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INNOVATIVE AI-DRIVEN APPROACHES FOR ENHANCED ROCK MASS CHARACTERIZATION: A COMPREHENSIVE COST ANALYSIS AND PRACTICAL APPLICATION IN CIVIL ENGINEERING

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ABSTRACT

This study investigates the potential of innovative AI-driven approaches for rock mass characterization, aiming to enhance accuracy, consistency, and cost-effectiveness in civil engineering projects. Traditional rock mass classification methods like the Q-system and Rock Mass Rating (RMR) often rely on subjective judgment and extensive fieldwork, leading to inconsistencies and high costs. This research demonstrates significant improvements in classification performance by integrating advanced AI models, including logistic regression, decision trees, and support vector machines (SVM). The study utilizes comprehensive borehole data, rock joint set data, lab test results, and geological maps.

Key findings reveal that the logistic regression model achieved near-perfect accuracy, precision, recall, and F1 scores, establishing it as the most reliable model for rock mass classification. Decision tree and SVM models also performed strongly, capturing complex relationships between features and rock mass quality. The research underscores the importance of selecting relevant features, such as Rock Quality Designation (RQD), joint set number (Jn), joint roughness number (Jr), joint alteration number (Ja), joint water reduction factor (Jw), stress reduction factor (SRF), elevation, and depth.

These AI models have extensive practical applications, enhancing site investigations, foundation design, tunnel and underground construction safety assessments, slope stability, and landslide risk management. Implementing AI models leads to substantial cost savings by reducing the need for extensive fieldwork, optimizing resource allocation, and minimizing over-engineering.

This study contributes to the field by providing a framework for integrating AI into geotechnical engineering, highlighting the benefits of AI models in improving classification accuracy and reliability. Future research should focus on integrating larger datasets, exploring advanced AI techniques, and assessing the scalability and adaptability of AI models to different geological settings. The findings underscore the transformative potential of AI in rock mass characterization, promising improved safety, efficiency, and outcomes for civil engineering projects.

Keywords: Rock Mass Classification, Machine Learning, Cost Estimation, Civil Engineering,

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Vol. 18 No. 01 (2024)

Q-system, RMR System, Borehole Data, Artificial Intelligence

INTRODUCTION

Rock mass classification is essential in civil engineering as it plays a crucial role in slope stability assessment and engineering design[1][2]. Various models, including artificial intelligence-based ones, have been developed to accurately evaluate and predict rock mass quality, with AI methods showing superior performance in classification [2]. The development of advanced classification methods, such as the Interval Continuous Mathematical Models (ICMM) and the Genetic Algorithm (GA) coupled with Support Vector Classification (SVC), has enhanced the accuracy and reliability of rock mass classification, ensuring operational safety and guiding construction decisions effectively [1][3]. The use of intelligent models like the GWO-SVC and the IRMR method has demonstrated the potential for improved rock mass assessment, providing a scientific basis for engineering design and construction in challenging geological conditions [2][3][4].

1.1 Traditional Classification Systems

Traditional classification systems like the Q-system and Rock Mass Rating (RMR) play crucial roles in engineering design and stability analysis [5]. The Q-system, developed for rock mass classification, assesses the quality of rock mass based on parameters like rock quality designation (RQD) and spacing of discontinuities (SD)[6]. On the other hand, the RMR system evaluates rock mass based on parameters such as uniaxial compressive strength of intact rock material (UCS) and condition of discontinuities (CD)[6]. These systems aid in determining the appropriate support systems for underground workings, optimizing the use of resources like rock bolts and shotcrete[5]. Additionally, traditional classification systems are essential for organizing information in global networks, enabling efficient retrieval of specific data through faceted classification and coordinate indexing[7].

