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Enhanced prediction of hard rock pillars stability using fuzzy rough feature selection followed by random forest

Pillar stability in underground hard rock mining task is one of the most challenging safety problems to be determined during mining task. This stability analysis requires proper input variables, which are also known as parameters. The prediction of pillar stability is a key task for which various machine learning based methodologies are available in the literature. In this study, we present a novel methodology to enhance the prediction of the stability of hard rock pillars by using fuzzy rough feature selection with rank search and evolutionary search. Initially, irrelevant and redundant features are removed, using fuzzy rough feature selection technique. Thereafter, machine learning techniques are used for reduced dataset and the findings are recorded. Then, fuzzy rough attribute evaluator is deployed to present the rank of different features according to their influence. The work presents schematic representation of the proposed methodology. Finally, a comparative study of the proposed approach with the existing techniques is presented. From the work and discussion, it can be observed that random forest (RF) is producing the best results till date as the average accuracy produced by present approach and existing approach are 83.3% and 79.2% respectively with percentage split of 80:20.

1. Introduction

Pillars are one of the important structural feature that are ubiquitous below in mining. It is defined as the *in situ* rock mass between two or more underground openings. The main function of pillars is to provide stability while mining of reserves. The conventional approach of the pillars stability is assessed by determination of safety factor, which is defined as the ratio of pillar strength to the pillar load. Whenever the safety ratio falls below one, the pillars fail. The estimation of the pillar load is done by various methods such as tributary area theory, numerical modelling and other computational methods. Similarly, strength of the pillars can be estimated by empirical equations derived from the analysis of failed and stable cases.

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As mining progress goes deeper and deeper the failure of pillars becomes more frequent, due to rise in stress. Thus, it is imperative to design the pillar for safety and to create economical extraction of ores. Thus, proficient methodology is essential for designing safe and economical pillars and its dimensions.

Estimation of the safety for the pillars designed is the most important aspect in pillar design related problems. Conventional pillar design methods compromise on the estimation of mean pillar stress that includes tributary area concept and analytical methods. Further, for the estimation of pillar loads two different methods are applied namely, empirical equations and the numerical modelling tools with suitable failure criterion (Martin and Maybee (2000); Kaiser et al. (2011), Malan and Napier (2012)). Some of the empirical equations are given by Headly and Grant (1972); Potvin et al (1988); Kraunland and Soder (1987); Sjoberg (1992).

In recent years, analytical, statistical, probabilistic, and artificial intelligence based methods and their hybrids had been introduced and conveniently used for designing pillars in coal and hard rock mining while in past years only numerical modelling assisted approaches are established and implemented for this task. Fluctuation in rock mass properties and mining factors could be incorporated in the hard rock plan by statistical techniques and point estimation technique demonstrated by Esterhuizen (1993). Probabilistic approach for underground pillar stability is examined by Griffiths et al. (2002); Cauvin et al. (2009). Impact of changeability in parameters by using Monte Carlo Simulation (MCS), for example, on uniaxial compressive strength of coal sample, pillar width, pillar height, entry width and cover depth on safety factor of the pillar is examined by Ghasemi et al. (2010). Pillar stability prediction by using support vector machine and fisher discriminant analysis is shown by Zhou et al. (2010). Logistic regression prediction of pillar stability in coal pillar is presented by Waatimena (2014) and important results are recorded. Apart from this, various kind of Artificial Neural Networks (ANNs) with combination of different learning techniques, for example, ensemble or hybrids techniques are used for pillar stability analysis in past few years. By combining finite element method, neural networks, and reliability analysis MCS is developed by Deng et al. (2003) for pillar design. Another method by combining four ANNs such as Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) are established for stability prediction of crown pillar by Tawadrous and Katsabanis (2007). For pillar stress prediction in bord and pillar method MLP neural network model is constructed by Monjezi et al. (2011). In recent days, Ghasemi et al. (2014) created two models for the assessment and prediction of global stability in room and pillar coal mines considering the retreat mining conditions by utilizing the logistic regression and the fuzzy logic methods. In these investigations, whole data are divided into training and testing sets.

