

Prediction models of rock quality designation during TBM tunnel construction using machine learning algorithms

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Abstract. An accurate estimation of the geotechnical parameters in front of tunnel faces is crucial for the safe construction of underground infrastructure using tunnel boring machines (TBMs). This study was aimed at developing a data-driven model for predicting the rock quality designation (RQD) of the ground formation ahead of tunnel faces. The dataset used for the machine learning (ML) model comprises seven geological and mechanical features and 564 RQD values, obtained from an earth pressure balance (EPB) shield TBM tunneling project beneath the Han River in the Republic of Korea. Four ML algorithms were employed in developing the RQD prediction model: k-nearest neighbor (KNN), support vector regression (SVR), random forest (RF), and extreme gradient boosting (XGB). The grid search and five-fold cross-validation techniques were applied to optimize the prediction performance of the developed model by identifying the optimal hyperparameter combinations. The prediction results revealed that the RF algorithm-based model exhibited superior performance, achieving a root mean square error of 7.38% and coefficient of determination of 0.81. In addition, the Shapley additive explanations (SHAP) approach was adopted to determine the most relevant features, thereby enhancing the interpretability and reliability of the developed model with the RF algorithm. It was concluded that the developed model can successfully predict the RQD of the ground formation ahead of tunnel faces, contributing to safe and efficient tunnel excavation.

Keywords: machine learning; rock quality designation; shapley additive explanations; tunnel boring machine

1. Introduction

Over the past few decades, there has been a substantial increase in population density in urban areas. This has led to a surge in tunnel excavations to construct underground infrastructure such as transportation, electricity, water and steam supply, and sewage treatment systems (Broere 2016, Kim *et al.* 2020, Sharafat *et al.* 2021, Kang *et al.* 2022). Shield tunnel boring machines (TBMs) have emerged as the preferred equipment for making underground spaces due to their capability to minimize vibration and noise while ensuring the stability of adjacent structures (Amir *et al.* 2019, Wen *et al.* 2019, Kim *et al.* 2020, Pourhashemi *et al.* 2022, Kwon *et al.* 2023).

However, during TBM tunnel excavations, the geological uncertainty significantly reduces the efficiency of tunnel excavation and may pose safety risks. (Zhao *et al.* 2007, Farrokh and Rostami 2009, Zhao *et al.* 2014, Xu *et al.* 2022). Therefore, accurately identifying the ground conditions ahead of a tunnel face is crucial for efficient and

safe TBM excavation.

While geotechnical investigations at the design stage provide the overall geological profiles along the tunnel route, these have limitations in precisely identifying the geological conditions ahead of a tunnel face. To address this limitation, various ground prediction techniques have been developed, including non-destructive exploration and borehole drilling with testing (Grodner 2001, McDowell *et al.* 2002, Kaus and Boening 2008, Carrière *et al.* 2013, Lee *et al.* 2019, Kang *et al.* 2023, Yoon *et al.* 2023). However, these methods often require installing numerous devices to acquire data on geological conditions at tunneling sites, which can be impractical.

With the rapid advancement of computer technology, numerous machine learning (ML) algorithms have been developed to address various engineering challenges across different fields (Arumugam *et al.* 2023, Kafy *et al.* 2023, Méndez *et al.* 2023, Pallathadka *et al.* 2023). Moreover, improvements in communication network technology and data transmission capability have yielded more extensive and higher-quality data from TBM tunneling projects. Consequently, ML approaches have gained widespread use in TBM tunneling in recent years, benefiting from the abundant data collected during these projects, including site-specific features (Eftekhari *et al.* 2018, Lee *et al.* 2022, Mahmoodzadeh *et al.* 2022, Li *et al.* 2023).

ML algorithms have shown significant potential for accurately estimating geotechnical parameters, including the rock mass rating (RMR) and uniaxial compressive

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strength (UCS) (Liu *et al.* 2019, Liu *et al.* 2020, Mahmoodzadeh *et al.* 2021, Sebbeh-Newton *et al.* 2021). Since these parameters play a vital role in defining the geological conditions ahead of a tunnel face, it is essential to predict them precisely for a safe and efficient tunnel excavation. Among these parameters, the rock quality designation (RQD) significantly influences the overall TBM tunneling process, thereby being a key consideration for tunnel excavation operations.

