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Intelligent Classification of Surrounding Rock of Tunnel Based on 10 Machine Learning Algorithms

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Abstract: The quality evaluation of the surrounding rock is the cornerstone of tunnel design and construction. Previous studies have confirmed the existence of a relationship between drilling parameters and the quality of surrounding rock. The application of drilling parameters to the intelligent classification of surrounding rock has the natural advantages of automatic information collection, real-time analysis, and no extra work. In this work, we attempt to establish the intelligent surrounding rock classification model and software system driven by drilling parameters. We collected 912 samples containing four drilling parameters (penetration velocity, hammer pressure, rotation pressure, and feed pressure) and three surrounding rock (grade-III, grade-IV, and grade-V). Based on the python machine learning toolkit (Scikit-learn), 10 types of supervised machine learning algorithms were used to train the intelligent surrounding rock classification model with the model parameter selection technology of grid search cross validation. The results show that the average accuracy is 0.82, which proves the feasibility of this method. Finally, the tunnel surrounding rock intelligent classification system was established based on three models with better comprehensive performance among them. The classification accuracy of the system was 0.87 in the tunnel test section, which indicates that the system has good generalization performance and practical value.

Keywords: drill and blast tunnel; machine learning; measure-while-drilling; drilling parameters; intelligent surrounding rock classification model

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1. Introduction

Unlike aboveground engineering, in tunnel engineering, tunnels are built underground. Tunnel design and construction are closely related to the stratum where it is buried. The quality evaluation of the surrounding rock is the cornerstone of tunnel design [1–3] and construction. Surrounding rock classification is a main evaluation method for the surrounding rock quality. It usually collects the information of surrounding rock by one or more means, and finally gives a comprehensive evaluation index based on specific rule. It can reflect the strength characteristics and deformation characteristics of the surrounding rock and stability characteristics of the tunnel face, and can be directly used to guide the tunnel design and construction. The classification of surrounding rock is a common method for the surrounding rock quality evaluation of tunnels in various countries. This method was started in Europe in 1774. After more than two hundred years of development, there have been hundreds of methods employed for this purpose, such as the Q-value method [4], the rock mass rating (RMR) method [5], and the surrounding rock basic quality index (BQ) method [6].

At present, the methods used to classify the rock surrounding tunnels are mainly qualitative, with quantitative verification using laboratory tests requiring extensive professional knowledge and engineering experience. Therefore, there is some randomness in the results. With the development of information technology, artificial intelligence, the Internet of Things, big data, and other technologies, the trend of tunnel construction automation and unmanned is becoming more and more obvious, and the intelligent classification of surrounding rock is the most important part. Thus, an automatic, rapid and accurate intelligent classification technology of surrounding rock is required for the construction of tunnel with high quality and high efficiency.

Machine learning is an important method of artificial intelligence research [7–9] that has been applied in many types of tunnel analyses, such as deformation prediction [10–14], prediction of energy consumption of cutter head drives [15], rock burst prediction [16], reliability analysis [17,18], stability analysis [19], optimization of blasting parameters [20], support pattern selection [21], the prediction of blast-induced ground vibrations [22], tunneling risk prediction and assessment [23,24], diagnosing tunnel collapse sections [25], and TBM tunneling construction and management [26–30]. Machine learning is also an important method in the intelligent classification of surrounding rock. The physical and mechanical parameters of rock mass have been applied to the RMR value prediction using a neural network [31,32]. These parameters include the bulk density, compressive strength, ingress of water, rock quality designation (RQD), average distance between leak, and seismic velocity. The prediction of RMR has also been realized by using a neuro-fuzzy inference system based on the uniaxial compressive strength, RQD, joint or discontinuity spacing, joint condition, and groundwater condition [33]. In addition, the geophysical parameters, such as the seismic velocity and resistivity [34,35], have been used to classify the surrounding rocks [36–38].

The machine learning algorithms used in these studies include a variety of single basic algorithms, optimization algorithms, and integrated algorithms. These previous studies all show that the appropriate machine learning algorithms have excellent performance in different fields when there is an internal connection between input index and output index and the number of samples is sufficient. Especially for the highly nonlinear problems, the machine learning method often has better performance and higher computational efficiency than traditional statistical analysis methods. More importantly, the machine learning methods have the intelligent characteristics of automatic analysis and continuous learning, which provides effective help for this study.

However, such methods generally require manual field testing of classification indices, such as rock strength and rock mass integrity, followed by manual input into the system. None of these parameters applied to the intelligent classification of surrounding rocks can achieve real-time automatic collection in the tunneling process.

The emergence of measure-while-drilling (MWD) technology provides a good solution to this problem. The correlation between the drilling parameters and the surrounding rock quality parameters was studied and explored by scholars as early as the 1960s and 1970s [39–43]. Using field experiments with statistical analysis, the correlations between drilling parameters and surrounding rock quality parameters, such as the uniaxial compressive strength [44–46], shear strength [47], Schmidt rebound hardness [48], cutting performance (Kerf angle d and specific energy) [49,50], RQD [51], and zones of volcanic weathering and decomposition grades [52] have been studied. In recent years, drilling parameters have been used for surrounding rock classification based on the Q method [53] or RMR method [54].

Although these previous studies have confirmed the existence of a relationship between drilling parameters and the quality of surrounding rock, the correlation based on current research of the drilling parameters and the surrounding rock quality parameters mostly refers to a certain lithology. Furthermore, the samples do not cover common rock lithology and are not universal. This is mainly because the use of an intelligent drill jumbo (which refers to a drill jumbo that can automatically collect and transmit drilling parameters) for tunnel construction is low, which makes it more difficult to collect sufficient drilling parameter samples for the surrounding rock classification. Thus, the classification method with more objective, intelligent, and efficient evaluation requires further study.

The purpose of this research is to introduce 10 machine learning algorithms to predict the quality of surrounding rock using MWD data (drilling parameters) obtained from five tunnels of the Zhengzhou–Wanzhou line of the high-speed railway project in China. Through comparative analysis, three machine learning models with better comprehensive performance among them were selected to establish the tunnel surrounding rock intelligent classification system by the drill and blast method. The results of this study lay a solid foundation for the dynamic design and intelligent construction of tunnels.

2. Materials and Methods

2.1. Proposed Methods and Procedures

In this study, we firstly collected sample data, and then conducted a range of data processing, including sample data cleaning, sample imbalance treatment, sample feature analysis, and sample data splitting. Finally, we trained some intelligent classification models of the surrounding rock, and selected the better of them.

The research flow chart about main procedures and proposed methods of this study is shown in Figure 1.