Machine learning has become consistently more mathematical and more efficient over the past few years. Implementations of machine learning algorithms for predictive data mining models are broadly recognized in mining and geotechnical field. On account of these considerations, the main objective of this work is to explore applicability of different machine learning algorithms for predicting pillar stability in underground mining. In order to achieve this goal, firstly, fuzzy rough feature selection with rank search is applied to obtain non-redundant and relevant features. Secondly, ranks of the features are calculated by using fuzzy rough feature evaluator technique. Then, performance of the various machine learning algorithms is recorded on both original as well reduced datasets. Furthermore, confusion matrices for various classifiers are obtained on percentage split of 80:20. Moreover, the work presents schematic representation of proposed methodology. Finally, it reports present Receiver Operating Characteristic (ROC) curve for the visualization of the experimental results. The schematic representation of entire study is given in Fig.1.

The present paper is broadly organized as follows:

Section 2: Materials and methods which include description of used database, input parameters, classifying tool and software used.

Section 3: Result and discussion.

Section 4: Conclusion

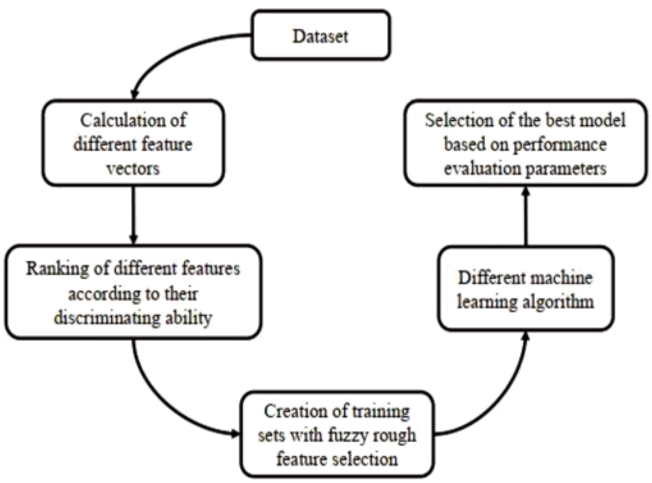

Fig.1 Flow diagram of the proposed methodology

2. Materials and methods

2 .1 Description of database

The data compiled by Lunder and Pakalnis (1997) is used for conducting the experiments. This is further used by.Wattimena at el. (2013) and Ghasemi at el (2014) for comparative and logistic regression study of hard rock pillars by using various algorithms. This dataset contains 178 hard rock pillar cases from various mines of Canada. In them 60 cases were stable, 50 cases were unstable and 68 were failed pillar cases. The details of data is presented in Wattimena (2014).

2.2 Input parameters

In the above mentioned datasets, two basics input parameters are discussed that included w/h ratio (pillar width to pillar height) and ratio of average induced pillar load over the UCS of the intact rock (PL/UCS). Furthermore, one output parameter namely: the pillar stability, which is characterized into three classes namely (a) stable (b) unstable and (c) failed. The detailed description of the dataset is given in Table 1.

Table 1: Characteristics of datasets

Data type	Parameters	Symbols	Value
Input	Pillar width to height ratio	w/h	0.31-4.5
	Average pillar load to UCS of intact rock ratio	PL/UCS	0.11-0.67
Output	Pillar stability condition	PS	0 for stable 1 for unstable 2 for failed

2.3 Feature ranking

Due to importance of features, feature ranking algorithm namely: fuzzy rough attribute evaluator is carried out to obtain rank of the features participated in the classification task. Then, experiments are conducted by using various classification algorithms by changing the number of features in the order of most significant to least significant. After performing the results of these experiments, it is possible to determine the redundant and irrelevant features and further remove them from the input feature set. This concept is extremely efficient when input features are in large number.

2.4 Fuzzy-rough set based feature selection technique

Fuzzy rough sets have two primary concepts including indiscernibility for rough sets and vagueness for fuzzy sets, the two concepts are established because of the uncertain knowledge available in various domains. The data of fuzzy sets always lacks definite boundaries. This is a common way of human communication and thinking. Rough sets can demonstrate ambiguity coming about due to an absence of information by setting approximations. In the current study, fuzzy rough set based feature selection technique had been applied to compute the reduct set, that could be given as follows as per Jenson and Shen (2008):

Algorithm 1: Fuzzy rough feature selection algorithm:

Input: C, the set of all conditional attributes;

Output: D, the set of decision attribute;

$P \leftarrow \{\}$

Do

$Q \leftarrow P$

for each $x \in (C - P)$

if $\gamma_{PU\ \{x\}}(D) > \gamma_Q(D)$

$T \leftarrow R\ U\ \{x\}$

$P \leftarrow Q$

until $\gamma_p(D) == \gamma_C(D)$

return P

2.5 Classification protocol

The experiments are conducted using different classifiers. From the experimental results, it could be observed that the random forest is the best performing algorithm. A brief description of this algorithm can be given as follows:

