Quantitative Risk Assessment of Rock Tunnel Faces Using Stacked Deep Learning and Multi-Source Data

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ABSTRACT: Quantitative tunnel face risk assessment is the characteristic challenge of rock tunnel excavation projects. This study establishes a multi-source database and proposes a stacked deep learning method for the quantitative tunnel face risk assessment. Both contact and non-contact methods are used to collect various data sources such as face images, site geological information, and rock mass properties. Thirteen multi-source variables describing the rock tunnel faces were considered as inputs, and Rock Mass Rating (RMR) system was adopted to generate the target output. The proposed model architecture combines a range of well-performing models to make accurate predictions of the tunnel face rock mass rating. Overall, this study establishes a comprehensive tunnel face risk assessment framework that leverages various data sources and stacked deep learning. The experimental results from a tunnel project in China demonstrate that our stacking deep learning model performs well in assessing rock tunnel face stability.

Keywords: Rock tunnel, Face stability, Machine learning, Risk Assessment, Multi-source Data.

1 INTRODUCTION

Rock mass rating systems are commonly used in rock engineering to conduct qualitative assessments of the risk at tunnel faces. These assessments take into account the principal engineering features that affect rock structure to determine the overall stability of the surrounding rock (Tzamos & Sofianos, 2007; Rehman et al., 2019). However, establishing a quantitative tunnel face risk assessment system is challenging due to the complexity and variability of rock masses encountered during tunnel construction. Accurately collecting and assessing multiple-source datasets is necessary to achieve this goal before proceeding to the next stage of construction.

Unlike empirical models that consider a limited number of input feature parameters, data-driven methods incorporating multi-source input data (Zhou et al., 2021) can adapt to regional characteristic input parameters and provide objective target outputs for field engineers. Therefore, this study aims to establish a multi-source database of tunnel faces to facilitate the implementation of data-driven methods. By doing so, this approach can provide more reliable and objective assessments of tunnel face risk to support field engineers in making informed decisions.

In recent years, deep learning techniques have gained popularity as a data-driven method for assessing rock mass quality (Lary et al., 2016). The flexibility of deep learning methods makes them effective in approximating and solving complex nonlinear engineering problems. However, three significant challenges may hinder the effectiveness of a deep learning hypothesis, namely representation challenges with high bias, computational challenges with high computational variance, and statistical challenges with high variance (Dietterich, 2002). These issues can be addressed using stacked deep learning models (SDLs), which update a series of predictions through "voting" for the next iteration instead of seeking a single best hypothesis for a given dataset (Brown and Mues, 2012).

This study aims to apply SDLs to conduct a multi-source data mining process of rock tunnel faces, which involves establishing the dataset, selecting appropriate deep learning algorithms, and determining optimal hyper-parameters. The Rock Mass Rating (RMR) system, which evaluates rock mass quality using a simple percentage measurement, serves as the benchmark. The experiments mainly employ tree-based deep learning models, such as Decision Tree (DT), Random Forest (RF), and Gradient Boosted Regression Tree (GBRT). To ensure a comprehensive comparison, a neural network-based model, namely Multiple Layers Perceptron (MLP), is also employed for performance evaluation. The tree-structured Parzen estimator (TPE), a Bayesian hyper-parameter optimization technique, is used to tune the hyper-parameters of the deep learning models. The prediction error of the k-fold cross-validation sets serves as the fitness function of the TPE algorithm for the deep learning models.

Overall, this study provides a comprehensive approach to establishing a multi-source database for rock mass quality indicators using both contact and non-contact measurement methods. The proposed methodology can help improve the accuracy and efficiency of assessing rock mass quality, which is important for ensuring the safety and stability of tunnel engineering projects.

2 MULTI-SOURCE DATABASE

This study established a multi-source database for training, validating, and testing proposed rock mass quality indicators using tunnel face data from thirteen different tunnels in the Jiaozhou Bay Second Submarine Tunnel, Qingdao, China. The Rock Mass Rating (RMR) values computed by experienced site engineers were considered as the target output for the models.

To calculate the RMR values, the six parameters of each tunnel face (uniaxial compressive strength (UCS), rock quality designation (RQD), groundwater condition (GW), joint spacing (JS), joint condition (JC), and orientation of discontinuities) were provided by the site engineers of the Jiaozhou Bay Second Submarine Tunnel project. A flowchart of the database establishment process is shown in Figure 1, which involves three main steps: multi-source data collection, determination of indicators, and database establishment.

