Research Article

Data-Driven Model for Rockburst Prediction

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Rockburst is an extremely complex dynamic instability phenomenon for rock engineering. Due to the complex and unclear mechanism of rockburst, it is difficult to predict precisely and evaluate reasonably the potential of rockburst. With the development of data science and increasing of case history from rock engineering, the data-driven method provides a good way to mine the complex phenomenon of rockburst and then was used to predict the potential of rockburst. In this study, deep learning was adopted to build the data-driven model of rockburst prediction based on the rockburst datasets collected from the literature. The data-driven model was built based on a convolutional neural network (CNN) and compared with the traditional neural network. The results show that the data-driven model can effectively mine the complex phenomenon and mechanism of rockburst. And the proposed method not only can predict the rank of rockburst but also can compute the probability of rockburst for each corresponding rank. It provides a promising and reasonable approach to predict or evaluate the rockburst.

1. Introduction

Rockburst is an extremely complex dynamic instability phenomenon in rock underground excavation. It usually causes injury to workers, damage to equipment, and economic losses. To prevent the rockburst disaster, various methods, such as field monitoring, laboratory test, theory model, empirical model, numerical model, and intelligent method, etc., were adopted to explore the mechanism of rockburst in the last decades [1–21]. With the depth increasing of mining and underground rock excavation, rockburst is becoming more and more serious and is a challenging rock engineering problem in China [14]. Due to the complexity and uncertainty of rockburst, its mechanism is not clearly understood till now. To decrease risk and losses of rockburst, predicting precisely or estimating the reasonable potential of rockburst is critical to the safety and efficient construction of rock underground excavation and mining engineering.

Various methods have been developed to predict or evaluate the rockburst since Cook et al. first proposed a method for predicting the rockburst in mining [22]. Zhou

et al. reviewed the state of the art and the prediction method of rockburst in brief and classified the method into the empirical method, experimental method, analytical method, intelligent method, and numerical method [23]. Sajjad et al. reviewed the prediction method, data preprocessing of rockburst, and developed an intelligent classification model for rockburst prediction [24]. But rockburst was influenced by multiple factors such as rock mass property, in situ stress, geology structure, and engineering position, etc.; it is difficult to predict rockburst precisely. Though a large number of methods were developed to predict or evaluate the rockburst, there is not much progress in the past few decades and not a universally accepted method which is better than other methods to predict rockburst. Rockburst prediction may now be a universal issue for deep buried underground excavation.

Though rockburst is an unsolved engineering issue for rock underground excavation, a deluge of rockburst data have been available; lots of case histories, monitoring in site, and various tests were implemented, analyzed, and published. The mechanism of rockburst was hidden in the above data about rockburst. Extracting the rockburst information

and knowledge from data is a good way to predict or evaluate rockburst. With the development of deep learning, it provides a good way to reveal the mechanism behind data [25]. Deep learning has achieved notable success in the fields of physics [26], chemistry [27], biology [28], and geoscience [29]. The combination of available data, deep learning, and the theory of rockburst offers an exciting new opportunity for expanding our knowledge about rockburst. In this study, deep learning was adopted to build the prediction model of rockburst. Various rockburst data were collected from the literature. The data-driven model of rockburst prediction was built based on deep learning. The prediction rank of rockburst was obtained and was in excellent agreement with the real rank in the engineering practice. The paper is structured as follows: firstly, the idea and algorithm of deep learning are reviewed in Section 2. Secondly, Section 3 introduces the influence factors and datasets of rockburst, and then the data-driven model was built based on deep learning in Section 4. Finally, some conclusions are given in Section 4.