Random Forest (RF): RF is a mix of tree indicators to such an extent that each tree relies upon the estimations of a random vector inspected freely and with a similar circulation for all trees in forest. This algorithm was first created by Brieman L (2001). Vital improvements in portrayal accuracy had been achieved on account of growing an outfit of trees and allowing them to cast a ballot for the most notorious class. In order to build up these collections, often unpredictable vectors are created that administer the improvement of each tree in the gathering. An early point of reference is packing Breiman, (1999) where to build up each tree an unpredictable assurance (without substitution) is created, utilizing the models in the arrangement set. Another model is randomly from among the K best parts. Breiman (1999) delivers new planning sets by randomizing the yields in the first preparing set. Another approach is to pick the preparation set from an erratic system of loads on the models in the preparation set. Barandiaran (1998) has formed different papers on "the irregular subspace" technique which finishes an arbitrary assurance of a subset of features to use to develop up each tree.

Each tree is constructed according to following procedure: (a) Accept the amount of cases in the preparation dataset is *N*; test *N* cases randomly. These examples form the preparation set for building up the tree. (b) At each center point, m features are picked randomly out everything being equivalent, and the advanced split subject to these m features is used to part the center point. (c) Each tree should be created as tremendous as possible without trimming. Resulting to building up all trees, another article would then have the option to be classified as the class name with the most votes, where each vote is picked by each tree in the forest.

2.6 Performance evaluation metrics

The relative prediction evaluation of the five machine learning algorithms is performed by utilizing threshold-dependent and threshold-independent parameters. These parameters are calculated from the values of the confusion matrix, namely: True positives (TP), that is the number of correctly predicted pillar stability, false negatives (FN), that is the number of incorrectly predicted pillar stability, true negatives (TN) that is the number of correctly predicted pillar unstability with failure and false positives (FP) that is the number of incorrectly predicted pillar unstability with failure.

Accuracy: The percentage of correctly predicted pillar stability and unstability with failure

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100$$

Area under curve (AUC): It represents the area under the receiver operating characteristic curve (ROC), the closer its value to 1 is, the better will be the predictor. It is considered as one of the evaluation parameters which are robust to the imbalance nature of the datasets.

MCC: Mathew's correlation coefficient is calculated using the following equation:

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}.$$

It is widely used performance parameter for binary classifications. An MCC value of 1 is considered the best for a predictor.

The open source Java based machine learning platform WEKA 3.8 is used to perform all the experiments in this study.

2.7 WEKA software

WEKA 3.8 software (Waikato Environment for Knowledge Analysis), created by an examination group from the University of Waikato in New Zealand, is a free programming coordinating a few state of-the-workmanships. It contains various classifications, attribute selection, visualization tools and clustering algorithm for predictive modelling together with graphical representations, which are very easy to access.

3. Result and Discussion

The experiments are conducted with five different machine learning algorithms namely: Navie Bayes, Jrip, Multilayer perception), PART, SMO and Random Forest on the original as well as reduced datasets containing pillar stability provided by Wattimena (2013). Firstly, we have applied fuzzy rough feature selection based on rank search to produce the reduced datasets by removing irrelevant and redundant features.

Entire experiments are performed based on the percentage split of 80:20. The confusion matrix for Navie bayes, Jrip, Multilayer perception, PART, SMO and Random Forest models are presented in the Tables 2 to 11.

Table 2: Confusion matrix for Naive Bayes model based on percentage split of 80:20 based on original dataset

Pillar stability condition	Actual	Predicated		
		Stable (0)	Unstable (1)	Failed (2)
Stable (0)	14	12	2	0
Unstable (1)	9	1	7	1
Failed (2)	13	1	4	8

Table 3: Confusion matrix for SMO model based on percentage split of 80:20 based on original dataset

Pillar stability condition	Actual	Predicated		
		Stable (0)	Unstable (1)	Failed (2)
Stable (0)	14	12	1	1
Unstable (1)	9	1	7	1
Failed (2)	13	1	3	9

Table 4: Confusion matrix for Jrip model based on percentage split of 80:20 based on original dataset

Pillar stability condition	Actual	Predicated		
		Stable (0)	Unstable (1)	Failed (2)
Stable (0)	14	11	1	2
Unstable (1)	9	2	7	0
Failed (2)	13	1	4	8

