

Shield TBM disc cutter replacement and wear rate prediction using machine learning techniques

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Abstract. A disc cutter is an excavation tool on a tunnel boring machine (TBM) cutterhead; it crushes and cuts rock mass while the machine excavates using the cutterhead's rotational movement. Disc cutter wear occurs naturally. Thus, along with the management of downtime and excavation efficiency, abrasioned disc cutters need to be replaced at the proper time; otherwise, the construction period could be delayed and the cost could increase. The most common prediction models for TBM performance and for the disc cutter lifetime have been proposed by the Colorado School of Mines and Norwegian University of Science and Technology. However, design parameters of existing models do not well correspond to the field values when a TBM encounters complex and difficult ground conditions in the field. Thus, this study proposes a series of machine learning models to predict the disc cutter lifetime of a shield TBM using the excavation (machine) data during operation which is response to the rock mass. This study utilizes five different machine learning techniques: four types of classification models (i.e., K-Nearest Neighbors (KNN), Support Vector Machine, Decision Tree, and Staking Ensemble Model) and one artificial neural network (ANN) model. The KNN model was found to be the best model among the four classification models, affording the highest recall of 81%. The ANN model also predicted the wear rate of disc cutters reasonably well.

Keywords: ANN; disc cutter wear; excavation data; machine learning classification models; shield TBM

1. Introduction

Owing to the advantages of low noise and vibration, tunnel boring machines (TBMs) are being increasingly used due to the growth of urban railway and highway tunnel constructions. Various researchers have highlighted the importance of special considerations in TBM construction, especially in urban areas with soft complex ground conditions (Kovari and Ramoni 2006, Wedekin *et al.* 2012, Ma *et al.* 2015, Jeong *et al.* 2018, Razaei *et al.* 2019, Eftekhari and Aalianvari 2019, Kim *et al.* 2018, Kim *et al.* 2020). TBMs comprise excavation tools, such as disc cutters and cutter bits mounted on the cutter head to crush and cut the ground and/or rock via the equipment thrust. In this process, disc cutters are worn not only normally but also abnormally, including cracks and falling-off of the disc cutter, depending on the ground conditions. Disc cutter wear causes damage to the surrounding disc cutter, increases the equipment thrust and torque, and decreases the penetration rate (PR), which consequently degrades the excavation efficiency of a TBM. Disc cutter wear is triggered by the geological conditions of the underground (e.g., rock type including strength, abrasiveness, mineral composition, rock mass including joint system and water content) and by the TBM operation, and it can be monitored during construction (Frenzel *et al.* 2008). In abrasive ground containing significant quartz mineral and mixed ground

wherein the soil and rock appear together on the face, abnormal wear, such as cracking and falling off, frequently occurs. Thus, some researchers studied the disc cutter lifetime and penetration rate evaluation for soft ground which is useful in both for scheduling and cost evaluation TBM projects (Farrokh 2021a, b, Kim *et al.* 2020).

The most commonly used methods for predicting a disc cutter replacement period are the CSM (Colorado School of Mines) model (Rostami 1997), Gehring model (Gehring 1995), and NTNU (Norwegian University of Science and Technology) model (Bruland 1998, Macias 2016). Existing prediction models have been developed considering homogeneous ground or hard rock conditions based on linear cutting tests and excavation data from the field. Disc cutter lifetime predictions using these models for heterogeneous ground or the soft soil conditions in urban ground environments are not accurate. Situations that require unexpected disc cutter replacement frequently occur due to abnormal wear, such as uneven disc cutter wear or ring breaking in complex grounds with a mixture of folds and multiple strata. The number of actual disc cutter replacement in the field has more than doubled due to the difference in the number of disc cutter replacement afforded by the NTNU model (Jung *et al.* 2010). Therefore, to overcome the limitations of the existing disc cutter consumption prediction models and improve the TBM excavation performance in complex/mixed grounds, a new model that can predict the TBM performance and disc cutter replacement cycle in such ground conditions needs to be developed.

Herein, shield TBM excavation data and ground characteristics at the OO~OO high-speed railway

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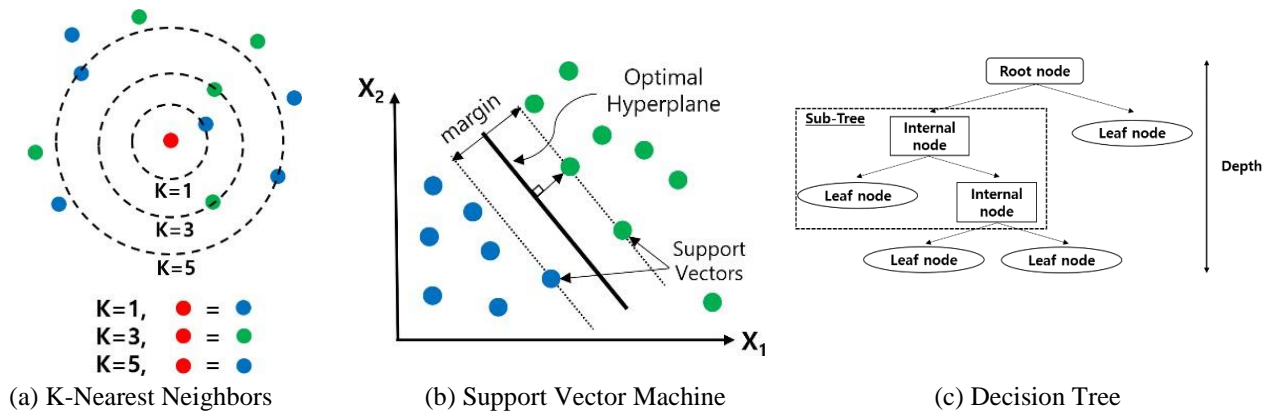


