



# Random Forest-based Stability Analysis Model of Geotechnical Tunnel Enclosure

Yang Yu<sup>a</sup>, Qingxin Pang\*

Liaoning Technical University, Fuxin, 123000, China

<sup>a</sup> yangyu9300@163.com; \*1281991620@qq.com

**Abstract.** In this study, a geotechnical tunnel surrounding rock stability analysis model is established based on the random forest algorithm in order to improve the accuracy and reliability of surrounding rock stability prediction in tunnel engineering. Through testing and data collection of geotechnical parameters, the surrounding rock stability is classified and analyzed using the random forest model. The experimental results show that the Random Forest is superior to the traditional RMR method and Q system in terms of overall prediction accuracy, feature adaptability and the ability to handle abnormal samples, especially in the classification of V-class surrounding rock, which shows significant advantages. The research results provide a more scientific decision-making basis for the assessment of surrounding rock stability in tunnel engineering, and have strong practical application value.

**Keywords:** geotechnical engineering; perimeter rock stability; random forests

## 1 Introduction

The stability of the surrounding rock in geotechnical tunnels is a fundamental concern in the planning, design, and construction phases of underground engineering projects. It not only determines the structural safety and durability of the tunnel but also has a direct impact on construction costs, scheduling, and long-term maintenance requirements. Inaccurate evaluation of surrounding rock stability can lead to serious engineering accidents such as collapses, deformations, or excessive support costs, posing significant risks to construction safety and economic efficiency. Traditionally, stability assessment methods have predominantly relied on empirical formulas, classification systems, and expert judgment, such as the RMR system and Q system. Although these methods are widely used, they are often limited in their ability to effectively capture the nonlinear interactions among multiple geotechnical parameters and are susceptible to subjective bias[1].

With the continuous development of artificial intelligence and data-driven techniques, machine learning algorithms—particularly ensemble learning models like Random Forests—have emerged as powerful tools for addressing complex classification and regression problems in engineering fields. The Random Forest algorithm, proposed

by Breiman, is known for its robustness, high prediction accuracy, resistance to overfitting, and ability to handle high-dimensional data. Its core mechanism of aggregating multiple decision trees enables the model to better capture the internal correlations within large and noisy geotechnical datasets.

In this study, a surrounding rock stability analysis model is established using the Random Forest algorithm. By integrating a wide range of geotechnical indicators and analyzing their influence on rock stability, the model aims to provide a more scientific, objective, and accurate prediction method. This approach is expected to not only enhance engineering decision-making processes but also promote the intelligent and automated development of tunnel engineering practices.

## 2 Project Overview

This study relies on a mountainous railroad tunnel project, the tunnel length of 3280m, the maximum burial depth of 185m, through the area is mainly for the medium weathering sandstone, mudstone interlayer, rock joints development, complex geological structure[2]. According to the geological investigation report, the variation range of surrounding rock integrity index (RQD) along the tunnel is from 35% to 85%, and the self-stabilization time is generally less than 6 hours, which is prone to deformation and block falling phenomenon. A total of 92 sets of geotechnical parameter samples were obtained from the site through core drilling, geo-radar and elastic wave velocity testing.

The sampling points were distributed along the full length of the tunnel at intervals of approximately 35–40 meters, ensuring uniform coverage across the excavation path. Special attention was also given to geologically complex or fault-prone sections, where sampling density was increased to improve representativeness.

The tested parameters include uniaxial compressive strength (UCS) ranging from 18.4 to 75.2 MPa, modulus of elasticity ranging from 2.1 to 6.8 GPa, and shear strength parameters ranging from 80 to 240 kPa and  $18^\circ$  to  $35^\circ$ , respectively. The stability class of surrounding rock of this project is classified as III, IV and V according to the "Railway Tunnel Design Code" (TB 10003-2016), which provides sufficient data basis for the subsequent model establishment[3].