Building on this background, this study introduced an ML approach for predicting the RQD values of the ground formations in front of a tunnel face. It adopted well-known ML algorithms, such as k-nearest neighbor (KNN), support vector regression (SVR), random forest (RF), and extreme gradient boosting (XGB). The ML model development utilized a database comprising seven geological and mechanical features along with 564 RQD values obtained from an earth pressure balance (EPB) shield TBM tunneling project beneath the Han River in the Republic of Korea.

To enhance prediction performance, the grid search method was employed to identify the optimal hyperparameter combinations for each ML algorithm. The Five-fold cross-validation was performed to validate the training results of the ML models. The prediction performances of these models were compared using two evaluation criteria: root mean squared error (RMSE) and the coefficient of determination (R^2). Finally, the contribution of each input feature to the model predictions was assessed using the Shapley additive explanations (SHAP) technique.

The remainder of this paper is organized as follows: Section 2 elaborates on the research background of ML algorithms, hyperparameter tuning, and SHAP. Section 3 provides details about the input database of the developed model and an overview of the applied TBM tunneling site. In Section 4, the prediction performance of the developed model is demonstrated along with the five-fold cross-validation. Finally, the conclusions of the study are presented in Section 5.

2. Methodology

2.1 Machine learning algorithms

In this study, four well-known ML algorithms were adopted to predict the RQD values of the ground conditions ahead of a tunnel face, including the KNN, SVR, RF, and XGB. The KNN algorithm operates on the fundamental principle that data points with similar characteristics tend to exhibit similar outcomes. The algorithm identifies the K-nearest neighbors for a given testing data point. Subsequently, it assigns the outcome that is most prevalent among these neighbors to the testing data point, as shown in Fig. 1(a). When implementing the KNN algorithm, the initial step involves selecting the number of neighbors (k) to be considered. Next, the algorithm computes the distance between the testing data point and all other data points in the dataset using a distance metric, such as the Euclidean or Manhattan distance. Following this, the K-nearest neighbors to the testing data point are determined by identifying the k data points with the smallest distances. Finally, the

algorithm assigns the outcome based on the majority of the K-nearest neighbors to the testing data point.

The SVR algorithm is built on the principle of establishing a margin around the predicted values to minimize error, as illustrated in Fig. 1(b). The algorithm aims to find a function that best fits the data while allowing for some errors. The margin is defined by two lines, one above and one below the predicted values, known as support vectors. To optimize prediction performance, the algorithm strives to minimize the error within this margin while constraining the margin size. The trade-off between minimizing error and limiting margin size is controlled by a hyperparameter (i.e., C). Once the SVR model is trained, it can make predictions on new data points.

The RF algorithm operates based on the concept of constructing multiple decision trees, each trained on a bootstrap sample (Fig. 1(c)). Bootstrap samples are created by randomly selecting subsets of the training data. To make a prediction, the algorithm aggregates the predictions obtained from all the decision trees. The average of these predictions provides a robust and accurate estimate of the target variables.

XGB is a robust ML algorithm that sequentially builds and combines multiple decision tree models, with each new model focused on correcting the errors of the previous ones, as shown in Fig. 1(d). The algorithm identifies prediction errors, and then creates new models to correct those errors. The final prediction is determined using the weighted average of the individual model predictions. This iterative process, along with regularization techniques, helps prevent overfitting and enhances the prediction performance.

2.2 Hyperparameter tuning

A hyperparameter is a configuration setting for an ML algorithm, which should be established before the training process. It can control various aspects of the learning process and significantly influence the performance of the ML algorithm. Hyperparameter tuning is the procedure of systematically selecting the best hyperparameters for the ML algorithm to achieve optimal performance in a specific prediction. There are several hyperparameter tuning techniques, including grid search, random search, and Bayesian optimization. In this study, the grid search and five-fold cross validation were adopted to conduct hyperparameter tuning, which allows for the evaluation of the ML models' performance while searching for the best set of hyperparameters.

The grid search is a hyperparameter optimization technique that involves defining a set of hyperparameters and their possible values before implementing an ML algorithm. It systematically explores all possible combinations of hyperparameters to identify the optimal combination of hyperparameters that yields the best prediction performance. This technique creates a grid of all conceivable hyperparameter values, and for each combination, the model is trained and evaluated. The grid search is typically combined with cross-validation to ensure that the selected hyperparameters generalize well to unknown data.

