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Rock Mass Classification in TBM Tunneling using Artificial Neural Network Techniques: A Case Study from Siwalik Region of Nepal

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Abstract

The Himalayan region exhibits a highly complex geological setting influenced by tectonic activities, resulting in faulted, folded, sheared, and deeply weathered rock masses. This study focuses on the Siwalik region of Nepal, where the geology is characterized by sandstone, mudstone, siltstone, and clay. Accurate rock mass characterization is crucial for Tunnel Boring Machine (TBM) tunneling projects, particularly in the challenging geological conditions of the Nepal Himalayas. Empirical rock mass classification systems, such as the Rock Mass Rating (RMR) and Q-system, often fall short in TBM operations due to limited access to the tunnel face and the dynamic nature of TBM excavation. To address these challenges, this research employs a machine learning (ML) technique to classify rock mass conditions using operational and geological data collected from the Sunkoshi Marin Diversion Multipurpose (SMDM) project in Nepal, where a double-shield TBM was used to excavate the 13.3 km long headrace tunnel. A comprehensive dataset comprising 3,173 TBM cycles, including parameters such as cutter head speed, torque, thrust, and penetration rates, was utilized for model development. An Artificial Neural Network (ANN) model was developed, trained, and optimized using grid search to identify the best hyperparameters. The Synthetic Minority Oversampling Technique (SMOTE) was applied to address the class imbalance, significantly improving the model's recall for Class V (poor rock mass class). Performance metrics such as accuracy, precision, recall, and F1-score were used to evaluate the model. Additionally, SHAP (Shapley Additive Explanations) analysis was conducted to interpret feature contributions for rock mass Class V, which revealed that torque and thrust had the highest influence on predicting poor rock mass conditions. This study highlights the effectiveness of ML models in improving rock mass classification, especially for underrepresented classes, and provides valuable insights for optimizing TBM operations in complex geological settings.

Keywords: Artificial neural network; Nepal Himalayas; Rock mass classification; TBM tunneling; SMOTE

1. Introduction

The complex geological structure of the Himalayas, shaped by the tectonic collision between the Indian and Eurasian plates, has resulted in extensive deformation, folding, faulting, shearing, and fracturing. These processes have caused anisotropy and weakened rock mass strength and deformability (Panthi, 2006). Consequently, classifying rock mass during the planning and design stages presented a challenging task (Panthi, 2006; Katuwal & Panthi, 2024a). The reliability of traditional rock mass classification

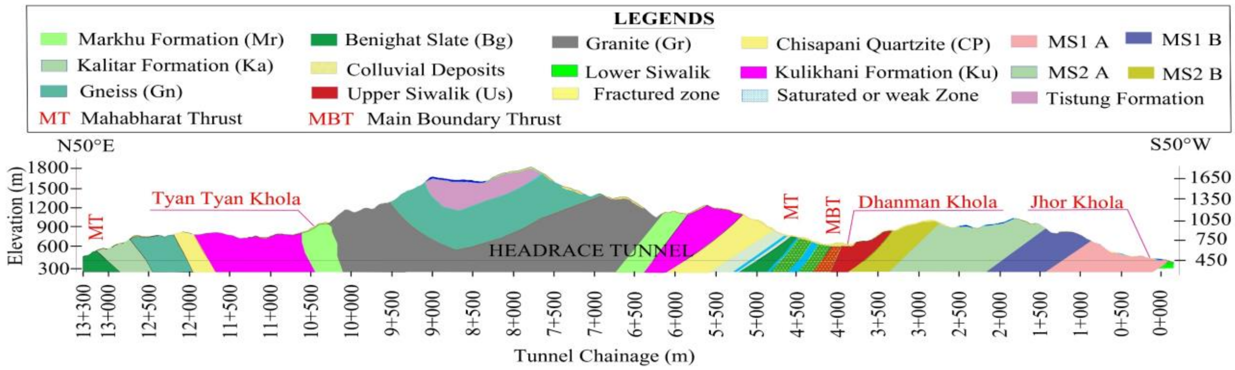

Figure 1: Longitudinal geological profile along headrace tunnel (HRT) of SMDM Project.

systems, such as the Rock Mass Rating (RMR) system (Bieniawski, 1989) and the Q-system (Barton, Lien, & Lunde, 1974), has been extensively used in the Nepal Himalayas. However, these empirical classification systems rely heavily on face mapping, which is challenging in Tunnel Boring Machine (TBM) tunneling due to limited access to the tunnel face and the restricted time available, i.e., only during TBM maintenance and service for mapping during excavation (Katuwal et al., 2024b).

