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Novel Ensemble Tree Solution for Rockburst Prediction Using Deep Forest

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Abstract: The occurrence of rockburst can cause significant disasters in underground rock engineering. It is crucial to predict and prevent rockburst in deep tunnels and mines. In this paper, the deficiencies of ensemble learning algorithms in rockburst prediction were investigated. Aiming at these shortages, a novel machine learning model, deep forest, was proposed to predict rockburst risk. The deep forest combines the characteristics of deep learning and ensemble models, which can solve complex problems. To develop the deep forest model for rockburst prediction, 329 real rockburst cases were collected to build a comprehensive database for intelligent analysis. Bayesian optimization was proposed to tune the hyperparameters of the deep forest. As a result, the deep forest model achieved 100% training accuracy and 92.4% testing accuracy, and it has more outstanding capability to forecast rockburst disasters compared to other widely used models (i.e., random forest, boosting tree models, neural network, support vector machine, etc.). The results of sensitivity analysis revealed the impact of variables on rockburst levels and the applicability of deep forest with a few input parameters. Eventually, real cases of rockburst in two gold mines, China, were used for validation purposes while the needed data sets were prepared by field observations and laboratory tests. The promoting results of the developed model during the validation phase confirm that it can be used with a high level of accuracy by practicing engineers for predicting rockburst occurrences.

Keywords: rockburst prediction; deep forest; bayesian optimization; ensemble model

MSC: 68Txx

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1. Introduction

Rockburst is a geological catastrophe induced by the sudden release of strain energy stored in rock mass during or after the excavation of underground engineering in high in-situ stress areas. Rockburst occurs in many countries around the world [1]. It is generally believed that intensity and frequentness of rockburst increase as depth increases. The occurrence of rockburst damages underground tunnels and facilities and poses a severe threat to the safety of the operators on site. The gold mines in South Africa have greater mining depths than those in other countries. Meanwhile, most rockburst disasters occur in South African gold mines. In 1975, 73 laborers died due to 680 rockburst incidents in 31 gold mines. From 1984 to 1993, 3275 laborers lost their lives in mining geological disasters due to the lack of mining technology to cope with the rockburst below 2000 m [2]. Rockburst is a complicated problem restricting the progress of underground engineering. It is necessary for researchers to study how to prevent and control rockburst.

Many scholars have taken various measures to evaluate rockburst risk. These methods contain empirical indicators, numerical modeling, rock mechanics tests, intelligent techniques, etc. [1,3]. Xue et al. [4] adopted the empirical method to estimate the rockburst

grade at the Jiangbian hydropower station, China. The empirical method is simple and easy to implement, but its effectiveness is poor. Zhai et al. [5] carried out rockburst tests with six hard brittle rocks subjected to one-free-face true triaxial mechanical tests. Their test results revealed that strength, fracturing, fragmentation characteristics, and failure modes had a remarkable impact on rockburst proneness. Due to scale effect considerations, experimental methods are suitable for investigating the failure process and mechanism of rockburst rather than predicting rockburst [6–8]. Moreover, the field condition is challenging to be reproduced in the laboratory. Wang et al. [9] summarized the numerical simulations, including the continuum, discontinued, and hybrid techniques for rockburst evaluation. The numerical simulation is economical, secure, and time-saving [1,3,10]. Nevertheless, choosing an appropriate constitutive model and simulation method is very important according to specific problems. With the blossom of artificial intelligence and big data, intelligent algorithms are increasingly used to predict rockbursts. Compared to empirical, numerical, and experimental methods, the intelligent model has high efficiency, good practicability and can foretell and prevent rockbursts in time. However, it requires high-quality data.

The machine learning (ML) algorithm is an essential part of the intelligent algorithm [11,12]. The ML algorithms for rockburst classification mainly include linear models (LM), decision trees (DT), artificial neural networks (ANN), *k*-nearest neighbor (KNN), Bayes classifiers, support vector machines (SVM), ensemble models, etc. Each ML model has its own supremacy and drawback, and no model can perform best for every practical engineering based on the ‘No Free Lunch theorem’. Table 1 compiles the ML techniques for rockburst estimation recently and compares their advantages and disadvantages.

Table 1. The superiority and drawback of ML techniques for rockburst estimation recently.