2. Deep Learning

Machine learning has proven to be powerful in capturing subtle, complex, nonlinear relationships between predictor and response variables in various research fields. Artificial neural network (ANN), which mimics biological neural networks, is a commonly used supervised machine learning algorithm and has been widely used in rock mechanics and engineering [30–32]. ANN is the basis of most deep learning methods and comprises more layers containing a series of neurons that accept inputs from neurons on the previous layer based on activate functions. Deep learning is a kind of representation machine learning method that demands that a computer must have the ability to automatically reveal data patterns needed for classification or detection [25]. The “deep” here represents the number of layers. With increasing depth of network, the sufficient transformation allows incorporating simpler features into complex features so that the most appropriate hierarchical representations can be extracted from data [25, 33]. Recently, neural networks (NNs) have been widely applied in a large amount of research field by deep neural networks (DNNs). A deep neural network can compute high-level features over data. Some DNNs are introduced briefly in the following.

2.1. Conventional ANN. An ANN typically consists of three-layered components: an input layer (inputs), an output layer (outputs), and several hidden layers between them. The general functionality of the hidden layers is to convert the inputs to final outputs. Each hidden layer contains a certain number of parallel processing units, which are referred to as neurons. A neuron is the basic unit of ANN and is used to receive, process, and deliver signals. Figure 1 shows the ANN architecture. ANN algorithm is used to adjust the connected weights between two neurons in the neighbor layer. The weight can be considered as a measure of the strength of the connection between the two neurons. The larger the weight, the stronger the connection. In the

output layer, the outputs are compared to the targets. The difference is called error. The weights in the ANN are iteratively tuned to yield the minimum error. The detailed algorithm is out of the scope of this study and can be found in the relevant literature [34].

2.2. Convolutional Neural Network. Convolutional neural network (CNN) is a well-known deep learning architecture inspired by the natural visual perception mechanism of the living creatures [25]. It is a type of feed-forward neural network. CNN neurons are only connected by a limited subarea of the previous layer according to the design of local receptive field (Figure 2). Aside from input and output layers, CNN involves different types of hidden layers, i.e., convolutional layer, pooling layer, and fully connected layer. Convolutional layers are used to abstract local features at different locations among the whole raw input or the intermediate feature maps with learnable filters (kernels). The advantage of convolution operation is reflected mainly in the implementation of weights sharing and spatial correlation among neighbors. Pooling layers, also called subsampling layers, aim to reduce the size of the input layer. Fully connected layers are added to the last pooling layer for classification or as feature representation for further processing and are similar to regular neural networks and contain most of the parameters of CNN. A deep CNN is built by stacking multiple CNNs aiming to integrate the low-level features into a higher level of representations. This kind of design is powerful for seizing local geometric features and spatial patterns and detecting larger-scale features in deeper layers. The advantages of CNN come from the differences in structures and operations of the convolutional layer and pooling layer. In addition, many neurons in the same layer of CNN share the same weight, thereby reducing the degree of freedom in the model.

In this study, deep learning was used to build the data-driven model for rockburst prediction. Keras is a minimalist Python library for deep learning that can run on top of Theano or TensorFlow [35]. It was adopted in the data-driven model based on deep learning.

3. Data-Driven Model of Rockburst Prediction

3.1. Influence Factors and Rank of Rockburst. It is difficult to properly evaluate rockburst because of its complicated and indistinct mechanism. The occurrence of rockburst was affected by many different factors such as geologic structure, mining and excavation methods, mechanical property of rock mass and in situ stress, etc. To predict precisely rockburst, it is very important to determine the influence factor reasonably. A vast number of single indicators and multi-indicators have been developed for evaluating the occurrence and intensity of rockburst [23]. These indicators are mainly based on properties of rock, energy, depth of excavation and support structure, etc. But the two necessary conditions are the rock mass and its environment which has the capability of accumulated strain energy and stress concentration. The mechanical

FIGURE 1: Artificial neural network architecture.

FIGURE 2: Convolutional neural network.

property of rock mass can be characterized by uniaxial compression and tensile strength, and the maximum shear stress of the tunnel wall can reflect the environmental conditions. In this study, uniaxial compression and tensile strength of rock mass, maximum shear stress of tunnel wall, and linear elastic energy were selected to predict the rank of rockburst based on the previous studies in the literature.