While rock mass classification systems are valuable tools for designing tunnel support in the early stages of project planning, they exhibit several limitations when predicting TBM performance (Hou et al., 2022; Hamidi & Bejari, 2013; Vaskou & Kasperski, 2020; Panthi, 2019). Unlike conventional tunneling methods, TBM operations depend heavily on real-time geological conditions, and the variability of the rock mass quality poses significant risks to excavation efficiency (Katuwal et al., 2024b). Additionally, rock mass classifications do not inherently reflect the rock types but rather the rock mass at specific projects, such as tunnels, caverns, shafts, or cut slopes. This interdependency means that different chainages in the same rock types may yield different Q or RMR values.

TBM performance is susceptible to adverse geological features such as fault zones, squeezing ground, lithological variations, and mixed face conditions, drastically affecting excavation rates and cutter wear. The uncertainty associated with rock mass conditions is a primary risk in TBM tunneling (Katuwal et al., 2024b; Hou et al., 2022). Hence, accurately perceiving rock mass characteristics ahead of the TBM face is crucial for optimizing and adjusting tunneling parameters.

Given these challenges, there is a growing need for advanced predictive models to enhance rock mass classification in TBM tunnelling. In recent years, machine learning techniques have been widely used in underground tunnelling for leakage assessment, rock mass classification, and TBM performance prediction (Katuwal et al., 2024b; Hou et al., 2022; Panthi et al., 2025; Katuwal et al., 2024c; Erharter et al., 2020).

These techniques offer promising solutions by leveraging large datasets of TBM operational parameters and geological conditions to develop more robust and adaptable classification models. With this in mind, the manuscript utilizes artificial neural network techniques to classify rock mass conditions encountered in the double-shield TBM-excavated headrace tunnel of the Sunkoshi Marin Diversion Multipurpose (SMDM) project in the Siwalik region of the Nepal Himalayas.

2. Project Background

The SMDM Project is a national pride project in the Sindhuli district of Nepal, which is under construction. SMDM is the second inter-basin water transfer project in Nepal. Upon completion, it will divert 67 m³/s of water from the Sunkoshi River to Marin Khola through a 13.3 km headrace tunnel with a gradient of 1:412 (Figure 1). It will also generate hydropower energy by utilizing a gross head of 64 m and will have an installed capacity of 31.07 MW. The 275 m long re-engineered double-shield TBM, with a 6.40 m excavation diameter, utilized main thrust cylinders for stable ground (using gripper shoes) and auxiliary thrust cylinders for unstable ground (pushing off tunnel segments) to excavate the headrace tunnel. The tunnel achieved a breakthrough in autumn 2024.

2.1 Project Geology

Geologically, the SMDM Project lies within the Siwalik and Lesser Himalayan geological formations. The tunnel passes through the maximum overburden of approximately 1350 m. The longitudinal geological profile is shown in Figure 1.

The Main Boundary Thrust (approx. 400m) and Mahabharat Thrusts (approx. 50m) were crossed at two locations, as seen in Figure 1. Since these two faults constitute highly fractured and sheared rock mass, the TBM got fully stuck (jammed) seven times and encountered situations of semi-stuck several times, which resulted in extremely slow advance rates (tunnel excavation progress) while crossing these faults. The semi-stuck conditions required immediate ground stabilization measures of chemical grouting to control water leakage and bypass excavation. The TBM stuck areas generally have lithologies consisting of mudstone and sandstone with highly developed joints in the MBT area. Similarly, highly weathered phyllite with unstable and collapsing ground, thinly foliated schist and weathered gneiss with poor diagenesis, having very low strength, dark grey colored slightly weathered, fine to medium grained, thinly foliated, low strength banded gneiss in the Mahabharat thrust (MT).

Rock mass characterization along the headrace tunnel was conducted through a small manhole located at the bottom left of the cutterhead during service and maintenance periods, along with visual inspections of muck during mucking operations (Bohara et al., 2023).

The Rock Mass Rating (RMR) classification system was used to classify the rock mass along the tunnel alignment. Figure 2 presents the distribution of various rock mass classes encountered over 3,173 TBM cycles in the Siwalik zone.

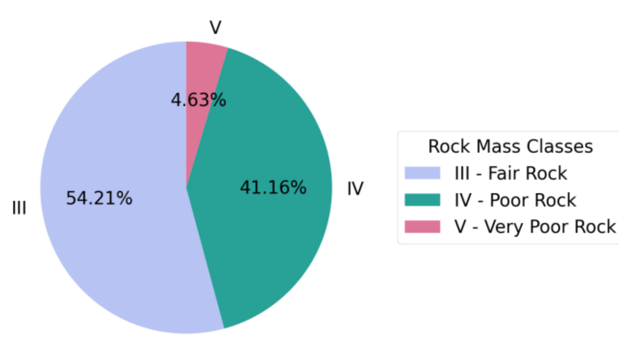

Figure 2: Rock mass quality class distribution on the Siwalik part.

