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Predicting the stability of open stopes using Machine Learning

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Keywords

open stope, machine learning, logistic regression, random forest

Predicting the Stability of Open Stopes Using Machine Learning

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Abstract

The Mathews stability graph method was presented for the first time in 1980. This method was developed to assess the stability of open stopes in different underground conditions, and it has an impact on evaluating the safety of underground excavations. With the development of technology and growing experience in applying computer sciences in various research disciplines, mining engineering could significantly benefit by using Machine Learning. Applying those ML algorithms to predict the stability of open stopes in underground excavations is a new approach that could replace the original graph method and should be investigated. In this research, a Potvin database that consisted of 176 historical case studies was passed to the two most popular Machine Learning algorithms: Logistic Regression and Random Forest, to compare their predicting capabilities. The results obtained showed that those algorithms can indicate the stability of underground openings, especially Random Forest, which, in examined data, performed slightly better than Logistic Regression.

Keywords: open stope, machine learning, logistic regression, random forest

1. Introduction

The stability of underground excavations in open stope methods is one of the mining industry's major concerns. Three essential aspects need to be considered while designing open stopes. The first one concerns the properties of the rock mass and its mineral components that directly impact the behaviour of the surrounding rocks. The second aspect is how stress fields are impacting the rock mass. Those stresses might develop zones of relaxation or increased compressive stresses in stope walls. The last aspect is the underground openings' geometry, size and orientation. Those three crucial features interact together and directly impact the complexity of underground stopes design [1].

The effectiveness of open stope mining methods depends on safety and high productivity. Usage of very large and non-entry excavations and mechanized mining equipment is necessary. However, the development of each stope is associated with large investment costs, which is the main reason for industries to reduce the number of stopes by increasing their dimensions. The significant difficulty facing that approach is that the consequences may be catastrophic when stopes are exceeded to their maximum dimensions. Another challenge for industries is that dilution in rock mass needs to be considered when designing open stopes. In addition, the dimensions need to be specifically adjusted to geotechnical conditions.

Original stability graphs developed by Matthews were based only on 50 history cases. That number was later extended to 176 cases by Potvin. In addition, Matthews's graph took three distinct separated by transition zones: stable, unstable and caved, Potvin modified that, and the number of zones was reduced to stable and caved, separated by transition [1].

The beginnings of the Artificial Intelligence and Machine Learning concepts date back to the mid-20th century. In 1943 the first mathematical model of a neural network was presented by Warren McCulloch and Walter Pitts, where the concepts of the neurophysiology of brain cells and calculus were combined [2]. This research was a foundation that triggered the interest of scientists in further

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investigation. The first Artificial Intelligence model in the modern sense has its origin in the research presented by psychologist Frank Rosenblatt. He created a machine to recognize letters which became a prototype of an Artificial Neural Network known today [3]. Although, in the beginning, Machine Learning was used as a training program for Artificial Intelligence, in the late 1970s, research focused on using knowledge-based and logical methods, which caused the separation of AI and ML [4]. From that point, computer programs, and more precisely Machine Learning, started to be more present, expanded and applied in various tasks.

Using Machine Learning might be considered a new approach to determine the stability of open stopes. In previous research, ML models presented promising effectiveness in various research disciplines in mining engineering. For example, those algorithms were applied in mineral processing to predict the outcome values recovered from various beneficiation processes, such as flotation [5]. In addition, the classification algorithms have been successfully applied in areas of mining engineering such as rockburst liability prediction [6] or for and image recognition of coal [7].

Researchers have approached the problem of open stopes stability assessment with computing sciences methods. Most popular include numerical modelling, presented by Vallejos and Diaz (2020) [5], which applies a new criterion for numerical modelling to evaluate a hangingwall overbreak.

Some of the Machine Learning and Artificial Intelligence models were employed to predict the stability of open stopes, such as Random Forest [8] and Artificial Neural Network [9]. Both of those studies presented promising capabilities of those models. However, a smaller database was investigated (115 and 35 examples, respectively). Extending that databases could have a crucial impact on predicting the capabilities of those models.