Fig. 1 Basic conceptual diagram of each classification model

construction site were analyzed to develop a new disc cutter wear prediction model. Data about five factors from the TBM machines during excavation that are highly correlated with disc cutter wear were selected and used as input after data preprocessing. After the disc cutter wear rates were analyzed using the disc cutter replacement history data, they were applied to a model target. Four classification models and one predictive model were established using machine learning techniques to determine the disc cutter replacement and predict disc cutter wear, respectively. The classification models were developed by applying the K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Decision Tree (DT), and ensemble classification methods, staking algorithms in python. An artificial neural network (ANN) algorithm was used to develop a disc cutter wear rate prediction model. The four classification models and the ANN model were evaluated for the entire shield TBM section and four divided ground conditions.

2. Data preprocessing and machine learning techniques

To apply data into machine learning algorithms, the obtained data needs to be properly processed. In this section, two data preprocessing methods, min–max scaling methods and synthetic minority oversampling technique (SMOTE), and three machine learning algorithms, classification machine learning algorithms, ensemble machine learning algorithms, and ANNs, are reviewed.

2.1 Data preprocessing methods

In machine learning, data preprocessing is an initial step that can improve the performance of models, where raw data are processed to make them understandable and readable. Among the various data preprocessing methods, the min–max scaling method and the SMOTE technique are employed herein. The min–max scaling technique rescales the range of features to the $[0,1]$ range to reduce the scale differences among each feature. SMOTE is an oversampling technique in classification problems that is used to handle imbalanced datasets (one class dominates a dataset).

2.2 Classification machine learning algorithms

Three machine learning algorithms were employed herein: KNN, SVM, and DT. The conceptual figure of each model is presented in Fig. 1.

2.2.1 K-Nearest Neighbors (KNN)

A nonparametric classification method, the KNN technique, was developed by Evelyn Fix and Joseph Hodges in 1951. The KNN model can be used for both classification and regression of target data using close KNN data to the target data. Various distance calculation methods, including Euclidean, Correlation, and Minkowski methods, can be employed to calculate the distance between the target and nearest data. The K value in the model is also considerable. The distance calculation method and K value both affect the model performance (Abu Alfeilat *et al.* 2019). The smaller the K value, the greater the tendency of the model to sensitivity and overfitting; the larger the K value, the greater the tendency of the model to insensitivity, over-normalization, and underfitting. Advantageously, this algorithm has little effect on the error data due to comparison with a relatively small number of data close to the target data. Disadvantageously, the algorithm calculation time increases with the amount of data.

2.2.2 Support Vector Machine (SVM)

The SVM technique (Schlkopf and Smola 2001) is a supervised learning model and is based on the VC theory proposed by Vapnik (1995) and Vapnik and Chervonenkis (1974). Moreover, it can be used for classification and regression analysis. Although countless boundaries can be employed to divide data into categories for classification analysis, the optimal hyperplane is judged based on the margin, which is the distance between the boundary line and support vector. The support vector refers to the data located closest to the determined hyperplane, and it plays a decisive role in determining the margin. In linear SVM, the classification error decreases and the model performance improves with increasing margin. In addition to the linear separation technique afforded by SVM, radial basis function (RBF) and polynomial kernels can efficiently perform nonlinear classification using kernel tricks. The

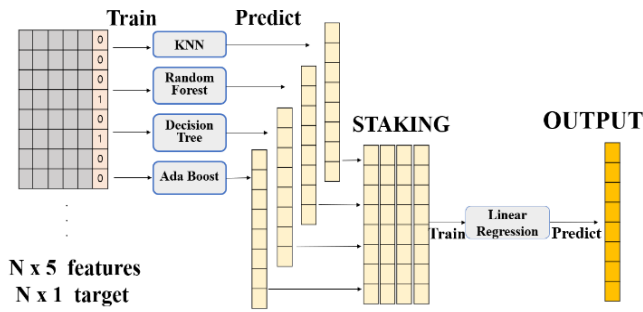


Fig. 2 Staking classification model in the study

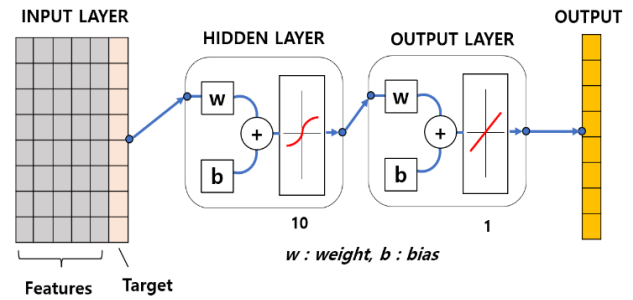


Fig. 3 A three-layer feed-forward neural network (ANN)

hyperparameters in the SVM are C and γ . Higher C denotes greater error, while higher γ affords a greater curvature hyperplane.