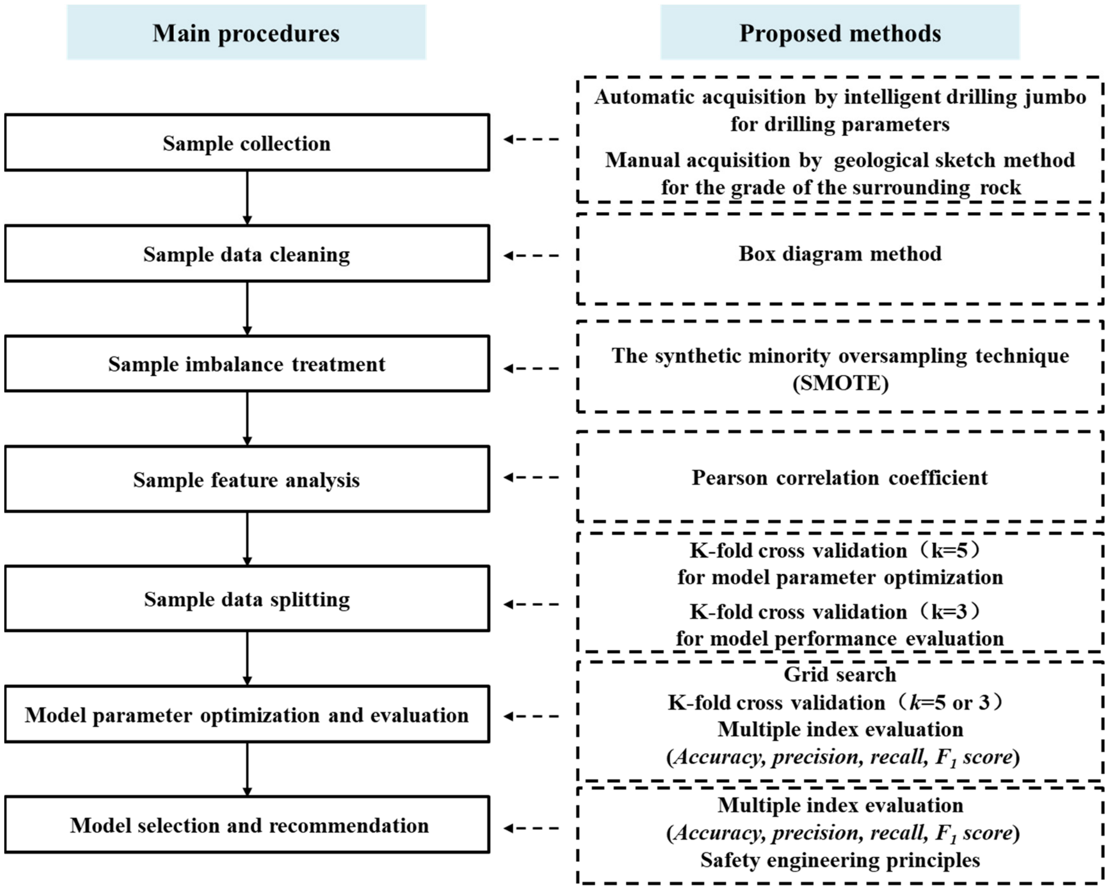


Figure 1. The research flow chart about main procedures and proposed methods.

2.2. Sample Collection

The sample of this study was obtained from some tunnels of the Zhengzhou–Wanzhou line of the high-speed railway project in China. This railway line runs from Zhengzhou East Railway Station to Wanzhou North Railway Station, with a total length of 818 km. It has 18 stations and a designed speed of 350 km/h, which connects Henan province, Hubei province, and Chongqing province. There are 32.5 tunnels in the Hubei province section, with a total length of 167.6 km, and the lithologies of stratum exposed by these tunnels are mainly dolomite, sandstone, limestone, shale, and mudstone. As shown in Figure 2, the sample collection was carried out in five tunnels in the Hubei province section. The New Austrian Tunneling Method was employed in these tunnels.

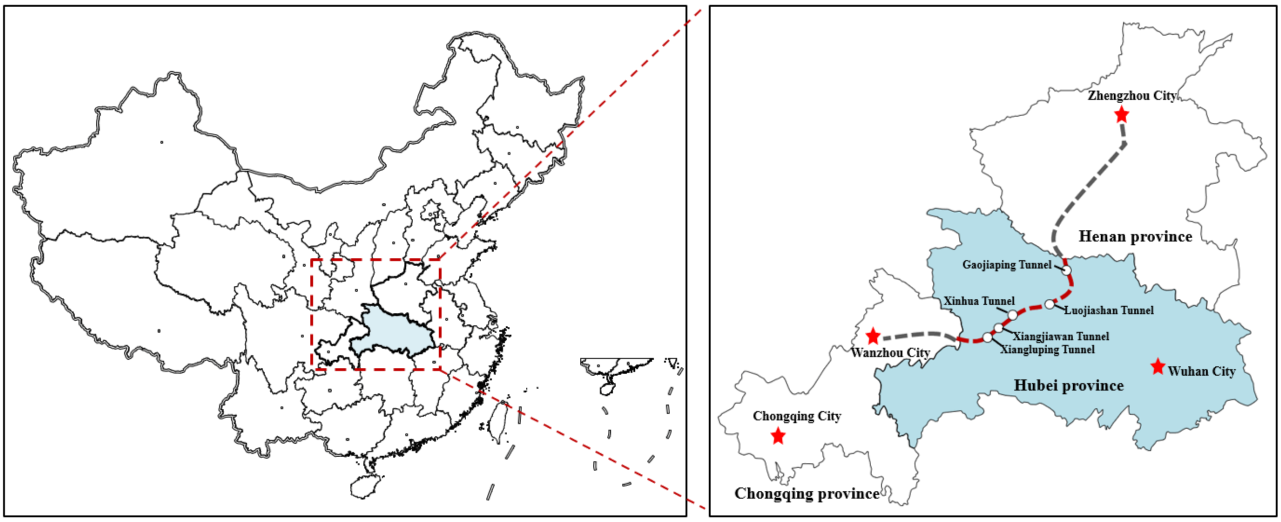


Figure 2. Locations of Zhengzhou–Wanzhou high-speed railway line and the tunnels where the samples were collected.

The sample of intelligent surrounding rock classification is composed of the drilling parameters and the surrounding rock grade of the tunnel face.

In this study, the drilling parameters were collected by using the intelligent drill jumbo (Figure 3), which was made by China Railway Construction Heavy Industry Corporation Limited.

Figure 3. Intelligent drill jumbo (made by China Railway Construction Heavy Industry Corporation Limited).

The intelligent drill jumbo has the functions of automatic positioning, automatic drilling and automatic recording of log. It can complete the drilling operation of pipe roof, anchor bolt and blast hole. In the process, the integrated sensors of the intelligent drill jumbo are used to automatically collect the drilling parameters (penetration velocity, hammer pressure, rotation pressure, and feed pressure) during the drilling of the borehole in the tunnel face.

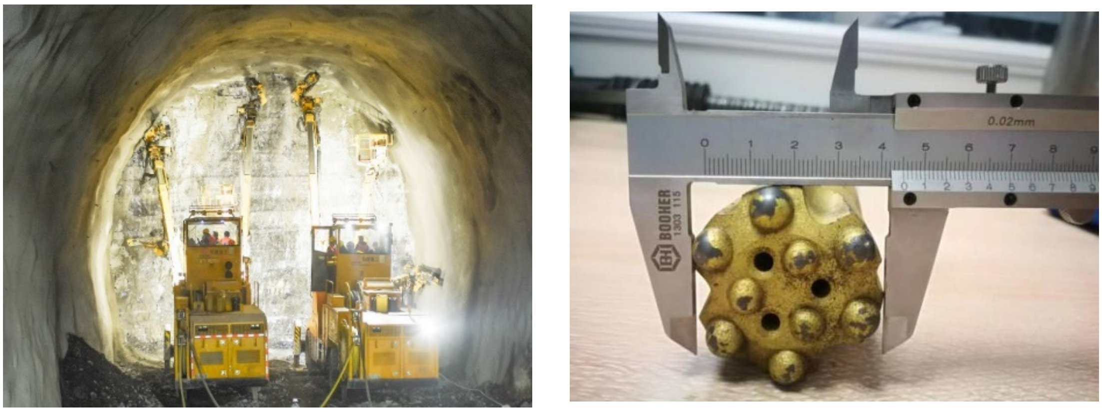
The drilling parameters are described below:

1. Penetration velocity (V_p, m/min): the rate of penetration of the drill bit through the rock mass.

2. Hammer pressure (P_h, bar): the measurement of the impact pressure of the bit against the rock mass.
3. Rotation pressure (P_r, bar): the pressure of the bit against the rock to maintain the required rotation.
4. Feed pressure (P_f, bar): the hydraulic pressure inside the cylinders required to keep the bit in contact with the bottom of the hole.

All of these parameters are recorded at equal depth intervals of 20 mm by the help of displacement transducer.