The Potvin database was passed to two ML algorithms in this research – Logistic Regression and Random Forest. Both showed satisfying predicting capability, with an average accuracy of 0.68 for *LR* and 0.71 for *RF*. However, the latter performed better, especially with predicting unstable zone, which was the most challenging for both algorithms to predict because of similar values to other classes.

2. Open stope mining method

An open stope mining method extracts an enormous block of material using the drill or blast method. Then, tunnels are mined underground to access that orebody. After the material is removed by heavy machinery, the open void or stope is created. Later, it's usually backfilled, which allows for the extraction of adjacent deposits by opening new stopes. The walls of rock mass surrounding the stopes are called hanging walls (HW), and their properties vary depending on the geology and mining constraints. The appearance of a hanging wall causes the stope to be less stable [10].

2.1. Matthew stability graph method review

The Mathews stability graph design method was established explicitly for deep underground mining excavations open stope surfaces. It was developed and presented for the first time in 1981.

This widely used method relates two calculated factors: shape factor (S) or hydraulic radius (HR) and stability number (N). The primary principle theory behind the Mathews stability graph is that the dimensions of an excavation surface can be associated with the rock mass conditions and indicate either instability or stability of the opening [11].

Stability Number N is explicitly developed for designing span dimensions and support, and it yields the physical conditions of the stopes. To calculate Stability Number specific rating systems are being applied. N is defined as follows:

$$N = Q' \cdot A \cdot B \cdot C, \tag{1}$$

where:

Q' – Modified Q value.
A – Rock stress factor.
B – Joint orientation adjustment factor.
C – Surface orientation factor.

Q value was first presented in 1974 by Barton et al. of the Norwegian Geotechnical Institute (NGI) to evaluate rock mass characteristics and ground condition [12]. The purpose of calculating the Q value was to determine the support required in mining excavations, tunnels and rock caverns. The formula is as follows:

$$Q' = \frac{RQD}{Jn} \cdot \frac{Jr}{Ja} \tag{2}$$

The first quotient ($\frac{RQD}{Jn}$) represents the structure of the rock mass, and the latter one ($\frac{Jr}{Ja}$) represents the roughness and frictional properties of the joint wall or filling material.

Rock Quality Designation (RQD) is a system developed by Deere [13]. It is widely used as a factor in classification systems and as a primary parameter for tunnel support selection. It quantifies the competence of a drill core, and it is defined as a ratio between the total lengths of entire pieces (larger than 10 cm) and the total length of a core. The values of *Jn*, *Jr*, and *Ja* are determined using NGI Classification Charts presented in Hoek and Brown [14].

Values of *A*, *B* and *C* factors are determined by graphs developed by Matthews and can be found in Matthews et al. [11] and Potvin [1]. Factor *A* factor is a function represented by a ratio of the intact rock strength, determined by the Uniaxial Compressive Strength (USC) test, and the induced stress, maximum tangential stress acting parallel to the exposed surface at the boundary of a stope. Factor *B* accounts for the orientation of the geological structures (joint sets) concerning the investigated plane. It is determined by the angle of intersection between the exposed surface and the most predominant structure. Finally, factor *C* stands for surface inclination, assuming that stopes backs are naturally less stable than walls. The reason for that is the impact of gravity.

2.2. Database

Potvin's database was collected from 34 mines using the open-stoping method between 1986 and 1987. The provided data includes the characteristics of the rock mass and the physical and stress conditions. In some situations, circumstances did not allow to estimate all the necessary conditions confidently caused by lack of access to the site or missing background information. Consequently, the entire database was divided into the main database that contained accurate and complementary data that was less accurate. The main data consisted of 84 cases, and the remaining 92 cases were complementary data created using the same parameters and principles as the main data. Potvin's database consists of several parameters regarding each open stope investigated. These parameters include: block size factor (*RQD*/*Jn*), stress conditions, the difference in the dip between the designed stope surface and the critical joint, the relative difference in the strike, the indication of anisotropy of the rock mass, the shear strength of the critical joint (*Jr*/*Ja*) and effect of the gravity. These features were used to calculate the input parameters necessary for the analysis – stability number and hydraulic radius (shape factor) [1].