As shown in Figure 2, 54.21% of the rock mass belongs to Class III (Fair rock mass), followed by Class IV (Poor rock mass), 41.16%, and Class V (Very Poor rock mass), 4.63%. The machine learning model must carefully address the rock mass class imbalance to ensure accurate predictions.

3. Methodology

This research utilizes a comprehensive dataset that combines geological and TBM operational data from the headrace tunnel of the SMDM project. The datasets include face mapping conducted during TBM operation and maintenance periods and real-time monitoring data recorded during TBM excavation. These data sources provide critical insights into rock mass conditions, TBM performance, and variations in rock mass class. The datasets are systematically structured and maintained to support model development and analysis. Data pre-processing techniques, including cleaning, normalization, and integration, were applied to ensure data quality, consistency, and completeness. These steps are crucial for developing reliable and robust machine learning models for predicting rock mass class. The analysis methodology is shown in Figure 3.

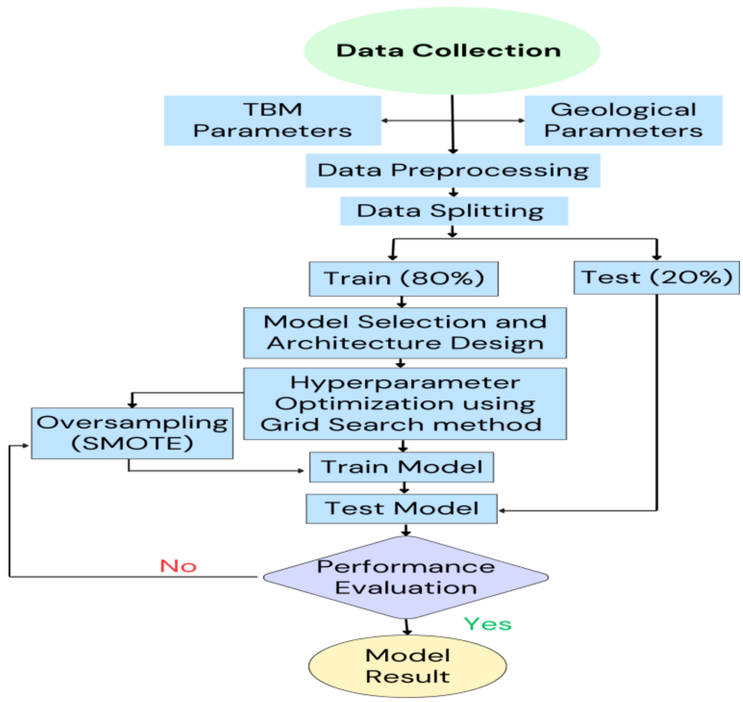

Figure 3: Flow chart for the rock mass characterization.

3.1 Data Acquisition

Data acquisition for the SMDM project integrates both geological and TBM operational parameters. Feature selection, a critical step in data preprocessing, plays a key role in enhancing the performance of machine learning models. Identifying the most influential variables from the dataset improves the prediction of the rock mass class. It ensures the model adapts well to the project-specific geological and operational conditions. Appropriate feature selection reduces noise, lowers computational complexity, and enhances model generalization for TBM tunneling applications.

This research selects key TBM operational and response parameters as input features for rock mass characterization. These include cutter head speed (CRS), torque, thrust, cutter head penetration rate (PRchd), and net penetration rate (PRnet).

The rock mass rating (RMR) is the target variable, representing actual ground conditions (GC). These parameters are crucial as they directly influence TBM performance in varying geological conditions. Table 1 provides a statistical summary of the selected parameters, offering insights into their variability and distribution across the dataset.

Table 1: Statistics of selected input variables

	CRS (rpm)	Torque (kNm)	Thrust (kN)	PRchd (mm/rev)	PRnet (mm/min)	RMR
Count	3173	3173	3173	3173	3173	3173
Mean	6.66	640.62	6516.92	8.22	54.25	39.63
Std	0.62	227.48	1467.66	1.49	8.14	8.04
Min	3.00	95.00	3067.00	3.20	22.3	16.00
25%	6.50	465.00	5456.00	7.20	49.30	35.00
50%	7.0	676.00	6375.00	8.10	54.40	41.00

75%	7.0	831.00	7439.00	9.10	59.40	46.00
Max	8.00	1700.00	28300.00	15.20	81.40	55.00

3.2 Data Correlation

The Pearson correlation coefficient was used to analyze the linear relationship between two continuous variables. A correlation coefficient of +1 indicates a perfect positive linear relationship, 0 indicates no linear relationship, and -1 indicates a perfect negative linear relationship. The heatmap in Figure 4 highlights the correlations between Geological Conditions (GC) and various TBM operational parameters.