2.2.3 Decision Tree (DT)

The DT algorithm is a machine learning algorithm that is intuitively easy to understand and creates a tree-based classification model to automatically identify patterns through input/features. As for the DT algorithm, various algorithms have been proposed in literature (Patel and Prajapati 2018), and the representative algorithms are AID (Automatic Interaction Detection), CHAID (Chi-squared Automatic Interaction Detection), and CART (Classification and Regression Trees). DT algorithms basically have a common structure, start from the root node, go through the internal node, and end at the leaf node, and they are classified by a specific separation criterion at each node. The data collected at one end node at the endpoint can be considered as a group with the same characteristics. Classification or prediction can be performed by applying new data to a model constructed using the given data. The hyperparameters that affect the model performance are tree depth, maximum features, minimum/maximum leaf of nodes, and minimum samples of splits.

2.3 Staking ensemble algorithm

The stacking technique is an ensemble model that converts prediction data into training data using individual machine learning algorithms and performs final prediction after learning. This model requires an individual base model and a final meta-model that learns by utilizing the prediction data of the individual base model as training data. As basic models in the stacking model, KNN, Random Forest, DT, and AdaBoost are introduced, and logistic regression is applied as the final model. The predicted results from each classification are used as input data in the logistic regression; the predicted results are illustrated in Fig. 2.

2.4 Artificial neural networks

ANN (Abiodun *et al.* 2018) is a subset of machine learning algorithms based on the concept of the biological neural network models and can recognize data characteristics and patterns through iterative training. An ANN is a multilayer perceptron with multiple hidden

layers between the input and output layers and is illustrated in Fig. 3. The input data, which are calculated by the weight and bias in the input layer, traverses through the activation function in the hidden layers and are converted into output in the output layer. To reduce the difference between the actual and desired outcomes, several hidden layers and activation functions can be modified. Herein, ANN is applied to develop a model to predict disc cutter wear rate using the MATLAB neural network fitting app. The prediction model evaluates model performance using root mean square error (RMSE), which can evaluate the difference between the input and predicted target values.

3. Project overview

3.1 Ground condition

At the 00~00 railway construction site, the total tunnel length is 3,930 m, of which the shield TBM construction section is 1,160 m. Ten samplings and resistivity survey were conducted to investigate the soil/rock conditions and geological profiles. In the laboratory, soil, and rock tests, uniaxial compressive strength and triaxial compression tests were performed to estimate the of stratum type and soil and rock strength parameters. As shown in the field and lab test results, weathered and sedimentary soil layers formed around the site, with soft and hard rocks appearing in some sections. Fig. 4 illustrates the four categories of the ground conditions: a mixed layer with many weathered rocks, a weathered rock layer, a sedimentary mixed layer mainly comprising soft rock, and a sedimentary layer. Fig. 5 illustrates the boulders with diameters of 18–70 cm distributed in the tunnel face at the expected hazardous section of the site.

3.2 Shield TBM equipment

The shield TBM equipment used in the field is a slurry-type shield manufactured by Herrenknecht in Germany. The shield TBM is equipped with a displacement cylinder, an articulation cylinder, and a drilling line to prevent face plate jamming, correct meandering, secure the ease of curvature construction, and identify the geological conditions in the front and reinforce the ground. It was manufactured to cope with the issues that may stem during tunneling in mixed

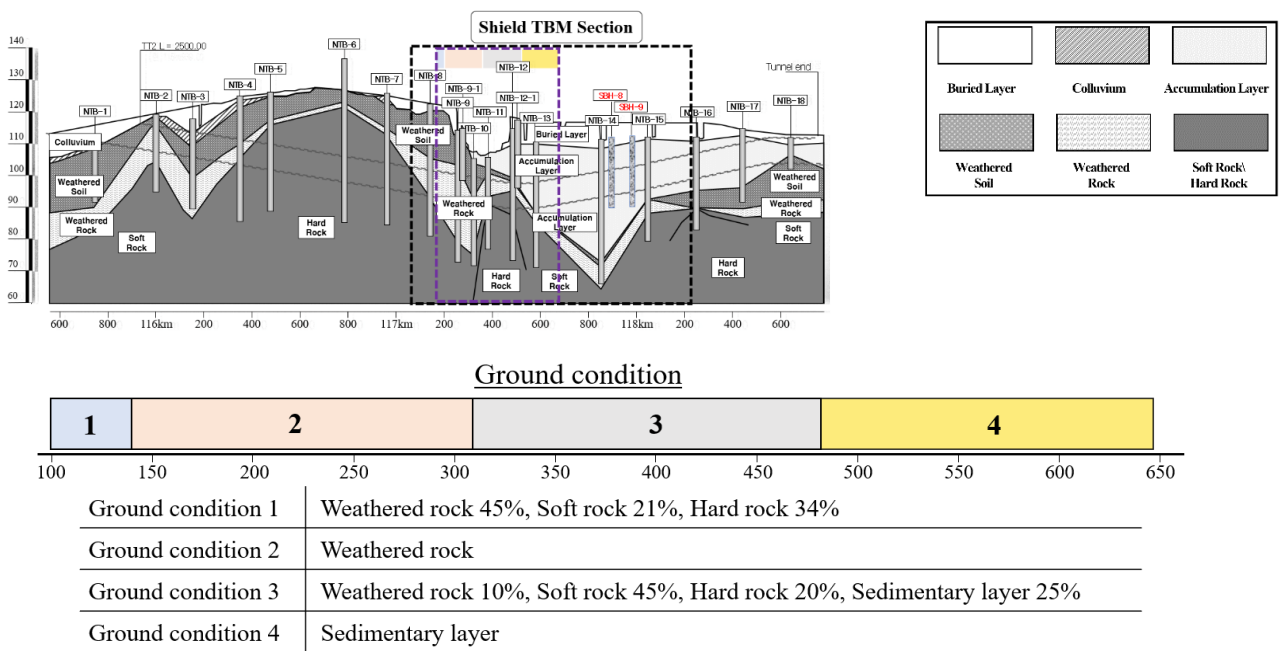


Fig. 4 Longitudinal geological profile of the tunnel and the four ground conditions classified in the study