The distribution of the data is shown in Fig. 1. The green dots are examples of stable cases, the blue ones unstable, and the red ones caved. Table 1 shows the first examples of the database.

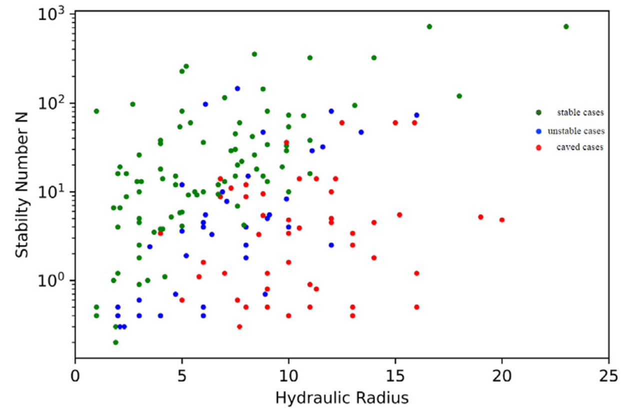

Fig. 1. Distribution of the data.

3. Model development, evaluation and results

The two most popular Machine Learning algorithms were investigated in this research and applied to Potvin's database. In order to achieve the most satisfying performance of the model, a few evaluation methods were applied to maximize the efficiency and obtain the highest accuracy. These methods were also beneficial for eliminating the risk of overfitting, a common problem for ML algorithms applied for data with few training examples.

3.1. K-fold cross-validation

The *k*-fold Cross Validation is sometimes called also rotation estimation. It is a powerful tool to measure the success rate of our models used for classification [15]. The dataset is randomly split into a chosen number (*k*) of mutually exclusive sets (the folds) approximately equal in size. The main advantage of using CV is that each observation can be tested, which means that in every run, the testing set consists of different cases from the provided data set. In *k*-fold CV, we iterate over our data set *k*-times. In every round, our data is split into *k* sets, one part is being used for validation, and the remaining $k-1$ sets are merged into a training set [16]. Fig. 2 presents the process of cross-validation where $k = 5$. That approach results in 5 different models fitted on partially overlapping training sets and tested on a non-overlapping validation fold. For every run, accuracy is established, and then the model performance is calculated as the arithmetic mean of all the accuracies.

Table 1. Database from Potvin 1988, first examples.

	BLOCK SIZE	STRESS FACTOR	JOINT ORIENTATION FACTOR	EFFECT OF GRAVITY (C)					
	RQD/Jn	(A)	CRITICAL JOINT (B)	*Jr/Ja*	SLIDING	FREEFALL/ SLABBING	HYD. RADIUS	N	ASSES.
1	18	1	0.64	3	6.5	–	5	228	STABLE
2	6	0.2	0.25	1	2.5	–	8.9	0.7	UNSTABLE
3	6	0.1	0.2	1	2.5	–	7.7	0.3	CAVE
4	7	1	0.2	1.5	–	3.7	7.1	7.8	UNSTABLE
5	40	1	1	1	–	8	14	320	STABLE
6	40	1	1	1	–	8	11	320	STABLE
7	40	1	1	1	–	6.5	5.2	260	STABLE
8	6	1	0.4	1.5	5	–	8.5	18	STABLE
10	4	0.3	0.2	0.8	3.5	–	4.7	0.7	UNSTABLE
12	7	1	0.2	0.6	–	6.5	9.1	5.5	UNSTABLE
13	15	1	0.2	2	–	7	8.3	42	STABLE
16	25	0.1	0.85	0.25	–	2	5.8	1.1	CAVE
17	25	0.1	0.85	0.25	–	2	4.2	1.1	STABLE
18	30	1	0.6	1	–	8	8.8	144	STABLE

Fig. 2. The process of k-fold Cross-Validation.