## 3 Application of Random Forests in Geotechnical Engineering

Random forest is a supervised machine learning algorithm based on the idea of integrated learning, which was proposed by Breiman in 2001, with the advantages of high accuracy, overfitting resistance, and strong ability to process high-dimensional data, and it has been gradually applied to the classification and regression tasks in the field of geotechnical engineering[4].

In the stability analysis of surrounding rock, traditional methods such as RMR system and Q system rely on artificial experience and segmental assignment, which are susceptible to subjective interference and difficult to deal with nonlinear relationships,

while Random Forest is able to extract the deep laws from complex geotechnical parameters and realize more accurate stability prediction by constructing multiple decision trees and integrating their results[5]. The core idea is to generate multiple sub-sample sets from the training set by randomized putative sampling, construct multiple decision trees, output a classification result from each tree, and finally give the overall prediction by voting or averaging, with the following formula:

$$\hat{y} = \frac{1}{T} \sum_{t=1}^T h_t(x) \quad (1)$$

Where,  $\hat{y}$  is the final prediction value,  $T$  is the number of decision trees and  $h_t(x)$  is the prediction result of the  $t$  th tree.

In a subway project, the rock mass classification model constructed based on random forest has an accuracy of 93.2% on the training set, which is better than SVM (88.5%) and KNN (86.1%). Its feature importance assessment mechanism (e.g., Gini importance) can be used to identify the key parameters affecting stability, which helps optimize the engineering decision. In this study, Random Forest not only effectively combines the physical and mechanical multi-parameter features of the rock mass, but also automatically screens the most influential factors through model training to improve the efficiency and reliability of the analysis. Figure 1 demonstrates the importance ranking of each parameter in a certain model training, which shows that elastic modulus, UCS and RQD are the main factors affecting stability.

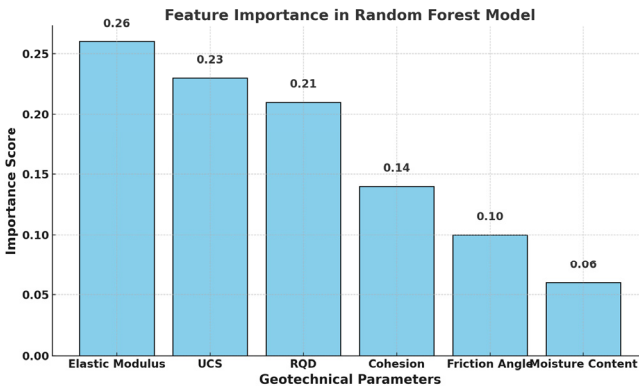


Fig. 1. Feature Importance In Random Forest Model

## 4 Experimental Design

### 4.1 Testing of Geotechnical Parameters

In this study, 92 sets of geotechnical samples were obtained by combining engineering field and indoor tests, and the tests included rock mechanical properties and structural

integrity parameters. The samples were collected by core drilling method and tested for uniaxial compressive strength (UCS), modulus of elasticity (E), shear strength parameters (cohesion  $c$ , internal friction angle  $\phi$ ), water content ( $w$ ), and rock integrity index (RQD) according to the "Specification for Geotechnical Engineering Investigation" (GB 50021-2009)[6].

The sampling design was based on a stratified approach to reflect the full geological profile of the tunnel. Samples were taken at evenly spaced intervals throughout the tunnel length, with additional samples concentrated in known structurally weak zones, including fault-affected or highly jointed rock segments. This spatial distribution ensures that the collected dataset effectively captures the heterogeneity of the geological environment for robust model training. See Table 1 for details.