Various studies of the potential of rockburst have been conducted in the last decades. Russnes proposed and classified the rockburst intensity into four ranks, i.e., none, weak, moderate, and severe [36]. Brauner classified the rockburst into three ranks based on the intensity of destruction to the surrounding rock mass [37]. Tan classified the rockburst into four ranks based on lots of laboratory tests and field investigations [38]. Cai et al. developed the four ranks of rockburst to evaluate the rockburst liability [39]. The four ranks' method of rockburst classification has been widely used in mining, tunnel, and other rock engineering. So, the four ranks of rockburst were adopted in this study. The input of deep learning was uniaxial compression and tensile strength of rock mass, maximum shear stress of tunnel wall, and linear elastic energy, respectively. The output is the ranks of rockburst, i.e., no rockburst, moderate rockburst, strong rockburst, and violent rockburst. Numbers

1, 2, 3, and 4 were adopted to represent the different ranks of rockburst in deep learning model (1—no rockburst, 2—moderate rockburst, 3—strong rockburst, and 4—violent rockburst).

3.2. Datasets. The training data are critical to the learning effect and are necessary to build a deep learning model. In the literature, lots of researchers collected lots of case history and laboratory tests and evaluated the potential of rockburst using different predicted models such as empirical models, numerical models, and intelligent models. In this study, the datasets were collected from the literature based on the previous works [19, 23]. The datasets consist of 165 samples which have four influence factors and a corresponding rank (label) of rockburst. The datasets were divided into 137 training samples and 28 test samples. Appendix listed the training samples (Table 1).

The relationship between each rockburst influence factor and its rank is shown in Figure 3. We can see from Figure 3 that the maximum shear stress of tunnel wall (σ_θ) and linear stress energy have higher impacts on the rockburst rank than uniaxial compression strength (σ_c) and uniaxial tensile strength (σ_t). It is quite clear that it is impossible to build the prediction model for rockburst based on individual influence factors.

TABLE 1: Training samples.

No.	Maximum shear stress of tunnel wall σ_θ (MPa)	Uniaxial compression strength σ_c (MPa)	Uniaxial tensile strength σ_t (MPa)	Linear stress energy	Rockburst rank
1	90.00	170.00	11.30	9	3
2	90.00	220.00	7.40	7.3	2
3	62.60	165.00	9.40	9	2
4	55.40	176.00	7.30	9.3	3
5	30.00	88.70	3.70	6.6	3
6	48.75	180.00	8.30	5	3
7	80.00	180.00	6.70	5.5	2
8	89.00	236.00	8.30	5	3
9	98.60	120.00	6.50	3.8	3
10	108.40	140.00	8.00	5	4
11	57.00	180.00	8.30	5.00	3
12	50.00	130.00	6.00	5.00	3
13	62.50	175.00	7.25	5	3
14	75.00	180.00	8.30	5	3
15	11.00	115.00	5.00	5.7	1
16	43.40	123.00	6.00	5	3
17	18.80	178.00	5.70	7.40	1
18	34.00	150.00	5.40	7.8	1
19	56.10	131.99	9.44	7.44	3
20	54.20	134.00	9.10	7.1	3
21	70.30	128.30	8.70	6.4	3
22	60.70	111.50	7.86	6.16	4
23	54.20	134.00	9.09	7.08	3
24	70.30	129.00	8.73	6.43	3
25	35.00	133.40	9.30	2.9	2
26	157.30	91.23	6.92	6.27	4
27	148.40	66.77	3.81	5.08	2
28	132.10	51.50	2.47	4.63	3
29	127.90	35.82	1.24	3.67	2
30	107.50	21.50	0.60	2.29	1
31	96.41	18.32	0.38	1.87	1
32	167.20	110.30	8.36	6.83	4
33	118.50	26.06	0.77	2.89	2
34	34.15	54.20	12.10	3.17	2
35	60.00	135.00	15.04	4.86	2
36	60.00	66.49	9.72	2.15	2
37	60.00	106.38	11.20	6.11	2
38	60.00	86.03	7.14	2.85	2
39	60.00	149.19	9.30	3.5	2
40	60.00	136.79	10.42	2.12	2
41	63.80	110.00	4.50	6.31	3
42	2.60	20.00	3.00	1.39	1
43	44.40	120.00	5.00	5.1	2
44	13.50	30.00	2.67	2.03	2
45	70.40	110.00	4.50	6.31	3
46	3.80	20.00	3.00	1.39	1
47	57.60	120.00	5.00	5.1	3
48	19.50	30.00	2.67	2.03	3
49	81.40	110.00	4.50	6.31	4
50	4.60	20.00	3.00	1.39	1
51	73.20	120.00	5.00	5.1	3
52	30.00	30.00	2.67	2.03	4
53	15.20	53.80	5.56	1.92	1
54	88.90	142.00	13.20	3.62	4
55	59.82	85.80	7.31	2.78	3
56	32.30	67.40	6.70	1.1	1
57	30.10	88.70	3.70	6.6	4
58	18.80	171.50	6.30	7	1
59	34.00	149.00	5.90	7.6	2