Algorithm	Superiority	Drawback
LDA [13] LR [14]	Fast training and prediction speed, and simple and easy to interpret.	Unsuitable for high-dimensional data.
C5.0 DT [15] DT [16]	Suitable for data with missing values, and can process continuous variables and discrete variables simultaneously.	Tend to produce an overly complex model to reduce its generalization.
KNN [13]	Simple and easy to implement.	Unsuitable for unbalanced samples.
Naïve Bayes [13] BN [17]	Simple and fast. Perform very well under the assumption that distribution is independent.	The assumption of independent distribution is difficult to meet in practical projects.
ANN [13,18–20]	Strong mapping ability and can deal with complex nonlinear problems.	Many hyperparameters to turn and easy to overfit.
SVM [13,21]	Solid theoretical basis and can be applied to complex nonlinear data.	Difficult to deal with multiple classification problems.
RF [13,22] Bagging [23]	Suitable for high dimension data and good generalization ability.	Overfitting appears when dealing with classification with high noise.
GBM [13] XGB [24]	Suitable for continuous values and discrete values. Robust to outliers using robust loss functions	Difficult to train data in parallel.

Note: LDA = linear discriminant analysis; LR = logistic regression; BN = Bayesian network; GBM = gradient boosting machines; RF = random forest; XGB = extreme gradient boosting;.

To overcome the limitations of single ML models, some researchers have combined multiple intelligent techniques to develop an ensemble model for rockburst estimation recently. Zhang et al. [25] combined seven extensively applied ML techniques using a voting strategy to construct an ensemble model, which had better performance than individual classifiers in rockburst prediction. Liang et al. [26] compared five ensemble models based on DT for forecasting short-term rockburst. They found that the RF was the optimal model. Liang et al. [27] utilized weighting voting to combine six intelligent techniques to forecast short-term rockburst. The capacity of the comprehensive combined model was better than that of the base classifiers. Yin et al. [28] used stacking to integrate KNN, SVM, deep neural networks, and recurrent neural networks for rockburst prediction. The ensemble model

that adopted KNN and RNN performed best in all ensemble models. Although these ensemble models show a high level of prediction accuracy, some practical problems [27,28] prevent them from being widely used.

- (1) Ensemble models are easy to overfit. For obtaining higher prediction accuracy, ensemble models, such as RF, become complex, which makes generalization of the model poor [13].
- (2) The selection of a base classifier and combination strategy is difficult [25,27–29]. Different problems require different combined strategies, there should be a difference between the base classifiers, and it is necessary to choose the combination strategy and base classifier. Otherwise, performance cannot improve.
- (3) Many hyperparameters need to be tuned. The parameter setting of the ensemble model has a significant effect on the capacity.

To address the above limitations, this study proposed a novel methodology, the deep forest model, for rockburst prediction. Motivated by the theory behind deep neural networks and ensemble models, Zhou et al. [30] proposed the deep forest (DF), which combines the characteristics of deep learning models and ensemble models. DF can deal with more complex problems such as deep learning models. However, it has fewer parameters to work with than deep learning models. The DF model is easy to use, and its complexity can be determined according to the data, which can effectively prevent overfitting. The DF model is suitable for small data sets. Through validation by different data in different fields, the DF model still performs better even if it adopts the default parameter configuration. It is meaningful to build the more powerful and robust intelligent model by DF model to predict and prevent rockburst.

Additionally, Bayesian optimization (BO) is applied for optimizing hyperparameters of DF. BO has been widely used in hyperparametric optimization in different ML studies (e.g., [31–33]). BO differs from other optimization algorithms, and it is a useful model for problems that are expensive to conduct. BO constructs a probabilistic model of the objective function to be optimized and then applies the probabilistic model to determine the next point to be evaluated [34]. BO has been increasingly applied to geotechnical engineering [31,35–37].

The structure of this study is as follows: the ‘Methodology’ section introduces the theory and composition of DF and BO. The ‘Data’ section presents the source and statistical description of the rockburst database. The ‘Simulation’ exhibits how to construct and optimize the DF model for rockburst prediction. In the ‘Discussion’ section, the capability of DF to predict rockburst is evaluated. Furthermore, the influence of variables on rockburst intensities is analyzed by sensitivity analysis. Finally, the DF is applied to forecast the rockburst in practical engineering.

2. Methodology

2.1. DF

Zhou et al. [38] presented the gcForest to build the DF model, which consists of the cascade forest and multi-grained scanning. When the gcForest addresses sequence or image-style data, it needs multi-grained scanning. The rockburst data does not have spatial or sequential relationships in this study, so the multi-grained scanning structure in gcForest is abandoned.

RF and complete random forest (CRF) are the base classifiers in the DF model. The RF is an ensemble model composed of K decision trees $\{h(X, \theta_k), k = 1, \dots, K\}$, where θ_k is a random vector that satisfies independent identically distributed [39]. Figure 1 shows flowchart to build RF.

Figure 1. The flowchart to establish RF model.