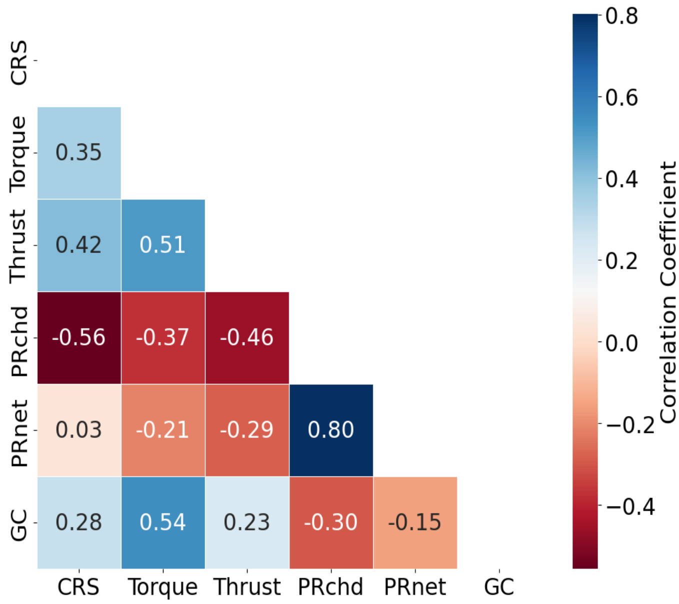

Figure 4: Pearson correlation coefficients between TBM parameters and geological conditions.

3.3 Data Distribution

The box-whisker plots in Figure 5 illustrate the distribution, variability, and outliers of key TBM operational parameters and rock mass quality conditions (RMR values). CRS shows a consistent distribution around 7 rpm with a narrow interquartile range (IQR), indicating stable cutting speeds. Torque displays greater variability centered around 700 kNm, with outliers reflecting fluctuations due to changing rock mass quality conditions. PRchd is found tightly distributed around 8 mm/rev, with outliers indicating variations in cutting efficiency. Thrust values are broadly spread around 6500 kN, highlighting the differing force requirements across various rock mass qualities. PRnet has a median of around 50 mm/min with significant variability, suggesting the impact of both operational adjustments and geological changes on TBM progress. RMR values range from 15 to 55, with a median of 41, representing considerable variability in the ground condition (GC), with outliers indicating particularly weak rock mass conditions.

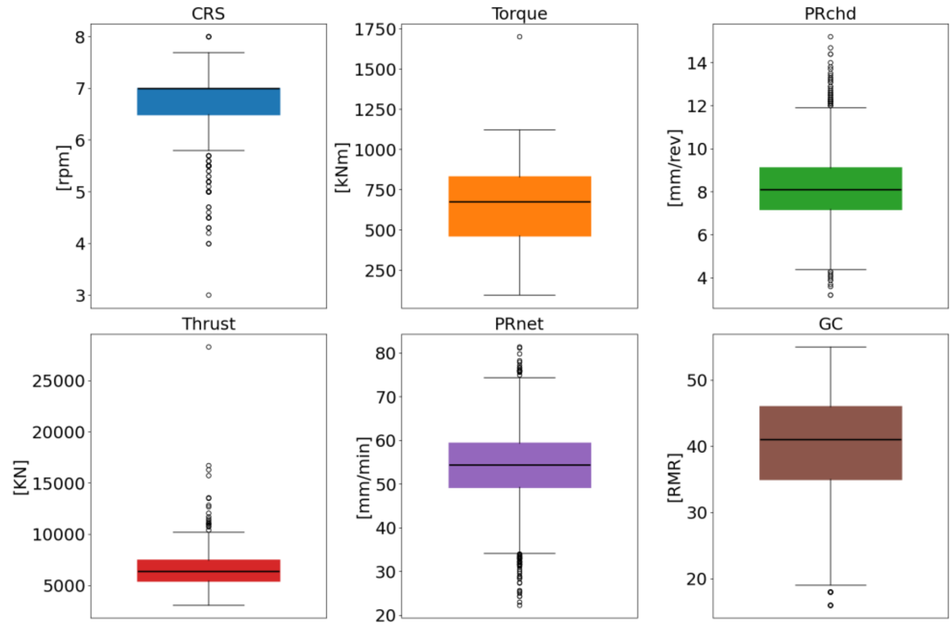

Figure 5: Data distribution in a box-whisker plot.

These distributions show how TBM parameters respond to geological conditions. Higher torque and thrust generally correlate with increased RMR (stronger rocks), while variations in PRchd and PRnet indicate changes in rock mass quality. Despite the growing uncertainty in machine learning models, outliers offer crucial insights into geological anomalies and TBM performance patterns, which are vital for accurate predictions of rock mass quality models.