TABLE 1: Continued.

No.	Maximum shear stress of tunnel wall σ_θ (MPa)	Uniaxial compression strength σ_c (MPa)	Uniaxial tensile strength σ_t (MPa)	Linear stress energy	Rockburst rank
60	38.20	53.00	3.90	1.6	1
61	11.30	90.00	4.80	3.6	1
62	92.00	263.00	10.70	8	2
63	62.40	235.00	9.50	9	4
64	43.40	136.50	7.20	5.6	4
65	11.00	105.00	4.90	4.7	1
66	46.40	100.00	4.90	2.00	2
67	23.00	80.00	3.00	0.85	2
68	46.20	105.00	5.30	2.30	2
69	13.90	124.00	4.22	2.04	1
70	17.40	161.00	3.98	2.19	2
71	19.00	153.00	4.48	2.11	2
72	19.70	142.00	4.55	2.26	2
73	18.70	82.00	10.90	1.5	1
74	28.60	122.00	12.00	2.5	3
75	29.80	132.00	11.50	4.6	3
76	33.60	156.00	10.80	5.2	3
77	26.90	92.80	9.47	3.7	3
78	55.90	128.00	6.29	8.1	4
79	59.90	96.60	11.70	1.8	2
80	68.00	107.00	6.10	7.20	4
81	105.50	187.00	19.20	7.27	3
82	105.50	170.00	12.10	5.76	3
83	105.50	190.00	17.10	3.97	3
84	47.56	58.50	3.50	5	2
85	43.62	78.10	3.20	6	2
86	25.70	59.70	1.30	1.7	1
87	26.90	62.80	2.10	2.4	2
88	40.40	72.10	2.10	1.9	2
89	39.40	65.20	2.30	3.4	3
90	38.20	71.40	3.40	3.6	3
91	45.70	69.10	3.20	4.1	3
92	35.80	67.80	3.80	4.3	3
93	39.40	69.20	2.70	3.8	3
94	40.60	66.60	2.60	3.7	3
95	39.00	70.10	2.40	4.8	3
96	57.20	80.60	2.50	5.5	4
97	55.60	114.00	2.30	4.7	3
98	56.90	123.00	2.70	5.2	3
99	62.10	132.00	2.40	5	3
100	29.70	116.00	2.70	3.7	2
101	29.10	94.00	2.60	3.2	2
102	27.80	90.00	2.10	1.8	1
103	30.30	88.00	3.10	3	2
104	55.60	114.00	2.30	4.7	3
105	41.60	67.60	2.70	3.7	3
106	40.10	72.10	2.30	4.6	3
107	58.20	83.60	2.60	5.9	4
108	56.80	112.00	2.20	5.2	3
109	89.56	190.3	17.13	3.97	3
110	89.56	170.28	12.07	5.76	3
111	89.56	187.17	19.17	7.27	3
112	48	120	1.5	5.8	3
113	63	115	1.5	5.7	3
114	49.5	110	1.5	5.7	3
115	30.9	82.56	6.5	3.2	2
116	89	128.6	13.2	4.9	4
117	12.3	237.1	17.66	6.9	1
118	55.6	256.5	18.9	9.1	3

TABLE 1: Continued.