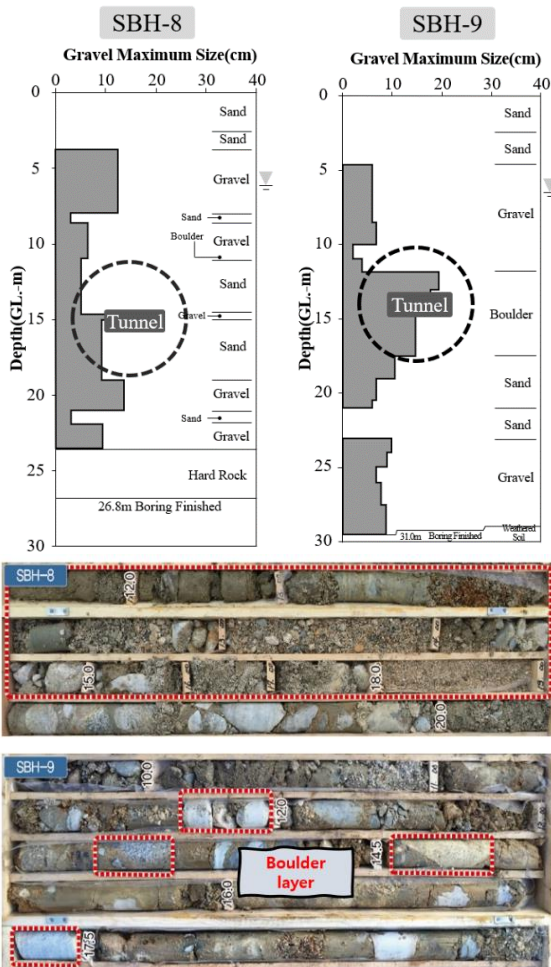


Fig. 5 Maximum gravel size distribution in depth (SBH-8 and SBH-9) and the samples

ground conditions. Additionally, the shield TBM is equipped with a bubble chamber to cope with the changes in chamber pressure and a crusher for crushing excavated rock or gravel layers to facilitate heterogeneous ground excavation. Totally, 44 17-inch disc cutters (40 single disc cutters and 4 double disc cutters) and 110 scrapers are installed in the cutter head. Table 1 describes the main specifications of the shield TBM equipment, and Table 2 presents the configuration of the excavation tools (disc cutters and scraper) on the TBM cutter head.

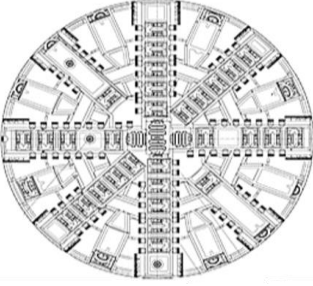
3.3 Excavation and cutter head intervention data

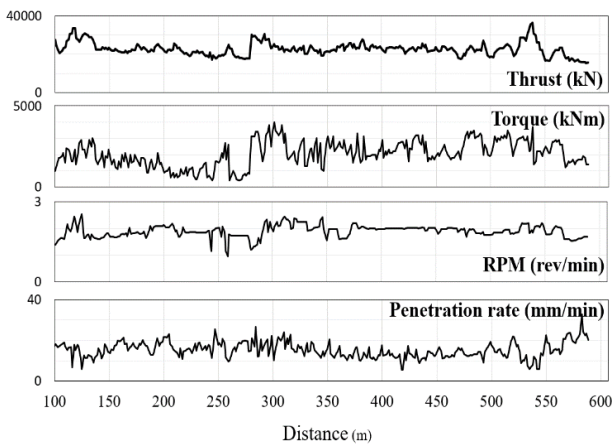
The TBM excavation data, i.e., thrust, torque, cutter head rotation speed (RPM), and penetration rate (PR) from 100 to 600 m of the TBM excavation length, that are used as input features are shown in Fig. 6 according to the ground conditions. Although ground conditions during tunnel excavation are the most influential factor for disc cutter wear, only excavation data were used for the analysis due to the difficulties of accurately judging the ground conditions at the tunnel face. The TBM machine is operated by a skilled operator with the ability to successfully work according to the ground conditions. Therefore, herein, the excavation data were judged to be sufficiently correlated to the ground condition. The detailed analysis of the excavation data is delineated further in La *et al.* (2019). In other words, thrust is the most basic standard for judging the rock strength. Furthermore, when accounting for increases in the rock strength, the operator should use higher thrust. Thrust and torque considerably vary with the severe ground changes with the appearance of gravel and boulder layers. Moreover, RPM was operated in a low range of 1–2.5 to ensure safe excavation for preventing construction problems. PR is the principal measure of TBM

Table 1 Major specifications of the shield TBM and cutter head

Classification		Specifications		Classification		Specifications	
Shield Machine	Cutter diameter (mm)	8,410		Number (EA)	28		
	External diameter (mm)	8,370~8,390		Thrust per jack (kN)	2,124		
	Length (mm)	10,500		Shield Jack	Total thrust (kN)	59,464	
Main Drive	Number of motor (EA)	8		Stroke (mm)	2,500		
	RPM (rpm)	Max. 3.1		Penetration Rate (mm/min)	50		
	Torque (kN·m)	4,680~6,786		Maximum tunnel face pressure (bar)	4.5		