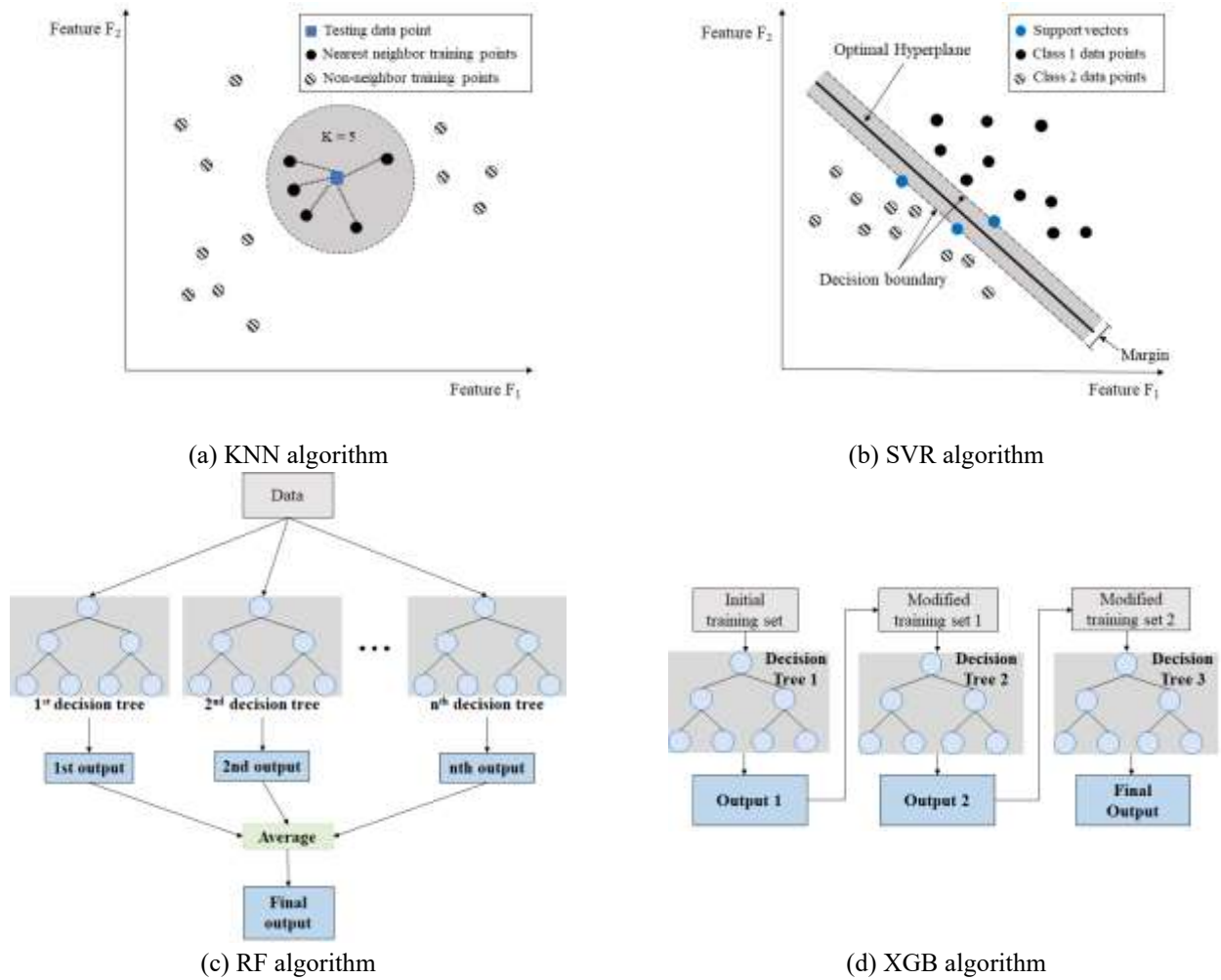


Fig. 1 Graphical descriptions of machine learning algorithms



Fig. 2 Five-fold cross-validation procedure

The five-fold cross-validation is a technique used to assess the ML model’s performance by dividing the dataset into five equally sized folds. In the context of hyperparameter tuning, each fold serves as a validation set, while the remaining four folds are utilized for training. This process is repeated five times, with every fold acting as the validation set once. The final assessment of the model’s performance is determined by averaging the results from the five tests (refer to Fig. 2).