The drilling parameters data in this study were collected through the process of blasting hole drilling in the tunnel face (Figure 4a), and the bit used was a cemented carbide bit with a diamond content of 7%, spherical shape, and nine teeth (Figure 4b).



(**a**) (**b**)

Figure 4. Field collection of the drilling parameters. (**a**) Blasting hole drilling in the tunnel face; (**b**) the cemented carbide bit.

The area of the tunnel face is about 150 m^2, containing about 200~300 blasting holes. The value of each drilling parameter for each sample is the average of all the drilling holes in the tunnel face.

The typical layout of the blasting hole is shown in Figure 5.

The grade of the surrounding rock in this study is specified in the current Code for Design of Railway Tunnel (TB10003-2016). According to the degree of hardness, integrity, groundwater state, crustal stress state, and major weak structural surface, the surrounding rocks are divided into Grades I~VI according to the quality.

The approximate correspondence between the surrounding rock grade in this study and the indices of other classification methods, such as the Q method, RMR method, and BQ method, is shown in Table 1 [55].

Table 1. Approximate correspondence between the surrounding rock grade in this study and other indices (Q, RMR, and BQ).

Method	Surrounding Rock Grade				
	I	II	III	IV	V
Q value	(10,000,40)	(40,10)	(10,1)	(1,0.1)	(0.1,0.001)
RMR value	(100,80)	(80,60)	(60,40)	(40,20)	(20,0)
BQ value	(700,550)	(550,450)	(450,350)	(350,250)	(250,0)

Note: Grade-VI generally refers to the special geology, such as the powdery fault fracture zone, aeolian sand, and seriously collapsible loess.

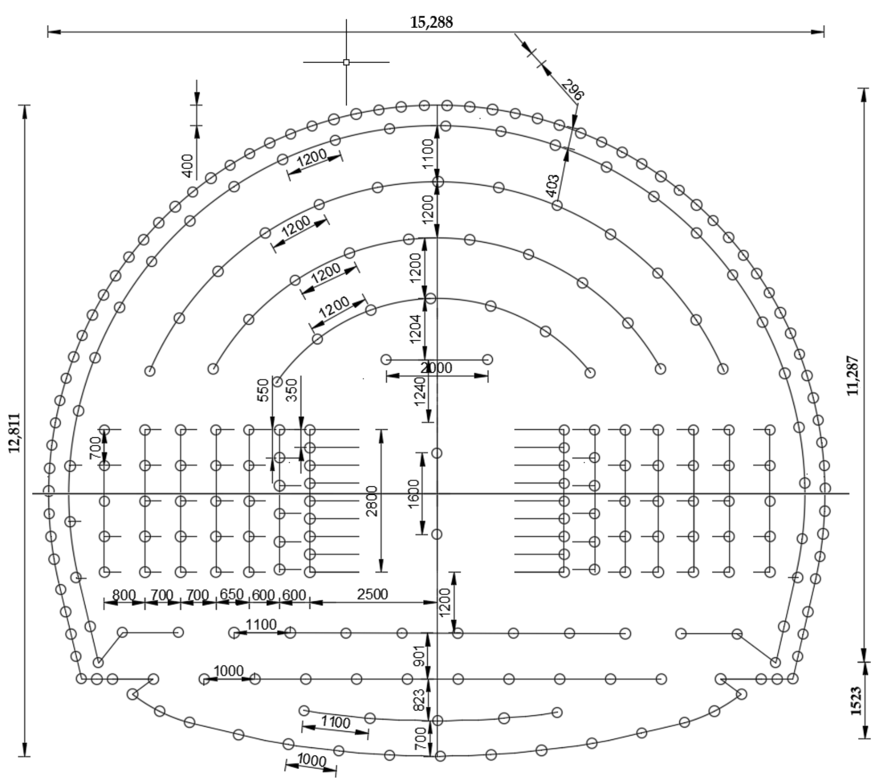


Figure 5. The typical layout of the blasting hole (mm).

The geological sketch method is usually adopted to determine the grade of the surrounding rock in the tunnel, which is analyzed and determined by professional geological engineers. The geological sketch record card of the tunnel face is shown in Table 2.

Table 2. Geological sketch record card of the tunnel face.

The Geological Sketch Record Card of Tunnel Face								
Project name: XXX Date: XXX			Mileage: XXX Construction unit: XXX					
No.	Item	State description						
1	Tunnel face and support type	Width (m)	Area (m^2)	Excavation method	Depth (m)	Advanced support	Primary support	Secondary lining
2	Lithology							
3	Weathering degree	Slightly		Weakly		Strongly		Totally
4	Degree of hardness (Mpa)	Extremely hard (>60)		Hard (30~60)	Relatively soft (15~30)		Soft (5~15)	Extremely soft (<5)
5	Number of structural surfaces	1		2		3		>3
6	Average spacing of the structural surface (m)	>1		0.4~1		0.2~0.4		0~0.2
7	Degree of structural surface development	Not developed		Relatively developed		Developed		Extremely developed
8	Crack width (mm)	0~1		1~3			>3	
9	Crack filling	None	Siliceous	Calcium		Argillaceous	Rock debris	Mud clamps rock debris

Table 2. *Cont.*

The Geological Sketch Record Card of Tunnel Face							
10	Degree of structural surface bonding	Good	Fair		Poor		Extremely poor
11	Integrity	Integrated	Relatively integrated	Relatively broken	Broken		Extremely broken
12	Groundwater state	None	Drip outflow		Linear outflow		Inrush outflow
13	The major weak structural surface	Occurrence			Angle with tunnel axis		
14	Crustal stress state	Low			High		Extremely high
15	Surrounding rock grade	I	II	III	IV	V	VI
	Tabulator: XXX				Reviewer: XXX		

By the method discussed above, 912 intelligent surrounding rock classification samples were collected in five tunnels of the Zhengzhou–Wanzhou high-speed railway. These samples cover three surrounding rock grades (grade-III, grade-IV, and grade-V) and five main lithologies (dolomite, sandstone, limestone, shale, and mudstone).

More details are shown in Table 3.

Table 3. Intelligent surrounding rock classification sample statistics.

Surrounding Rock Grade	Tunnel	Lithology	Sample Size	Total
III	Luojiashan Tunnel	Dolomite	110	325
	Chufeng Tunnel	Dolomite	28	
	Xinhua Tunnel	Sandstone	31	
	Xiangjiawang Tunnel	Limestone	156	
IV	Gaojiaping Tunnel	Shale/Sandstone	105	420
	Luojiashan Tunnel	Dolomite	75	
	Chufeng Tunnel	Dolomite	44	
	Xinhua Tunnel	Sandstone	125	
	Xiangjiawang Tunnel	Limestone	30	
	Xiangluping Tunnel	Mudstone/Sandstone	41	
V	Gaojiaping Tunnel	Shale	84	167
	Luojiashan Tunnel	Dolomite	62	
	Chufeng Tunnel	Dolomite	4	
	Xinhua Tunnel	Dolomite	15	
	Xiangjiawan Tunnel	Limestone	2	
Total				912

2.3. Sample Data Cleaning

To analyze the sample data outliers, four box diagrams are shown in Figure 6 according to the drilling parameter class and surrounding rock grade.