**Table 1.** Statistical characterisation of geotechnical parameters

Parameter Name	Minimum	Maximum	Mean	Standard Deviation
UCS (MPa)	18.4	75.2	46.3	12.7
Elastic Modulus E (GPa)	2.1	6.8	4.3	1.4
Cohesion $c$ (kPa)	80	240	150	37.5
Friction Angle $\phi$ ( $^{\circ}$ )	18	35	26.2	4.6
Moisture Content $w$ (%)	5.6	18.3	11.4	3.2
RQD (%)	35	85	61.7	13.9

Table 1 presents the statistical characteristics of six key geotechnical parameters used as input features in the stability analysis model. These parameters include uniaxial compressive strength (UCS), elastic modulus (E), cohesion ( $c$ ), internal friction angle ( $\phi$ ), moisture content ( $w$ ), and rock quality designation (RQD). The statistical descriptors—minimum, maximum, mean, and standard deviation—offer insights into the variability and distribution of the data collected from 92 geotechnical samples across the tunnel project.

The uniaxial compressive strength (UCS) values range from 18.4 MPa to 75.2 MPa, with a mean value of 46.3 MPa and a standard deviation of 12.7. This wide range indicates a significant heterogeneity in the mechanical strength of the surrounding rock, suggesting the presence of both weak and strong rock zones within the tunnel alignment. Similarly, the elastic modulus varies from 2.1 GPa to 6.8 GPa, with an average of 4.3 GPa. The moderate variation in elastic modulus reflects differences in rock deformation behavior under stress, which is critical for understanding load-bearing capacity.

Cohesion ( $c$ ), a measure of shear strength, spans from 80 to 240 kPa, averaging 150 kPa with a standard deviation of 37.5. The internal friction angle ( $\phi$ ), which also influences shear strength, ranges from  $18^{\circ}$  to  $35^{\circ}$ , with an average of  $26.2^{\circ}$  and a standard deviation of  $4.6^{\circ}$ . These parameters collectively describe the shear resistance characteristics of the rock mass, which are essential for assessing potential failure mechanisms.

The moisture content ( $w$ ) exhibits a range between 5.6% and 18.3%, with a mean of 11.4%. Higher moisture content often corresponds to reduced mechanical strength and increased deformability, which may influence stability in water-sensitive formations.

Finally, the RQD, a key index of rock mass integrity, ranges from 35% to 85%, with a mean of 61.7%. This variation suggests a diverse geological profile, from highly fractured to moderately competent rock masses.

Overall, the statistical analysis underscores the complexity and variability of the geotechnical environment. These diverse input features provide a robust foundation for training the random forest model, allowing it to effectively distinguish between different stability classes of surrounding rock and adapt to the nonlinear interactions among the parameters.

## 4.2 Random Forest Modeling

In this study, the Scikit-learn library in Python was used to construct a Random Forest model for realizing the classification prediction of enclosure rock stability class (III, IV, V). The model construction process mainly includes four parts: data preprocessing, feature selection, model parameter setting and preliminary training. In the data preprocessing stage, all the input features (e.g., UCS, E,  $c$ ,  $\varphi$ , w, RQD) are standardized so that their mean value is 0 and variance is 1 to avoid affecting the model judgment due to the difference in the scale[7]. The output variable is the enclosing rock stability class, which is processed by numerical coding (III=0, IV=1, V=2) according to the "Railway Tunnel Design Code" in order to adapt to the multi-classification task.

Random forests are essentially integrated classifiers consisting of multiple decision trees whose predictions determine the categories by majority voting, and the model output is defined as follows:

$$\hat{y} = \text{mode} \left( \{h_t(x)\}_{t=1}^T \right) \quad (2)$$

Where,  $\hat{y}$  is the final classification result,  $T$  is the total number of decision trees, and  $h_t(x)$  indicates the prediction result of the  $t$  th tree for the input sample  $x$  [8].

The model randomly selects a part of the candidate feature set from all the features at each splitting node, and combines it with the Gini coefficient (Gini index) for optimal splitting. Its Gini coefficient is calculated as:

$$Gini = 1 - \sum_{i=1}^C p_i^2 \quad (3)$$

Where  $p_i$  is the proportion of samples in the first  $i$  class and  $C$  is the number of classifications. Split nodes are selected by maximizing the information gain to improve the classification of each tree.