Similarly, CRF randomly selects a feature for split, and the others are the same as the process of RF. As shown in Figure 2, the RF and CRF are implemented to construct cascade layers. The input features are input to the first cascade layer. After all this, the output of the previous cascade layer and the input features are input to the next layer. At this step, the training set is divided into a growing set and an estimating set. When the cascade forest increases by one layer, the estimating set tests the whole generated DF model. If the performance of the estimating set is lower than that of the previous layer, the DF model stops growing, and the cascade layer does not increase. In the last layer, the average of all the output probability vectors is calculated, and the label with the maximum probability is output as the prediction result. When the cascade layer does not increase, the DF model is retained based on the whole training set. The structure of the DF model is automatically determined, which reduces the risk of overfitting.

Figure 2. Schematic diagram of cascade forest.

2.2. BO

BO is appropriate for tasks with expensive evaluation costs [40]. BO consists of two parts, the surrogate model and the acquisition function [41]. The Gaussian process (GP) [42] is the most extensively applied surrogate model in BO due to its flexibility and tractability [40]. BO has three basic acquisition functions (AF), which are the probability of improvement [43], expected improvement [44,45], and upper/lower confidence bound. It is vital to choose an appropriate acquisition function to match the surrogate model. GP-Hedge is proposed to select an appropriate AF in each iteration, and detailed information about GP-Hedge can be found in previous studies [46].

3. Data

3.1. Data Collection and Description

The database, including 329 real rockburst cases worldwide, was established, as shown in Table 2. According to the criteria for the classification of rockburst in Table 3, rockburst levels can be grouped into four categories: none (53 cases), light (101 cases), moderate (119 cases), and strong (56 cases). In the collected database (Supplementary Materials), the number of light and moderate rockbursts is greater than that of none and strong rockbursts.

Rockburst often occurs on the excavation face in deep underground construction, it is induced by the sudden release of strain energy stored in the rock mass, and the most common phenomenon is strain burst. Rockburst mechanisms are complicated [47], and it is connected with stress in the earth's crust, rock property, rock mass structure, groundwater, and so on [48]. In this study, seven factors, including maximum tangential stress (σ_θ), uniaxial compressive strength (σ_c), tensile strength (σ_t), elastic strain energy index (W_{et}), stress concentration factor (SCF or σ_θ/σ_c), rock brittleness index B_1 ($B_1 = \sigma_c/\sigma_t$), and rock brittleness index B_2 ($B_2 = (\sigma_c - \sigma_t)/(\sigma_c + \sigma_t)$), are adopted as the input variables in the DF

model [13,28]. Table 4 displays the statistical description of the four rockburst intensities. Pearson correlation coefficients (Equation (1)) between variables are calculated, as shown in Figure 3. Figure 4 exhibits the boxplots and histograms of the seven input variables of four rockburst intensities. The boxplots are not symmetrical, there are many points outside the upper and lower whiskers of boxplots, and the collected database does not satisfy a normal distribution.

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (1)$$

Table 2. The database source.

No.	Number of Cases	Reference
1	N (43 cases), L (78 cases), M (81 cases), S (44 cases)	Zhou et al. [13]
2	L (1 case), M (11 cases)	Pu et al. [49]
3	N (3 cases), L (4 cases), M (8 cases), S (1 case)	Liu et al. [50]
4	N (3 cases), L (7 cases), M (7 cases), S (3 cases)	Xue et al. [51]
5	L (1 case), M (5 cases), Strong (1 case)	Wu et al. [52]
6	N (1 case), L (2 cases), S (4 cases)	Du et al. [53]
7	L (3 cases), M (3 cases)	Jia et al. [54]
8	N (3 cases), L (5 cases), M (4 cases), S (3 cases)	Xue et al. [55]
Sum	N (53 cases), L (101 cases), M (119 cases), S (56 cases)	329 cases

Table 3. Standard of classification for four intensities of rockburst [48].

Rockburst Label	Failure Characteristics
None	No sound of rockburst and rockburst activities.
Light	The surrounding rock is spalled, cracked, or striped, and there is no ejection phenomenon and a weak sound.
Moderate	The surrounding rock is deformed and fractured, and there is a considerable number of rock chip ejection, loose and sudden destruction, accompanied by crisp crackling, and often presented in the local cavern of surrounding rock.
Strong	The surrounding rocks are severely bursted and suddenly thrown or shot into the tunnel, accompanied by strong bursts and roaring sounds, air jets, the continuity of storm phenomena, and the rapid expansion into deep surrounding rocks.

Table 4. Statistical description of the input parameters.