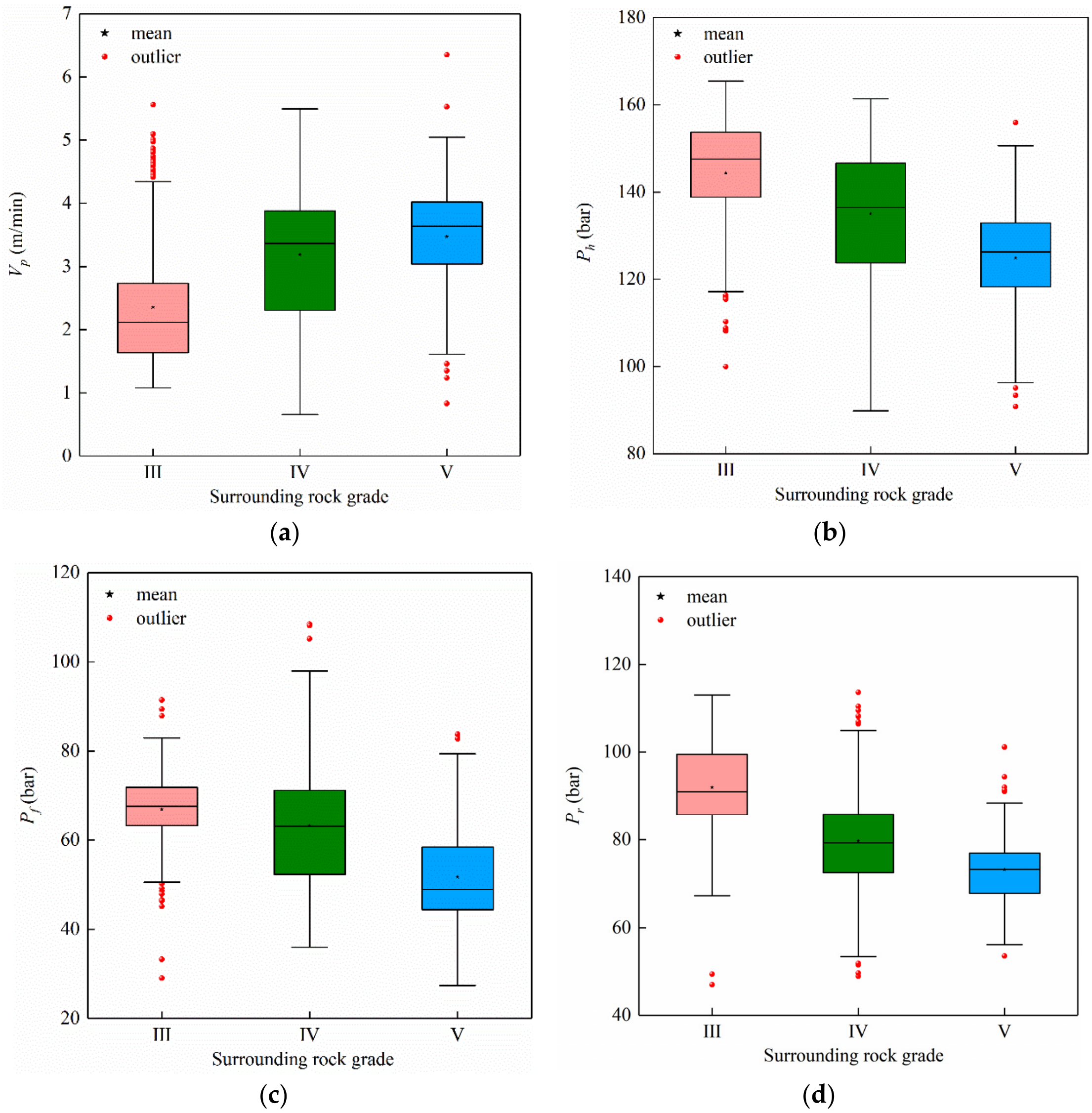


Figure 6. Drilling parameter box diagrams for each surrounding rock grade. (**a**) Penetration velocity (V_p, m/min); (**b**) hammer pressure (P_h, bar); (**c**) feed pressure (P_f, bar); (**d**) rotation pressure (P_r, bar).

According to the box diagram method, when the value is not within the interval represented by the following formula Equation (1), it is regarded as an outlier

$$[\text{Q1} - 1.5 \times \text{IQR}, \text{Q3} + 1.5 \times \text{IQR}] \tag{1}$$

where Q1 is the first quartile, namely the equal to the 25th percentile of all values in the sample from small to large, Q3 is the third quartile, namely the equal to the 75th percentile of all values in the sample from small to large, IQR is the interquartile range, namely IQR is equal to Q3 minus Q1.

In Figure 6, under different surrounding rock grades, all four drilling parameters contained outliers. To eliminate the effects of the outliers, the average value of each parameter was used to replace the outlier of each surrounding rock in this study.

The changes in data characteristics before and after cleaning are compared in Table 4.

Table 4. Comparison of the data characteristics before and after cleaning.

Surrounding Rock Grade	Index	V_p		P_h		P_f		P_r	
		Before	After	Before	After	Before	After	Before	After
III	mean	2.35	2.04	144.32	148.85	66.95	67.69	91.91	92.18
	std	0.97	0.51	12.59	5.98	8.02	5.91	10.29	9.69
	min	1.08	1.08	99.95	132.88	29.05	53.70	46.94	67.27
	max	5.56	3.39	165.41	165.41	91.45	81.44	112.97	112.97
IV	mean	3.19	3.19	135.06	135.06	63.17	62.86	79.68	79.25
	std	1.03	1.03	14.00	14.00	13.21	12.67	11.24	9.59
	min	0.66	0.66	89.79	89.79	35.97	35.97	48.84	55.38
	max	5.49	5.49	161.38	161.38	107.41	97.95	113.53	102.29
V	mean	3.47	3.54	124.96	125.87	51.75	50.72	73.18	72.62
	std	0.85	0.67	11.68	9.85	11.06	9.59	7.59	5.65
	min	0.83	1.97	90.82	101.39	27.43	27.43	53.47	57.70
	max	6.35	5.05	155.88	150.65	83.75	73.60	101.17	86.72

Note: The full name of each index and corresponding abbreviated in the table is the mean value (mean), the standard deviations (std), the minimum value (min) and the maximum value (max).

In Table 4, after cleaning, under different surrounding rock grades, the distributions of these drilling parameters are more centralized. Specifically, the maximum value is smaller, the minimum value is larger, and the standard deviation is smaller.

2.4. Sample Imbalance Treatment

Referring to machine learning classification, when the difference in the number of samples of all the classes is too large, the training model will pay too much attention to the sample characteristics with a greater proportion, so the classification effect of the samples with a smaller proportion is not ideal. This is called the problem of sample imbalance.

These data sets cover three classes of surrounding rock (namely, grade-III, -IV, and -V), and each class contains 325, 420, and 167 samples belonging to the imbalance sample set.

There are three common approaches to deal with unbalanced samples in machine learning:

1. Over-sampling

The over-sampling method achieves sample balance by increasing the number of minority samples in the classification. The most direct method is to simply copy the minority samples to form multiple records. The improved over-sampling methods produce new composite samples by adding random noise, interference data to a few classes, or certain rules such as the synthetic minority over-sampling technique (SMOTE) and adaptive synthetic sampling (ADASYN).

2. Under-sampling

The under-sampling method achieves sample balance by reducing the number of majority samples in the classification. The most direct method is to randomly remove some majority class samples. The disadvantage of this method is that some important information from the majority class samples may be lost.

3. Sample weight adjustment

This method is used to guide models to learn more features of the minority samples in the classification by assigning higher weights to them during the machine learning model training. Generally, the weights of various samples are set to be inversely proportional to the sample size.

Considering the small size of the sample data set, to sufficiently learn the characteristics of all types of samples during the machine learning model training and to improve the universality of the model, the SMOTE over-samples to replenish samples in grade-III and grade-V of the surrounding rock.

The scatter diagram of the data set after over-sampling is shown in Figure 7.