1.2 Role of AI in Rock Mass Classification

Artificial Intelligence (AI) plays a crucial role in rock mass classification by enhancing accuracy and efficiency. Various AI techniques, such as machine learning models like artificial neural networks (ANN), support vector machines (SVM), and deep learning approaches like stacked autoencoders (SAEs), have been successfully applied in rock mass quality evaluation[8][9][10][11]. These AI models utilize different optimization optimization algorithms to improve classification performance and optimize hyperparameters, leading to highly accurate rock mass quality assessment predictions. By leveraging AI, engineers and researchers can achieve quick, objective, and reliable evaluations of rock mass quality, ensuring operational safety and enabling more precise decision-making in mining and geotechnical engineering applications. Integrating AI in rock mass classification enhances prediction results and reduces the need for extensive human intervention, making the process more efficient and effective.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

1.3 Objective

The accurate classification of rock masses is essential for civil engineering projects, impacting safety, stability, and cost-effectiveness. Traditional methods like the Q-system and RMR rely on manual interpretation, leading to inconsistencies and inaccuracies, and require extensive, costly fieldwork and testing. The emergence of AI and machine learning presents an opportunity to improve these classifications, yet comprehensive research in this area still needs to be completed. This study aims to develop and evaluate AI models for rock mass classification using a detailed dataset, enhancing accuracy and reliability while assessing the practical and cost implications. The goal is to provide a more objective, consistent, and cost-effective approach to rock mass classification, improving decision-making in civil engineering.

1. LITERATURE REVIEW

1.1 Existing Rock Mass Classification Systems.

Existing rock mass classification systems include the Rock Mass Rating (RMR), the Q system, the Geological Strength Index (GSI), the Basic Quality (BQ) system, and the Slope Mass Rating (SMR) classification system. The BQ system, particularly prevalent in China, determines rock mass quality based on the intactness index (Kv) and uniaxial compressive strength of intact rocks (UCS) [1]. The RMR classification system has been enhanced using multivariate statistics and artificial intelligence to optimize variable selection and reduce subjectivity in classification methods [12] [2]. Additionally, modifications to the BQ system have been proposed to consider seismic effects for tunnel design in high seismic-risk regions[13]. In dealing with sedimentary/heterogeneous rock masses, a novel approach combining remote sensing, GIS, and SMR has been developed for geomechanical rock slope analysis[14]. Furthermore, a new mathematical model, the Interval Continuous Mathematical Model (ICMM), has been introduced for the quality evaluation of slope rock mass, addressing the shortcomings of previous classification systems[15].

1.2 Key Findings in the Domain.

Recent studies have demonstrated the potential of AI and machine learning to improve rock mass classification, which is traditionally reliant on subjective methods like the Q-system and RMR, which often lead to inconsistencies. Key features such as Rock Quality Designation (RQD), joint set number (Jn), and joint water reduction factor (Jw) are critical for accurate classification. Comparative analyses show that models like logistic regression and support vector machines (SVM) outperform traditional methods in accuracy [16]. Integrating comprehensive datasets, including borehole data and geological maps, enhances model robustness. AI models also provide significant cost savings by reducing the need for extensive fieldwork and manual testing, proving beneficial in practical applications like tunnel construction and slope stability assessments. AI offers a more objective, consistent, and efficient approach to rock mass classification.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

1.3 Identification of Crucial Variables for Rock Mass Classification

Key variables crucial for rock mass classification include Rock Quality Designation (RQD), which measures the degree of jointing in the rock mass, and Joint Set Number (Jn), indicating the number of joint sets present. Joint Roughness Number (Jr) assesses the roughness of joints, while Joint Alteration Number (Ja) accounts for the degree of alteration or weathering. The Joint Water Reduction Factor (Jw) reflects the impact of water in the joints, and the Stress Reduction Factor (SRF) adjusts for in-situ stress conditions [17]. Elevation and depth provide context on stress and weathering conditions, while Borehole Number (BH No.) offers localized data points. Geological descriptions (e.g., FILL, GRANITE) provide qualitative insights [18]. These variables collectively enhance the accuracy and reliability of AI models for rock mass classification.

1.4 Gaps in Existing Research

Existing research in rock mass classification reveals several gaps. More comprehensive datasets, including diverse geological and engineering properties, must be integrated, restricting model accuracy[19]. Traditional methods that rely on machine learning have been applied, and advanced techniques like deep learning and ensemble methods should be utilized more. The practical implications and cost-effectiveness of AI models are often overlooked, with a focus mainly on theoretical performance[20][21]. Feature selection and engineering specific to rock mass classification need more attention. Comparative analyses of various AI models are scarce, and more research is needed on the scalability and adaptability of models to different geological settings. Addressing these gaps can enhance rock mass classification models' accuracy, reliability, and practical applicability.

