

## Research Article

# Prediction of Rockburst Intensity Grade in Deep Underground Excavation Using Adaptive Boosting Classifier

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Rockburst phenomenon is the primary cause of many fatalities and accidents during deep underground projects constructions. As a result, its prediction at the early design stages plays a significant role in improving safety. The article describes a newly developed model to predict rockburst intensity grade using Adaptive Boosting (AdaBoost) classifier. A database including 165 rockburst case histories was collected from across the world to achieve a comprehensive representation, in which four key influencing factors such as maximum tangential stress of the excavation boundary, uniaxial compressive strength of rock, tensile rock strength, and elastic energy index were selected as the input variables, and the rockburst intensity grade was selected as the output. The output of the AdaBoost model is evaluated using statistical parameters including accuracy and Cohen's kappa index. The applications for the aforementioned approach for predicting the rockburst intensity grade are compared and discussed. Finally, two real-world applications are used to verify the proposed AdaBoost model. It is found that the prediction results are consistent with the actual conditions of the subsequent construction.

## 1. Introduction

In underground rock engineering, a rockburst is a type of dynamic geological disaster. It is a dynamic instability phenomenon that occurs when a rock mass or geological structure is subjected to high stress or is in a state of limit equilibrium. A rockburst, which still draws a lot of interest today, has a significant impact on rock stability in deep underground conditions [1–3]. Because rockbursts occur suddenly and intensely, they frequently result in harm, including death of workers, equipment damage, and even significant interruption and loss of revenue in underground deep excavation. Various strategies for controlling rockbursts have been proposed, such as

temporary and permanent rock support structures; however, these efforts are ineffective since the severity of rockbursts is difficult to predict precisely. To record and evaluate the rockburst occurrences, different monitoring systems, such as a microseismic system, were used [4]. The rockburst intensity is recorded by the microseismic monitoring system after the rockburst occurs and thus cannot predict the rockburst in advance. The tendency and intensity of rockburst were contrastively analyzed by Chen and Guo [5] using the strain energy index model of rockburst. As a result, estimating and predicting rockburst intensity is critical for a safe and cost-effective deep underground excavation or mining in burst-prone soils before it occurs.

Machine learning (ML) algorithms have been widely used to tackle real-world problems in the last ten years, particularly in civil engineering. ML algorithms have been successfully used to a variety of real situations, paving the way for several promising opportunities in civil engineering and other domains such as environmental [6], geotechnical and geological [7–20], and other sciences [21–24] including rockburst hazards prediction [25–27]. Furthermore, a variety of machine learning methods have been used, for example, Support Vector Machine (SVM) [28], Artificial Neural Networks (ANNs) [29], Distance Discriminant Analysis (DDA) [30], Bayes Discriminant Analysis (BDA) [31], and Fisher Linear Discriminant Analysis (LDA) [32], and some systems are based upon hybrid (Zhou et al. [33]; Adoko et al. [34]; Liu et al. [35]) or ensemble (Ge and Feng [36]; Dong et al. [37]) analyzing long-term prediction of rockburst. These studies provided new concepts and ways for predicting rockbursts. However, each of the methods listed above has its own set of benefits and drawbacks. Understanding, predicting, and controlling rock bursts still pose a considerable challenge for underground engineering. Furthermore, the number of data and the type of ML algorithms have an influence on the accuracy of rockburst intensity prediction. As a result, developing a high-performing and time-saving ensemble classifier for a larger dataset is critical. Many researchers have increasingly implemented the AdaBoost-based method for prediction problems such as rock mass class and soil classification as a vital means in recent years [38, 39]. For classification, prediction, and recognition issues, the AdaBoost methodology is widely regarded as the most successful and reliable artificial intelligence method. The article aims to add the following described contributions to this field: (1) A machine learning classifier for rockburst prediction based on case histories data is proposed. (2) The performance of AdaBoost is compared with other classifiers to confirm that the algorithm has superior or at par classification precision. (3) The effectiveness and feasibility in engineering practice applications and real-world examples are analyzed to predict rockburst intensity grade.

The rest of this paper is arranged as follows. The second section introduces the selection of indicators and the data collection, AdaBoost algorithm, and performance measures. The establishment of the algorithm model is described in the third section. In the fourth section, results are discussed, and the proposed algorithm is compared with the developed empirical criteria, widely used models, and two real-world applications are used to verify the proposed model. Finally, the conclusions are drawn in the fifth section.