Table 2 Major specifications of the cutter head and disc cutter

Cutter head diagram	Classification	Specifications
	Disc cutter diameter (inch)	17
	Number of disc cutter (EA)	44
	Number of single disc cutter (EA)	40
	Number of double disc cutter (EA)	4
	Number of scrapper (EA)	110
	Disc cutter diameter (inch)	17

Fig. 6 Shield TBM excavation data (after La *et al.* 2019)

performance and is calculated by multiplying the disc cutter press-in depth (mm/rev) and RPM. Additionally, the rotation distance for each disc cutter was introduced as an input, and the input significantly influenced the disc cutter wear. The rotation distance is calculated using Eq. (1).

$$RD_i = \frac{D \times 1000}{PR} \times RPM \times 2 \times \pi \times R \quad (1)$$

where RD_i is the rotation distance for disc cutter i (m), D is the excavation distance (m), PR is the penetration rate (mm/min), and R is the distance from the center of the cutterhead to the disc cutter. A total of 24 TBM machines were stopped to replace worn disc cutters during the entire shield TBM section, and only 18 replacement periods

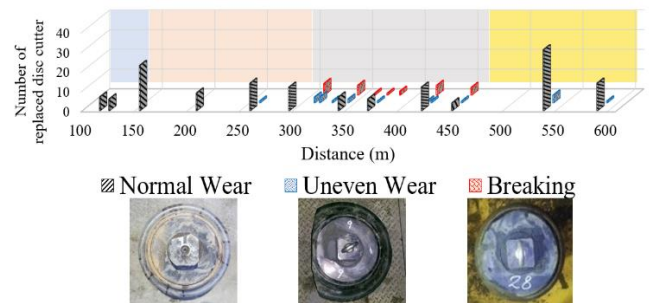
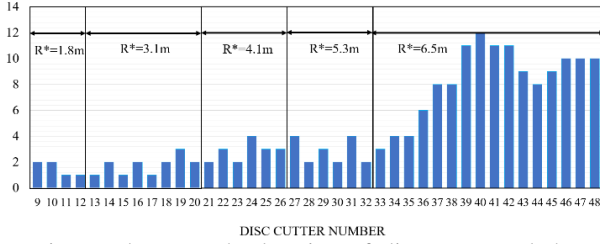


Fig. 7 Number of replaced disc cutters in the distance and types of disc cutter wear

correlated with the data used in the analysis. During the 18 cutter replacements, 145, 19, and 24 disc cutters were replaced due to normal wear, uneven wear, and cracking or elimination, respectively. Fig. 7 displays the number of replaced disc cutters in the excavation distance and the types of disc cutter wear. Most of the disc cutters were replaced due to normal wear; however, in ground condition 3, many disc cutters were replaced due to cracking or abnormal wear related to other ground conditions. To maximize cutting and energy efficiency, disc cutters are installed on cutterheads with different radii, and each disc cutter rotates with a different trajectory during excavation. The 40 disc cutters used herein were divided into five orbits to calculate the rotation distance. Fig. 8 illustrates the number of replaced disc cutters in each disc cutter in different orbit. Disc cutter wear at the replacement time was presumed to be 100% wear, and the disc cutter wear



*R: Distance between the location of disc cutter and the center of the cutter head

Fig. 8 Number of replaced disc cutters in each disc cutter

without data was linearly interpolated. To classify the disc cutter replacement, disc cutters with wear of over 80% were assumed to be replaced.

4. Results and discussion

4.1 Results of classification models

The classification and ensemble models were developed using python. The confusion matrix was used to evaluate the classifiers and is shown in Table 3. The accuracy, precision, recall, f1-score, area under the curve (AUC), and error rate were calculated using Eqs. (2)-(5).

Accuracy (Eq. (2)) denotes the proportion of accurately predicted data among the total data, and it presents the rate at which a predictive model correctly classifies the disc cutter replacement. Precision (Eq. (3)) denotes the rate at which the disc cutter replacement occurred according to the model prediction. Recall (Eq. (4)) is the ratio between the actual disc cutter replacement data and the disc cutter replacement by predictive model, and it is used as a performance indicator when all the positive data need to be identified and false negatives are not desired. Herein, the recall index was employed to increase the discrimination of disc cutters that need to be replaced. AUC is between 0.5 and 1 and is the area under the receiver operating characteristic (ROC) curve. ROC focuses on two indexes: true positive rate (Recall (Eq. (4))) and false positive rate (Error rate (Eq. (5))).

Table 4 presents the hyperparameters adjusted to afford an optimum classification model for all features through the entire excavation distance. The hyperparameters in the

$$\text{Accuracy (\%)} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}} \times 100 \quad (2)$$

$$\text{Precision (\%)} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100 \quad (3)$$

$$\text{Recall (\%)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100 \quad (4)$$

$$\text{Error rate (\%)} = \frac{\text{FP}}{\text{FP} + \text{TN}} \times 100 \quad (5)$$

staging ensemble model employ the same values for each classification model.