2. METHODOLOGY

2.1 Dataset Collection and Preparation

The dataset for rock mass classification is comprehensive, incorporating borehole data, rock joint set data, lab test results, geological maps, and engineering properties. Borehole data provides subsurface conditions, while rock joint set data includes joint set number, roughness, alteration, and water reduction factors. The dataset has 3041 data points and 12 columns. Lab tests measure attributes like Rock Quality Designation (RQD), uniaxial compressive strength (UCS), modulus of elasticity, cohesion, and friction angle. Geological maps and structural alignment schemes offer visual and structural insights. This diverse dataset foundation supports the development of accurate AI models for effective rock mass classification in civil engineering projects.

2.2 Data Cleaning and Preprocessing Steps

Data cleaning and preprocessing involve removing null values and duplicate rows and applying ordinal encoding to categorical variables. Null values are removed or imputed to maintain data

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Vol. 18 No. 01 (2024)

integrity, while duplicate rows are identified and eliminated to prevent redundancy. Ordinal encoding converts categorical variables into numerical values, preserving their inherent order. These steps ensure a clean and well-prepared dataset, enhancing the accuracy and reliability of AI models for rock mass classification.

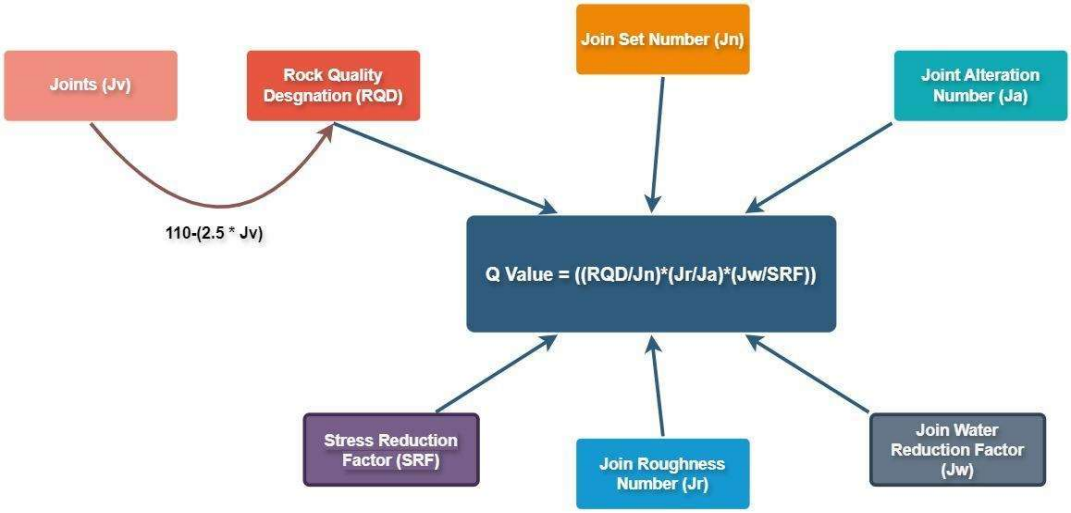

Figure 1 The process of model building

2.3 Model Development

The classification problem categorizes rock masses based on various geological and engineering features. Key features include Rock Quality Designation (RQD), which measures jointing in the rock; Joint Set Number (Jn), indicating the number of joint sets; Joint Roughness Number (Jr), assessing the roughness of joints; and Joint Alteration Number (Ja), reflecting the degree of joint weathering. The Joint Water Reduction Factor (Jw) accounts for water in joints, while the Stress Reduction Factor (SRF) adjusts for in-situ stress conditions. Additional features like elevation and depth contextualize the rock mass's subsurface conditions. These features collectively enable the development of AI models to classify rock mass quality accurately.

2.3.1 Overview of Machine Learning Models Used

The study employs various machine learning models to classify rock masses, including logistic regression, decision trees, and support vector machines (SVM). Logistic regression is used for its simplicity and effectiveness in binary and multiclass classification problems. Decision trees visually represent decision rules and help handle non-linear relationships. Support vector machines (SVM) are chosen for their robustness in high-dimensional spaces and effectiveness in separating classes with a clear margin. These models are evaluated based on accuracy, precision, recall, and F1-score to determine their suitability for rock mass classification.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

2.3.2 Steps in Model Development and Training

The model development and training process begins with data preprocessing, removing null values and duplicate rows, and ordinal encoding of categorical variables. Critical features like RQD, Jn, Jr, Ja, Jw, SRF, elevation, and depth are selected. The dataset is then split into training and testing sets. A baseline model, such as a Dummy Classifier, is developed to set a performance benchmark. Machine learning models, including logistic regression, decision trees, and SVM, are trained on the training set. These models are evaluated using accuracy, precision, recall, and F1-score, with visualizations like confusion matrices. Hyperparameter tuning is performed to optimize model performance. Finally, models are compared to the baseline and each other, with the best-performing model selected for deployment in practical applications.