Grade	Statistical Indicators	σ_θ	σ_c	σ_t	SCF	B_1	B_2	W_{et}
None	Mean value	25.27	101.96	5.98	0.30	21.08	0.87	2.78
	Standard deviation	16.32	49.39	3.90	0.25	12.72	0.07	1.94
	Min value	2.60	20.00	0.40	0.05	5.38	0.69	0.81
	25th percentiles	12.30	67.40	3.00	0.13	10.75	0.83	1.50
	50th percentiles	21.50	96.41	5.00	0.21	18.75	0.90	2.04
	75th percentiles	31.20	123.60	7.60	0.31	29.40	0.93	3.60
	Max value	77.69	241.00	17.66	1.05	47.93	1.00	7.80

Table 4. Cont.

Grade	Statistical Indicators	σ_θ	σ_c	σ_t	SCF	B_1	B_2	W_{et}
Light	Mean value	44.42	116.64	6.68	0.41	21.53	0.89	3.72
	Standard deviation	20.63	39.56	3.91	0.19	10.12	0.07	1.54
	Min value	13.50	30.00	1.90	0.10	2.52	0.43	0.85
	25th percentiles	29.70	88.00	3.60	0.26	12.70	0.85	2.53
	50th percentiles	43.21	117.00	5.90	0.38	23.60	0.92	3.20
	75th percentiles	57.97	142.00	8.95	0.56	28.10	0.93	4.61
	Max value	126.72	263.00	22.60	0.90	69.69	0.97	9.00
	Mean value	44.42	116.64	6.68	0.41	21.53	0.89	3.72
Moderate	Mean value	51.50	116.58	6.12	0.47	25.20	0.90	5.06
	Standard deviation	22.91	43.03	3.80	0.20	16.34	0.05	2.69
	Min value	13.02	30.00	1.30	0.10	0.15	0.69	1.20
	25th percentiles	37.15	84.30	2.98	0.34	15.02	0.87	3.66
	50th percentiles	51.50	112.50	5.26	0.47	21.69	0.91	5.00
	75th percentiles	65.84	147.53	8.30	0.59	27.76	0.93	5.91
	Max value	118.77	237.20	17.66	1.27	80.00	0.98	21.00
	Mean value	51.50	116.58	6.12	0.47	25.20	0.90	5.06
Strong	Mean value	119.65	129.08	10.34	1.18	14.12	0.85	8.91
	Standard deviation	83.11	52.37	4.67	1.17	5.94	0.06	6.02
	Min value	16.43	30.00	2.50	0.10	5.53	0.69	2.03
	25th percentiles	61.98	91.30	7.04	0.53	11.16	0.84	5.86
	50th percentiles	91.37	127.09	10.27	0.72	13.27	0.86	7.20
	75th percentiles	126.71	158.60	13.86	0.97	16.84	0.89	9.03
	Max value	297.80	304.20	22.60	4.87	32.20	0.94	30.00
	Mean value	119.65	129.08	10.34	1.18	14.12	0.85	8.91

Figure 3. The heatmap of correlations between different variables.

Figure 4. Boxplots and histograms of the seven variables of four rockburst intensities.

3.2. Step-by-Step Study Flowchart

The database is divided into a training set (Tr) and a testing set (Te) according to three split ratios, Tr (75%)-Te (25%), Tr (80%)-Te (20%), and Tr (85%)-Te (15%). Z-score (Equation (2)) is utilized to process the input parameters. As shown in Figure 5, the training part is applied to build the DF model for rockburst estimation. BO is implemented to tune the hyperparameters of the DF. 5 fold cross-validation is implemented to choose the optimized DF model. The permutation feature importance algorithm and partial dependence plots are introduced to interpret the DF model. A sensitivity analysis is employed to analyze effective variables on rockburst intensities and the robustness of the DF model. Finally, the intelligent model is applied to foretell rockburst in practical engineering.

$$X' = \frac{X - \bar{X}}{\sigma} \quad (2)$$

In Equation (2), $\bar{X}$ depicts the average value and σ represents the standard deviation.

Figure 5. The flowchart to develop DF model for rockburst prediction.