Table 5: Confusion matrix for PART model based on percentage split of 80:20 based on original dataset

Pillar stability condition	Actual	Predicated		
		Stable (0)	Unstable (1)	Failed (2)
Stable (0)	14	7	6	1
Unstable (1)	9	1	8	0
Failed (2)	13	1	2	10

Table 6: Confusion matrix for RF model based on percentage split of 80:20 based on original dataset

Pillar stability condition	Actual	Predicated		
		Stable (0)	Unstable (1)	Failed (2)
Stable (0)	14	12	2	0
Unstable (1)	9	2	7	0
Failed (2)	13	1	3	9

Table 7: Confusion matrix for Naive Bayes model based on percentage split of 80:20 based on reduced dataset

Pillar stability condition	Actual	Predicated		
		Stable (0)	Unstable (1)	Failed (2)
Stable (0)	14	13	0	1
Unstable (1)	9	1	7	1
Failed (2)	13	1	4	8

Table 8: Confusion Matrix for SMO model based on percentage split of 80:20 based on reduced dataset

Pillar stability condition	Actual	Predicated		
		Stable (0)	Unstable (1)	Failed (2)
Stable (0)	14	13	0	1
Unstable (1)	9	1	7	1
Failed (2)	13	1	3	9

Table 9: Confusion matrix for Jrip model based on percentage split of 80:20 based on reduced dataset

Pillar stability condition	Actual	Predicated		
		Stable (0)	Unstable (1)	Failed (2)
Stable (0)	14	11	1	2
Unstable (1)	9	2	7	0
Failed (2)	13	1	3	9

Table 10: Confusion matrix for PART model based on percentage split of 80:20 based on reduced dataset

Pillar stability condition	Actual	Predicated		
		Stable (0)	Unstable (1)	Failed (2)
Stable (0)	14	13	0	1
Unstable (1)	9	2	7	0
Failed (2)	13	2	3	8

Table 11: Confusion matrix for RF model based on percentage split of 80:20 based on reduced dataset

Pillar stability condition	Actual	Predicated		
		Stable (0)	Unstable (1)	Failed (2)
Stable (0)	14	12	1	1
Unstable (1)	9	2	7	0
Failed (2)	13	1	1	11

The prediction performances of these algorithms are recorded in Tables 12 and 13. Furthermore, feature ranking is performed to obtain the discriminating ability of different features and recorded in Table 14. From the experimental results, it could be observed that the values of different evaluation metrics for various classifiers are better for reduced dataset when compared to original dataset. Moreover, it could be concluded that the random forest is the best performing algorithm with an accuracy of 83.3%, AUC of 0.920, and MCC of 0.740, that are better than the previously reported results.

TABLE 12: PERFORMANCE METRICS FOR DIFFERENT MACHINE LEARNING ALGORITHM ON ORIGINAL DATASET

Machine learning algorithm	Accuracy	AUC	MCC
Naïve Bayes	75.0	0.890	0.652
Jrip	72.2	0.810	0.593
SMO	77.8	0.845	0.674
PART	69.4	0.813	0.581
Random Forest	77.8	0.934	0.691

TABLE 13: PERFORMANCE METRICS FOR DIFFERENT MACHINE LEARNING ALGORITHM ON REDUCED DATASET

Machine learning algorithm	Accuracy	AUC	MCC
Naïve Bayes	77.8	0.912	0.675
Jrip	75.0	0.827	0.628
SMO	80.6	0.854	0.711
PART	77.8	0.877	0.674
Random Forest	83.3	0.920	0.748

TABLE 14: RANKING OF DIFFERENT FEATURE BASED ON FUZZY ROUGH FEATURE EVALUATOR

Features	Rank
w/h	0.04185
σ_p/σ_c	0.02747
$UCS(MPa)\sigma_c$	0.00745
$(MPa)\sigma_p$	0.00566