3.2. Confusion matrix and ROC AUC score

A Confusion Matrix is one of the methods to evaluate the model's performance. It is a valuable tool to visualize how our model classifies the testing set. A Confusion Matrix is a size $n \times n$ where the predicted class and actual class are compared [17]. Table 2 shows a Confusion Matrix where $n = 2$ and entries have the meaning as follows:

TN – True Negative, the number of correct negative predictions.

TP – True Positive, the number of correct positive predictions.

FN – False Negative, the number of incorrect negative predictions.

FP – False Positive, the number of incorrect positive predictions.

Based on the confusion matrix, important metrics can be derived that are useful to evaluate the model's performance. The Recall (Sensitivity/True Positive Rate) shows the proportion of the positive class that was correctly classified. False Negative Rate (*FNR*) is the proportion of the positive class that the model classified incorrectly. Specificity (True Negative Rate) indicated the proportion of correctly classified negative class and False Positive Rate (*FPR*), which shows the proportion of incorrectly classified negative class.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \tag{3}$$

$$\text{FNR} = \frac{\text{FN}}{\text{TP} + \text{FN}}, \tag{4}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}, \tag{5}$$

$$\text{FPR} = \frac{\text{FP}}{\text{TN} + \text{FP}}, \tag{6}$$

The ROC (Receiver Operator Characteristic) curve is a probability measurement tool that plots *TPR* vs *FPR*. AUC (Area Under the Curve) is a measure of the model's performance for classification problems, it shows the capability of the model to distinguish differences between classes, and it is defined as the summary of the ROC curve [18]. The higher the AUC score, the better the performance. An excellent model should have AUC close to 1, indicating satisfying separability [19]. According to Hosmer JR et al. [20], a model with an outstanding performance would achieve an AUC score above 0.9. Values between 0.8 and 0.9 would

Table 2. The Confusion Matrix.

	Predicted Negative	Predicted Positive
Actual Negative	*TN*	*FP*
Actual Positive	*FN*	*TP*

be considered excellent, and 0.7–0.8 indicate acceptable classification.

3.3. Logistic regression

Logistic Regression is one of the most popular machine learning algorithms used for classification problems. It is a predictive algorithm based on the concept of probability, which uses a cost function defined as the Sigmoid function.

3.3.1. Development of the model

As the input parameters to the logistic regression algorithm, the stability number (N) and shape factor (HR) were used. In this case, a multiclass classification problem was considered. The model predicted if the stope would be classified as Stable, Unstable, or Caved based on input parameters.

The data were randomly split into training and test sets, 80 and 20%, respectively. After that, a built-in sklearn library Standard Scaler was used to scale our data, so the distribution has a mean equal to 0 and a standard deviation equal to 1. The purpose of that is to standardize our futures in cases when some of them have a larger magnitude and might dominate the estimation function, causing it to be unable to learn the features as correctly as we would expect [21].

3.3.2. Results

The Logistic Regression algorithm from the sklearn library was fitted to our model. Fig. 3 shows the decision boundary fitted to our data separating the unstable, stable and caved zone. It is noticeable that the model had the most problems with plotting decision boundaries for unstable cases. This is because these cases have similar values to either stable or caved ones and are hard to separate.

A confusion matrix was plotted to evaluate our model more carefully (Fig. 4). Stable cases were

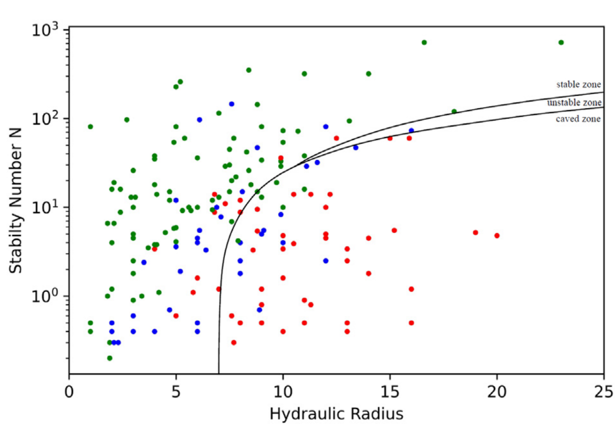

Fig. 3. Decision boundaries for logistic regression.