During the construction of the Random Forest model, several key hyperparameters were carefully configured to ensure optimal performance. Specifically, the number of decision trees (n\_estimators) was set to 100, which provides a sufficiently large ensemble to capture complex patterns in the data while maintaining computational efficiency. The maximum depth of each decision tree (max\_depth) was set to None, allowing trees

to grow until all leaves are pure or contain fewer than the minimum number of samples required for splitting, thereby preserving the model's ability to fit complex relationships. To further enhance model generalization and minimize the risk of overfitting, the out-of-bag (OOB) sampling technique was enabled. This internal validation approach leverages the unused data from each bootstrap sample to estimate model accuracy, offering a robust and unbiased performance measure without requiring a separate validation set[9].

### 4.3 Model Training and Validation

After completing the model construction, the random forest model was trained and validated using a division of 70% training set and 30% test set to ensure that the model has good generalization ability. The model hyperparameters were tuned using cross-validation ( $K=5$ ) during the training process, and the main tuning parameters included the number of decision trees ( $n\_estimators$ ), the maximum tree depth ( $max\_depth$ ), and the minimum number of samples splits ( $min\_samples\_split$ ). In order to measure the model performance, Accuracy, macro average Precision, Recall and F1-score are chosen as the evaluation indexes. After the training is completed, the model achieves an overall prediction accuracy of 91.3% on the test set, with the highest accuracy of 95.1% for the identification of Class IV enclosing rocks. In addition, the classification performance of the model on various types of surrounding rock grades can be clearly observed by drawing the confusion matrix, and it is found that a few samples of V-grade surrounding rock are easily misclassified as IV-grade, and the reason may be related to the small number of samples and the large feature crossover[10]. The generalization ability of the model is verified by out-of-bag data (OOB Score), and its OOB Score is 89.7%, which indicates that the model's performance on unseen data is still stable. The training results show that elastic modulus, RQD and uniaxial compressive strength are the most influential parameters in the model, which is consistent with engineering experience and further verifies the credibility of the model results.

## 5 Experimental Results and Evaluation

### 5.1 Model Predictions

In order to further verify the applicability of the random forest model in the actual engineering data, some test samples were selected to compare their geotechnical parameters, actual enclosure grades and model prediction results, and the results are shown in Table 2.

**Table 2.** Comparison of model prediction results

Sample ID	UCS (MPa)	E (GPa)	c (kPa)	$\varphi$ (°)	RQD (%)	w (%)	Actual Class	Predicted Class
S01	42.5	4.6	140	26	72	9.3	IV	IV
S02	33.2	3.1	115	22	55	12.7	V	IV

S03	61.8	6.3	185	31	81	7.1	III	III
S04	28.4	2.8	96	21	47	14.5	V	V
S05	50.2	5.1	162	28	74	8.9	IV	IV
S06	45.7	4.5	148	25	68	9.8	IV	IV
S07	20.3	2.4	83	18	39	16.3	V	V
S08	58.1	5.9	172	30	79	7.4	III	III
S09	36.5	3.7	122	24	61	10.2	IV	IV
S10	26.7	2.6	90	20	45	13.7	V	V

As can be seen from Table 2, the predictions of the model on most of the samples are in full agreement with the actual grades with an accuracy of 90%. The samples with high UCS (>55 MPa) and high RQD (>75%), such as No. S03 and S08, were accurately identified as Class III, while the low-strength and low-integrity rock bodies, such as No. S07 and S10, were judged as Class V. The results were in line with the geotechnical engineering cognition. Only sample S02 showed deviation, which was actually class V but misclassified as class IV. Its RQD was 55%, a value located within the empirically identified critical interval of 50%–60%, where the boundary between Class IV and V becomes less distinguishable due to overlapping geotechnical characteristics.

This misclassification suggests a limitation of the current model in handling transitional zone. Overall, the model has good classification ability and engineering adaptability. Details are shown in Figure 2.