4. Simulation

4.1. Model Metrics

Accuracy is often used as the metric index in the ML classification problem. Equation (3) shows the equation to calculate accuracy. According to the actual label and the predicted

label, the sample can be divided into true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). The sum of the samples = TP + FP + TN + FN. According to these, the precision and recall can be calculated, as shown in Equations (4) and (5). In precision and recall, usually, when one is higher, the other is lower. In order to integrate precision and recall, their harmonically average value, i.e., f_1 , is usually taken (Equation (6)). Additionally, a receiver operating characteristic (ROC) curve is introduced to evaluate the capability of single rockburst types. The area under the ROC curve is between 0 and 1. A larger area of the ROC curve indicates a better prediction effect of the model.

$$Accuracy = \frac{n'}{n} \quad (3)$$

$$precision = \frac{TP}{TP + FP} \quad (4)$$

$$recall = \frac{TP}{TP + FN} \quad (5)$$

$$f_1 = \frac{2 \times precision \times recall}{precision + recall} \quad (6)$$

In Equation (3), n represents the number of all datasets, and n' stands for the number of instances of which the predicted labels are equal to actual labels.

4.2. Cross-Validation

When the hyperparameters of ML models are optimized, the generalization of the model needs to be evaluated to select the optimal model. K fold cross-validation is often adopted in model evaluation. In cross-validation, k is usually set to 10 or 5 [56]. In this study, k was set to 5 by referring to a previous study [25] to reduce the running time. As shown in Figure 6, the training set is divided into five pieces of data equal to each other, four pieces of data are selected to train each time, and the remaining piece of data is used for validation. The process is repeated five times, and finally, the average value of the five validation scores is taken.

Figure 6. The steps to perform 5 fold CV.

4.3. DF Optimization

σ_θ , σ_c , σ_t , SCF , B_1 , B_2 , and W_{et} were input to the DF to develop a rockburst prediction model. The cascade layers in the DF can be automatically determined according to the training set. The number of forests, the trees in each forest, and the maximum number of cascade layers are the key parameters that influence the performance of DF. Referring to previous studies by Zhou et al. [30], the optimization range of these hyperparameters was determined, as shown in Table 5.

Table 5. The optimization range of hyperparameters in the DF model.

Hyperparameters	Optimization Range
The number of forests	(1, 4)
The trees in the forest	(10, 100)
The maximum number of cascade layers	(10, 30)

BO was implemented to optimize the hyperparameters of the DF to choose an optimal model. Before performing BO, the objective function needed to be defined, and BO was utilized to optimize this objective function. The cross-entropy loss function is commonly used for classification problems in ML areas, as shown in Equation (7). The smaller the value is, the better the capability of the model. To improve the generalization of the DF model, the cross-entropy loss function in 5 fold cross-validation was chosen as the objective function, as shown in Equation (8).

$$loss = -\frac{1}{n} \sum_{i=1}^n \log p_{\text{model}}[y_i \in C_{y_i}] \quad (7)$$

$$\text{Objective_function} = \frac{1}{5} \sum_{i=1}^5 loss_i \quad (8)$$

In Equation (7), $p_{\text{model}}[y_i \in C_{y_i}]$ is the prediction probability in the actual label. Equation (8) means that the training set is split into five folds, four folds are applied to train the DF model, and the cross-entropy loss function of the DF on the remaining one fold is calculated. Repeating the process five times, the average value of the cross-entropy loss function is chosen as the objective function.

BO was performed using *Scikit-Optimize*, an open-source *Python* library [57]. The parameters of BO utilized the default value of *Scikit-Optimize*. Table 6 lists the values of hyperparameters in BO in this study. Gaussian process was chosen as the surrogate model, and GP-Hedge was selected as the acquisition function. Figure 7 exhibits the flowchart in which BO tunes the hyperparameters of the DF model. In the BO process, GP-Hedge determines the following points that need to be evaluated. The DF model trains according to the hyperparameter value recommended by the GP-Hedge. After the DF is built, the objective function is calculated, and the GP model is updated. By repeating this process N times, the optimal hyperparameters can be obtained. Figure 8 exhibits the convergence of the objective function with the process of BO. BO can efficiently minimize the objective function to find the optimal DF model. Table 7 shows the optimal hyperparameters of the DF model with different training sets at the end of BO.

Table 6. The parameters of BO.

Surrogate Model	Acquisition Function	Surrogate Model Hyperparameters
GP	GP-Hedge	1. Kernel function: Matern Kernel and White Kernel 2. Noise: Gaussian distribution

Table 7. The optimal hyperparameters in the DF model.

Datasets	Hyperparameters	Value
Tr (75%)-Te (25%)	The number of forests	4
	The trees in the forest	36
	The maximum number of cascade layers	30
Tr (80%)-Te (20%)	The number of forests	4
	The trees in the forest	18
	The maximum number of cascade layers	19
Tr (85%)-Te (15%)	The number of forests	4
	The trees in the forest	25
	The maximum number of cascade layers	25

Figure 7. The flowchart of BO.

Figure 8. Convergence of objective function during BO.