## 2. Materials and Methods

**2.1. Dataset.** A total of 165 cases of rockburst events reported in the literature were collected to build a dataset [33, 40]. The maximum tangential stress of the excavation boundary ( $\sigma_\theta$ ), the uniaxial compressive strength of rock ( $\sigma_c$ ), the tensile rock strength ( $\sigma_t$ ), and the elastic energy index ( $Wet$ ) are selected as input parameters in this study by referring to the previous research [41, 42] and rockburst

intensity as the output. These input variables are commonly applied in rockburst classification and can provide fundamental understandings about rockburst occurrence in underground conditions.  $\sigma_c$ ,  $\sigma_t$ , and  $Wet$  were obtained by rock mechanics experiments, and  $\sigma_\theta$  was calculated according to the stress of the surrounding rock. Through field observation and evaluation, the rockburst grade was obtained. According to rock failure properties, the output parameter, i.e., rockburst intensity, contains four different classes, namely, no, moderate, strong, and violent, which are indicated by 1, 2, 3, and 4, respectively, as shown in Table 1 [40].

Figure 1 shows a boxplot of each affecting parameter for the four rockburst levels. As shown in Figure 1, the rockburst hazard intensity grades are associated with each attribute. Table 2 contains an overview of the case histories, as well as parameter statistics. The following is a brief summary of various input parameters.

**2.1.1. Maximum Tangential Stress of the Surrounding Rock.** The maximum tangential stress is frequently used to determine the angle at which a rock fractures [43]. For example, Ryder [44] determined that the fault-slip and shear fracture modes had a significant role in African metal mines in his investigation of the influence of excess shear stress on rockburst-prone circumstances, whereas Qian et al. [45] proposed two rock burst dynamic failure modes: one strain mode resulting from the rock failure and one sliding mode caused by the fault-slip and shear fracture events. Qian et al. [45] also analyzed two rockburst accidents in coal mines in China, stating that the instability due to rockburst occurrence could also be classified as fault-slip and shear fracture modes. As a result, past studies show that the maximum tangential stress has a significant impact on the incidence of shear fracture instabilities in tunnels, making it an important parameter for rockburst prediction. It is also an often used parameter in the data set.

**2.1.2. Uniaxial Compressive and Tensile Strength.** Other characteristics that can influence rockburst include uniaxial compressive strength (UCS) and uniaxial tensile strength (UTS), both of which have been used in the past. UCS and UTS values are widely known parameters for rockburst hazards prediction modeling.

**2.1.3. Elastic Energy Index.** The proportion of residual strain energy that dissipated during a single loading-unloading cycle under uniaxial compression is defined by the elastic energy index,  $Wet$  [46, 47]. This parameter is related to the rockburst hazards, and Wang et al. [48] developed a rockburst prediction criterion based on  $Wet$ . The  $Wet$  values can be easily obtained through laboratory tests and direct (double-hole method) or indirect (rebound method) in situ evaluations.

**2.2. AdaBoost Algorithm.** The AdaBoost algorithm, short for Adaptive Boosting, is a boosting approach used in machine learning as an ensemble method that uses decision trees as

TABLE 1: Grading criteria of rockburst intensity.

| Rockburst grade          | No rockburst (1) | Moderate rockburst (2) | Strong rockburst (3) | Violent rockburst (4) |
|--------------------------|------------------|------------------------|----------------------|-----------------------|
| $\sigma_\theta/\sigma_c$ | <0.3             | 0.3–0.5                | 0.5–0.7              | >0.7                  |
| $\sigma_c/\sigma_t$      | >40              | 26.7–40                | 14.5–26.7            | <14.5                 |
| $W_{et}$                 | >5               | 3.5–5.0                | 2.0–3.5              | <2.0                  |

Note.  $\sigma_\theta/\sigma_c$  = stress concentration factor;  $\sigma_c/\sigma_t$  = rock brittleness.