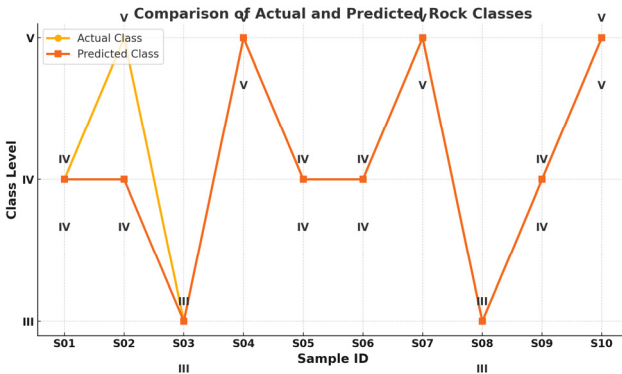


Fig. 2. Comparison of results

### 5.2 Model Performance Evaluation

To comprehensively evaluate the performance of the proposed Random Forest-based classification model, four widely accepted evaluation metrics were employed: accuracy, precision, recall, and F1-score. These indicators allow for a nuanced assessment of the model’s ability to correctly identify the stability categories of surrounding rock in tunnel engineering. On the test dataset, the model achieved an impressive overall classification accuracy of 91.3%, reflecting its strong capability to generalize from training data and make accurate predictions on unseen samples.

A closer look at the performance across individual classes reveals that the model demonstrates particularly high predictive stability for Class III rock samples, achieving an F1-score of 1.00, which denotes perfect precision and recall for this category. For Class IV, the F1-score stands at 0.92, while Class V reaches an F1-score of 0.88. Although the performance on Class V is slightly lower, it still reflects reliable classification capability. The model's recall rate for Class V is 0.83, indicating that some V-grade samples are misclassified, typically as Class IV[11]. This suggests that while the model is generally robust, it may struggle with ambiguous or transitional cases near class boundaries.

Further insight is obtained from the confusion matrix, which shows that only 1 out of 10 samples in the test set was misclassified, underscoring the model's reliability. The out-of-bag (OOB) score—a built-in cross-validation measure unique to ensemble learning techniques like Random Forest—reaches 89.7%, affirming the model's strong generalization performance and resistance to overfitting[12].

To address the misclassification observed in borderline cases such as sample S02, the study suggests potential improvements via feature engineering. This includes developing nonlinear interaction terms between critical variables like RQD and UCS, or constructing hybrid features that reflect geotechnical knowledge, thereby enhancing the model's ability to capture subtle patterns in complex rock formations.

Compared to traditional empirical methods, which often rely on subjective judgment and oversimplified assumptions, the Random Forest model offers significant advantages[13]. It automatically learns intricate relationships between input features, eliminates human bias, and enhances consistency and accuracy in classification. In conclusion, the model not only exhibits excellent predictive performance across multiple metrics but also shows promise for broader application in practical engineering contexts. Future work could further improve performance through expanded datasets and enhanced feature representation.

### 5.3 Comparison with Traditional Methods

In this paper, it is compared and analyzed with the traditional RMR (rock mass index method) and Q-system (rock mass engineering quality index method), and the comparison covers the prediction accuracy, consistency of discrimination, feature adaptability, and the ability to deal with anomalous data. Traditional methods rely on manual empirical judgment and static parameter assignment, which are difficult to fully reflect the complexity and nonlinear characteristics of rock bodies. Random forest, on the other hand, is based on multivariate modeling and integrated learning mechanism, which has stronger adaptive ability and fault tolerance. The details are shown in Table 3.