3.4 Data Normalization

The Robust Scaler technique was employed for data standardization due to its effectiveness in handling outliers, which are critical in TBM tunneling and rock mass quality prediction. The Robust Scaler, given in Equation 1, uses the median and interquartile range, minimizing the impact of outliers while preserving their valuable contribution. Outliers, often indicative of extreme geological conditions or minority rock mass classes, provide essential insights into TBM performance under challenging ground conditions. This approach ensures that data variability, particularly in rare but significant scenarios, is retained for accurate model training and rock mass characterization.

$$X_{Robust} = \frac{x - median(x)}{IQR(x)} \quad (1)$$

$$IQR(x) = (Q_3)_x - (Q_1)_x \quad (2)$$

where, $(Q_1)_x$ and $(Q_3)_x$ denotes the 25^{th} and 75^{th} percentile values.

4. ANN Model Development and Training

Artificial Neural Networks (ANNs) are computational models inspired by the human brain, consisting of interconnected layers of neurons that process data through weighted connections (Lundberg & Lee, 2017). They are widely used in machine learning for complex pattern recognition, classification, and regression tasks due to their ability to learn non-linear relationships from large datasets (Aggarwal, 2018; Lundberg & Lee, 2017; Thapa, 2024). The Artificial Neural Network (ANN) was chosen to characterize rock mass quality classes. The target variables represent the three distinct rock mass quality classes, namely Class III, Class IV, and Class V. Since machine learning models operate on numeric

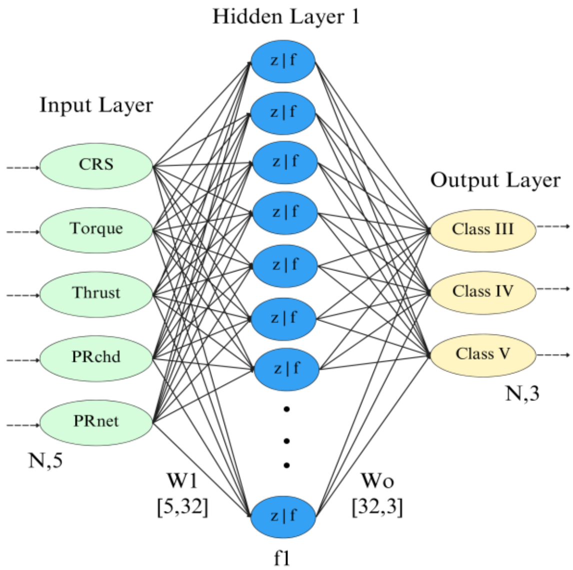

Figure 6: Model diagram of ANN.

data, these classes were converted into numeric values using label encoding and one-hot encoding to transform numeric values into binary vectors. After preprocessing the 3173 data points, the dataset was randomly split into an 80% training set and a 20% test set. The grid search method was applied to establish various optimal hyperparameters. The results of hyperparameter optimization are presented in Table 2. These hyperparameters notably reduce the model's overfitting and underfitting, enhancing the performance of the models (Erharter et al., 2020; Lundberg & Lee, 2017; Thapa, 2024).

Table 2: Selected Hyperparameters for ANN model

Hyperparameters	Value
Input layer	Neurons = 5
Hidden layer	Number = 1, neurons = 32, activation function = relu, kernel initializer = 'he_normal'
Output layer	Neurons = 3, activation function = SoftMax
Loss function	Categorical Cross-Entropy
Number of epochs	240
Batch size	32
Optimizer	Adaptive optimization algorithms (Adam)
Early stopping	Patience = 10 (Restore best weights)
Learning rate	0.01

Based on the optimal hyperparameters identified, a single hidden layer containing 32 neurons and utilizing ReLU activation was established between the input and output layers, as shown in Figure 6.
The weight matrix W1 (5,32) connects the input layer (5 features) to the hidden layer, while Wo (32,3) links the hidden layer to the output layer. The output layer contains three neurons with SoftMax activation, representing three rock mass classes (Class III, IV, and V). The model produces multi-class probability predictions, which are compared with actual values to compute the categorical cross-entropy loss. Minimizing this loss indicates improved prediction performance. However, discrepancies between predicted and actual values are observed, highlighting the need for suitable optimization algorithms to reduce loss through the backpropagation process.
The chain rule was applied to calculate the loss gradient, and the Adaptive Moment Estimation (Adam) optimizer was employed to update weights W_1 and Wo along with biases during backpropagation.
The iterative process of forward propagation, loss computation, backward propagation, and parameter adjustment continued until it reached the defined number of epochs (240) or the early stopping criteria (patience = 10). The effectiveness of the ANN classification model was significantly influenced by its

hyperparameters, including the number of neurons, learning rate (0.01), batch size (32), activation functions, and kernel initializer.
Further, the SMOTE (Synthetic Minority Over-sampling Technique) was applied to handle data imbalance by generating synthetic samples for the minority rock mass class (Katuwal et al., 2024b; Hou et al., 2022; Panthi et al., 2025). This technique helped improve model performance by ensuring a balanced class distribution, which was crucial for achieving accurate predictions and reducing bias during training.