2.3 SHAP

SHAP is one of the techniques used for interpreting the

contributions of individual features to the prediction results of ML models (Lundberg and Lee, 2017). It can be utilized to determine how each feature contributes toward a specific output of the ML model. This approach relies on the concept of establishing an explanation model, denoted as “ g ” for predicting the original trained model “ f ” using an additive feature attribution method (refer to Eq. (1)).

$$g(z') = \varphi_0 + \sum_{i=1}^M \varphi_i x'_i \quad (1)$$

where z' is a simplified local input, φ_0 is the baseline of the model, M is the number of input features, and φ_i is the SHAP value corresponding to the i -th feature.

To assess feature importance, SHAP employs Shapley values, a concept derived from game theory (Shapley 1953). The Shapley values for the i -th feature (φ_i) can be computed as the average of the marginal contributions of the i -th feature calculated across all subsets S of N , except for the i -th feature itself (refer to Eq. (2)).

$$\varphi_i = \frac{1}{n!} \sum_{S \subseteq N \setminus \{i\}} |S|! (n - 1 - |S|)! [f(S \cup \{i\}) - f(S)] \quad (2)$$

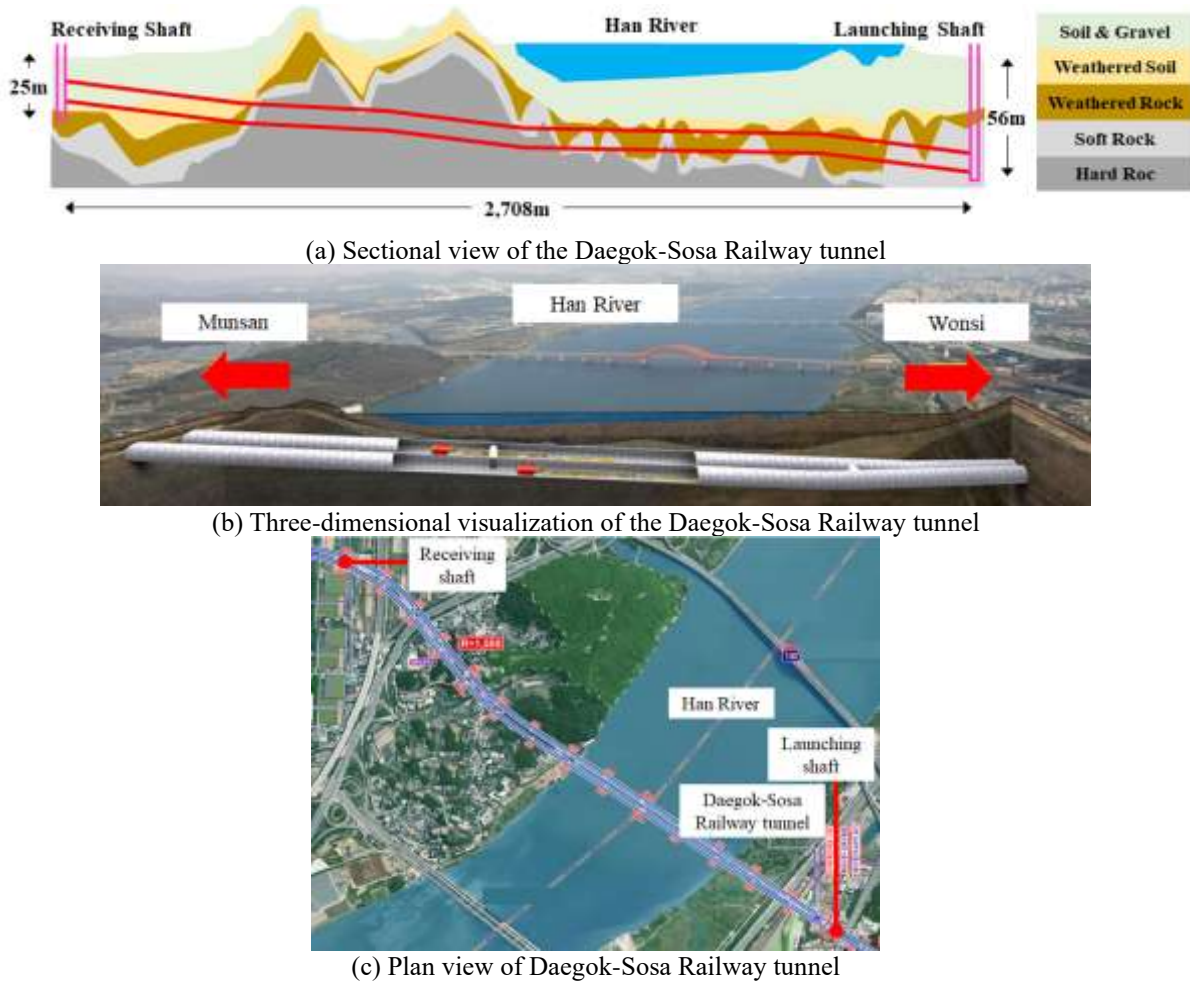


Fig. 3 Graphical descriptions of machine learning algorithms

Table 1 EPB shield TBM specifications

Description	Specification
Excavated tunnel diameter (m)	8.1
Torque (kNm)	7,510–12,843
Thrust force (kN)	66,523
Rotational Speed (rpm)	0–3.7
Power (kW)	2,080 (13 × 160)

where f is the original prediction model, S is a subset of features, N is the set of all features, i is the specific features, and n is the total number of features.

In other words, the Shapley values can be treated as representing the impact of a feature on the variation between the actual prediction (with the i -th feature) and the average prediction (without the i -th feature). This marginal contribution of the i -th feature can be expressed by $f(S \cup \{i\}) - f(S)$.