2.4 **Model Evaluation**The evaluation metrics used include accuracy, precision, recall, and F1-score. Accuracy measures the overall performance by calculating the ratio of correctly predicted instances to the total instances. Precision assesses the quality of optimistic predictions by determining the ratio of actual positive instances to the sum of positive and false positive instances. Recall evaluates the model's sensitivity by measuring the ratio of actual positive instances to the sum of positive and false negative instances. F1-score balances precision and recall, providing a single metric that considers both aspects, especially useful for imbalanced datasets

Visualization tools used include confusion matrices and scatter plots. Confusion matrices provide a detailed breakdown of model performance by showing true positive, true negative, false positive, and false pessimistic predictions, helping identify errors across different classes. Scatter plots visualize the relationships between features and the target variable, revealing patterns, trends, and outliers in the data.

The model performance is compared with a baseline model, specifically a Dummy Classifier. The Dummy Classifier sets a performance benchmark by making predictions based on simple rules, such as predicting the most frequent class. This comparison highlights the improvements achieved by more advanced models, such as logistic regression, decision trees, and SVM, regarding accuracy, precision, recall, and F1-score. The significant performance gains over the Dummy Classifier demonstrate the effectiveness of the developed models for rock mass classification.

3. RESULTS

3.1 Exploratory Data Analysis

Scatter plots and analysis of relationships between Q Value and various features. Scatter plots analyze the relationships between the