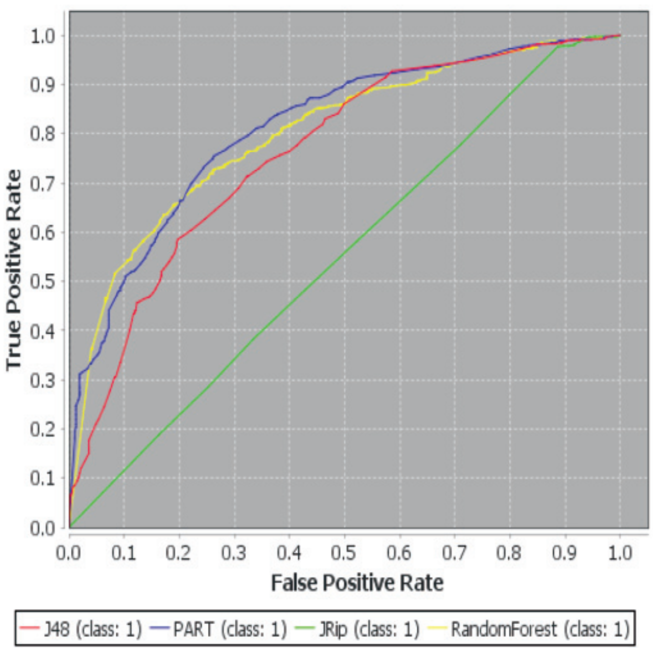

Fig.2 AUC for various machine learning algorithms on original dataset

ROC curve is used to perform visual representation of the classifiers. It is the one of the best way to estimate the overall performance of different classifiers at different decision thresholds. The ROC curves for different classifiers are shown in Figs.2 and 3. The performance of random forest is superior

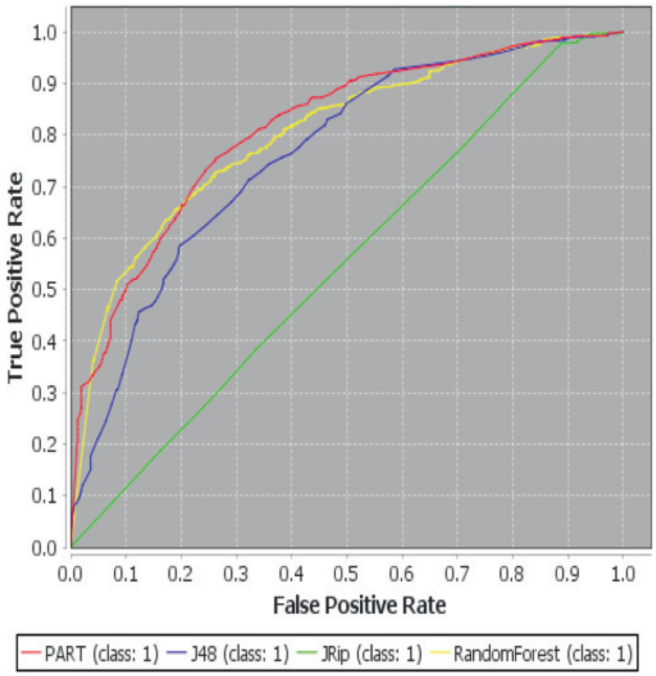

Fig.3 AUC for various machine learning algorithms on reduced dataset

among all the machine learning algorithms applied for experiment.

4. Conclusion

In this paper, five machine learning algorithms namely: JRip, PART, SMO, Naïve Bayes, and Random Forest are used to evaluate the hard rock pillar stability prediction. Entire experiment is performed on a validation technique of percentage split of 80:20. Firstly, a feature selection approach based on fuzzy rough set with rank search is applied to calculate the reduced set. Furthermore, feature ranking is performed by using fuzzy rough attribute evaluator, that justified the fact that the major contributing parameters are w/h and PL/UCS for constructing the models for predicting the stability of hard rock pillars. Moreover, we explored the performance of various machine learning algorithms by applying them on this reduced dataset. From the experimental results, we observed that performances of various classifiers are improving after applying fuzzy rough feature selection technique. The best performance is produced by random forest with an accuracy of 83.3%, AUC of 0.920, and MCC of 0.740, which is the best result so far.

V: References

1. Barandiaran I. (1998): The random subspace method for constructing decision forests. *IEEE Trans. Pattern Anal. Mach. Intell.* Aug; 20(8):1-22
2. Breiman L. (1999): Random forests. Machine learning. 2001 Oct 1; 45(1): 5-32. Breiman L. Random forests. UC Berkeley TR567. Sep.

3. Breiman L.(1999): Using adaptive bagging to debias regressions. Technical Report 547, Statistics Dept. UCB; Feb.

4. Cauvin M, Verdel T, Salmon R. (2009): Modeling uncertainties in mining pillar stability analysis. *Risk Analysis: An International Journal.* Oct; 29(10): 1371-80.

