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Rockburst conditions prediction based on a decision tree algorithm

Prédiction des conditions d'éclatement des rochers basée sur un algorithme d'arbre de décision

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ABSTRACT: This research article explores an innovative method for predicting rockbursts using Machine Learning (ML) algorithms. The study utilizes a decision tree (DT) algorithm and tests two distinct approaches: (1) utilizing a DT model for each rock type (DT-RT) and (2) developing a single DT model (Unique-DT) for all rock types. The dataset comprises 210 records from China, Canada, the United States, Japan, and Italy and includes five input variables for training and testing. The effectiveness of the DT models is compared to other ML algorithms, including Random Forest (RF) and Gradient Boosting (AdaboostM1). The results show that the Unique-DT model performs well and has an F1 score of 0.65 in predicting rockburst conditions. Although RF and AdaboostM1 with F1 (0.66) outperform the Unique-DT model slightly, the Unique-DT model is recommended due to its superior ease of use, effectiveness, and accuracy.

RÉSUMÉ: Cet article de recherche explore une méthode innovante pour prédire l'éclatement des roches à l'aide d'algorithmes d'apprentissage automatique. L'étude utilise un algorithme d'arbre de décision (DT) et teste deux approches distinctes: (1) l'utilisation d'un modèle DT pour chaque type de roche (DT-RT) et (2) le développement d'un modèle DT unique (Unique-DT) pour tous les types de roches. L'ensemble de données comprend 210 enregistrements provenant de Chine, du Canada, des États-Unis, du Japon et d'Italie et inclut cinq variables d'entrée pour la formation et les tests. L'efficacité des modèles DT est comparée à d'autres algorithmes de ML, notamment Random Forest (RF) et Gradient-Boosting (AdaboostM1). Les résultats montrent que le modèle Unique-DT est performant et a un score F1 de 0.65 pour prédire les conditions d'éboulement. Bien que RF et AdaboostM1 (F1 = 0.66) soient légèrement plus performants que le modèle Unique-DT, ce dernier est recommandé en raison de sa facilité d'utilisation, de son efficacité et de sa précision supérieure.

Keywords: Rockburst; decision tree; machine learning; metrics; prediction.

1 INTRODUCTION

Underground activities, such as mining, railway, and road constructions, are intricate geotechnical works. This complexity can be partly attributed to the limited understanding of the subsurface, which makes underground constructions challenging due to the variability of the geology. Although underground operations at depths of 2000 m have become increasingly common, and efforts have been made to perfect underground constructions, uncertainties still arise occasionally. These uncertainties can lead to the waste of resources such as time, money, and properties, and even loss of life. It is important to address these uncertainties in order to minimize risk and improve outcomes in underground construction. One such uncertainty is the instability of rock mass, caused by factors including the type of rock, its strength, and brittleness. External conditions also contribute to the instability of the rock mass (Askaripour et al., 2022; Meng et al., 2017; Owusu-Ansah et al., 2023). These include dynamic disturbances, the magnitude of in situ stresses, and the order of excavation (Owusu-Ansah et al., 2023).

Rockburst is regarded as a form of rock mass failure in deep excavations involving hard and brittle rocks subjected to high-stress conditions (Askaripour et al., 2022; Lu et al., 2018; Meng et al., 2017; Owusu-Ansah et al., 2023). Rockburst is defined as the sudden and intense movement, accompanied by rock failure, in underground spaces under high-stress conditions. It transpires due to overburdening the rock mass (unaltered, brittle rock) when the stresses exceed the material's compressive strength (Dietz et al., 2018; Kidybiński, 1981; Owusu-Ansah et al., 2023; Xu and

Yu, 2016). Since rockburst is an unforeseen phenomenon, it presents a range of issues including loss of life, property damage, and in some instances, financial and temporal setbacks. Therefore, comprehending this phenomenon and determining its triggers is critical to prevent such vulnerabilities. This paper applies a rockburst intensity or rockburst conditions (RBC) grading system, consisting of four predetermined classes built on rock displacement, damage, and failure characteristics, as demonstrated in Table 1 (Blake & Hedley, 2003; Liu et al., 2023; Owusu-Ansah et al., 2023; Russenes, 1974; Zhou et al., 2012, 2021). The prediction of rockburst mechanisms has been extensively researched over the years. Numerous authors have produced thoughtful and profound works that demonstrate successful outcomes.