To collect raw data for the rock mass features, a photogrammetry-based method was used as a non-contact approach, which generated 3000 tunnel face images from over 130 excavation rock tunnel faces. These images were used to establish image datasets for the rock mass features, and specific deep learning frameworks were developed to extract the required data features through training, verification, and testing. Quantitative indicators based on non-contact measurement were obtained by statistical analysis of the extracted features.

The uniaxial compressive strength (UCS) and weathering degree were obtained through contact measurement. A rock mass sample was gathered from each tunnel face, and an on-site uniaxial compression test was performed to measure the UCS of each sample. The weathering degree was evaluated by field investigations using a geological hammer and rebound instrument. Additionally, the tunnel depth and tunnel strike at each tunnel face were manually recorded by the field engineer.

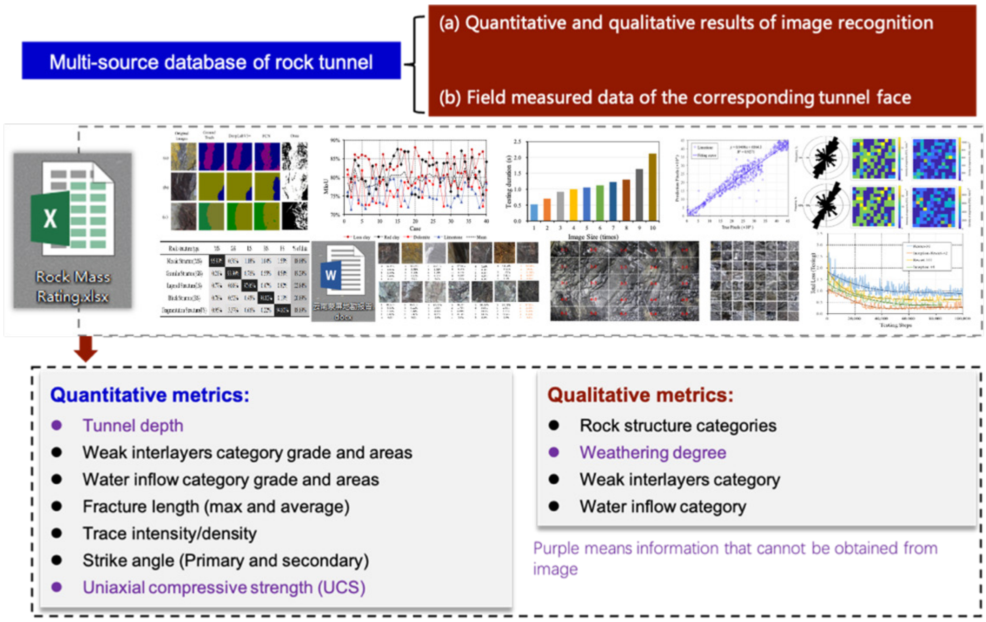

Figure 1. Establishment of multi-source datasets in rock tunnels.

3 MODEL PERFORMANCE

The architecture and learning process of a deep learning model is defined by its hyper-parameters. The choice of hyper-parameters significantly impacts the learning performance of deep learning models, which tend to have a higher number of hyper-parameters. Therefore, automatic hyper-parameter optimization is crucial for training and validating stacked deep learning models (SDLs). The hybridization of hyper-parameter optimization and SDLs provides several advantages, including reduced model deployment effort, improved model performance, and increased reproducibility of results (Bergstra et al., 2013).

In this study, we used the TPE algorithm to tune the hyper-parameters of three tree-based algorithms (DT, GBRT, and RF) and the MLP algorithm. The TPE algorithm optimizes the hyper-parameters within a 'tree' structure and requires that the estimated hyper-parameters be independent of each other. We introduce the cost function f(x), which is expensive to evaluate, and the cheaper approximate function TPE. The goal is to maximize the target model at the point where the target value would be predicted. The expected improvement (EI) value is a standard approach that performs well and is intuitive. We obtained the optimized hyper-parameters through the training process and performed validation and evaluation on preassigned datasets using a 10-fold CV.