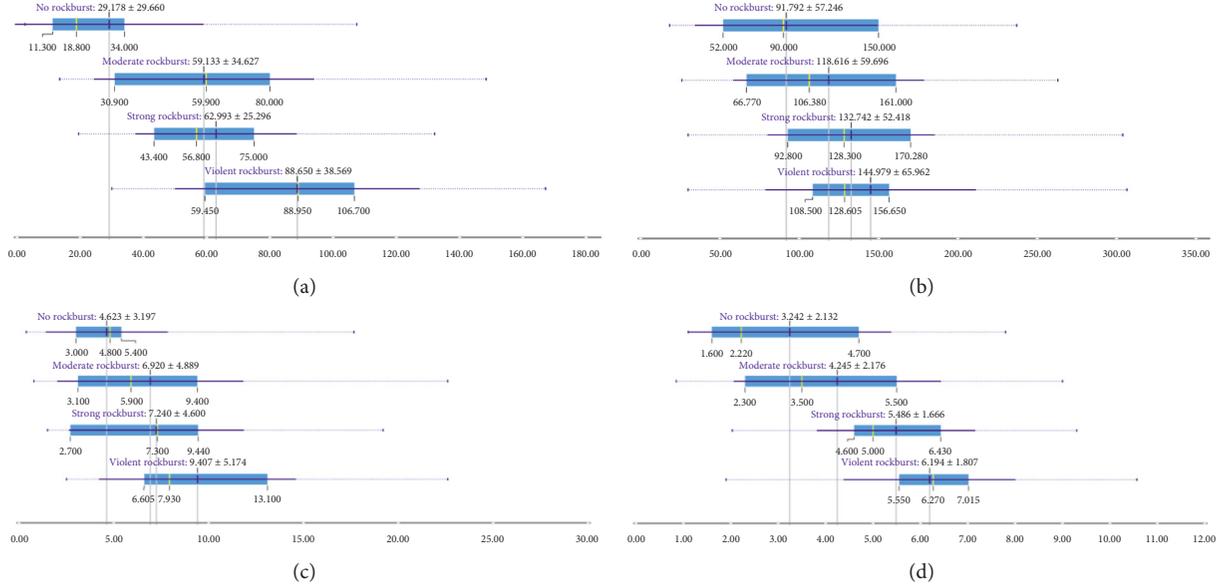


FIGURE 1: Boxplot of each influencing parameter to corresponding rockburst intensity grade. (a)  $\sigma_\theta$ , (b)  $\sigma_c$ , (c)  $\sigma_t$ , and (d)  $W_{et}$ .

TABLE 2: Inputs and output statistics of the present study.

| Rockburst rank     | Tangential stress, $\sigma_\theta$<br>(MPa) | Uniaxial compression strength, $\sigma_c$<br>(MPa) | Uniaxial tensile strength, $\sigma_t$<br>(MPa) | Elastic energy index,<br>$w_{et}$ |
|--------------------|---|--|--|-----------------------------------|
| 3                  | 90  | 170  | 11.3   | 9                                 |
| 2                  | 90  | 220  | 7.4  | 7.3                               |
| 2                  | 62.6  | 165  | 9.4  | 9                                 |
| ...                | ...   | ...  | ...  | ...                               |
| 3                  | 89  | 236  | 8.3  | 5                                 |
| 3                  | 98.6  | 120  | 6.5  | 3.8                               |
| 4                  | 108.4                                       | 140  | 8  | 5                                 |
| Mean               | 59.988                                      | 123.443  | 7.03   | 4.861                             |
| Standard error     | 2.811                                       | 4.71   | 0.37   | 0.17                              |
| Standard deviation | 36.108                                      | 60.498   | 4.79   | 2.185                             |
| Sample variance    | 1303.799                                    | 3660.031   | 22.98  | 4.773                             |
| Skewness           | 0.785                                       | 0.621  | 1.22   | 0.194                             |
| Minimum            | 2.6   | 18.32  | 0.38   | 0.85                              |
| Maximum            | 167.2                                       | 306.58   | 22.6   | 10.57                             |
| Count              | 165   | 165  | 165  | 165                               |

the main classifier. It is called Adaptive Boosting as the weights are reassigned to each instance, with higher weights assigned to incorrectly classified instances. Freund and Schapire's AdaBoost is the most widely used version of the boosting algorithm [49], making maximum use of a classifier by improving its accuracy. It is a simple learning approach that creates a strong classifier from a small number of efficient but weak classifiers (see Figure 2). The goal is to

combine the weak classifiers to improve their performance. As a result, the final robust classifier generated a data set for a model that can predict the class of a new observation. AdaBoost improves the classification efficiency of a simple learning algorithm by combining sets of weak classifiers to build a more robust classifier. In the language of boosting algorithms, the simple learning algorithm is known as a weak learner, and it selects a small, effective set of weak