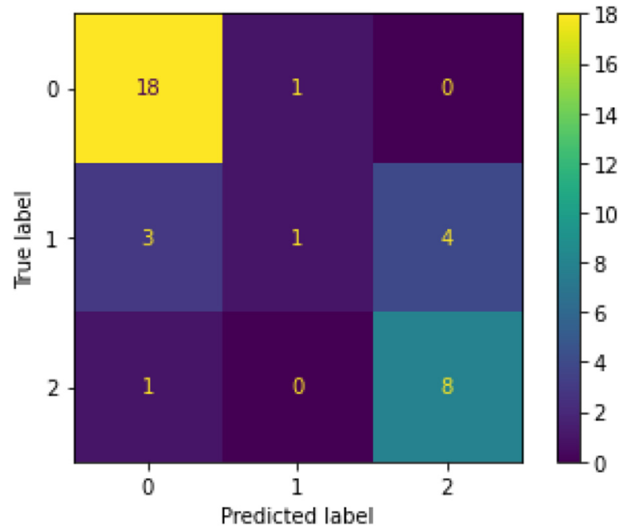

Fig. 4. Confusion matrix for logistic regression.

mapped as 0, unstable as 1 and Cave as 2. We can see that Logistic Regression did a very satisfying prediction performance for stable and caved cases. Unfortunately, it did not perform well for unstable zones, which supports the results obtained by plotting decision boundaries.

The Area under the ROC Curve was also calculated for the training and testing set. The obtained values were 0.81 and 0.78, respectively, which according to Hosmer JR et al. [20], would be considered excellent for the training set and acceptable for the test set.

Cross-Validation was performed to determine the average accuracy of our model. The number of folds for our data was set to be equal to 5, which means five different accuracies were calculated for five different validation sets. The number of folds is determined by the size and characteristics of the datasets. It needed to be ensured that the training set and validation set are taken from the same distribution and that both sets include acceptable variation. For our dataset, the number of folds equal to 5 is sufficient, and it means that in every run the model was validated on 20% of the data [15]. The accuracies for our data were: 0.68, 0.64, 0.71, 0.71, 0.64. The average is 0.68, with a standard deviation of 0.03.

3.4. Random forest

A Random Forest is a powerful meta-estimator that can be applied to solve classification problems. The *RF* algorithm was presented by Breiman [22] and has been successfully applied in many fields by researchers. The *RF* algorithm consists of a group of decision trees operating as a committee. The output is the value predicted by a larger number of decision

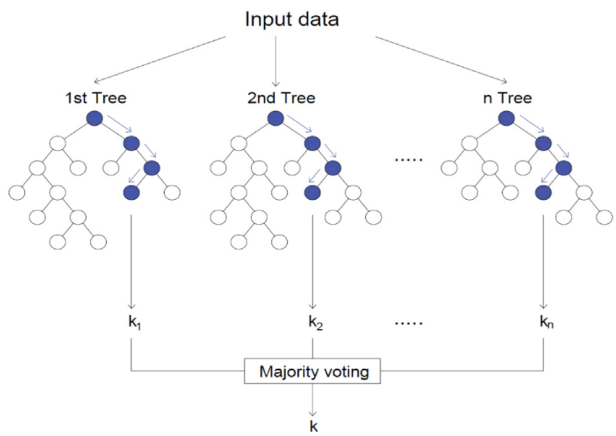

Fig. 5. The architecture of Random Forest algorithm. Modified from [8].

trees. An example of Random Forest architecture is shown in Fig. 5. The *n* represents the number of estimators (decision trees) that create the *RF*, and *k*1, *k*2, …, *kn* are the results obtained by each decision tree [8].