Table 1. Classification of rockburst intensities.

Rockburst Condition	Failure Characteristics
None	No sound of rockburst and rockburst activities.
Light	The surrounding rock is deformed, cracked, or rib-spalled, there is a weak sound, and no ejection phenomenon.
Moderate	The surrounding rock is deformed and fractured, and there is a considerable number of rock chip ejections, loose and sudden destruction, accompanied by crisp cracking, and often presented in the local cavern of surrounding rock.
Strong	The surrounding rock is busted severely, and suddenly thrown out or ejected into the tunnel, accompanied by a strong burst and roaring sound, air spray, and storm phenomena, with continuity that rapidly expands to the deep, surrounding rock.

Recent studies on the application of Machine Learning (ML) algorithms for predicting rockburst have revealed notable effectiveness when given sets of input and output data from earlier rockburst cases. This success confirms their capability. Thus, the objective of this paper is to explore the use of decision trees (DT), a type of ML algorithm, to determine rockburst conditions in diverse rock types. The objective is to create a distinctive model that can competently forecast rockburst conditions, irrespective of the type of rock. Two decision tree-based methods have been developed and assessed using performance metrics. Moreover, ML algorithms, specifically Random Forest (RF) and AdaBoostM1, are used for comparison (Owusu-Ansah et al., 2023). The study relies on a rockburst dataset and a pre-defined four-level classification scale (see Table 1).

2 METHODOLOGY

The decision tree is an ML algorithm used for both classification and regression tasks. It is a tree-like model, where each internal node represents a test on an attribute, each branch represents the outcome of the test, and each leaf node represents a class label or a numeric value. The algorithm works by recursively splitting the data based on the most important attribute at each level of the tree, thus forming a decision path from the root of the leaf node.

This paper focuses on the implementation of decision trees (J48) with a nominal classification method. The R statistical environment, in conjunction with the Rweka package, is utilized to execute various algorithms throughout this study. A cross-validation technique with a K-fold value of 10 is implemented for validating the results.

Two decision tree approaches, DT-RT, and the Unique-DT, are utilized to forecast rockburst conditions. The former predicts rockburst conditions for each rock category using three distinct models, namely Igneous (IG), Metamorphic (MT), and Sedimentary (SD). The latter utilizes all datasets (210 occurrences) to predict rockburst conditions, thereby reducing analysis work and increasing accuracy. Both approaches aim to enhance the efficiency of the algorithm in predicting rockburst conditions. The alternative technique employs RF and AdaboostM1 algorithms to predict rockburst conditions by using a dataset that comprises 210 records. The goal is to create a comparison of performance metrics with other approaches.

2.1 Data characterization and evaluation

The rockburst condition database comprises 210 records from studies conducted by multiple authors. Table 2 summarizes the data distribution by rock category.

Table 2. Rock category distribution.

Rock category	Number of records
Igneous	103
Metamorphic	58
Sedimentary	49

The database comprises five input variables used for predicting rockburst conditions: depth, elastic energy index (EEI), Brittle Index BI — (σ_c/σ_t), Stress Index SI — (σ_θ/σ_c), and Rocktype exclusively for Unique-DT approach. With σ_c, σ_t, and σ_θ denoting uniaxial compressive strength, tensile strength and maximum tangential stress. To evaluate model performance, the metrics employed are F1-score (F1) and Accuracy (ACC). The F1-score is regarded as a superior metric for evaluating the classifier's performance when compared to the standard accuracy measure. Accuracy represents the percentage of correctly placed data points. In both cases, the closer the metric value is to one, the better the prediction. Furthermore, a sensitivity analysis (relative importance) (Cortez & Embrechts, 2013) was also performed on the two DT approaches. The aim was to identify the pertinent input variables that contribute to the prediction of rockburst conditions.

3 RESULTS AND DISCUSSIONS

The performance metrics for the models are presented in Table 3. The DT algorithm trained to predict metamorphic rock type exhibited the best F1 score (0.74) and accuracy (0.86), demonstrating superior performance compared to the trained model for sedimentary rock type, which performed the poorest. This difference may be ascribed to the intricate geological material and the scarcity of data.

Table 3. Metrics for Algorithms.