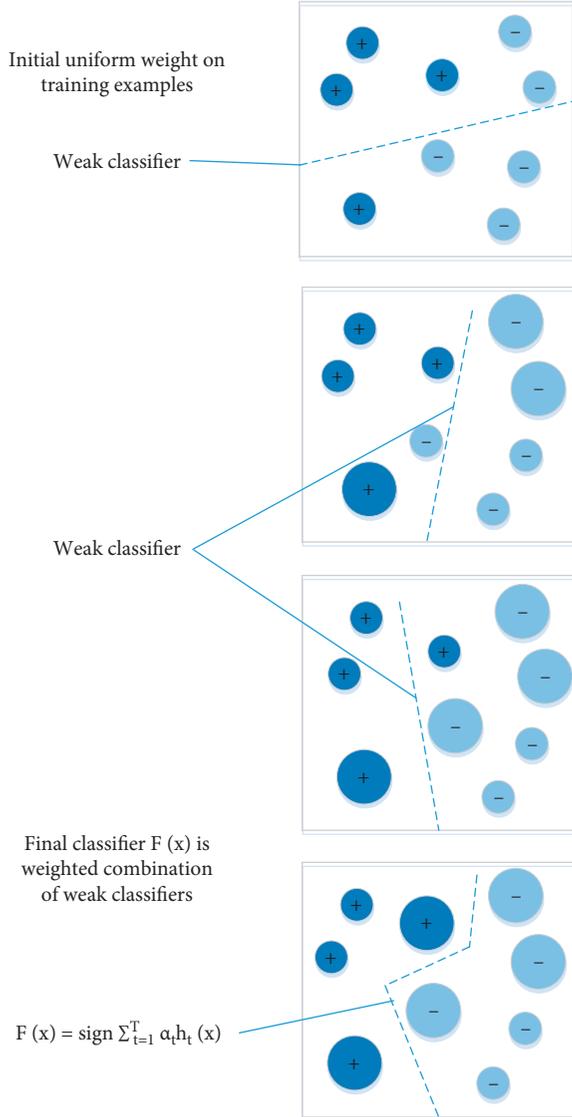


FIGURE 2: AdaBoost builds a strong classifier from a set of weak classifiers, as shown in this simple example.

classifiers with the lowest classification error from a wide number of potential features. The weak learner does not categorise the training data well even using the best classification function. To enhance the weak learner, it is necessary to solve a series of learning challenges. After the first learning cycle, the instances are reweighted to highlight those that were inaccurately categorised by the previous weak classifier. The final robust classifier uses a weighted combination of the weak classifiers to determine the best threshold classification function for each feature.

Algorithm 1 [50] shows the AdaBoost technique used to solve a prediction problem.

**2.3. Performance Metric.** In this study, the classical methods for model evaluation are used. The accuracy (ACC) and Cohen's kappa index were used to evaluate rockburst classification. A confusion matrix is commonly used as a

standard for evaluating the performance of a classification model on training and testing datasets with known true values.

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mm} \end{bmatrix}, \quad (1)$$

where  $m$  represents the number of rockburst levels,  $x_{11}$  is the number of features accurately predicted for the class  $m$ , and  $x_{mm}$  denotes the number of class features categorised to class  $n$ . Based on the confusion matrix, ACC and Cohen's kappa index are determined by (2) and (3), respectively.

$$ACC = \left( \frac{1}{n} \sum_{i=1}^m x_{ii} \right) \times 100\%, \quad (2)$$

$$Kappa = \frac{n \sum_{i=1}^m x_{ii} - \sum_{i=1}^m (x_{i+} \times x_{+i})}{n^2 - \sum_{i=1}^m (x_{i+} \times x_{+i})}. \quad (3)$$

A kappa value of less than 0.4 indicates poor agreement, while a value of 0.4 and above indicates good agreement [51, 52]. The ideal condition of a good model should have high ACC and kappa values simultaneously.

### 3. Model Development

The proposed model for predicting rockburst intensity grade was developed using Orange software. The model structure was based on an input matrix ( $x$ ) defined by  $x = \{\sigma_\theta, \sigma_c, \sigma_b, W_{et}\}$  that provided the predictor variables, while the target variable ( $y$ ) is rockburst intensity grade. During every modeling step, the most critical task is to identify the appropriate size of the training and testing datasets. The way data is split into training and research sets has a substantial impact on data mining results [53]. The main goal of the statistical analysis was to ensure that the statistical properties of the subsets were as similar as possible, and thus they represented the same statistical population. The dataset was divided into 137 (83%) training cases and 28 (17%) test cases and was kept the same as that of Zhao and Chen [41] owing to fairly evaluating the predictive performance of the proposed AdaBoost model in this work. The AdaBoost model was tuned to optimize the rockburst intensity grade prediction using a trial and error method. Figure 3 depicts the prediction model's construction.