No.	Maximum shear stress of tunnel wall σ_θ (MPa)	Uniaxial compression strength σ_c (MPa)	Uniaxial tensile strength σ_t (MPa)	Linear stress energy	Rockburst rank
119	91.3	225.6	17.2	7.3	4
120	61	171.5	22.6	7.5	2
121	108.4	138.4	7.7	1.9	4
122	69.8	198	22.4	4.68	2
123	105	171.3	22.6	7.27	4
124	105	237.16	17.66	6.38	4
125	105	304.21	20.9	10.57	4
126	25.49	54.2	2.49	3.17	2
127	72.07	147.09	10.98	6.53	3
128	21.8	160	5.2	2.22	1
129	20.9	160	5.2	2.22	1
130	12.1	160	5.2	2.22	1
131	75	170	11.3	9	3
132	105	128.61	13	5.76	4
133	105	304	9.12	5.76	3
134	105	306.58	13.9	6.38	4
135	7.5	52	3.7	1.3	1
136	24.93	99.7	4.8	3.8	1
137	14.96	99.7	4.8	3.8	1

Note. 1: no rockburst; 2: moderate rockburst; 3: strong rockburst; 4: violent rockburst.

FIGURE 3: The relation between each rockburst influence factor and its rank, (a) σ_θ , (b) σ_c , (c) σ_t , (d) linear stress energy.

FIGURE 4: The bivariate relation between each pair of rockburst influence factor.

Figure 4 shows the bivariate relation between each pair of rockburst influence factor. It shows that the relationship between rockburst and its influence factor is very complex, uncertain, and nonlinear. There is no apparent dependence between them. It is impossible to evaluate and predict the rockburst using the bivariate relation. It is difficult to characterize the mechanism of rockburst using the traditional statistical method. Figure 5 also shows the relationship between rockburst rank and its influence factors. It is obvious that the rockburst rank depends on the influence factor and their relationship is very complex. For the complex and nonlinear relationship, it is difficult to build the

mathematical model and recognize the rank of rockburst using the traditional mathematical model.

3.3. Rockburst Prediction. In the past few decades, machine learning such as neural network and support vector machine has been used to predict or evaluate rockburst. To verify and illustrate the data-driven model of rockburst prediction, NN and CNN were used to build a prediction model and evaluate the potential of rockburst based on the training samples in Table 2. And the comparisons have been implemented and some results were obtained, which

FIGURE 5: The relationship between rockburst rank and its influence factor.

TABLE 2: The test samples and the predicted results using neural network.

No.	Maximum shear stress of tunnel wall σ_θ (MPa)	Uniaxial compression strength σ_c (MPa)	Uniaxial tensile strength σ_t (MPa)	Linear stress energy	Rockburst rank	
					Real	Predicted
1	34	150	5.4	7.8	1	1
2	60.7	111.5	7.86	6.16	4	4
3	54.2	134	9.09	7.08	3	3
4	70.3	129	8.73	6.43	3	3
5	35	133.4	9.3	2.9	2	2
6	157.3	91.23	6.92	6.27	4	4
7	148.4	66.77	3.81	5.08	2	2
8	132.1	51.5	2.47	4.63	3	2
9	127.9	35.82	1.24	3.67	2	2
10	107.5	21.5	0.6	2.29	1	1
11	96.41	18.32	0.38	1.87	1	1
12	167.2	110.3	8.36	6.83	4	4
13	38.2	53	3.9	1.6	1	1
14	11.3	90	4.8	3.6	1	1
15	92	263	10.7	8	2	2
16	62.4	235	9.5	9	4	4
17	43.4	136.5	7.2	5.6	4	3
18	11	105	4.9	4.7	1	1
19	90	170	11.3	9	3	3
20	90	220	7.4	7.3	2	2
21	62.6	165	9.4	9	2	2
22	55.4	176	7.3	9.3	3	4
23	30	88.7	3.7	6.6	3	3
24	48.75	180	8.3	5	3	3
25	80	180	6.7	5.5	2	2
26	89	236	8.3	5	3	3
27	98.6	120	6.5	3.8	3	3
28	108.4	140	8	5	4	4