3. Input database

3.1 Site overview

This study employed datasets acquired from a TBM tunneling project spanning 18.4 km in the Republic of Korea. This project involved the construction of a railway tunnel beneath the challenging ground conditions of the Han River. To meet the demanding excavation schedule and overcome the harsh ground conditions, an EPB shield TBM was selected to construct 2.7 km twin tunnels, including a challenging 1.2 km section under the Han River, as shown in Fig. 3. Table 1 summarizes the technical specifications of the EPB shield TBM adopted in this study. Various mechanical parameters, such as the advance speed, torque, thrust force, chamber pressure, and rotational speed, were recorded and compiled to assess the TBM's performance during tunneling. When it comes to rotational speed, this parameter is adjusted by the operator. However, the operator considers both ground conditions and machine load during tunneling, which results in a strong association with RQD.

The geological profile of the tunnel alignment is shown in Fig. 3(a). The tunneling site is located in the Gyeonggi massif and features alluvial deposits with fluctuating groundwater levels. Notably, the project encountered mixed ground conditions, including decomposed granite soil and weathered rock beneath the Han River.

Table 2 Statistical characteristics of input factors

Category	Factors	Min.	Median	Max.	Average	Standard deviation	Unit
TBM Operational factor	Rotation speed	1.49	3.02	3.73	3.04	0.31	Rpm
	Torque	0.58	1.12	2.58	1.14	0.27	MN·m
	Thrust force	6,045.0	13,089.5	31,702.0	13,690.3	4,091.3	kN
	Advance speed	5.1	12.3	18.0	12.2	1.8	mm/min
	Chamber pressure	0	0.22	3.22	0.42	0.71	bar
Geological factor	Distance from GWL to tunnel crown	21.57	29.96	37.30	29.87	3.04	m
Target	RQD	2.17	68.27	80.00	59.98	18.94	%