4.1 Model Evaluation Metrics

The performance of the classification models was assessed using key evaluation metrics, including accuracy, precision, recall, and F1-score, which were calculated using Equations (3)-(6). These metrics provide a comprehensive understanding of the model's ability to classify rock mass quality classes correctly.

$$Accuracy\ (ACC) = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

$$Precision\ (PRE) = \frac{TP}{TP+FP} \quad (4)$$

$$Recall\ (REC) = \frac{TP}{TP+FN} \quad (5)$$

$$F1-Score = \frac{2 \times PRE \times REC}{PRE+REC} \quad (6)$$

where TP (True Positive) is correctly predicted positive samples, TN (True Negative) is correctly predicted negative samples, FP (False Positive) is incorrectly predicted positive samples, and FN (False Negative) are missed positive samples.

5. Results and Discussions

The evaluation metrics provide crucial insights into their predictive performance for rock mass classification in TBM tunneling. The performance of the ANN model was evaluated, both without and with SMOTE, as shown in Table 3.

Table 3: Model evaluation metrices per class

Without SMOTE				
RMC	ACC (%)	PRE	REC	F1score
III		0.82	0.82	0.80
IV	78.40	0.75	0.78	0.77
V		0.67	0.36	0.47
With SMOTE				
III		0.85	0.83	0.82
IV	79.38	0.77	0.80	0.79
V		0.46	0.86	0.58

Without SMOTE, the model achieved an overall accuracy of 78.40%. As seen in Table 3, for Class III, the precision (PRE) and recall (REC) are 0.82, and the F1-score is 0.80, indicating balanced and reliable predictive capability. In Class IV, PRE is 0.75, REC is 0.78, and F1-score is 0.77, reflecting moderate performance. However, the classifier struggled significantly for Class V, with a PRE of 0.67, REC of 0.36, and F1-score of 0.47, highlighting challenges in predicting the minority class due to its underrepresentation.
With SMOTE applied to address class imbalance, the overall accuracy of the model has increased to 79.38%. For Class III, PRE increased to 0.85, REC to 0.83, and F1-score to 0.82, indicating a slight

enhancement in predictive performance. In Class IV, PRE is 0.77, REC is 0.80, and F1-score is 0.79, reflecting an improvement in performance compared to the scenario without SMOTE. However, the most notable improvement was observed for Class V, where PRE dropped to 0.46, indicating an increase in false positives, but REC increased to 0.86 and F1-score to 0.58, demonstrating a significant boost in the model's ability to detect rock mass Class V.

The receiver operating characteristic (ROC) curve and the area under the curve (AUC) are valuable tools for assessing the performance of classification models. The prediction results were further evaluated using ROC and AUC curves, with performance summarized by both micro-average and macro-average curves, as shown in Figure 7. The micro-average curve represents the overall performance of the classifier across all classes, while the macro-average curve describes the performance for each class separately.

The ROC curves in Figure 7 compare model performance before and after applying SMOTE for rock mass classification. Without SMOTE, the model has achieved AUC values of 0.86 (Class III), 0.78 (Class IV), and 0.93 (Class V) with micro-average and macro-average values of 0.88 and 0.85, respectively. Despite strong performance for Class V, the model struggles with Class IV due to class imbalance. After applying SMOTE, AUC values are 0.86 (Class III), 0.82 (Class IV), and 0.93 (Class V) with micro-average and macro-average decreasing to 0.91 and 0.87, respectively. While SMOTE enhances Class IV detection, it maintains strong performance for Class V and Class III, reflecting a balanced improvement and the typical trade-off in handling class imbalance.