Most ML algorithms have hyperparameters that need to be tuned [54]. The optimization method attempts to find the appropriate parameters for the AdaBoost model in order to achieve the best prediction accuracy. Some critical hyperparameters in the AdaBoost model are tuned in this study, as shown in Table 3. The definitions of these hyperparameters are also clarified in Table 3. First, the search range of different hyperparameters values is specified randomly and then adjusted throughout the trials until the best fitness metrics shown in Table 3 were reached.

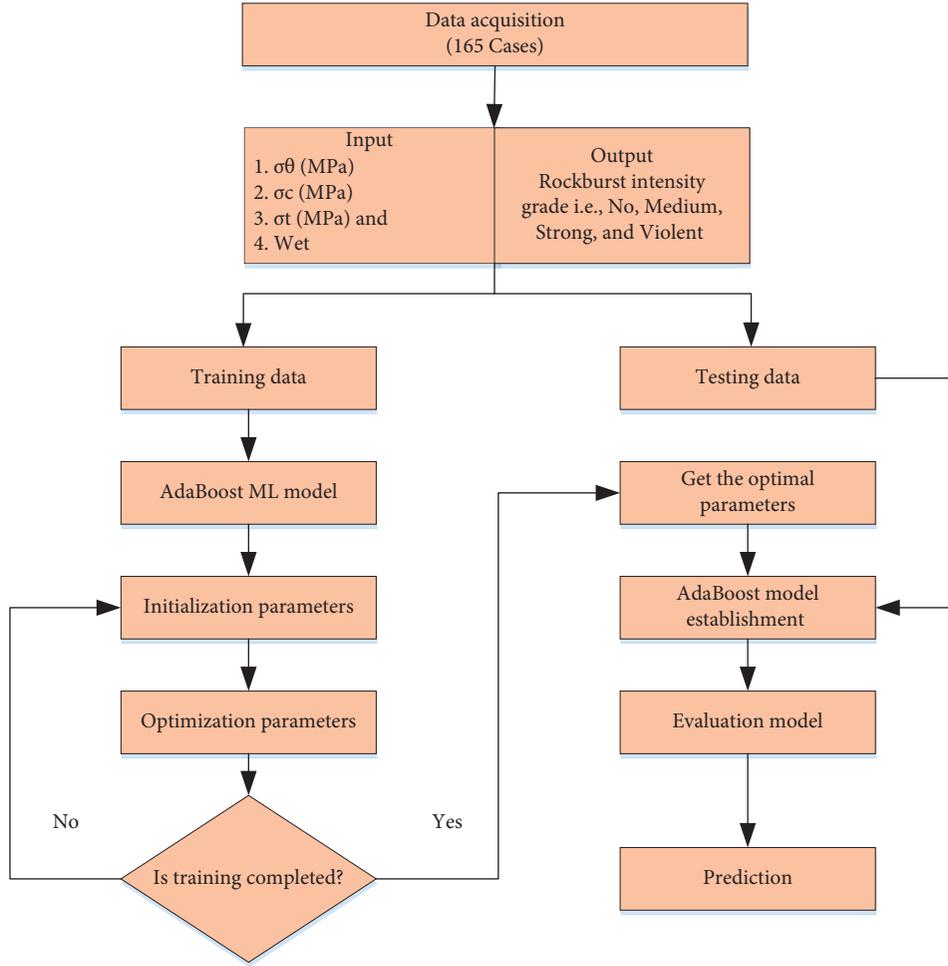
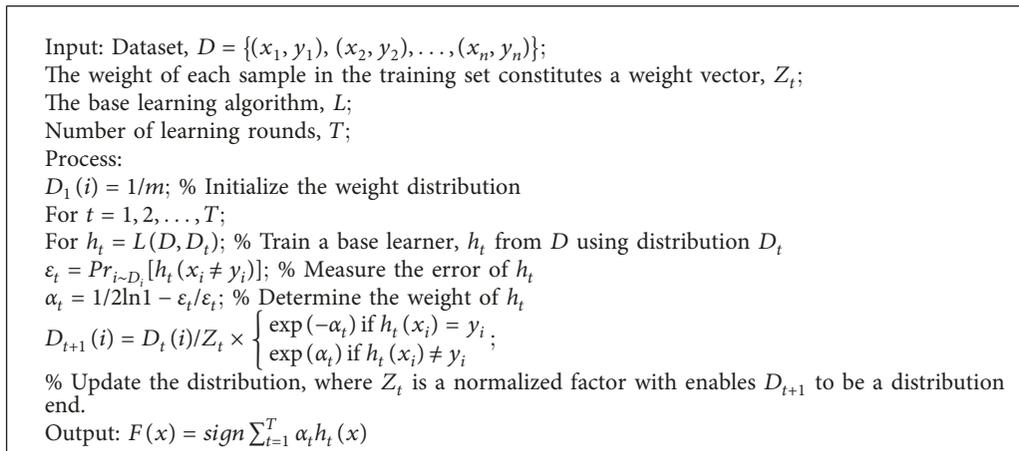


FIGURE 3: Flowchart of AdaBoost model for prediction of rockburst intensity grade.