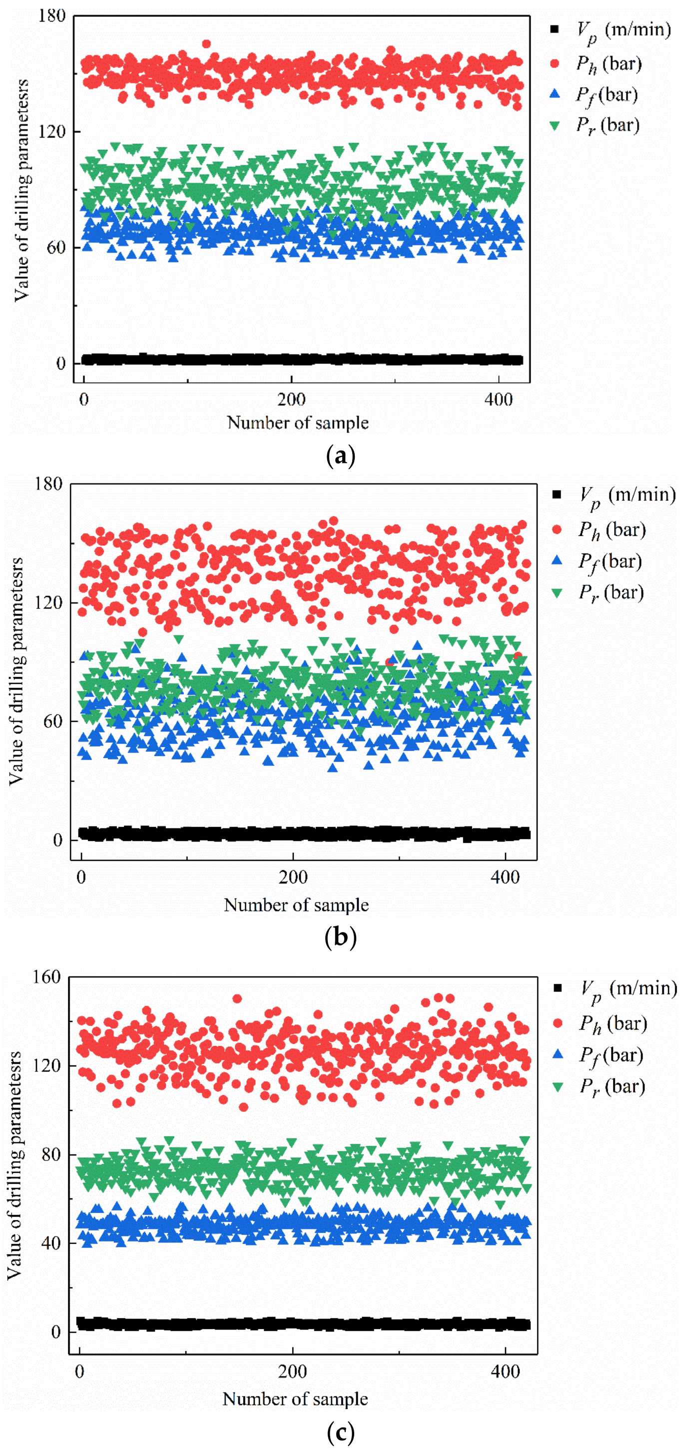


Figure 7. Scatter diagram of the data set after over-sampling (1260). (**a**) Drilling parameters of surround rock grade-III (420); (**b**) drilling parameters of surround rock grade-IV (420); (**c**) drilling parameters of surround rock grade-V (420).

2.5. Sample Feature Analysis

Figure 6 shows that all median, mean, and upper and lower quartile values of each drilling parameter in the box diagram monotonically change with the surrounding rock grade, which preliminarily indicates a correlation between the drilling parameters and the surrounding rock grade.

Pearson correlation coefficient [56] was used to analyze the correlations between the surrounding rock grade and the drilling parameters in 1260 samples, and the correlation coefficients are shown in Table 5.

Table 5. Correlation coefficients between the surrounding rock grade and each drilling parameter.

Index	V_p	P_h	P_f	P_r
R	0.59	−0.64	−0.52	−0.65

In Table 5, all the absolute value of the correlation coefficients between the four drilling parameters and the surrounding rock grades are above 0.5, which is a weak correlation, and the correlation coefficients are close to each other. Therefore, these four indices were selected for the surrounding rock classification.

2.6. Sample Data Splitting

According to the above 1260 data samples, the intelligent surrounding rock classification sample database was established.

In order that the selected parameters can represent the majority of samples, the majority samples are selected for training and the minority samples for prediction in the parameter optimization stage (validation process). As to the model evaluation stage (testing process), we selected more samples for prediction than the previous stage so that the performance evaluation of the model is more convincingly.

Thus, the sample database after random sequencing was divided into the training set and prediction set using the five-fold cross verification method in the validation process, and as to the testing process, the ratio is three-fold.

The specific distribution is shown in Table 6.

Table 6. Intelligent surrounding rock classification sample database distribution.

Item		Surrounding Rock			
		III	IV	V	Total
Validation process	Training set	336	336	336	1008
	Prediction set (Validation set)	84	84	84	252
Testing process	Training set	280	280	280	840
	Prediction set (Testing set)	140	140	140	420

In the field of machine learning, different evaluation indexes (that is, different features in feature vectors are described as different evaluation indexes) often have different dimensional and dimensional units, which will affect the results of data analysis. In order to eliminate the dimensional influence between indexes, data normalization is required.

Normalization means that the input data are limited to a certain range, and this time the data are limited 0 to 1. The data are normalized using the min–max normalization method, as defined in Equation (2).

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{2}$$

where x is the value of the original data, x_{max} is the max value of the original data, x_{min} is the min value of the original data, x' is the normalized value.

The normalization needs to be carried out in the training set in Table 6 first, and then the normalization of the prediction set is completed by taking the normalization parameters (x_{max} and x_{min}) of the training set.

2.7. Model Parameter Optimization and Evaluation

Based on the python machine learning toolkit (Scikit-learn), 10 types of supervised machine learning algorithms were used to train the intelligent surrounding rock classification model: the support vector machine (SVM), back propagation neural network (BP) [55,56], radial basis function neural network (RBF), K-nearest neighbor (KNN), Gaussian naive Bayes (GNB), decision tree (DT), random forest (RF), extra trees (ET), bootstrap aggregating (Bagging) and gradient boosting (GB) algorithms.

The model parameters were optimized and evaluated by the grid search K-flod cross validation method ($k = 5$), and the model performance was externally unbiased when using the method of K-flod cross validation ($k = 3$).

In the model performance optimization process, the average accuracy was adopted to determine the optimum hyperparameter combinations. The average accuracy was calculated by first averaging the accuracy of each validation set over the three surrounding rock grades, and then averaging the averages over the five validation sets.

In the final evaluation of the model performance, the precision, recall, F_1 score, and accuracy were adopted for a comprehensive evaluation. And these indexes are the average of the results of the three test sets.

The process is shown in Figure 8.

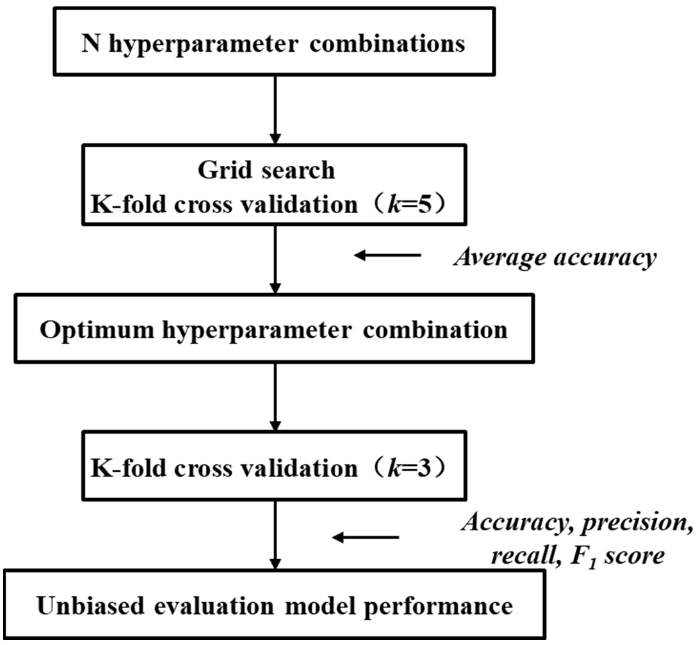


Figure 8. Model parameter optimization and evaluation process.