Figure 2 shows the predicted results of the training and testing sets based on the hyper-parameter tuning process. The trained SDLs obtained all predicted results within a fraction of a second. We computed the performance indicators (MAE, RMSE, and R2) for the training and test sets recorded in Table 1. The TPE-GBRT algorithm had the most consistent predicted outputs for the measured outputs, followed by TPE-RF, TPE-DT, and TPE-MLP. The TPE-GBRT algorithm also showed the best prediction performance with the lowest values of MAE, RMSE, and R2.

It should be noted that, variable importance is measured via examining the impact on the Gini index of the variations in the input variables. Then, the Gini indexes are normalized to get the relative variable importance. The results suggest that weak interlayer area, rock structure category, water inflow area and USC are the most sensitive variables affecting the RMR value. Although the variable importance values may vary for different tunnel sites, the proposed methodology at least provides a more objective manner for assessing the rock mass quality of the tunnel face.

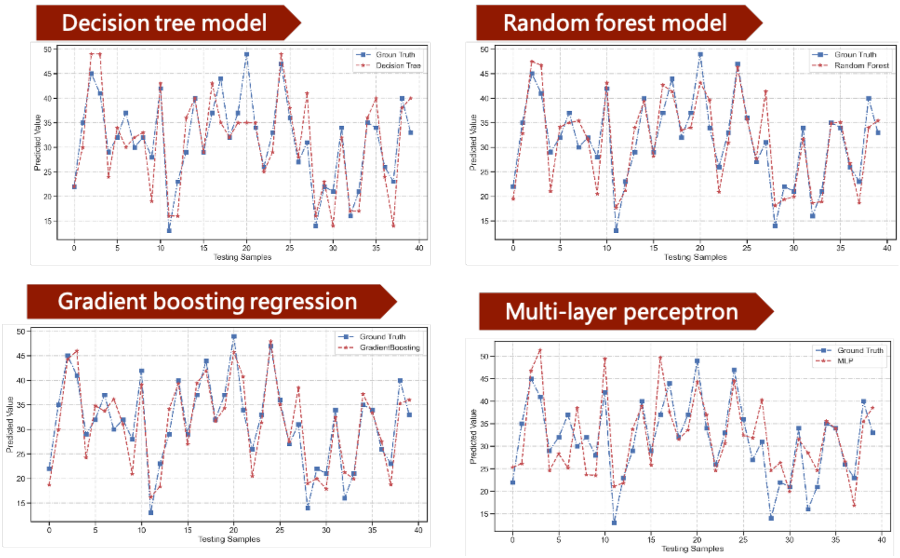

Figure 2. Predicted rock mass RMR values by four SDLs.

Table 1. Comparison of four algorithms to predict RMR.

	TPE-DT	TPE-MLP	TPE-RF	GBRT
MAE	4.52	4.94	3.14	3.16
RMSE	5.174	6.061	3.931	3.722
R2	0.64	0.5	0.79	0.81

4 CONCLUSION

This research aims to evaluate the performance of four machine learning (ML) algorithms commonly used to predict rock mass quality. The four algorithms include three tree-based deep learning models and one neural network-based model. The study consisted of four phases: database collection, algorithm selection, model robustness enhancement, and hyper-parameter optimization. Thirteen multi-source predictive variables were considered as input variables to construct the ultimate database. Bayesian optimization using TPE was utilized to optimize the hyper-parameters of the proposed deep learning algorithms.

The results show that TPE-GBRT had the best agreement with the measured results for training and testing processes, followed by TPE-RF, TPE-DT, and TPE-MLP, respectively. The proposed multi-source data-driven method considers the geological characteristics of a particular tunnel site and enhances the objectivity of the rock mass classification system. The approach can effectively predict rock mass quality, providing valuable insights for engineering design and construction.

It should be noted that the RMR is a hundred-mark system where all of the parameters are categorized and rated according to their impact on the stability of the tunnel. The grade of rock mass quality is evenly divided into five parts, among which the ranges [0, 20], (20, 40], (40, 60], (60, 80], and (80, 100] belong to grades V, IV, III, II, and I, respectively. A larger grade represents a poorer rock mass quality. In practice, unfavourable geological conditions draw more attention from field engineers. However, the importance of a global database is self-evident for a system that pursues robust discrimination. Therefore, datasets from different tunnel projects should be added continuously to the established database. An enhanced TPE-GBRT model can be trained and tested to improve its practical scope in future work.

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