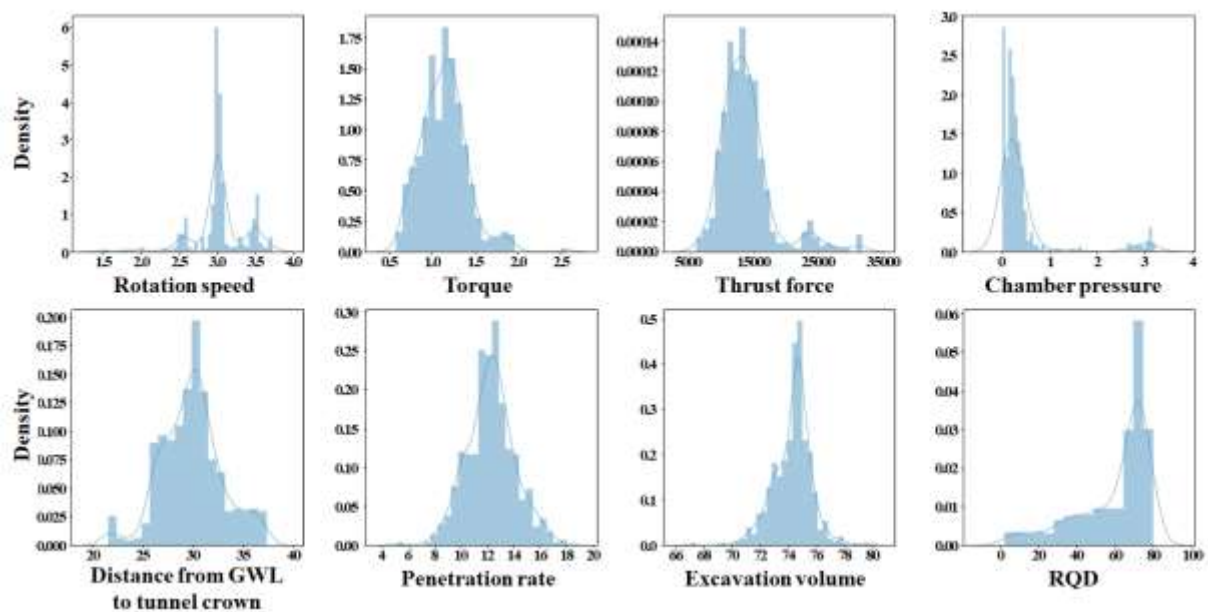


Fig. 4 Histograms of the database applied to the ML algorithm

3.2 Characteristics of database

This study considered seven mechanical and geological features to predict the RQD values of the ground formations ahead of the tunnel face. The mechanical features of the EPB shield TBM included five primary controls, including rotational speed, torque, thrust force, and chamber pressure. On the other hand, the geological characteristics at the tunnel face were represented by the distance from groundwater table level (GWL) to tunnel crown and the RQD values measured at the tunnel axis (i.e., the prediction target). Table 2 presents the statistical variables of the database. The database distribution is represented with respect to input features and summarized in Fig. 4.

4. Model implementation

4.1 Implementation procedure

In this study, an ML model was developed to predict the RQD values using the established database, employing the SVR, KNN, RF, and XGB algorithms. The standardized dataset was divided into training and test datasets, with 70% (i.e., 395 data points) and 30% (i.e., 169 data points), respectively. Furthermore, the grid search and five-fold cross-validation were performed to identify the optimal hyperparameters of each ML algorithm.

This study employed the root mean squared error (RMSE) and the coefficient of determination (R^2) to evaluate the prediction performance of the ML models based on the KNN, SVR, RF, and XGB algorithms. These metrics are defined in Eqs. (3) and (4).

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (3)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (4)$$