The performance of the models after training is shown in Figure 9 and Table 7.

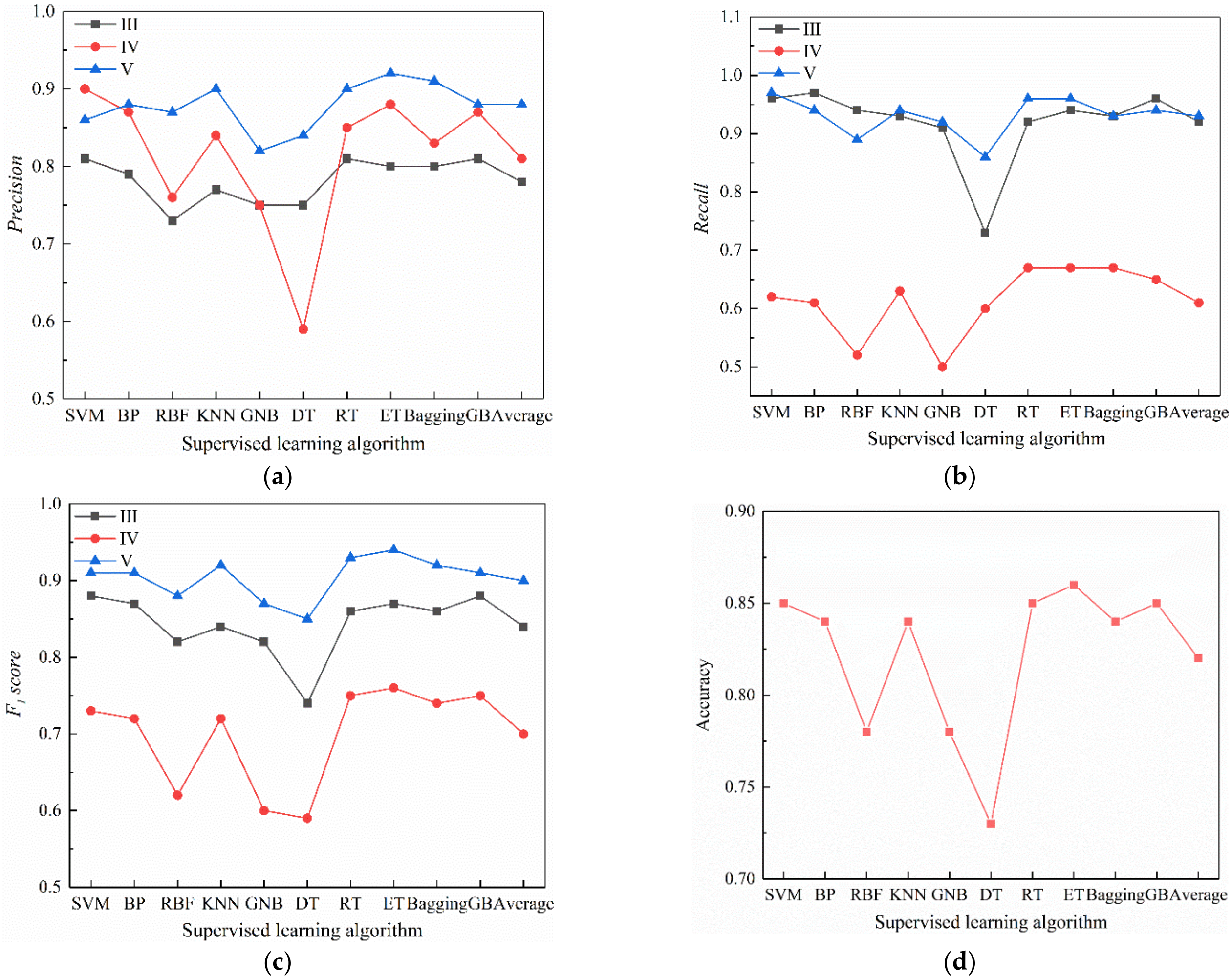


Figure 9. Model parameter optimization and evaluation process: (**a**) precision; (**b**) recall; (**c**) F_1; (**d**) accuracy.

Table 7. Performance of the intelligent surrounding rock models.

Performance Index	Rock Grade	Supervised Learning Algorithm										Average
		SVM	BP	RBF	KNN	GNB	DT	RT	ET	Bag-ging	GB	
Precision	III	0.81	0.79	0.73	0.77	0.75	0.75	0.81	0.80	0.80	0.81	0.78
	IV	0.90	0.87	0.76	0.84	0.75	0.59	0.85	0.88	0.83	0.87	0.81
	V	0.86	0.88	0.87	0.90	0.82	0.84	0.90	0.92	0.91	0.88	0.88
Recall	III	0.96	0.97	0.94	0.93	0.91	0.73	0.92	0.94	0.93	0.96	0.92
	IV	0.62	0.61	0.52	0.63	0.50	0.60	0.67	0.67	0.67	0.65	0.61
	V	0.97	0.94	0.89	0.94	0.92	0.86	0.96	0.96	0.93	0.94	0.93
F_1 score	III	0.88	0.87	0.82	0.84	0.82	0.74	0.86	0.87	0.86	0.88	0.84
	IV	0.73	0.72	0.62	0.72	0.60	0.59	0.75	0.76	0.74	0.75	0.70
	V	0.91	0.91	0.88	0.92	0.87	0.85	0.93	0.94	0.92	0.91	0.90
Accuracy	-	0.85	0.84	0.78	0.84	0.78	0.73	0.85	0.86	0.84	0.85	0.82

The following conclusions can be drawn from Figure 9 and Table 7.

Among 10 machine learning algorithm models, the average precision, recall, F_1 score and accuracy were above 0.7, except for the recall of grade-IV surrounding rock. In particular, the average recalls of grade-III and -V were greater than 0.90.

Thus, these machine learning models established by the drilling parameters are feasible and reliable in the intelligent classification of surrounding rocks.

2.8. Model Selection and Recommendation

When comprehensively considering the precision, recall, F_1 score, and accuracy, three types of models (SVM, RT, and ET) had better performance among the 10 machine learning algorithm models. Their average precision, recall, F_1 score, and accuracy were above 0.8, except for the recall of grade-IV surrounding rock. In particular, the recall of the grade-V surrounding rock, which has a great influence on the safety of the tunnel, was above 0.95.

Thus, these machine learning models based on SVM, RT, and ET have some degree of safety and high practical value.

3. Case Study

3.1. Intelligent Surrounding Rock Classification System Software

The tunnel surrounding rock intelligent classification system by the drill and blast method was established based on the intelligent surrounding rock classification models based on SVM, RT, and ET. It can automatically record and transmit the drilling parameters and intelligently classify the surrounding rock with carriers of the intelligent drill jumbo.

Specifically, the surrounding rock grade of the tunnel face is determined by the votes of three models (SVM, RT, and ET). When all types of the surrounding rock levels are not superior, the higher grade is taken as the surrounding rock grade of the tunnel face in consideration of safety.

In addition, these samples for the models do not require consideration of the modification conditions (i.e., low crustal stress, without groundwater or drip outflow of groundwater, and without a main weak structure surface). Therefore, in consideration of safety and popularization, the grade determined from these models is the basic surrounding rock grade; the grade amended by the groundwater state, major weak structural surface, and crustal stress state is the final surrounding rock grade.

The specific process is shown in Figure 10.