4.4. Results

The optimized DF models with different training sets were obtained according to Table 7, and in three different training sets, the training accuracies of DF models were 100%. The remaining three testing sets were adopted to evaluate the capability of DF models. Tables 8–10 present the performances of DF models on the different testing sets. The three DF models developed by different training datasets had the same capabilities in predicting strong rockburst. In terms of testing accuracy, the DF model with Tr (80%)-Te (20%) has the best capacity. Accordingly, it is appropriate to develop DF models to predict rockburst by 80% training set and 20% testing set.

Table 8. The testing performance of DF models with Tr (75%)-Te (25%).

Rockburst Type	Precision	Recall	f_1	Number
None	0.86	0.92	0.89	13
Light	0.95	0.76	0.84	25
Moderate	0.88	1.00	0.94	30
Strong	1.00	1.00	1.00	14
Accuracy		91.5%		82

Table 9. The testing performance of DF models with Tr (80%)-Te (20%).

Rockburst Type	Precision	Recall	f_1	Number
None	0.91	0.91	0.91	11
Light	0.94	0.80	0.86	20
Moderate	0.89	1.00	0.94	24
Strong	1.00	1.00	1.00	11
Accuracy		92.4%		66

Table 10. The testing performance of DF models with Tr (85%)-Te (15%).

Rockburst Type	Precision	Recall	f_1	Number
None	1.00	0.88	0.93	8
Light	0.92	0.80	0.86	15
Moderate	0.86	1.00	0.92	18
Strong	1.00	1.00	1.00	8
Accuracy		91.8%		49

5. Discussion

5.1. Model Performance Comparison

DF model consists of RF and CRF, and to analyze the advantages of DF compared to its base classifiers, RF and CRF are also independently built with the same hyperparameters (Tr (80%)-Te (20%)) in Table 7. The training accuracy in RF and CRF was 100% and 99.6%, respectively, and Tables 11 and 12 display the testing performance of RF and CRF, respectively. According to Table 9, the DF has higher testing accuracy than RF and CRF, which reveals that model combination can improve the capability for predicting rockburst. The ROC curve is introduced to compare the performance of each rockburst intensity in DF, RF, and CRF. Figure 9 exhibits the ROC curves of the four rockburst intensities in DF, RF, and CRF. The larger area of the ROC curve is associated with better model performance. DF, RF, and CRF perform similarly in terms of strong rockburst prediction, but DF outperforms RF and CRF in terms of none, light, and moderate rockburst prediction.

Table 11. The testing performance of the RF model.

Rockburst Type	Precision	Recall	f_1	Number
None	0.75	0.82	0.78	11
Light	0.74	0.85	0.79	20
Moderate	0.95	0.83	0.89	24
Strong	1.00	0.91	0.95	11
Accuracy		84.8%		66

Table 12. The testing performance of the CRF model.

Rockburst Type	Precision	Recall	f_1	Number
None	0.75	0.82	0.78	11
Light	0.75	0.75	0.75	20
Moderate	0.84	0.88	0.86	24
Strong	1.00	0.82	0.90	11
Accuracy		81.8%		66

Additionally, to explore the power of the DF model, widely used ML models were also developed in this study, and they included LR, Naive Bayes, KNN, SVM, DT, adaptive boosting (AdaBoost), ANN, XGB, and GBM. XGB was built using the default parameters in *XGBoost* (a *Python* library) [51], and other models used the *Scikit-learn* [52] default parameters. Training set (80%) was applied to develop these models, and testing set (20%) was adopted to evaluate these models. Figure 10 displays the training and testing accuracy of these models. The DT suffers from serious overfitting, and its performance differs markedly between the training and testing sets. Many ensemble tree models, i.e., GBM, XGB, and RF, perform better than other ML models. Taylor diagrams [58,59] were introduced to determine the strength of the DF model compared to other models. In this study, Taylor diagrams combine the Matthews correlation coefficient (MCC), centered root mean square error (green dotted lines in Figure 11), and standard deviation into a polar diagram. Equation (9) shows the equation to calculate MCC. The reference points with black star shapes depict the actual rockburst, and when other points are closer to

the reference points, the corresponding models have better performance in predicting rockburst. It is worth noting that the DF model outperforms other commonly used tree models in the training and testing sets, according to Figure 11.

Figure 9. Model performance comparison in each rockburst by ROC curve.

Figure 10. Training and testing results of the developed models. (a) Training accuracy; (b) Testing accuracy.

Figure 11. Taylor diagrams for comparing the performance of developed models. (a) Training results; (b) Testing results.