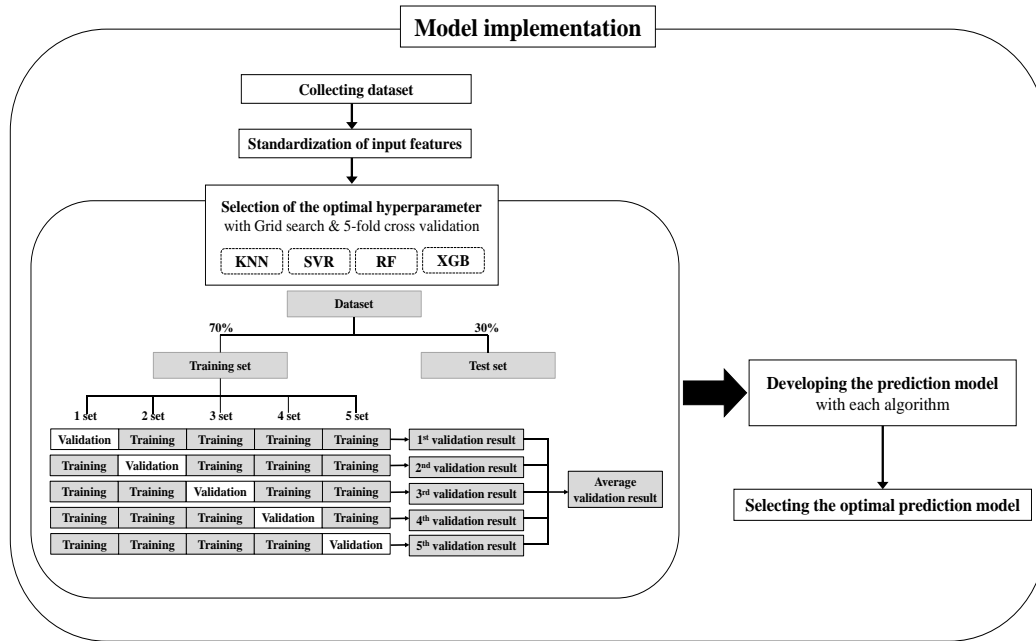


Fig. 5 Flowchart of implementation procedure for RQD prediction model

where, N is the total number of datasets, y_i and \hat{y}_i are the actual and predicted RQD values, respectively, and \bar{y} is the mean of the actual RQD values.

In summary, Fig. 5 shows the detailed model implementation procedure of the developed RQD prediction model.

4.2 Prediction results

The prediction performance of the ML models, which include the KNN, SVR, RF, and XGB algorithms, was evaluated using the RMSE and R^2 values. Table 3 summarizes the optimal hyperparameters, RMSE, and R^2 for each ML algorithm in the prediction model. Furthermore, Fig. 6 demonstrates the test set output results for the four ML models. The clustering of prediction errors around the actual RQD of 70% is attributed to the unique conditions of the tunneling site. Specifically, the RQD values at the site tend to be around 70% in anomalous ground conditions, such as mixed ground and areas beneath the river.

Among the ML models considered, the RF algorithm exhibited the highest prediction performance. It achieved the lowest RMSE value of 7.38 and the highest R^2 value of 0.81, establishing it as the most suitable model for predicting RQD values of ground formations ahead of a tunnel face.

Although there are limitations associated with using data from a single site that pertains to particular TBM equipment and ground conditions, the ML model, developed using the RF algorithm, has effectively predicted RQD values for the ground formations ahead of a tunnel, utilizing geological and mechanical databases. As a result, this model can serve as a robust tool for identifying ground conditions during TBM excavation.

Table 3 Prediction performance and optimal hyperparameters of each ML model

Algorithm	RMSE(%)	R^2	Optimal hyperparameter Type	Optimal values or types
KNN	9.22	0.74	Metric	Euclidean
			N neighbors	5
			Weights	Distance
SVR	8.93	0.75	C	155
			Kernel	rbf
			Max depth	12
RF	7.38	0.81	Min samples split	2
			N estimators	500
			Learning rate	0.1
XGB	8.04	0.80	Max depth	6
			Min child weight	1
			N estimators	940
			Subsample	0.5