ALGORITHM 1: AdaBoost.

## 4. Results and Discussion

**4.1. Comparison of the AdaBoost with Baseline Models.**  
 The performance of the AdaBoost model was evaluated with ANN, convolutional neural network (CNN), J48, and

random tree (RT) models. The AdaBoost model prediction result was the same as the performance of CNN and RT models, having an accuracy of 100% (Table 4), and was found better than the ANN and J48 models. The ANN, CNN, and J48 model's accuracy achieved 89.286%, 100%,

TABLE 3: Hyperparameter optimization results.

| Algorithm | Hyperparameter           | Explanation   | Optimal value/function |
|-----------|--------------------------|---|------------------------|
|           | Number of estimators     | Number of trees   | 0.5                    |
|           | Learning rate            | It determines to what extent the newly acquired information will override the old information | 0.75                   |
| AdaBoost  | Boosting algorithm       | Updates base estimator's weight with probability estimates or classification results          | SAMME.R                |
|           | Regression loss function | Linear/square/exponential   | Exponential            |

TABLE 4: Performance metrics of each model for test data.

| Method                                      | ACC (%)    | Kappa        |
|---|------------|--------------|
| Russenes criterion [55]                     | 42.867     | 0.222        |
| Rock brittleness coefficient criterion [48] | 53.571     | 0.352        |
| Elastic energy index [46]                   | 39.286     | 0.138        |
| ANN [41]                                    | 89.286     | 0.856        |
| CNN [41]                                    | <b>100</b> | <b>1.000</b> |
| Random tree [42]                            | <b>100</b> | <b>1.000</b> |
| J48 [42]                                    | 92.857     | 0.904        |
| AdaBoost (present study)                    | <b>100</b> | <b>1.000</b> |

Note. Bold values indicate the highest value for each model.

TABLE 5: Comparison of prediction results by different methods for the testing samples.