Table 3 Confusion matrix of the binary classification model

		Predicted class	
		Replaced (1)	Unreplaced (0)
Actual class	Replaced (1)	TP (True Positive)	FN (False Negative)
	Unreplaced (0)	FP (False Positive)	TN (True Negative)

Table 4 The hyperparameters used in each optimum classification model

Classification model	Hyperparameters used for the optimum model	
	KNN	K-value
Distance method		Euclidean
SVM	Kernel	RBF
	C	2
	Gamma	0.7
	Max iteration	10000
DT	Max depth	7
	Max leaf nodes	10

The model performance results for the entire excavation section data and each ground condition set are presented in Fig. 9. Accuracy, precision, recall, and AUC are the only performance evaluators presented. The model performance result of all the strata dataset in Fig. 9(a) exhibits the best accuracy in the staging ensemble model and the best recall in the KNN model. The KNN model is the most suitable for the entire shield TBM section with regards to recall, which is considered the most important factor herein. The staging ensemble algorithm affords the best accuracy and precision for all the datasets, and the model that afforded the best recall in each dataset differed. The SVM model afforded the best recall for ground conditions 1 and 4 (Figs. 9(b) and 9(e)), while the DT model afforded the best recall for ground conditions 2 and 3 (Fig. 9(c) and 9(d)) Furthermore, the more complex and difficult the ground condition (ground condition 3), the lower the recall index which can detect the disc cutter that need to be replaced.

4.2 Results of ANN model

The ANN disc cutter wear prediction model was evaluated using the MATLAB neural network fitting application, the coefficient of determination (R^2), and the RMSE function given in Eq. (6). R^2 is used to explain the correlation of one factor to other factors; a value close to 1 indicates a strong correlation. RMSE is a standard index used for measuring the model error to predict quantitative data.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^N (x_i - \hat{x}_i)^2}{N}} \quad (6)$$

where x_i is the assumed disc cutter wear rate (%), \hat{x}_i is the ANN-predicted disc cutter wear rate (%), and N is the amount of data. Plots of the assumed disc cutter wear rate

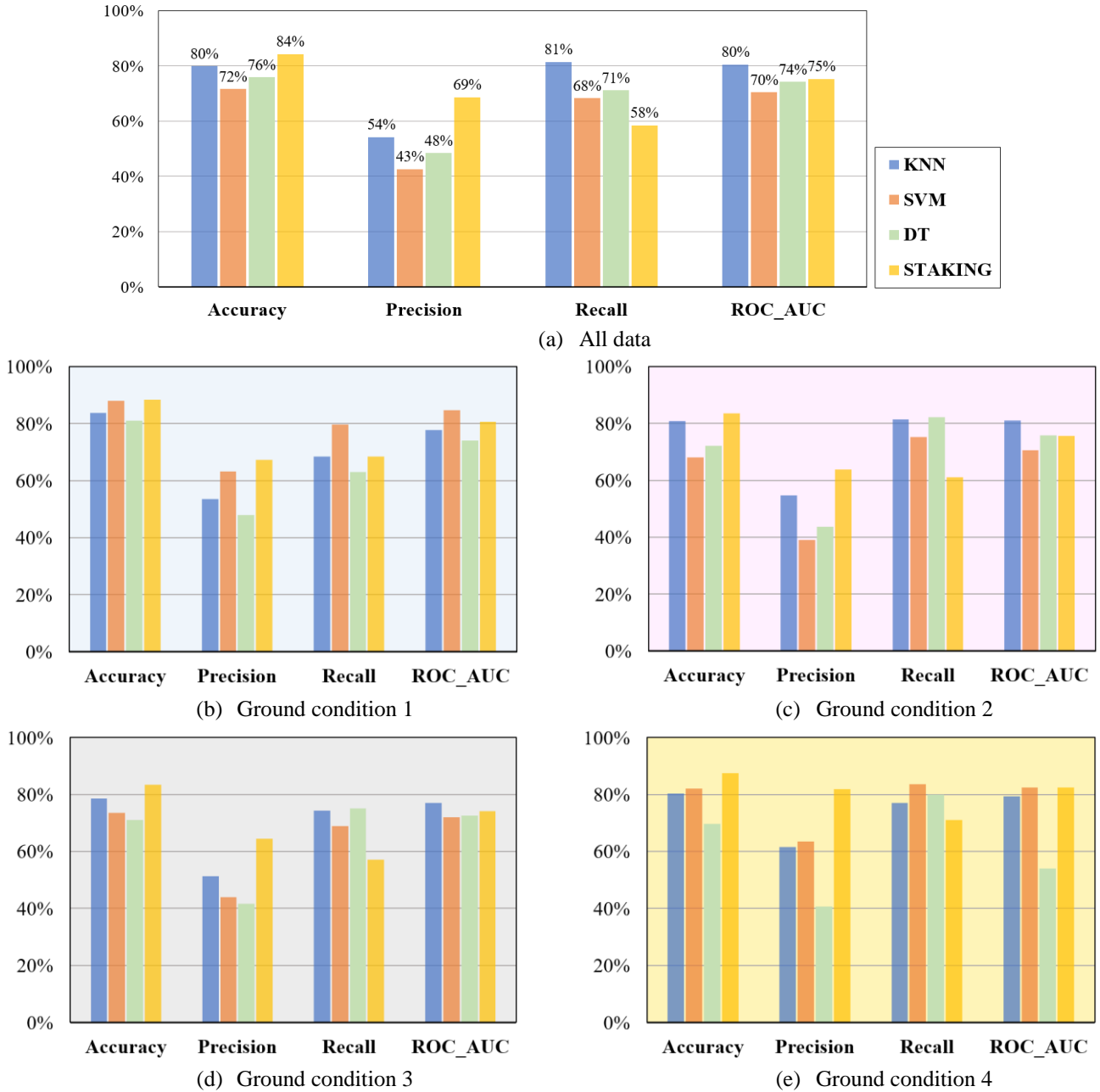


Fig. 9 Results of the classification models for the different datasets

based on the actual disc cutter wear and ANN-predicted disc cutter wear rate for the entire excavation section data and each ground condition are shown in Fig. 10. The plot in Fig. 10(a) displays the difference between the predicted and assumed values analyzed for the entire excavation section. The plot distribution is widely spread from the regression line, and the RMSE is higher than 20. As expected from the classification results, the highest R^2 and lowest RMSE were obtained for ground condition 1, which is a more homogeneous condition than the other ground conditions (Fig. 10(b)). Ground condition 3, which comprises the most mixed ground, exhibited considerable abnormal wear and attained the lowest R^2 and highest RMSE (Fig. 10(d)). Figs. 10(c) and 10(e) show the model performance results for ground conditions 2 and 4.