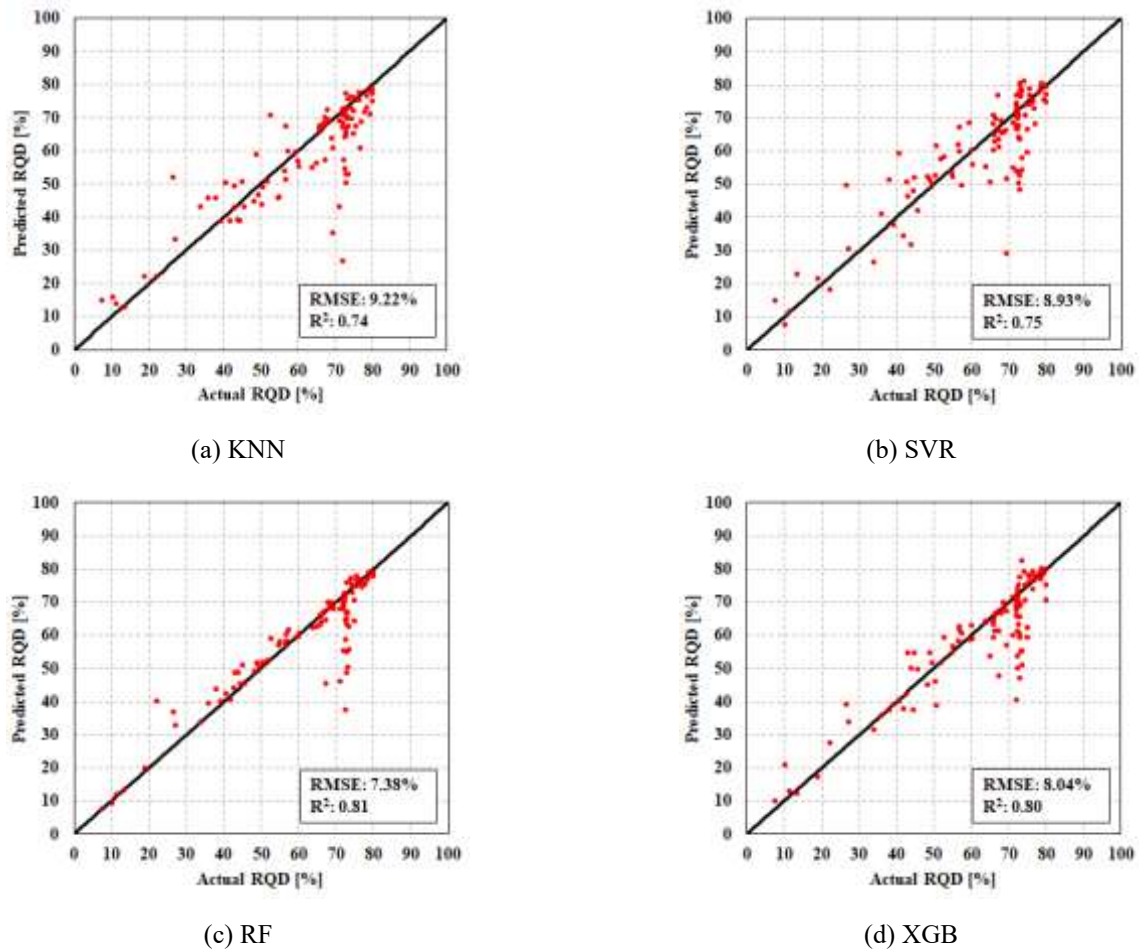


Fig. 6 Prediction results obtained by each ML model



Fig. 7 SHAP analysis results

4.3 Feature analysis using SHAP

This study adopted the SHAP analysis to assess the feature importance of input variables in predicting the RQD values using the RF model. Fig. 7 indicates the absolute SHAP values for the global feature importance corresponding to each input feature. The analysis showed that the rotation speed and the distance from GWL to tunnel

crown were the most influential features in determining the RQD values of the ground formations among the input features. However, the excavation volume and penetration rate had a relatively lower impact on the prediction of the RQD values, as depicted in Fig. 7(a).

In addition, Fig. 7(b) illustrates the SHAP values according to the feature values, considering all seven features in the database. For the rotation speed, thrust force,

and penetration rate, the SHAP values increased with higher feature values, indicating a positive correlation with the predicted RQD values. This suggests that these input features (i.e., rotation speed, thrust force, and penetration rate) tend to have higher values during tunneling in competent rock formations with high RQD values. On the contrary, the distance from GWL to tunnel crown and torque exhibited a reverse trend. It can be inferred that this trend is a result of the specific characteristics of the tunneling site, due to the complexity of the correlation between these features and the RQD values.

5. Conclusions

This study aimed to develop a machine learning (ML) model for predicting the RQD values in the ground formations ahead of a tunnel face using four well-known algorithms (KNN, SVR, RF, and XGB). The database used for model development was obtained from an EPB shield TBM tunneling project in the Republic of Korea. To improve the model accuracy and reliability, the optimal hyperparameters for the ML algorithms were selected through the grid search and five-fold cross-validation. The study also conducted the SHAP analysis to identify the most relevant input features for RQD prediction, enhancing model interpretability and reliability. Key findings and contributions include:

- Among the four ML algorithms (KNN, SVR, RF, and XGB), the RF algorithm demonstrated the best prediction performance, achieving the lowest RMSE of 7.38% and the highest R^2 of 0.81.
- The combination of grid search and five-fold cross-validation for hyperparameter tuning exhibited excellent performance, resulting in high prediction accuracy for ML models. This robust hyperparameter search process is crucial for RQD prediction models due to the need to capture the complex relationship between numerous input features and RQD values.
- The SHAP analysis revealed that the rotation speed was the most dominant feature for predicting RQD values, while the torque, excavation volume, and penetration rate had less impact on the predicted RQD values.
- While the developed model showed promising prediction performance, further research is necessary to create a model that can simultaneously predict other geotechnical parameters (e.g., SPT N value, RMR, and UCS) to comprehensively enhance the safety and efficiency of TBM tunneling.

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