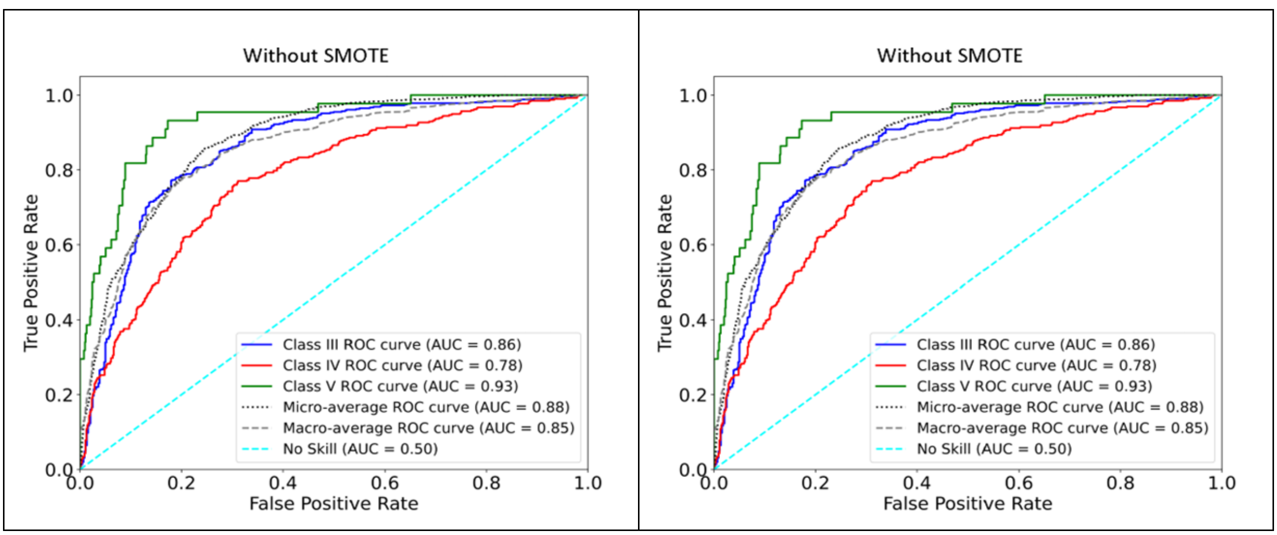

Figure 7: The ROC-AUC curve for the ANN model without and with SMOTE.

In TBM tunneling, false negatives (FN) are more critical than false positives (FP) due to the potential risks of misclassifying poor rock mass conditions, which can lead to safety hazards and project delays (Katuwal et al., 2024). Therefore, recall that prioritizing minimizing false negatives was used as the primary evaluation metric. A recall-based confusion matrix was constructed to assess the predictive performance of the model, providing a clearer representation of its ability to identify challenging rock mass conditions. The recall-based confusion matrix is illustrated in Figure 8.

The confusion matrices compare the model's performance on test data before and after applying SMOTE.

As shown in Figure 8, without SMOTE, the model has achieved a recall of 0.82 for Class III, indicating strong performance in identifying this class with relatively few false negatives. For Class IV, the recall is 0.78, showing moderate performance with some misclassifications into other classes. However, the model performs poorly for Class V, achieving only 0.36 recall, highlighting its poor performance in identifying the minority class. Most Class V samples are misclassified as Class IV, indicating that the class imbalance heavily impacts the model's predictive capability for the minority class.

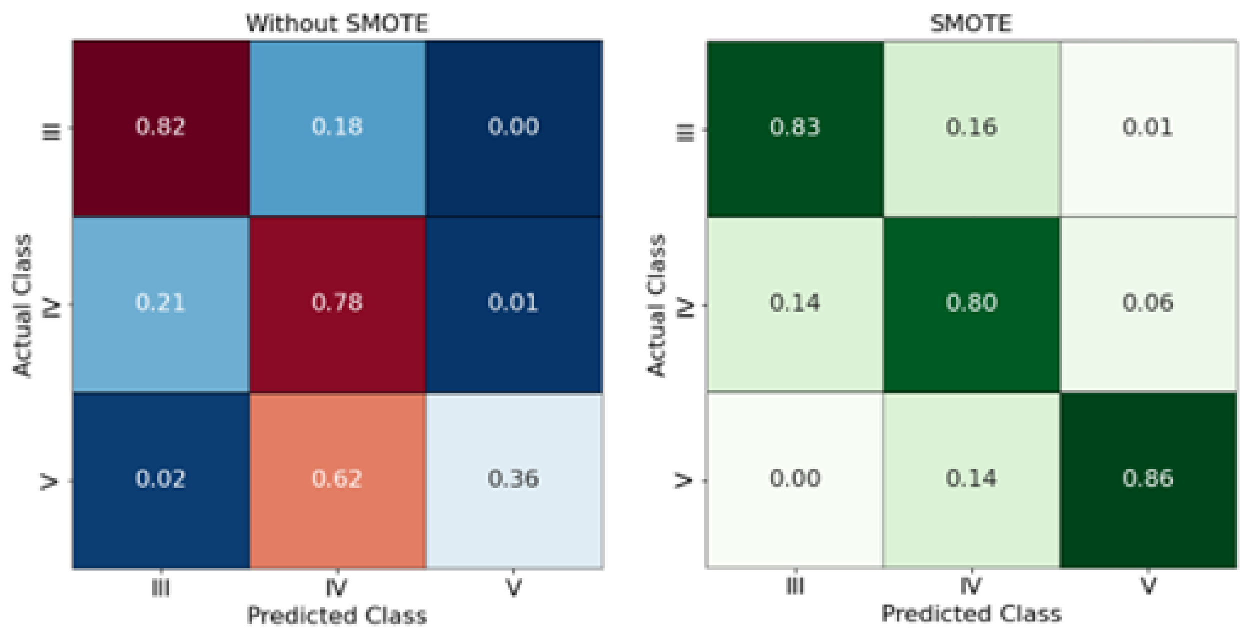

Figure 8: The recall-based confusion matrix for the ANN model without and with SMOTE.