proved that deep learning is a promising tool for predicting rockburst precisely.

3.3.1. NN Model for Rockburst Prediction. NN was built based on the training samples in Appendix. Figure 6 shows the neural network structure trained based on

the samples in Appendix. 28 testing samples were used to verify the NN model. Table 2 lists the predicted results and their comparison with the real rank of rockburst. The predicted rank of 25 samples was in good agreement with the real rank and Nos. 8, 17, and 22 were not classified correctly. The error ratio was about 11%. The results were in good agreement with the previous research using NN

FIGURE 6: Neural network structure.

[17]. This showed that NN can effectively mine the relationship between rockburst and its influence factors. Meanwhile, NN can estimate the probability of rockburst rank. Figure 7 shows the comparison between real rank and predicted rank for testing samples. The error prediction occurred at the neighboring rank for Nos. 8, 17, and 22 samples. As we know, the mechanism of rockburst is complex and not clear. The relationship between rockburst and its influence factors is not clear and uncertain. It is difficult to classify the rank of rockburst which falls in between two neighboring ranks. The rank probability of each sample can be obtained using the NN model. Figure 8 shows the rank probability of rockburst for each testing sample. The probabilistic results were more reasonable than the deterministic value. Figure 9 shows the probability of each rank for Nos. 1, 8, 17, and 22 testing samples. The real rank of No. 1 is no rockburst and is predicted correctly by the NN model. The probabilities of no rockburst and weak rockburst were very close to each other and the probability of no rockburst is a little bigger than the probability of weak rockburst. But the ranks of Nos. 8, 17, and 22 do not classify correctly the rank of rockburst.

3.3.2. CNN Model for Rockburst Prediction. CNN was also adopted to build a prediction model of rockburst based on the same training samples. Figure 10 shows the predicted results and their comparison with the real rank of rockburst. It was obvious that the predicted rank of 28 samples was in excellent agreement with the real rank and all samples are classified correctly. The results are better than using the NN model. This showed that deep learning can effectively mine the relationship between rockburst and its influence factors.

Figure 11 shows the rank probability of each sample using the CNN model. Compared with the NN model (Figure 8), the CNN model can reduce the uncertainty of rank and improve the predicted results. In other words, the CNN model can distinguish effectively the neighboring rank of rockburst. The predicted result and rank probability of Nos. 1, 8, 17, and 22 are shown in Figure 12. It further proved the above statement. For the NN model, the probability of no rockburst and weak rockburst is almost the same for the No. 1 sample. The NN model cannot separate the proper rank from the neighboring rank for the No. 8, 17, and 22 samples. But the CNN model can determine correctly the rank of rockburst from the neighboring rank and the probability of the corresponding rank was far from the other ranks (compared with Figure 9).

3.4. Comparison. To illustrate and verify the data-driven model of rockburst, the developed method was compared with the traditional empirical criteria of the rockburst including the Russenes criterion [36], the rock brittleness coefficient criterion [40], and the elastic energy index [41]. Table 3 lists the results of 28 testing samples. Additionally, Zhou et al. and Sajjad et al. reviewed the various prediction methods of rockburst [23, 24]. The results of this study are of higher accuracy than other methods (including empirical method and intelligent method). So, the comparison shows that the data-driven model (NN and CNN) has superiority. The data-driven model can reveal the complex and uncertain phenomenon behind data and present well the relationship between rockburst and its influence factor. With the increasing of case history, the data-driven model provides a promising tool for rockburst prediction.