Additionally, Table 13 compares the capabilities of DF and some intelligent models proposed by other scholars in recent years, and the DF model has better performance than other models during training and testing phases. The results reveal that the DF model is a powerful technique to forecast and prevent rockburst.

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (9)$$

Table 13. Comparison of DF and other ML models proposed in recent years.

Algorithm/Model	Input Parameters	Data Size	Accuracy	
			Training	Testing
Voting model [25]	$H, \sigma_\theta, \sigma_c, \sigma_t, W_{et}$	188	94%	80%
PSO-ELM [55]	$\sigma_\theta, \sigma_c, \sigma_t, SCF, B_1, W_{et}$	344	98.99%	88.89%
Bagging [23]	$\sigma_\theta, \sigma_c, \sigma_t, SCF, B_1, W_{et}$	102	100%	88.24%
Boosting [23]	$\sigma_\theta, \sigma_c, \sigma_t, SCF, B_1, W_{et}$	102	100%	91.18%
Stacking model [28]	$\sigma_\theta, \sigma_c, \sigma_t, SCF, B_1, B_2, W_{et}$	246		88.52%
DF	$\sigma_\theta, \sigma_c, \sigma_t, SCF, B_1, B_2, W_{et}$	329	100%	92.40%

Note: Voting model is the combination of back propagation neural network, KNN, SVM, LR, linear model, DT, and Naive Bayes; H = depth; POS = particle swarm optimization; ELM = extreme learning machine; stacking model is the combination of KNN, SVM, deep neural network, and recurrent neural network.

5.2. Sensitivity Analysis

The permutation feature importance was implemented to determine crucial variables that affected rockburst in the DF model. The permutation feature importance was beneficial for analyzing the relative importance of input variables in nonlinear or opaque ML models [60], and it is introduced to determine the importance score of input parameters. Figure 12 shows the importance score of the input parameters in the DF model. According to this Figure 12, σ_θ , W_{et} , and SCF are the vital parameters that influence the performance of rockburst prediction.

Figure 12. The relative importance of input variables in the DF model.

To determine the impact of parameters on the rockburst levels, partial dependence plots (PDP) [61] were introduced to analyze the relationship between variables and predicted results of the DF model, as shown in Figure 13. The PDP displays the dependence of the predicted probability of different rockburst levels on the variable of interest when other variables are fixed. With the increase of σ_θ , W_{et} , and SCF , the predicted probability of a strong rockburst increases, and the predicted probability of a none rockburst decreases. There is no apparent relationship between the other variables and the predicted probability of rockburst in the DF model. These results indicate that larger σ_θ , W_{et} , and SCF values are accompanied by more serious rockburst. Accordingly, it is vital to reduce the σ_θ , W_{et} , and SCF of surrounding rock in underground engineering to mitigate the rockburst risk. Some measures, such as smooth blasting, pressure relief blasting, and deformable bolts and mesh, can be applied to prevent rockburst on-site [62].

The key parameters affecting rockburst intensities are determined, which makes it possible to analyze the performance variation of the DF model under different influential variables. According to the relative importance of the input variables, seven models that adopted different input parameters were developed, as shown in Table 14. These seven models adopted the same hyperparameters (Tr (80%)-Te (20%)) in Table 7. Figure 14 displays the variations of training and testing accuracy with the input variable number varying. With the decrease of input parameters, DF has low accuracy, which suggests that considering more factors is beneficial to improving the generalization of DF and predicting and preventing rockburst due to the complexity of rockburst. Additionally, with only three input parameters, the testing accuracy of the DF model is still 81.82%, which indicates that the DF model has good robustness and is suitable for fewer input parameters.

Figure 13. PDP to analyze the influence of variables on the rockburst predicted probability. (a) σ_{θ} ; (b) σ_c ; (c) σ_t ; (d) SCF ; (e) B_1 ; (f) B_2 ; (g) W_{et} .

Table 14. Seven models and their input parameters.

Model	Input Parameters	Input Parameters Number
M 1	$\sigma_{\theta}, \sigma_c, \sigma_t, SCF, B_1, B_2, W_{et}$	7
M 2	$\sigma_{\theta}, \sigma_c, SCF, B_1, B_2, W_{et}$	6
M 3	$\sigma_{\theta}, SCF, B_1, B_2, W_{et}$	5
M 4	$\sigma_{\theta}, SCF, B_1, W_{et}$	4
M 5	$\sigma_{\theta}, SCF, W_{et}$	3
M 6	σ_{θ}, W_{et}	2
M 7	σ_{θ}	1

Figure 14. Model performance variation with the input parameters variation.