Fig. 11 illustrates a comparison between the assumed disc cutter wear and the ANN-predicted disc cutter wear of the five disc cutters and predicted disc cutter wear rate is underpredicted in most excavation sections. In Fig. 11, one disc cutter was selected from each orbit shown in Fig. 8.

Using the theoretical prediction method and by reviewing similar cases, KTA (2016) studied the prediction of the shield TBM performance and the condition for passing through the soil or weathered rock layers. In the KTA report, the disc cutter replacement period in the site was predicted using the method proposed by the Japan shield Construction Estimation Research Group. The number of replacements was predicted as seven, which included no replacement in the weathered soil layer, 2.4 in the bedrock, and 4.1 in the sedimentary layers. Although the

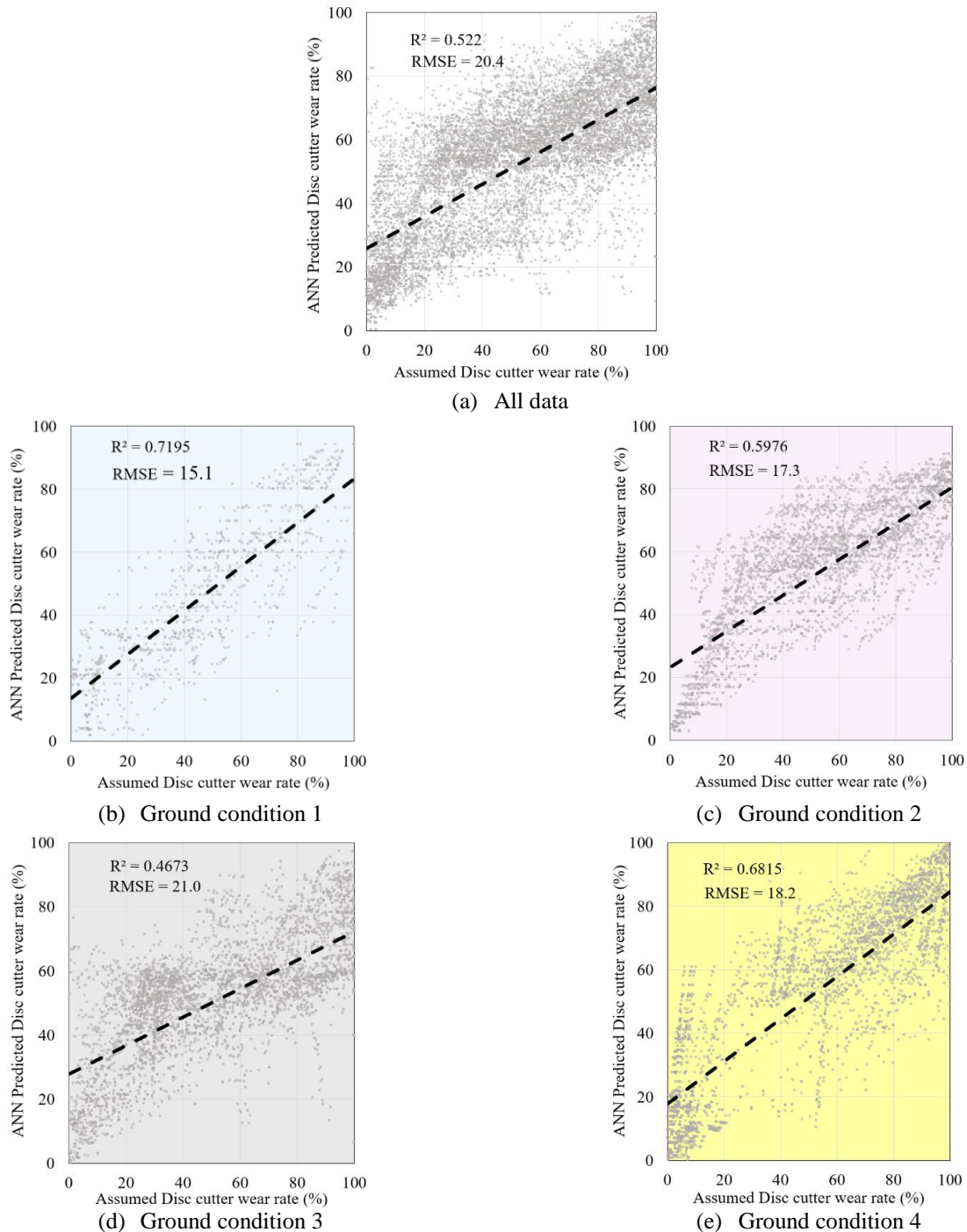


Fig. 10 Results of the ANN models for the different datasets

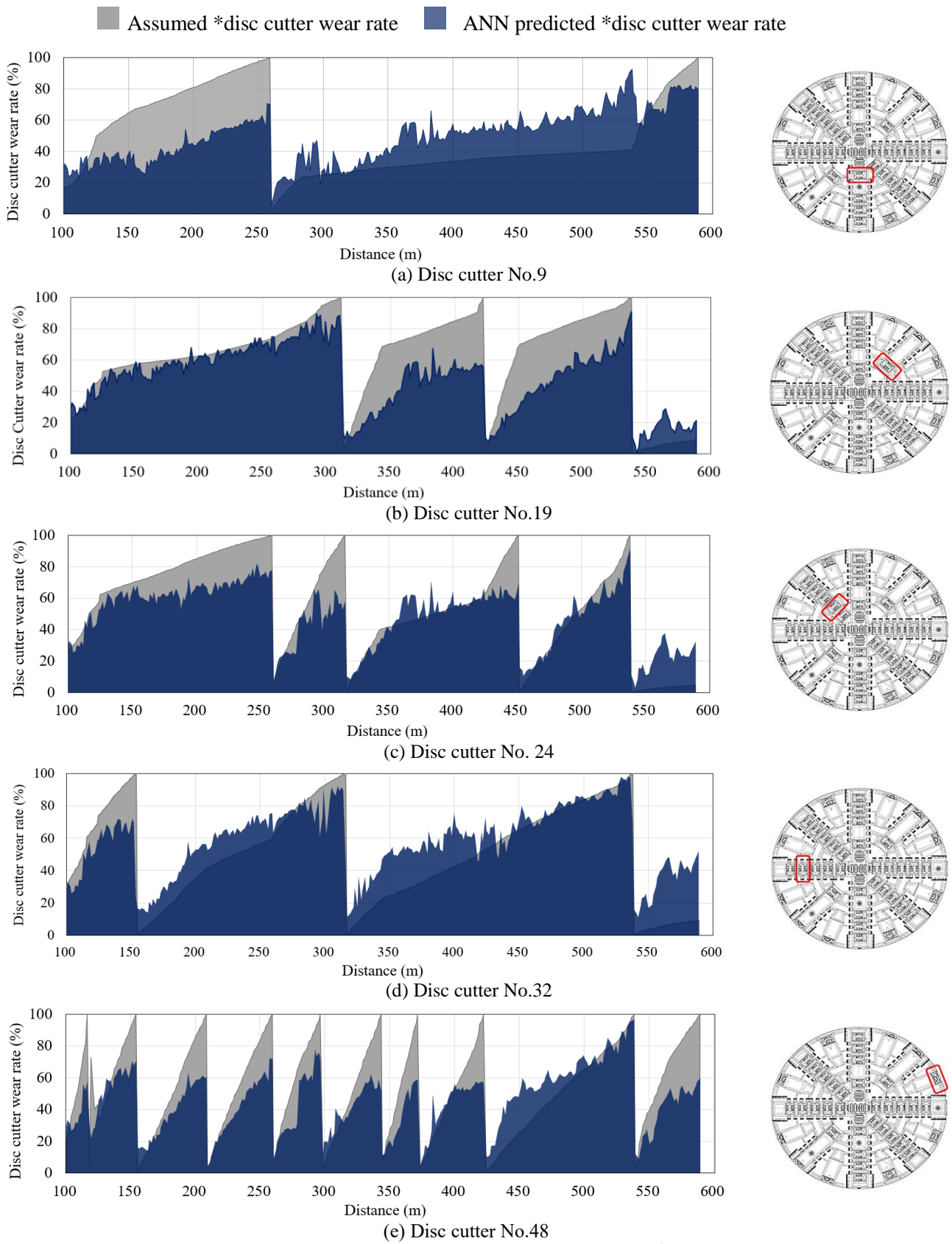
predicted number of disc cutter replacement was seven, the number of disc cutters replaced in the field was over 20. Furthermore, the section where most of the replacement occurred was in ground condition 3, which is the most complex ground.

5. Conclusions

This study presented a series of machine learning models that were developed to predict proper replacement

time and wear rate of disc cutters for a shield TBM. The study results are as follows

