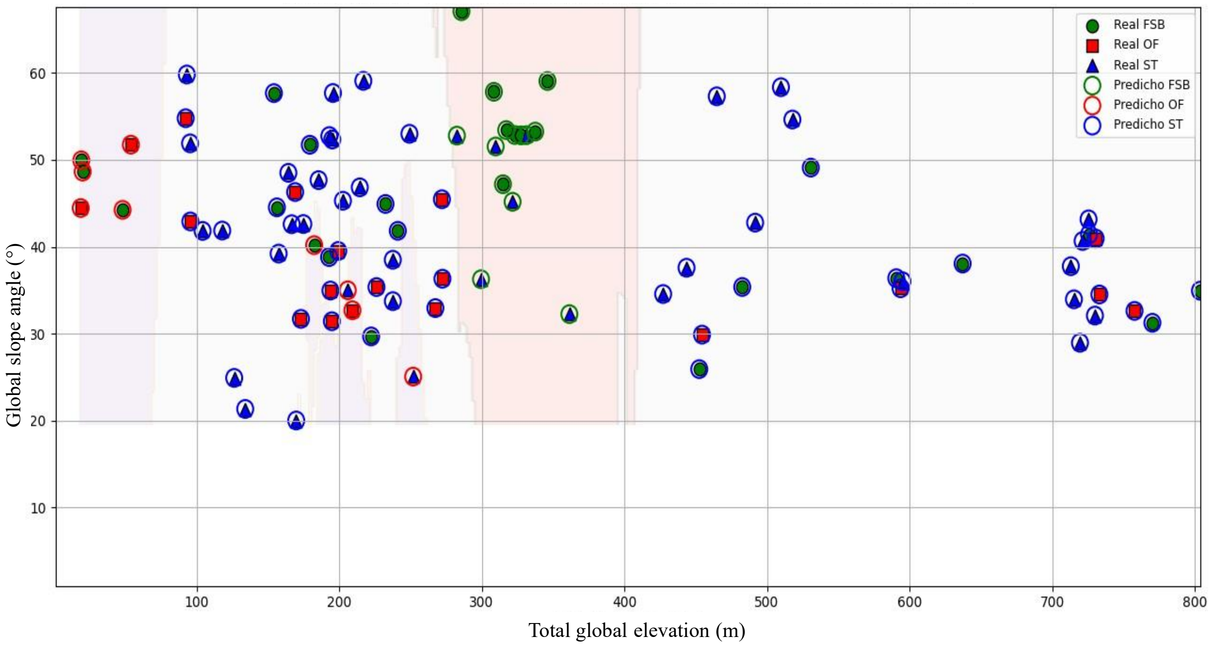

Figure 9. Inclination vs elevation and their predictions

In Figure 9, it is illustrated that the combination of total elevation and slope inclination effectively distinguishes the various categories of slope stability. Slopes with low elevation and steep inclination are often classified as unstable (FSB), while those with higher elevation and moderate slopes are primarily classified as stable (ST). Low elevation slopes (0 – 150 m): OF (medium stability), some FSB (unstable) → Lower slopes with steep inclinations tend to be considered as having intermediate stability. Medium elevation slopes (200 – 400 m): FSB (unstable), OF (medium), ST (stable) → At medium heights, inclination is considered the most decisive factor in stability. High elevation slopes (400 – 800 m): ST (stable)

3.2. Evaluate the effectiveness of the KNN model using classification accuracy metrics and the confusion matrix

3.2.1. The confusion matrix obtained for the KNN model with k = 11

$$\begin{matrix} 5 & 1 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 9 \end{matrix} \qquad (1)$$

3.2.1.1. FSB category (unstable) — Row 1
5 instances were correctly identified as FSB
1 instance was incorrectly labeled as OF
1 instance was wrongly labeled as ST
3.2.1.2. OF Category (medium stability) — Row 2
1 actual instance of OF was correctly identified as OF
There were no misclassifications in this category
ST Category (Stable) — Row 3
9 instances were correctly identified as ST
1 instance was misclassified as FSB