With SMOTE applied, the model's ability to detect Class V has improved significantly, with recall increasing from 0.36 to 0.86. This demonstrates the effectiveness of SMOTE in addressing class imbalance and reducing false negatives for the minority class. Additionally, a slight increase in performance was observed for Classes III and IV, with recall values of 0.83 and 0.80, respectively. Hence, SMOTE has considerably enhanced recall for the minority class (Class V) without severely impacting the majority classes (Class III and Class IV). While some trade-offs exist, the improvement in detecting underrepresented rock mass classes is crucial for accurate geological assessments in TBM tunneling projects.

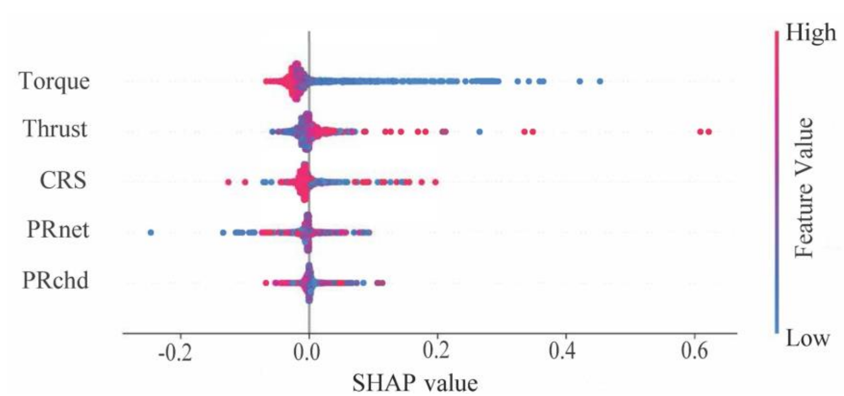

Figure 9: Feature importance analysis using the SHAP method for Rock mass class 'V'.

Further, the Shapley Additive Explanations (SHAP) method was employed to assess the contribution of input features in predicting target variables, as shown in Figure 9. SHAP values provide a detailed understanding of how each input feature influences the model's output, highlighting both positive and negative impacts on the prediction (Aggarwal, 2018; Lundberg & Lee, 2017; Thapa, 2024). This approach offers a transparent, feature-level interpretation, making it easier to identify which parameters most significantly affect rock mass quality class, which is critical in TBM tunneling.

The SHAP summary plot in Figure 9 highlights the contribution of input features in predicting rock mass conditions. Each dot represents a prediction with SHAP values on the x-axis indicating feature impact. Among the features, torque has the strongest influence, with high values negatively impacting predictions and low values pushing predictions positively. Thrust also plays a significant role, showing a moderate influence where higher values tend to indicate better rock conditions. CRS contributes meaningfully, though its impact is more balanced compared to torque and thrust. PRnet and PRchd have relatively smaller effects, with their SHAP values mostly centered around zero. Overall, torque and thrust emerge as the most critical predictors, reinforcing their importance in TBM tunneling and rock mass classification.

6. Conclusions

This research demonstrated the effectiveness of machine learning techniques, specifically an Artificial Neural Network (ANN) model, for rock mass characterization using TBM operational and geological data from the headrace tunnel of the SMDM project in the Siwalik region of the Nepal Himalayas.

The ANN model was optimized using grid search and trained on 3,173 TBM cycles, effectively classifying rock mass conditions (Classes III, IV, and V). However, class imbalance initially affected the model's ability to predict Class V (poor rock mass class). The application of the Synthetic Minority Oversampling Technique (SMOTE) significantly improved Class V recall from 0.36 to 0.86, thereby enhancing the model's ability to detect the most critical poor rock mass class. Despite a slight performance improvement for Classes III and IV, this enhancement is vital for risk management and TBM operation.

A comprehensive SHAP (Shapley Additive Explanations) analysis provided feature-level interpretability, identifying torque and thrust as the most influential parameters for predicting rock mass quality conditions. CRS also demonstrated a notable impact, while PRnet and PRchd exhibited relatively lower influence. This insight not only aligns with geological behavior but also aids in adjusting real-time TBM operational strategies to manage challenging ground conditions.

The combined use of ANN, SMOTE, and SHAP analysis demonstrated a powerful, data-driven approach for rock mass characterization, offering a scalable and interpretable framework for future TBM projects in complex geological environments such as those in Nepal.

For future studies, it is recommended to incorporate datasets from both the Siwalik and Lesser Himalayan regions, along with cross-project TBM data, to develop more generalized and reliable ML models. This will enhance prediction accuracy and support optimized decision-making in the complex Himalayan geology.

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