Algorithms	Metrics	
	F1	ACC
DT-IG	0.62	0.81
DT-MT	**0.74**	**0.86**
DT-SD	0.35	0.72
Unique-DT	*0.65*	*0.82*
RF	*0.66*	*0.83*
AdaboostM1	*0.66*	*0.82*

NB.: Best Value in Bold and Italics are comparison values

The Unique-DT model, which covers all rock types, exhibited promising performance with an F1 score of 0.65 and an accuracy of 0.82. It must be emphasized that the two other DT-RT models (for IG and SD prediction) demonstrated poorer performances than the Unique-DT. Additionally, when comparing the performance metrics of RF and AdaboostM1, they were found to be similar to the Unique-DT, with RF showing a slight advantage based on ACC metric. The study indicates that the Unique-DT model presents a viable approach over other ML algorithms for predicting rockburst conditions.

Figure 1 summarizes the relative importance of model attribute, illustrating that the elastic energy index (EEI), with a percentage of 36.13%, has the greatest impact on the Unique-DT model. Additionally, Depth (25.84%), Brittle index (BI = 16.13%), and Stress Index (SI = 13.85%) are other input variables with a significant impact in rockburst prediction. The influence of the variables on rockburst due to the rock type varies among the three DT-RT models. The DT-RT model's significance in sedimentary research highlights EEI (43.01%) as the primary factor, followed by Depth (21.19%), BI (18.71%), and SI (17.09%). Similarly, the IG and MT models prioritize BI (27.37%) and SI (32.21%), respectively, with EEI ranking second in importance for both.

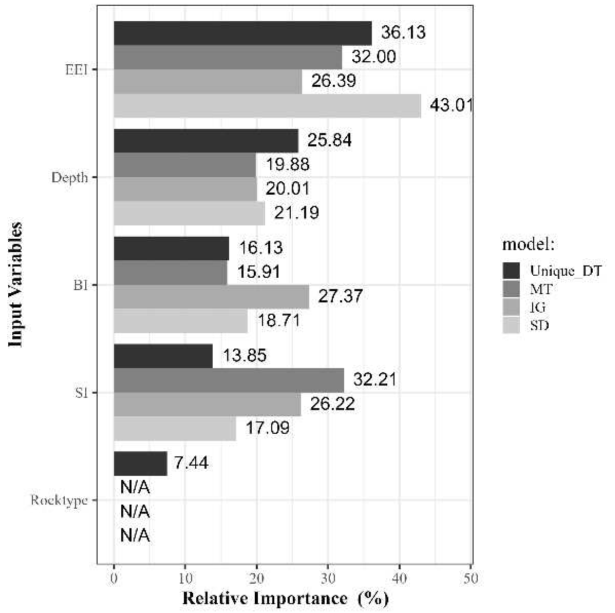

Figure 1. The relative importance of the two DT approaches for predicting rockburst condition.

These findings are consistent with previous studies on predicting rockburst conditions, stressing the significance of accurately identifying underlying factors by closely examining input data. It is worth noting that all models prioritize the elastic energy index (EEI), which aligns with the method presented by Owusu-Ansah et al. (2023) and Xu and Yu (2016) for predicting rockburst based on this index.

4 CONCLUSIONS

This paper proposes a novel model integrating rock type datasets to predict rockburst conditions using Machine Learning (ML) algorithms such as Decision Tree, Random Forest (RF), and AdaboostM1. Training and testing were conducted on a dataset comprising

210 records with 5 input variables, revealing that the Unique-DT model outperforms individual DT models for each rock type (DT-RT), achieving a promising F1 score of 0.65. RF and AdaboostM1 slightly outperformed Unique-DT with F1 scores of 0.66.

However, due to its simplicity and effectiveness, the unique-DT model is advised for rockburst prediction.

Based on this work, some future research should concentrate on improving the proficiency of ML models. Two viable approaches to explore are feature engineering which examine the formation of new features, or the transformation of existing features, to better capture the underlying patterns in rockburst conditions and hybrid models that integrate data-driven ML approaches with physics-based models. These hybrid models have the potential to improve prediction accuracy by leveraging the strengths of both approaches.

To summarise, this study highlights the potential of machine learning algorithms, specifically decision trees, in forecasting rockburst conditions by taking into account variables such as depth, elastic energy index, and rock strength parameters. Future research should focus on further enhancing the performance of machine learning models in this area.

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