5.3. Engineering Validation

Xincheng Gold Mine and Sanshangao Gold Mine are located in Yantai, Shandong, China. Figure 15 presents their locations. After years of mining production, the two gold mines have become mines with a mining depth of more than 1000 m in China. To meet production needs, it is necessary to excavate ores in deeper strata. Due to the complexity of deep high stress and geological conditions, many engineering problems are inevitably faced in deep mining operations, among which rockburst poses a severe threat to the safety of facilities and workers. A series of field investigations and rock mechanics tests were carried out in the two gold mines to avoid the threat of rockburst to shaft construction. Seven rock blocks were taken in different locations in the Xincheng Gold Mine, and five rock blocks were taken in the Sanshandao Gold Mine. These rock blocks were processed into standard specimens for rock mechanics tests and in-situ stress analysis [63]. Table 15 presents the rock parameters used to foretell rockburst. According to the standard of classification for intensities of rockburst in Table 3, the rockburst level of each site was determined. The DF model was used to evaluate the rockburst, and Table 15 shows the predicted results. The predicted results of the DF model are consistent with the actual rockburst situation. These results suggest that the DF model has superior engineering practicability.

Table 15. Application of DF model in practical engineering.

No.	Engineering	σ_θ/MPa	σ_c/MPa	σ_t/MPa	SCF	B_1	B_2	W_{et}	Actual Grade	Predicted Grade
1	Xincheng Gold Mine	87.60	139.07	10.63	0.63	13.08	0.86	5.56	S	S
2		108.31	149.99	11.97	0.72	12.53	0.85	6.88	S	S
3		89.46	155.45	12.05	0.58	12.90	0.86	3.98	S	S
4		100.00	137.52	13.73	0.73	10.01	0.82	5.27	S	S
5		107.25	182.67	12.11	0.59	15.08	0.88	5.48	S	S
6		107.87	140.38	12.06	0.77	11.64	0.84	8.50	S	S
7		109.57	174.34	12.07	0.63	14.44	0.87	7.69	S	S
8	Sanshandao Gold Mine	94.64	160.94	9.74	0.59	16.52	0.89	4.94	M	M
9		32.45	138.25	9.04	0.23	15.29	0.88	3.73	L	L
10		23.13	146.29	19.6	0.16	7.46	0.76	6.45	N	N
11		34.12	154.28	13.98	0.22	11.04	0.83	4.61	L	L
12		34.07	128.5	11.71	0.27	10.97	0.83	1.92	N	N

Figure 15. The location of Xincheng Gold Mine and Sanshandao Gold Mine.

6. Limitations and Future Studies

Rockburst is a complex geological disaster that is related to many factors, such as geological structure, in-situ stress conditions, rock strength, excavation method, excavation size, etc. However, in this study, only seven related parameters were considered to build the intelligent model for rockburst prediction. Other parameters, such as rock quality index, rock integrity coefficient, and the geometric size of the cross-section of the excavation, are also essential to determine rockburst level. In the future, more influential factors should be considered to add to the database. Additionally, increasing the size of the database contributes to building a more powerful intelligent rockburst prediction model. As for the DF model, to apply DF to predict rockburst in different engineering problems, it is necessary to tune the hyperparameters of DF according to the size and complexity of data.

7. Conclusions

- (1) Deep forest, a novel tree-based ensemble model, was proposed to build the rockburst prediction model based on 329 collected real rockburst cases. Bayesian optimization was used to turn the hyperparameters of the DF. The DF had 100% accuracy in the training set and 92.4% accuracy in the testing set, and it performed better than other ML models and can forecast massive rockburst disasters.
- (2) σ_θ and W_{et} are the essential parameters that affect the performance of the DF model for rockburst prediction. Sensitivity analysis reveals that more factors can be taken into account to build a more accurate rockburst prediction model for the complexity of rockburst. Moreover, it also confirms that the proposed DF model has good performance with fewer input parameters.
- (3) A field investigation was carried out in the Xincheng Gold Mine and Sanshandao Gold mine, Shandong, China, and the collected rock blocks were tested in the laboratory. The obtained parameters were input into the trained DF model, and the predicted results matched the rockburst situation on site. The validation datasets from gold mines can expand the rockburst database to establish more powerful models.
- (4) The DF model is trained by the datasets from mines, tunnels, large underground chambers, traffic tunnels, etc., and it is validated by the cases from two gold mines.

Accordingly, it is worth noting that the proposed DF model is not only applied to gold mines with a high level of accuracy but also is suitable for other deep mine and underground excavation engineering.

Supplementary Materials: The collected rockburst database can be found be downloaded at: <https://www.mdpi.com/article/10.3390/math10050787/s1>, Table S1: Collected rockburst database.

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