3.2.2. Optimal slope status report

Table 6. Optimal classification report

	Precision	Recall	F1 - Score	Support
FSB	0.83	0.71	0.77	7
OF	0.50	1.00	0.67	1
ST	0.90	0.90	0.90	10

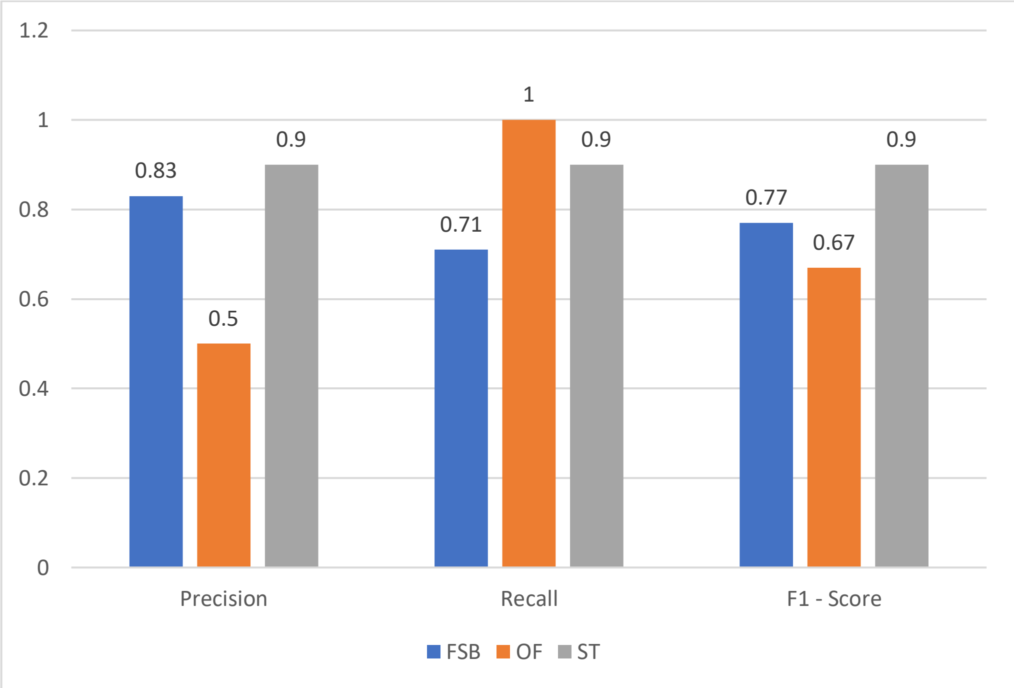

Figure 10. Precision and recall report

In Figure 10, the model's performance is shown to be excellent.

3.2.2.1. Precision
Measures the correct predictions made by the model:
FSB: 0.83
OF: 0.50
ST: 0.90
3.2.2.2. Recall (Sensitivity)
Measures the percentage of actual cases correctly detected by the model:
FSB: 0.71
OF: 1.00
ST: 0.90
3.2.2.3. F1-Score
Balances precision and recall:
FSB: 0.77
OF: 0.67
ST: 0.90

3.2.3. Global metric measurements

Table 7 Accuracy, macro average, and weighted average scores

	Precision	Recall	F1 - Score	Support
Accuracy			0.83	18
Macro average	0.74	0.87	0.78	18
Weighted average	0.85	0.83	0.84	18