The Random Forest algorithm allows us to regulate some of the parameters that directly impact the model's performance and are helping to control the overfitting or underfitting of the model. For example, we can change one of the parameters to control the algorithm's performance in several decision trees. The higher the number of decision trees, the better the chance for the model to properly learn the data. However, including too many estimators may slow down the process and increase the risk of overfitting.

Another parameter that helps to improve our model is the maximum depth of each tree in the forest. Developing deeper trees means that each tree would have more splits to better capture information about the data. However, if the decision trees are too deep for provided data, it might cause the same problems as too many estimators, slow processing time and overfitting of the data.

3.4.1. Development of the model

Potvin's database was passed to the Random Forest algorithm using the sklearn library in Python language. The input parameters were stability number (N) and shape factor – hydraulic radius (HR). The output was the range of stabilities labelled to each stope – either stable, unstable or caved. The data was separated into training sets – used to train the data, and the test set – used to test the algorithm's performance. The size of the test set was equal to 36 examples, representing 20% of the whole data set.

3.4.2. Hyper-parameters tuning

In order to achieve the best performance of the *RF* model, the optimum number of estimators and the depth of each tree need to be established. These Hyper-parameters are necessary because the different values have special predictive performances. The AUC (Area Under the ROC Curve) score was used as the evaluation metric to find the optimum values. For our multiclass classification problem, the value of the AUC score was calculated using the One-vs-Rest scheme, and the macro average was reported.

AUC score was calculated for several estimators to find the most favourable number of decision trees for our data. Fig. 6 shows the AUC score vs the number of estimators for the training and test sets. We can notice that the model achieves the best performance for the number of estimators, around 15. The performance decreases for more decision trees, and our model overfits the training data. The number of estimators was set to 15.

The same method was used to choose the optimum depth of each decision tree. The AUC score vs max depth was plotted for several values. On Fig. 7,

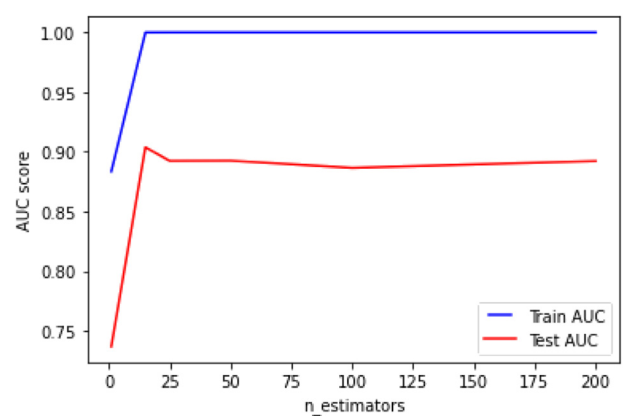

Fig. 6. The AUC score for several numbers of decision trees.

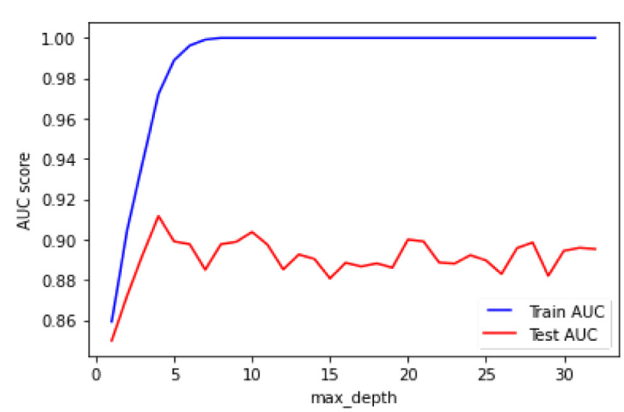

Fig. 7. The AUC score for different values of decision trees depth.