5. Deng J, Yue ZQ, Tham LG, Zhu HH. (2003): Pillar design by combining finite element methods, neural networks and reliability: a case study of the Feng Huangshan copper mine, China. *International Journal of Rock Mechanics and Mining Sciences.* Jun 1; 40(4):585-99.

6. Dietterich TG. (2000): An experimental comparison of three methods for constructing ensembles of decision trees: Bagging, boosting, and randomization. *Machine learning.* Aug 1; 40(2):139-57.

7. Esterhuizen GS. (1993): Variability considerations in hard rock pillar design. In Proceedings Symposium on Rock Engineering problems related to Hard Rock Mining at Shallow to Intermediate depth Mar (pp.4-5).

8. Ghasemi E, Ataei M, Shahriar K. (2014): An intelligent approach to predict pillar sizing in designing room and pillar coal mines. *International Journal of Rock Mechanics and Mining Sciences.* Jan 1; 65:86-95.

9. Ghasemi E, Ataei M, Shahriar K. (2014): Prediction of global stability in room and pillar coal mines. *Natural hazards*. Jun 1; 72(2):405-22.

10. Ghasemi E, Shahriar K, Sharifzadeh M, Hashemolhosseini H. (2010): Quantifying the uncertainty of pillar safety factor by Monte Carlo simulation-a case study. *Archives of Mining Sciences*; 55(3): 623-35.

11. Griffiths DV, Fenton GA, Lemons CB. (2002): Probabilistic analysis of underground pillar stability. *International Journal for Numerical and Analytical Methods in Geo mechanics.* Jul; 26(8):775-91

12. Hedley DG, Grant F. (1972): Stope-and-pillar design for Elliot Lake uranium mines. *Canadian Mining and Metallurgical Bulletin.* Jan 1; 65(723):37.

13. Jensen R, Shen Q. (2008): New approaches to fuzzy-rough feature selection. *IEEE Transactions on Fuzzy Systems.* Apr 30; 17(4):824-8

14. Kaiser PK, Kim B, Bewick RP, Valley B. (2011): Rock mass strength at depth and implications for pillar design. *Mining Technology.* Sep 1; 120(3):170-9.

15. Krauland N, Soder PE. (1987): Determining pillar strength-from pillar failure observation. *E&MJ-Engineering and Mining Journal*. Aug 1; 188(8):34-40.

16. Lunder PJ, Pakalnis RC. (1997): Determination of the strength of hard-rock mine pillars. *CIM bulletin;* 90(1013):51-5.

17. Malan DF, Napier JA. (2012): Design of stable pillars in the Bushveld Complex mines: a problem solved.

18. Martin CD, Maybee WG. (2000): The strength of hard-rock pillars. *International Journal of Rock Mechanics and Mining Sciences.* Dec 1; 37(8):1239-46.

19. Monjezi M, Hesami SM, Khandelwal M. (2011): Superiority of neural networks for pillar stress prediction in bord and pillar method. *Arabian Journal of Geosciences.* Aug 1; 4(5-6):845-53.

20. Potvin Y, Hudyma M, Miller H. (1988): Design guidelines for open stope support. *CIM bulletin*. Jan 1.

21. Sjoberg JS. (1992): Failure modes and pillar behaviour in the Zinkgruvan mine. In the 33th US Symposium on Rock Mechanics (USRMS) Jan 1. American Rock Mechanics Association.

22. Tawadrous AS, Katsabanis PD. (2007): Prediction of surface crown pillar stability using artificial neural networks. *International journal for numerical and analytical methods in geo mechanics*. Jun; 31(7):917-31.

23. Wattimena RK, Kramadibrata S, Sidi ID, Azizi MA. (2013): Developing coal pillar stability chart using logistic regression. International Journal of Rock Mechanics and Mining Sciences. Feb 1; 58:55-60

24. Wattimena RK. (2014): Predicting the stability of hard rock pillars using multinomial logistic regression. *International journal of rock mechanics and mining sciences*; 100(71):33-40.

25. Wattimena RK. (2014): Predicting the stability of hard rock pillars using multinomial logistic regression. *International journal of rock mechanics and mining sciences*; 100(71):33-40

26. Zhou J, Shi XZ, Dong L, Hu HY, Wang HY. (2010): Fisher discriminant analysis model and its application for prediction of classification of rock burst in deep-buried long tunnel. *Journal of Coal Science and Engineering (China).* Jun 1; 16(2):144-9.

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