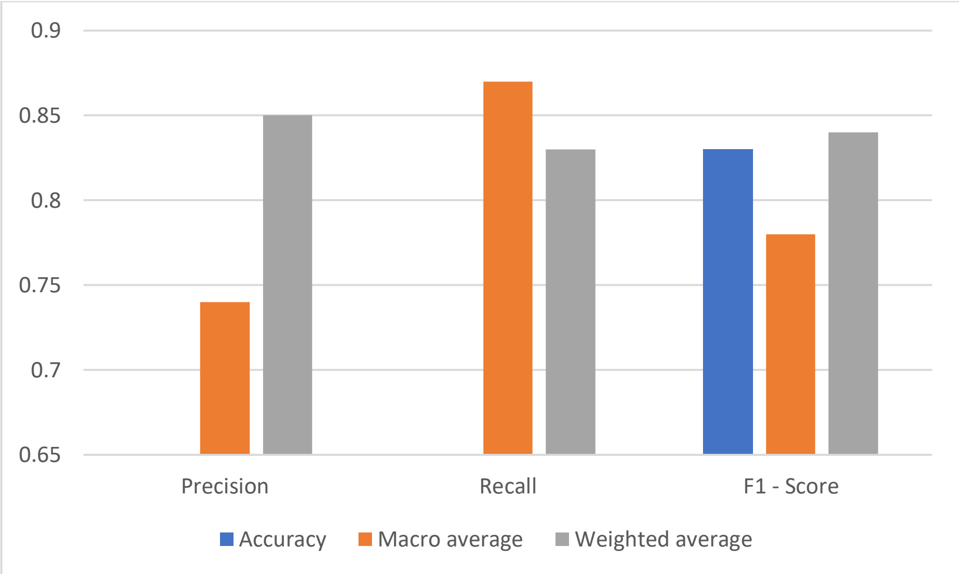

Figure 11. Precision, recall, and F1-Score for K = 11

3.2.3.1. Macro Average.
Precision: 0.74
Recall: 0.87
F1: 0.78

3.2.3.2. Weighted Average
Precision: 0.85
Recall: 0.83
F1: 0.84

3.2.3.3. Accuracy: 83.33%

The matrix provides a dataset indicating that the KNN model with k equal to 11 performs satisfactorily in classifying slopes (ST). This model correctly categorizes most of the FSB (unstable) and ST (stable) class cases, showing high values for both precision and recall, especially in the ST class (0.90).

3.3. Analyze how the data are distributed in relation to the model fitting and testing using the K-Nearest Neighbor (KNN) algorithm to anticipate slope collapse

In Figure 12, the data distribution illustrates the behavior of all geotechnical variables analyzed through the training dataset samples. Each line in the graph represents a variable, facilitating the visualization of its variability, range, and its connection with other parameters. Persistence spans the widest range of values, while most variables cluster between 2 and 5 units. The line corresponding to the target allows identifying class transitions (FSB, OF, and ST) and examining how slope conditions change at those points. Overall, this chart validates that the variables exhibit an adequate distribution, without significant outliers and with sufficient variability, which is essential for the functioning of the KNN algorithm that is based on distances.