FIGURE 7: The predicted results of deep learning and their comparison for the testing samples.

FIGURE 8: The rank probability of rockburst for the testing samples using NN model.

FIGURE 9: The probability of each rank for (a) No. 1, (b) No. 8, (c) No. 17, and (d) No. 22 testing sample.

FIGURE 10: The predicted results and their comparison using CNN for the testing samples.

FIGURE 11: The rank probability of rockburst for the testing samples using CNN model.

FIGURE 12: The probability of each rank for the (a) No. 1, (b) No. 8, (c) No. 17, and (d) No. 22 testing sample using CNN.

TABLE 3: Comparison with the empirical model.

Sample no.	Russenes criterion	Rock brittleness coefficient criterion	Elastic energy index	NN	CNN	Real
1	2	2	3	1	1	1
2	3	4	3	4	4	4
3	3	3	3	3	3	3
4	3	3	3	3	3	3
5	2	4	2	2	2	2
6	4	4	3	4	4	4
7	4	3	3	2	2	2
8	4	3	2	2	3	3
9	4	2	2	2	2	2
10	4	2	2	1	1	1
11	4	1	1	1	1	1
12	4	4	3	4	4	4
13	4	4	1	1	1	1
14	1	3	2	1	1	1
15	3	3	3	2	2	2
16	2	3	3	4	4	4
17	3	3	3	3	4	4
18	1	3	2	1	1	1
19	3	3	3	3	3	3
20	3	2	3	2	2	2
21	3	3	3	2	2	2
22	3	3	3	4	3	3
23	3	3	3	3	3	3
24	2	3	3	3	3	3
25	3	2	3	2	2	2
26	3	2	3	3	3	3
27	4	3	2	3	3	3
28	4	3	3	4	4	4
Correct rate (%)	42.86	53.57	39.29	89.29	100	—

4. Conclusions

It is critical to evaluate rationally and efficiently the potential rank of rockburst for avoiding and preventing the disaster of rockburst. In this study, a data-driven model was developed to evaluate the rank of rockburst and its probability of corresponding rank using deep learning. Deep learning was adopted to build the relationship between the rank of rockburst and its influence factors based on the collected datasets. The developed method was used to predict the testing samples and compared with the other method. The results showed that the data-driven model is reasonable and feasible to rock engineering with the increasing of rock case history and data. It provides a scientific, promising, and rational way to evaluate the potential of rockburst for rock underground excavation. The following conclusions were obtained.

- (1) Rockburst is a complex dynamic phenomenon and engineering disaster. The relationships between rockburst rank and its influence factor are complex, uncertain, and nonlinear. It is difficult to predict the potential of rockburst and understand the mechanism of rockburst using the traditional method such as empirical method, laboratory or in-site test, numerical method and intelligent method, etc.
- (2) With the development of data science and deep learning technology, a data-driven model provides

a good way to utilize lots of data in the case history and laboratory test for mining the complex mechanism and phenomenon of rockburst. Data-driven models can improve our understanding and evaluate comprehensive rockburst models and data.

- (3) A deep learning model (CNN) can represent well the relationship between rockburst rank and its influence factors. It has been proven to be more powerful and flexible than previous models such as the empirical model, numerical model, and physical model. The combination of data and data-driven model based on deep learning offers an exciting new opportunity for expanding our knowledge about rockburst from data.
- (4) The data-driven model provides a promising and challenging approach for understanding rockburst through combining rock mechanics, engineering geology, rockburst model, and deep learning. It also provides a good way to solve and understand the complex rock mechanics issue in the field of rock engineering.
- (5) The data-driven model is a black box and of poor interpretability. More data and expertise can improve the interpretation of the model.

Data Availability

All data and models generated or used during the study can be obtained if the reader required.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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