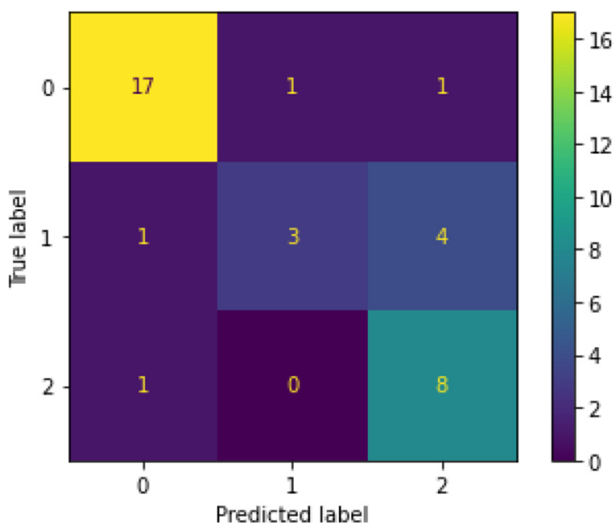

Fig. 8. Confusion Matrix for Random Forest multiclass classification.

we can see that the model's performance decreases for depths higher than 4. We can also see that it overfits for large depth values. It predicts training data perfectly. However, it fails to generalize the findings for the test set. For our data, the tree depth was set to 4.

3.4.3. Results

Random forest showed a favourable classification capability on Potvin's database. After choosing the number of decision trees and the depth of each tree, the model predicted the stability of stopes with satisfying accuracy. At first, the data were randomly separated into training and testing sets. The accuracy for training data was 0.84, and for the test set, 0.75. The Confusion Matrix (Fig. 8) was plotted to illustrate the model's performance. The label Stable was mapped as 0, Unstable as 1 and Cave as 2. It is noticeable that the model primarily has the most difficulties assigning the Unstable class. As shown in Fig. 3, the plot of the distribution of our data, Stability Number vs Hydraulic Radius, the examples marked as Unstable are challenging to distinguish, and it's challenging for Machine Learning models to assign that class correctly similar values to either stable or Cave condition. The model shows the best performance for the Stable class; 17 out of 19 cases were predicted correctly.

In the next step, Cross-Validation was performed. The number of folds was chosen to be 5, and the obtained output was five accuracy values for five different training and validating sets. The values for each set were: 0.61, 0.75, 0.71, 0.78, 0.68. The average accuracy equals 0.71 with the standard deviation of +/−0.06.

Then the Area Under the ROC Curve score for 15 decision trees with depth equal to 4 was calculated. For training data, the AUC score was 0.96 and 0.83 for test data. According to Hosmer JR et al. [20], that score can be considered excellent for the test set and outstanding for the training set.

4. Summary and conclusions

The two most popular Machine Learning algorithms, Logistic Regression and Random Forest, were presented in this research to predict open stopes' stability. The total number of 176 history cases investigated was collected from Potvin [1]. Two variables from the data were selected, Stability Number (N) and the shape factor (HR), all of them with condition (label) assigned: stable, unstable or Cave.

Both models were evaluated using k-fold Cross-Validation, Confusion Matrix and ROC − AUC score to obtain the most satisfying results. Random Forest performed slightly better than Logistic Regression, mainly predicting the unstable class. The reason for that is that an unstable class has values of N and HR similar to other classes, and it is' hard to separate them with a line.

In Radom Forest, hyper-parameter turning was performed to develop our model and achieve the best performance. First, the Area under the ROC curve was calculated for several estimators (decision trees) and different values of tree depth. Then the AUC vs number of estimators/tree depth were plotted to find the most optimum values for our model.

Confusion Matrix was plotted for both algorithms. It helped conclude that the model has the most difficulties predicting unstable classes. All three classes were investigated in the original Matthew stability graph method, but Potvin later reduced the number of classes to stable and Cave separated by a transition zone. That approach might be good for future investigation to increase the model's accuracy and achieve better performance since the unstable class is most difficult for ML models to predict.

In general, both algorithms showed satisfying capabilities and could be used in further investigation and have great potential in predicting the stabilities of open stopes. In future research, the data could be expanded to more historical cases to obtain even better results, as well as other ML or AI algorithms might be investigated.