| S. No. | $\sigma_\theta$ (MPa) | $\sigma_c$ (MPa) | $\sigma_t$ (MPa) | $W_{et}$ | Actual | Russenes criterion [55] | Rock brittleness coefficient criterion [48] | Elastic energy index [46] | ANN [41] | CNN [41] | RT [42] | J48 [42] | AdaBoost (present study) |
|--------|-----------------------|------------------|------------------|----------|--------|-------------------------|---|---------------------------|----------|----------|---------|----------|--------------------------|
| 1      | 34                    | 150              | 5.4              | 7.8      | 1      | 2                       | 2   | 3                         | 1        | 1        | 1       | 1        | 1                        |
| 2      | 60.7                  | 111.5            | 7.86             | 6.16     | 4      | 3                       | 4   | 3                         | 4        | 4        | 4       | 4        | 4                        |
| 3      | 54.2                  | 134              | 9.09             | 7.08     | 3      | 3                       | 3   | 3                         | 3        | 3        | 3       | 3        | 3                        |
| 4      | 70.3                  | 129              | 8.73             | 6.43     | 3      | 3                       | 3   | 3                         | 3        | 3        | 3       | 3        | 3                        |
| 5      | 35                    | 133.4            | 9.3              | 2.9      | 2      | 2                       | 4   | 2                         | 2        | 2        | 2       | 2        | 2                        |
| 6      | 157.3                 | 91.23            | 6.92             | 6.27     | 4      | 4                       | 4   | 3                         | 4        | 4        | 4       | 4        | 4                        |
| 7      | 148.4                 | 66.77            | 3.81             | 5.08     | 2      | 4                       | 3   | 3                         | 2        | 2        | 2       | 2        | 2                        |
| 8      | 132.1                 | 51.5             | 2.47             | 4.63     | 3      | 4                       | 3   | 2                         | 2        | 3        | 3       | 3        | 3                        |
| 9      | 127.9                 | 35.82            | 1.24             | 3.67     | 2      | 4                       | 2   | 2                         | 2        | 2        | 2       | 2        | 2                        |
| 10     | 107.5                 | 21.5             | 0.6              | 2.29     | 1      | 4                       | 2   | 2                         | 1        | 1        | 1       | 1        | 1                        |
| 11     | 96.41                 | 18.32            | 0.38             | 1.87     | 1      | 4                       | 1   | 1                         | 1        | 1        | 1       | 1        | 1                        |
| 12     | 167.2                 | 110.3            | 8.36             | 6.83     | 4      | 4                       | 4   | 3                         | 4        | 4        | 4       | 4        | 4                        |
| 13     | 38.2                  | 53               | 3.9              | 1.6      | 1      | 4                       | 4   | 1                         | 1        | 1        | 1       | 1        | 1                        |
| 14     | 11.3                  | 90               | 4.8              | 3.6      | 1      | 1                       | 3   | 2                         | 1        | 1        | 1       | 1        | 1                        |
| 15     | 92                    | 263              | 10.7             | 8        | 2      | 3                       | 3   | 3                         | 2        | 2        | 2       | 2        | 2                        |
| 16     | 62.4                  | 235              | 9.5              | 9        | 4      | 2                       | 3   | 3                         | 4        | 4        | 4       | 3        | 4                        |
| 17     | 43.4                  | 136.5            | 7.2              | 5.6      | 4      | 3                       | 3   | 3                         | 3        | 4        | 4       | 4        | 4                        |
| 18     | 11                    | 105              | 4.9              | 4.7      | 1      | 1                       | 3   | 2                         | 1        | 1        | 1       | 1        | 1                        |
| 19     | 90                    | 170              | 11.3             | 9        | 3      | 3                       | 3   | 3                         | 3        | 3        | 3       | 3        | 3                        |
| 20     | 90                    | 220              | 7.4              | 7.3      | 2      | 3                       | 2   | 3                         | 2        | 2        | 2       | 2        | 2                        |
| 21     | 62.6                  | 165              | 9.4              | 9        | 2      | 3                       | 3   | 3                         | 2        | 2        | 2       | 2        | 2                        |
| 22     | 55.4                  | 176              | 7.3              | 9.3      | 3      | 3                       | 3   | 3                         | 4        | 3        | 3       | 3        | 3                        |
| 23     | 30                    | 88.7             | 3.7              | 6.6      | 3      | 3                       | 3   | 3                         | 3        | 3        | 3       | 3        | 3                        |
| 24     | 48.75                 | 180              | 8.3              | 5        | 3      | 2                       | 3   | 3                         | 3        | 3        | 3       | 3        | 3                        |
| 25     | 80                    | 180              | 6.7              | 5.5      | 2      | 3                       | 2   | 3                         | 2        | 2        | 2       | 2        | 2                        |
| 26     | 89                    | 236              | 8.3              | 5        | 3      | 3                       | 2   | 3                         | 3        | 3        | 3       | 3        | 3                        |
| 27     | 98.6                  | 120              | 6.5              | 3.8      | 3      | 4                       | 3   | 2                         | 3        | 3        | 3       | 3        | 3                        |
| 28     | 108.4                 | 140              | 8                | 5        | 4      | 4                       | 3   | 3                         | 4        | 4        | 4       | 4        | 4                        |

and 92.857%, respectively. Furthermore, we compared the results (summarized in Table 4) with conventional empirical models, such as the rock brittleness coefficient criterion,

elastic energy index, and Russenes criterion. The AdaBoost model performed better than the empirical models. The calculated results of AdaBoost, ANN, CNN, J48, RT, and

TABLE 6: Applications in real-world Rockburst prediction of the proposed AdaBoost model.

| Project           | $\sigma_\theta$ (MPa) | $\sigma_c$ (MPa) | $\sigma_t$ (MPa) | $W_{et}$ | Actual condition | Prediction |
|-------------------|-----------------------|------------------|------------------|----------|------------------|------------|
| Duoxiongla tunnel | 87.3                  | 137.7            | 9.62             | 7.14     | Strong           | Strong     |
| Anlu tunnel       | 17.02                 | 85.09            | 1.3              | 6.14     | Moderate         | Moderate   |
|                   | 16.7                  | 83.5             | 1.3              | 6.53     | Moderate         | Moderate   |
|                   | 17.35                 | 86.77            | 1.3              | 3.22     | Moderate         | Moderate   |
|                   | 16.87                 | 80.33            | 1.3              | 6.92     | Moderate         | Moderate   |

conventional empirical models, such as the rock brittleness coefficient criterion, elastic energy index, and Russenes criterion, are listed in Table 5. Obviously, the predicted rank of 28 samples was in excellent agreement with the actual rank, and all samples were classified correctly. The comparison analysis confirmed that the proposed AdaBoost model achieved a better performance than the other machine learning classifiers which can effectively mine the relationship between rockburst and its influence factors.