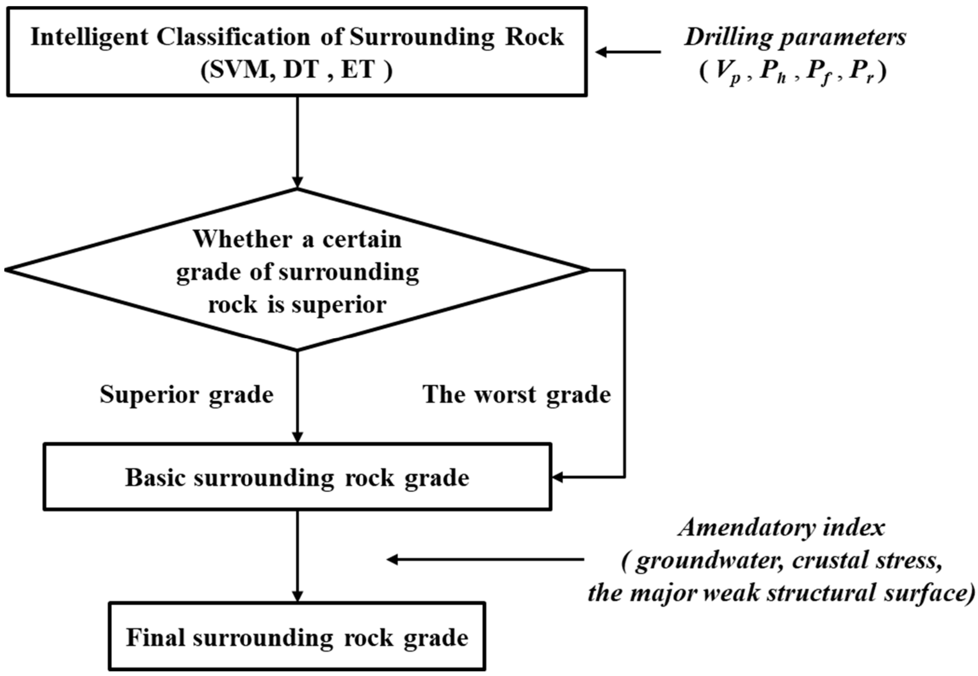


Figure 10. Classification process of the intelligent surrounding rock classification system.

The system interface is shown in Figure 11.

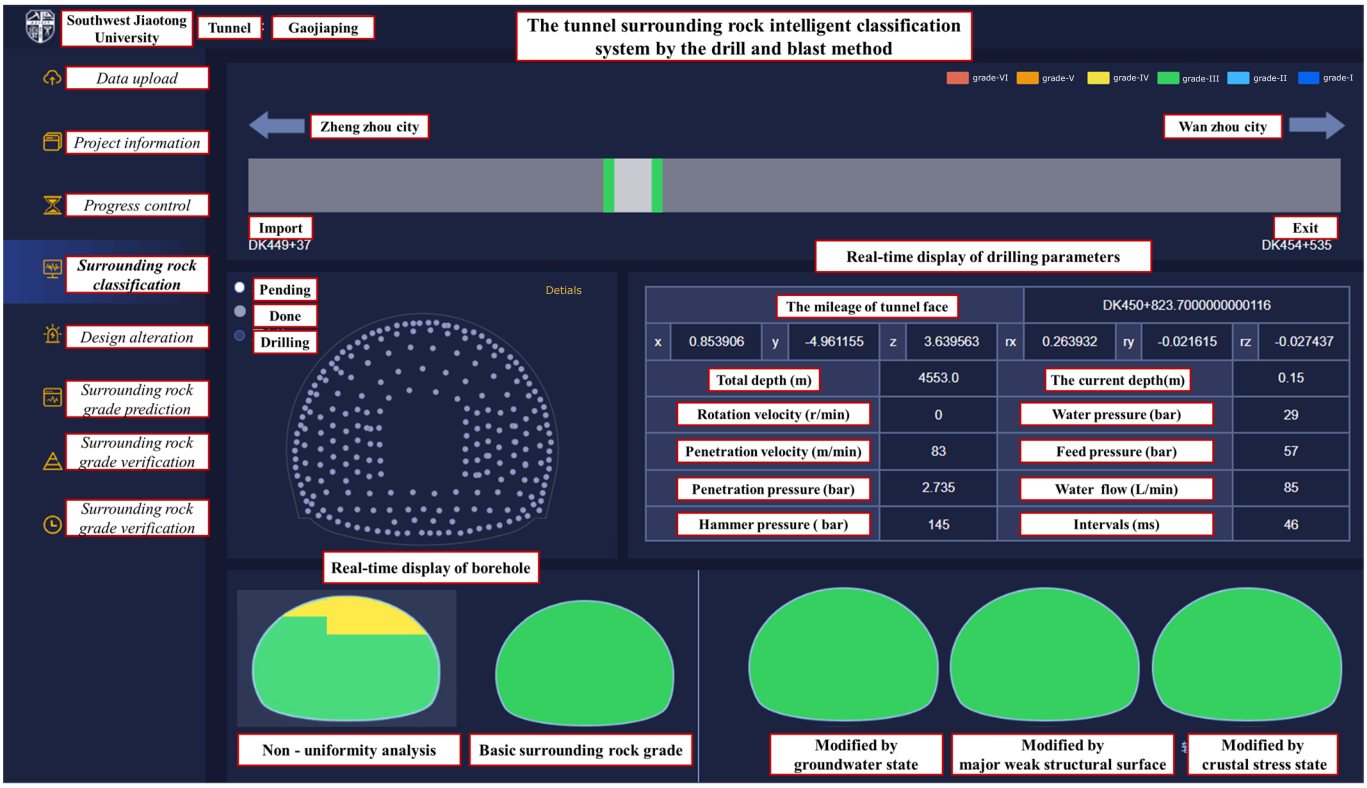


Figure 11. Interface of the 'tunnel surrounding rock intelligent classification system by the drill and blast method'.

3.2. Project Overview of Test Tunnel

The Gaojiaping Tunnel of the Zhengzhou–Wanzhou high-speed railway is located in Nanzhang county, Xiangyang city, Hubei province, China. The tunnel is 5498 m in length with a maximum buried depth of 320 m. The main lithologies of the surrounding rock are limestone and shale, and the grades of the surrounding rocks are III (1493 m), IV (1050 m), and V (720 m).

The method of construction of this tunnel is the full-section method with large machinery, i.e., the tunnel face (150 m^2) is excavated and formed by blasting once, and the primary support is closed once. With this method, the circular footage is 2–4.8 m, and the monthly progress is 60–150 m in this tunnel.

The tunnel position is shown in Figure 12.

This test section is DK450 + 834~DK451 + 126, which is 292 m in total length. The excavation revealed that the surrounding rock was grade-III; the lithology was bluish grey, a massive structure, and hard limestone rock. The stability of the tunnel face was good without developed joints, fractures, or groundwater.

The test section of this tunnel is shown in Figure 13, and the tunnel face is shown in Figure 14.