Ethical statement

The authors state that the research was conducted according to ethical standards.

Conflict of interest

The authors declare no conflict of interest.

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References

[1] Potvin Y. Empirical open stope design in Canada. 1988. Available from: https://doi.org/10.14288/1.0081130.
[2] McCulloch WS, Pitts W. A logical calculus of the ideas immanent in nervous activity. Bull Math Biophys 1943 Dec; 5(4):115–33.
[3] Rosenblatt F. The perceptron, a perceiving and recognizing automaton project para. Cornell Aeronautical Laboratory; 1957. book.
[4] Carbonell JG, Michalski RS, Mitchell TM. Machine learning: a historical and methodological analysis. AI Mag 1983 Sep 15; 4(3). 69–69.
[5] Pu Y, Szmigiel A, Apel DB. Purities prediction in a manufacturing froth flotation plant: the deep learning techniques. Neural Comput Appl 2020 Sep;32(17): 13639–49.
[6] Pu Y, Apel DB, Wang C, Wilson B. Evaluation of burst liability in kimberlite using support vector machine. Acta Geophys 2018 Oct;66(5):973–82.
[7] Pu Y, Apel DB, Szmigiel A, Chen J. Image recognition of coal and coal gangue using a convolutional neural network and transfer learning. Energies 2019 May 8;12(9):1735.
[8] Qi C, Fourie A, Du X, Tang X. Prediction of open stope hangingwall stability using random forests. Nat Hazards 2018 Jun;92(2):1179–97.
[9] Santos AEM, Amaral TKM, Mendonça GA, Silva D de FS da. Open stope stability assessment through artificial intelligence. REM - Int Eng J. 2020 Sep;73(3):395–401.
[10] Capes GW. Open stope hangingwall design based on general and detailed data collection in unfavourable hangingwall conditions. 2009 [cited 2022 Feb 9]; Available from: https://harvest.usask.ca/handle/10388/etd-04072009-143339.
[11] Mathews KE, Hoek DC, Wyllie, Stewart SBV. Prediction of stable excavation spans for mining at depths below 1000 metres in hard rock. 1981. Ottawa, ON.
[12] Barton N, Lien R, Lunde J. Engineering classification of rock masses for the design of tunnel support. Rock Mech Felsmech Mec Roches 1974 Dec;6(4):189–236.
[13] Deere DU. Technical description of rock cores for engineering purpose. Rock Mech Eng Geol 1963;1:16–22.
[14] Hoek E, Brown ET. Underground excavations in rock. Rev. London: Institution of Mining and Metallurgy; 1980. p. 527.
[15] Marcot BG, Hanea AM. What is an optimal value of k in k-fold cross-validation in discrete Bayesian network analysis? Comput Stat 2021 Sep;36(3):2009–31.
[16] Kohavi R. A study of cross-validation and bootstrap for accuracy estimation and model selection. In: Proceedings of the 14th international joint conference on Artificial intelligence - volume 2. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc.; 1995. p. 1137–43 (IJCAI'95).
[17] Visa S, Ramsay B, Ralescu A, Knaap EVD. Confusion matrix-based feature selection. Available from: http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.666.8961.
[18] Bradley AP. The use of the Area under the ROC curve in the evaluation of machine learning algorithms. Pattern Recogn 1997 Jul;30(7):1145–59.
[19] Janitza S, Strobl C, Boulesteix AL. An AUC-based permutation variable importance measure for random forests. BMC Bioinf 2013 Dec;14(1):119.
[20] Hosmer DW, Lemeshow S, Sturdivant RX. Applied logistic regression. 3rd ed. Hoboken, New Jersey: Wiley; 2013. p. 1 (Wiley series in probability and statistics).
[21] Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, et al. Scikit-learn: machine learning in Python. J Mach Learn Res 2011;12(85):2825–30.
[22] Breiman L. Random forests. Mach Learn 2001;45(1):5–32.