The proposed AdaBoost model was compared with the findings of the previous studies. Zhou et al. [56] compared the performance of 10 machine learning algorithms to analyze rockburst events, including 246 cases, considering seven input variables. Lin et al. [57] investigated rockburst events using machine learning models considering 246 rockburst cases having six input variables. The accuracy performances of the RF model developed by Zhou et al. [56] and Lin et al. [57] were 0.73 and 0.61, respectively. Although both models developed by Zhou et al. [56] and Lin et al. [57] considered seven and six input variables, they still provide lower prediction accuracy compared to the developed model.

**4.2. Applications in Real-World Rockburst Prediction.** Two real-world examples are analyzed using our proposed AdaBoost-based rockburst prediction model to study the effectiveness and feasibility in engineering practice applications. Five rockburst events in two different tunnel projects were predicted by the AdaBoost model. The field data were collected from available literature, including the Duoxiongla tunnel [58] and Anlu tunnel [59]. The prediction outcomes are summarized in Table 6, indicating that the rock burst intensity was predicted correctly for all cases. The prediction results in the real-world rockburst prediction cases are basically consistent with this strong-to-moderate intensity grading. This study proves that the AdaBoost model is a robust alternative tool for the rockburst intensity grade assessment, and it can be successfully applied in various geotechnical engineering projects.

## 5. Limitations and Future Works

The proposed approach obtains desirable prediction results, although some limitations should be addressed in the future.

- (1) The dataset is relatively small and unbalanced. The prediction performance of ML algorithms is heavily affected by the number and quality of dataset. Generally, if the dataset is small, the generalization and reliability of model would be influenced, although AdaBoost algorithm works well with small

datasets. Furthermore, the suggested model is open to further development, and the accumulation of more data will lead to a much better prediction capacity. It is important to note that the validity of the proposed model is limited by the data ranges used to train the model.

- (2) Other variables may have an effect on the prediction outcomes. Numerous factors influence the risk of a rockburst, including rock properties, energy, excavation depth, and support structure, among others. Although the four indicators used in this study can define the required conditions for rockburst hazard assessment to some degree, some other indicators, such as the buried depth of the tunnel, failure duration time, and energy-based burst potential index, may also have an impact on rockburst hazard. As a consequence, it is crucial to look into the effects of these variables on the prediction outcomes.

## 6. Conclusions

In this paper, the AdaBoost classifier's application was investigated to evaluate the rockburst phenomenon. The predictive variables for the AdaBoost model included the main effective parameters on rockburst, i.e.,  $\sigma_\theta$ ,  $\sigma_c$ ,  $\sigma_t$ , and  $W_{et}$ . The model was developed and tested using Orange software based on a database including 165 rockburst case histories. The main conclusion points are summarized below:

- (1) The comparison of proposed model efficiency and previously developed empirical criteria revealed that the AdaBoost model is remarkably better than empirical criteria with accuracy and kappa value obtained as 100% and 1.00, respectively.
- (2) The proposed approach was compared with other machine learning-based models in the literature. The comparison results have shown that the prediction accuracy of the proposed model is as adequate as other techniques such as CNN and RT models.
- (3) Two real-world rockburst examples are used to verify the proposed model's accuracy and effectiveness. It can be concluded that the AdaBoost classifier is a feasible and efficient tool for the classification of rockburst intensity grades. The proposed model can be applied in the initial stages of underground projects and the rockburst phenomenon can be assessed by an acceptable accuracy, which can reduce casualties due to rockburst.

## Data Availability

The data that support the findings of this study are openly available in [33, 40].

## Conflicts of Interest

The authors declare no conflicts of interest.

## Authors' Contributions

M.A. and R.A.A.-M. conceptualized the study; M.A., F.A., and H.Y.K. were responsible for methodology; M.A. was responsible for software, performed formal analysis, and prepared the original draft; M.A., R.A.A.-M., and F.A. validated the data; M.A., F.A., and M.S. investigated the data; M.A., M.S., and F.A. reviewed and edited the manuscript; H.Y.K. was responsible for resources and was involved in visualization, funding acquisition, and project administration; R.A.A.-M. carried out study supervision. All authors have read and agreed to the published version of the manuscript.

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