- When the data for all ground conditions (i.e., the data for entire excavation section) was incorporated into the four classification models (i.e., KNN, SVM, DT, and stacking ensemble), the stacking ensemble model afforded the highest accuracy (84%) the KNN model afforded the highest recall value, which is a major index representing the model prediction performance.
- For each ground condition, however, the predictive performance differed with the model. The differences in the



$$*Disc\ cutter\ wear\ rate = \frac{Wear\ at\ the\ excavation\ time\ (mm)}{Maximum\ wear\ length\ standards\ for\ each\ disc\ cutter\ (mm)}$$

Fig. 11 Comparison between the assumed disc cutter wear and ANN-predicted disc cutter wear

model performance may be attributed to the different variability and quality of excavation data, including different replacement cycles of disc cutters depending on the ground conditions.

- The ANN model predicted the wear rate of the disc cutters with the R2 and RMSE accuracy ranging from 0.4673 to 0.7195 and 15.1 to 21, respectively, depending on the ground conditions. This shows that the model performance decreases with increasing ground complexity.
- Since disc cutter wear is largely affected by ground conditions, there may be a limitation in the model proposed in this study where they could not be fully considered. Employing the information on the type and strength of the ground/rock, the content of quartz, joint conditions etc. in the model prediction through further study, therefore, is expected to increase greatly the accuracy of the model.

Acknowledgments

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