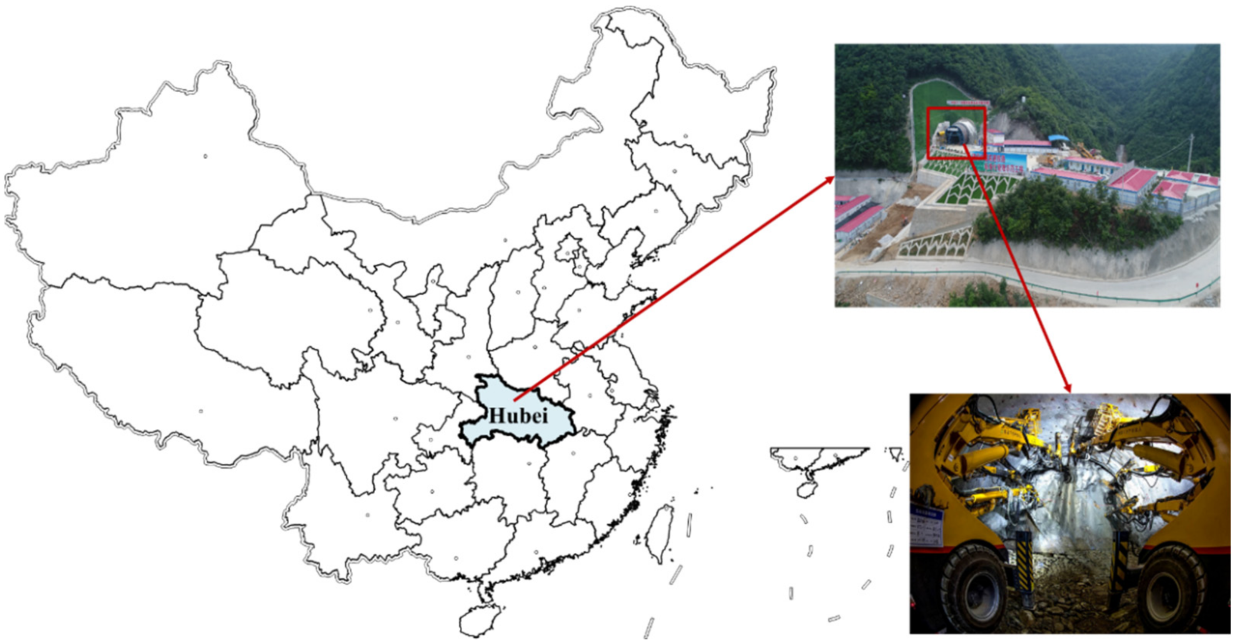


Figure 12. Interface of the position of the Gaojiaping Tunnel of the Zhengzhou–Wanzhou high-speed railway.

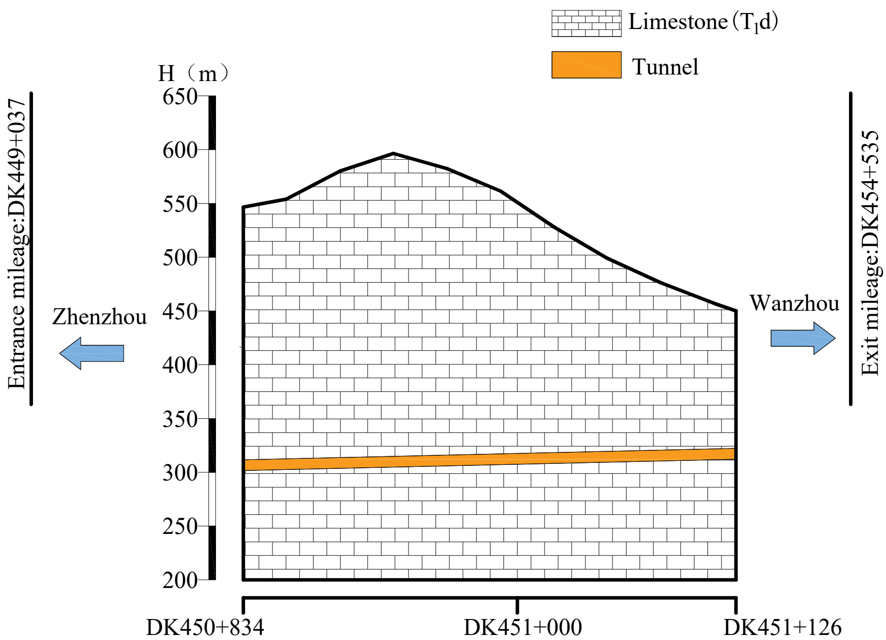


Figure 13. Test section of Gaojiaping Tunnel.

Figure 14. Tunnel face of this test section of the Gaojiaping Tunnel.

3.3. Intelligent Surrounding Rock Classification in Test Tunnel

Among the test section, drilling parameter information from 30 tunnel faces was collected by the intelligent surrounding rock classification system. The intelligent classification results of the surrounding rock on each tunnel face are shown in Table 8.

Table 8. Intelligent classification of surrounding rock on each tunnel face.

Number	Mileage	Predicted Results	Actual Results	Right/Error
1	DK450+834	III	III	Right
2	DK450+837	III	III	Right
3	DK450+840	III	III	Right
4	DK450+916	III	III	Right
5	DK450+919	III	III	Right
6	DK450+922	III	III	Right
7	DK450+926	III	III	Right
8	DK451+014	III	III	Right
9	DK451+017	III	III	Right
10	DK451+021	III	III	Right
11	DK451+024	III	III	Right
12	DK451+027	III	III	Right
13	DK451+030	III	III	Right
14	DK451+034	III	III	Right
15	DK451+037	III	III	Right
16	DK451+042	III	III	Right
17	DK451+046	III	III	Right
18	DK451+051	III	III	Right
19	DK451+055	III	III	Right
20	DK451+060	III	III	Right
21	DK451+064	III	III	Right
22	DK451+100	III	III	Right
23	DK451+103	III	III	Right
24	DK451+106	III	III	Right
25	DK451+109	III	III	Right
26	DK451+113	IV	III	Error
27	DK451+116	IV	III	Error
28	DK451+119	IV	III	Error
29	DK451+123	IV	III	Error
30	DK451+126	III	III	Right
Accuracy				86.7%

In Table 8, the classification accuracy of the surrounding rock intelligent classification system on-site is 86.7%, which indicates that the system has good generalization.

However, due to the single lithology and surrounding rocks (limestone, grade-III) in the field test section, its generalization performance must be further verified.

4. Conclusions

Based on 912 drilling parameters of the Zhengzhou–Wanzhou high-speed railway tunnel project, 10 intelligent surrounding rock classification models were established using multiple machine learning algorithms. With three models (SVM, RT, and ET), an intelligent surrounding rock classification system was established and verified by the field test section.

The main conclusions of this study are:

1. All the absolute values of the correlation coefficients between the four drilling parameters (V_p, P_h, P_r, and P_f) and the surrounding rock grades (III, IV, and V) are above 0.5.

Thus, there is a correlation between the drilling parameters and the surrounding rock grade, so the method of surrounding rock classification by drilling parameters is feasible.

2. The 10 models based on supervised machine learning algorithms all have good performance. The average accuracy of them is 0.82. In particular, the average recalls of grades-III and -V were greater than 0.90.

Thus, these machine learning models established by drilling parameters are feasible and reliable in the intelligent classification of surrounding rocks.

3. By comprehensively considering precision, recall, F_1 score, and accuracy, we observe that three types of models containing SVM, RT, and ET have better performance among 10 machine learning algorithm models. In particular, the recall of grade-V surrounding rock, which has great influence on the safety of the tunnel, was above 0.95.

Thus, these three machine learning models have a degree of safety and high practical value.

4. The classification accuracy of the surrounding rock intelligent classification system on-site is 86.7%, which indicates that these models have good generalization.

This study found that the drilling parameters V_p, P_h, P_f, and P_r can be used to grade the surrounding rock directly by training the machine learning model. Compared with the traditional manual method, the proposed method is faster and has fewer indices, higher classification accuracy, and better stability. When carried on an intelligent jumbo, it can realize automatic recording and transmission of drilling parameters and intelligent classification of surrounding rock grade by using the intelligent surrounding rock classification system established in this study. This is what most previous studies have failed to do.

However, there is still room to improve the classification accuracy of this system. In this study, three models have been used to determine the most unfavorable results to ensure the safety of site construction, and its essence is a management means. Therefore, the research on data preprocessing and algorithm optimization should be strengthened to further improve the reliability of the technology. In addition, the samples collected in this study only covered five lithologies and three surrounding rock grades. Thus, the sample types and numbers should be further expanded in the future to improve the application range of the technique.

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