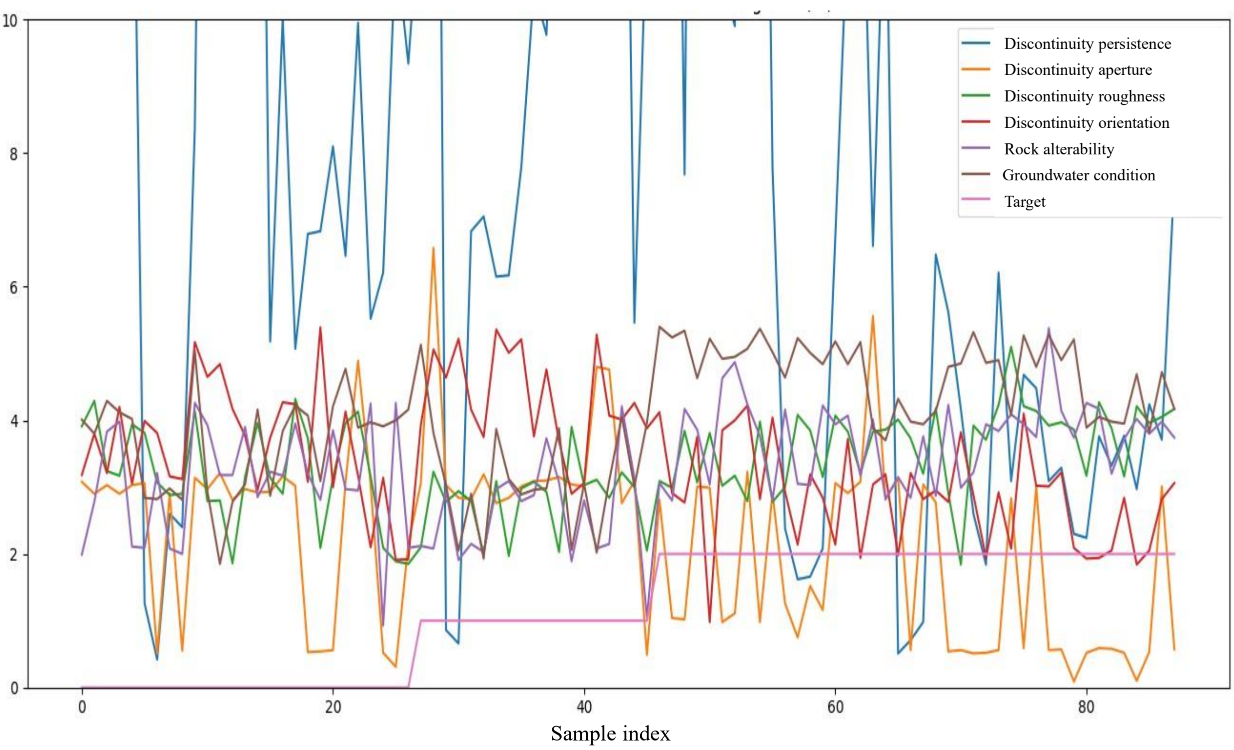

Figure 12. Data distribution

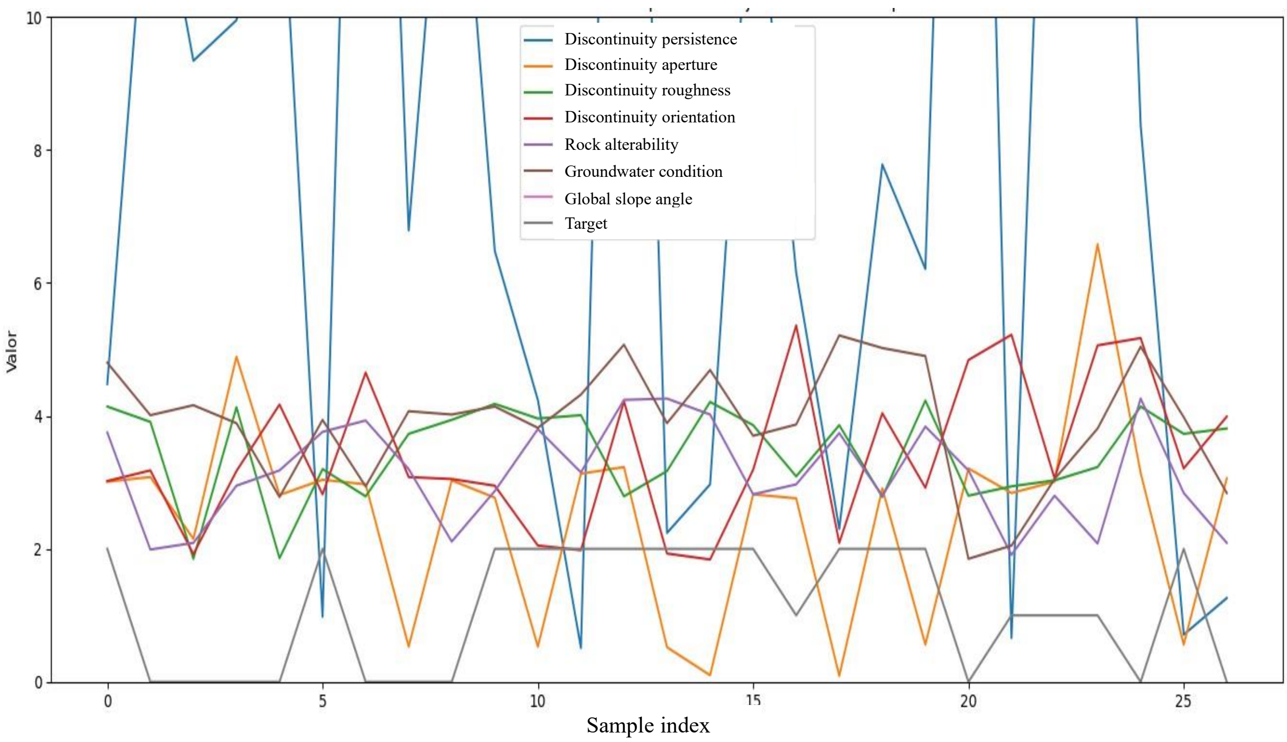

Figure 13. Test data distribution

In Figure 13, the test group is shown, demonstrating how the geomechanical parameters used by the KNN algorithm to assess slope stability vary. It can be observed that the variables follow patterns similar to those in the training group, suggesting that the model was tested with characteristic data. Furthermore, changes in the target class (stable, moderately stable, and unstable) are related to changes in persistence, aperture, weathering, and discontinuity direction, confirming the model's relevance in anticipating slope behavior in real situations.

Table 8. Predictions with the KNN Model developed

Parameters	Results
12.1, 2.2, 2, 4.1, 2, 5.2, 168, 48	0 (FSB)
12.3, 3,1, 4, 3, 2.2, 4, 188, 92	0 (FSB)
12.3, 3, 2.1, 4, 2, 5.3, 168, 31	1 (OF)
14, 1, 2, 6, 2, 5.1, 25.1, 26	2 (ST)
11.1, 3, 4.2, 1, 3, 5.2, 401, 36	2 (ST)
22.3, 3, 2, 1.2, 3, 5, 800, 42	0 (FSB)
17, 6.3, 2, 1, 2, 5, 501, 22	1 (OF)
13, 0.55, 3.1, 1, 3, 4, 503, 22	2 (ST)
20.1, 1, 4, 2.3, 3, 5, 401, 21	2 (ST)
18.1, 3, 5.2, 4, 3.1, 5, 661, 30.2	1 (OF)

In Table 8, the predictions made by the KNN algorithm indicate that, out of 10 slopes with the given parameters, the model predicts greater stability for 7 slopes based on the 11 nearest neighbors (k = 11), showing good performance.

4. Conclusions

Geotechnical and geometric data such as persistence, aperture, roughness, discontinuity orientation, weathered rock, groundwater condition, slope height, and slope inclination were used to identify the stability states: stable (ST), intermediate (OF), and unstable (FSB). The predictions made using K-Nearest Neighbor (KNN) with K = 11 and an accuracy of 73.73% were developed through the relationships of slope parameters to determine whether a slope would remain stable or experience landslides.
The performance of the (KNN) model was evaluated in the prediction of landslides using classification metrics such as precision (0.90), recall (0.90), and F1-score (0.90) for stable slopes (ST), and an accuracy of 83.33%, determining the model's capability to correctly classify slopes.
The speed of the KNN method must be related to the number of input data and the number of nearest neighbors. The analysis of data distribution with K = 11 was very helpful in assigning the data to build and train the model, later validating its performance with the reserved test data. It should be noted that the training data represented 83.33%, and also indicates that with new parameters from 10 slopes, 7 slopes (ST and OF) showed greater stability according to their 11 nearest neighbors.

5. Conflict of interest

The author declares that there is no conflict of interest.

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