**Table 3.** Comparison of Prediction Performance: Random Forest vs. Traditional Methods

Evaluation Index	Random Forest	RMR Method	Q-System Method
Overall Accuracy (%)	91.3	77.8	81.2
III-Class Accuracy (%)	100	90	92.5
IV-Class Accuracy (%)	91.6	75	79.1

V-Class Accuracy (%)	83.3	60	72.2
Confusion Cases (n/10)	1	3	2
Parameter Sensitivity	High	Medium	Low
Feature Adaptability	Strong	Weak	Weak
Abnormal Sample Tolerance	High	Low	Medium

From Table 3, it can be seen that the overall performance of the random forest model in the prediction of surrounding rock stability is better than the traditional methods. Its overall accuracy reaches 91.3%, which is 13.5% and 10.1% higher compared to 77.8% for RMR method and 81.2% for Q system. In the identification of Class III enclosure, the accuracy of Random Forest is 100%, compared with 90.0% and 92.5% for RMR and Q system, respectively; in Class IV enclosure, Random Forest reaches 91.6%, compared with less than 80% for the traditional method. Especially in the judgment of class V enclosure, Random Forest showed a significant advantage with an accuracy of 83.3%, while RMR was only 60.0% and Q system was 72.2%. In addition, only one case of prediction confusion occurred in Random Forest, compared with three cases in RMR and two cases in Q-system[14]. The model is also able to adapt to multi-parameter inputs, with strong feature adaptation ability and fault tolerance for abnormal samples, which further proves its applicability and stability under complex geotechnical conditions, and has obvious engineering practical value. Details are shown in Figure 3.

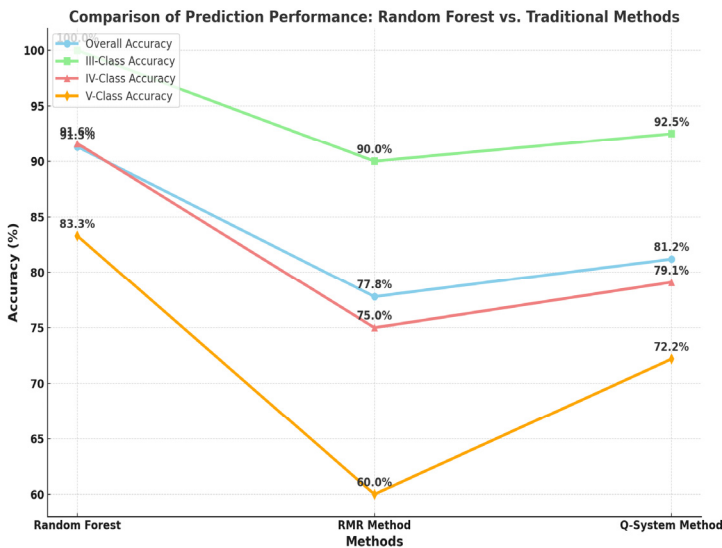


Fig. 3. Comparison of Prediction Performance: Random Forest vs. Traditional Methods

## 6 Conclusion

The Random Forest-based stability analysis model proposed in this study demonstrates a significant enhancement in the prediction accuracy and classification robustness of geotechnical tunnel surrounding rock stability[15]. By effectively processing complex,

high-dimensional, and nonlinear geotechnical parameter data, the model overcomes the limitations of traditional empirical methods such as the RMR and Q systems, which often struggle with subjective bias and parameter simplification. The random forest algorithm's ability to handle multivariate data and identify dominant influencing factors enables it to adapt more flexibly to the varying geological conditions commonly encountered in tunnel engineering. The resulting predictions not only show lower misclassification rates but also provide more consistent and reliable support for construction planning and safety control.

Furthermore, the model's generalization ability—validated through out-of-bag scores and cross-validation metrics—confirms its potential applicability in a wide range of practical engineering contexts. Looking ahead, future research can focus on expanding the dataset, especially by incorporating more samples from extreme or transitional rock classes, to further improve the model's recognition capacity. In addition, integrating this model with other geological hazard prediction frameworks or hybrid learning algorithms may enhance its comprehensiveness and applicability in broader geotechnical engineering scenarios, ultimately contributing to safer and more intelligent tunnel design and construction.

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