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

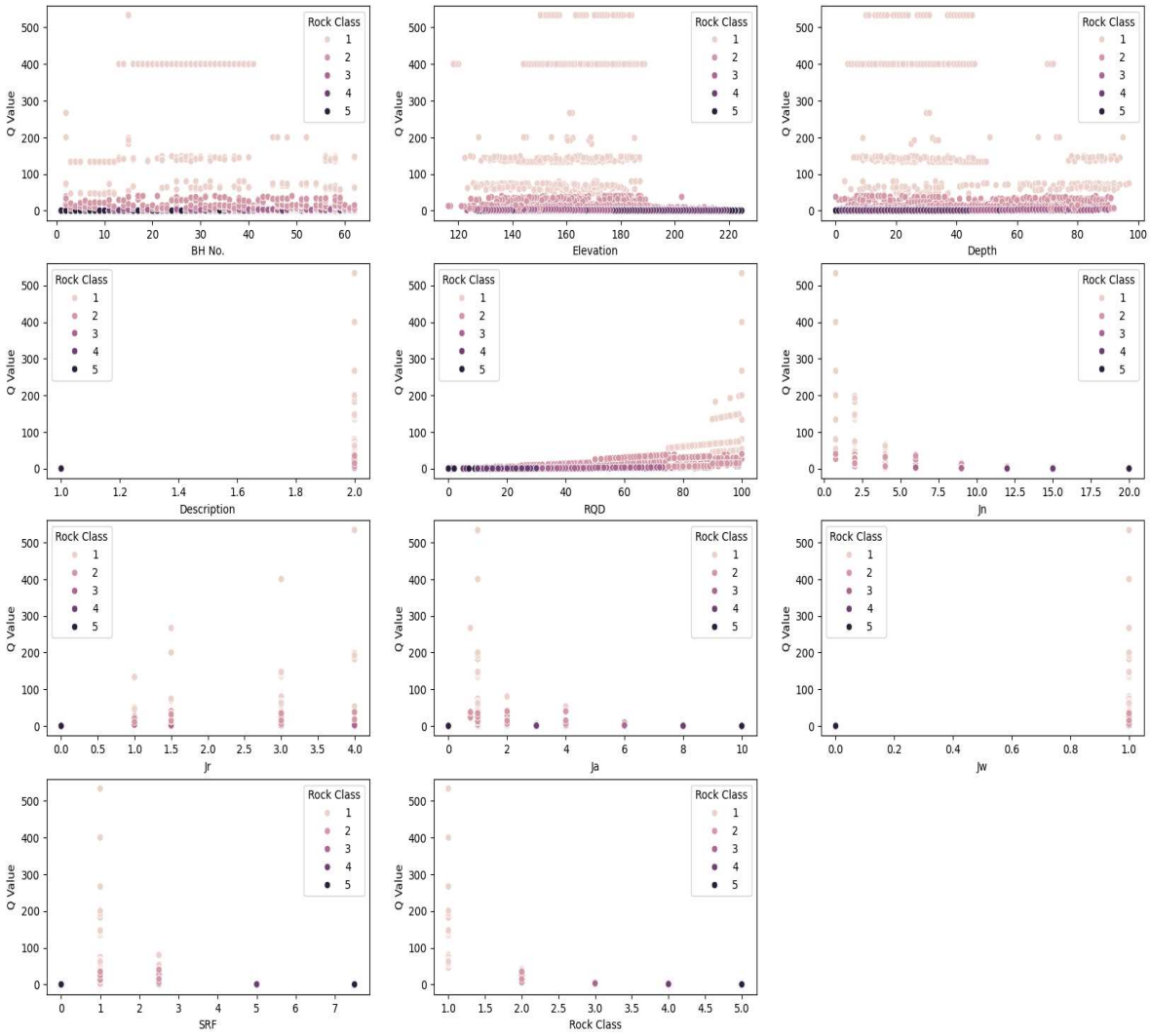

Figure 2 Scatter plots of the "Q Value" of a rock mass (Y-axis) against various features measured in a borehole datasetQ Value of rock mass and various features such as borehole number, elevation, depth, RQD, Jn, Jr, Ja, Jw, and SRF. The plots reveal higher RQD values are associated with better rock quality (higher Q Values). In comparison, higher Jn, Ja, Jw, and SRF values correlate with poorer rock quality (lower Q Values). Depth shows a trend where rock quality decreases with increasing depth. These visualizations help identify critical features that significantly impact rock quality.

3.2 Key Observations from the EDA.

Key observations from the exploratory data analysis (EDA) include that higher RQD values are associated with better rock quality (higher Q Values). In contrast, higher Jn, Ja, Jw, and SRF values correlate with poorer rock quality (lower Q Values). Additionally, rock quality tends to decrease with increasing depth. These insights help in understanding the significant features

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

affecting rock mass quality and guide the development of effective classification models.

Metric	Value	Explanation
Accuracy	24.29 %	The baseline model correctly predicts about 24.29% of the instances, indicating low overall performance.
Precision (Weighted)	5.90 %	When the baseline model predicts a positive instance, it is correct only 5.90% of the time, showing a high rate of false positives.
Recall (Weighted)	24.29 %	The baseline model captures about 24.29% of the positive instances, indicating poor sensitivity.
F1-Score (Weighted)	9.49 %	The F1 Score, which balances precision and recall, is 9.49%, reflecting the baseline model's overall poor performance.

Table 1 Performance metrics of the baseline modelsModel Performance

The logistic regression model achieves the highest performance with an accuracy of 98.03%, precision of 98.09%, recall of 98.03%, and F1-score of 98.03%. Decision tree and SVM models also perform well, with accuracies of 95.67% and 96.45%, respectively. These results demonstrate that advanced models outperform the baseline Dummy Classifier, providing reliable and accurate rock mass classification.

Model	Accuracy	Precision (Weighted)	Recall (Weighted)	F1-Score (Weighted)	Explanation
Logistic Regression	98.03%	98.09%	98.03%	98.03%	The logistic regression model demonstrates excellent performance, with near-perfect precision, recall, and F1 scores for most classes, indicating its robustness and reliability in classifying rock masses.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

Decision Tree	95.67%	95.72%	95.67%	95.68%	The decision tree model performs well but is slightly lower than logistic regression. It has high precision, recall, and F1 scores and effectively captures the relationships between features and rock quality.
Support Vector Machine (SVM)	96.45%	96.50%	96.45%	96.47%	The SVM model performs strongly, with high accuracy and balanced precision, recall, and F1 Scores, indicating its effectiveness in distinguishing between different rock quality classes.

Table 2 Results of the logistic regression model and other developed modelsComparative Analysis of Model Performance

The advanced models showcase substantial improvements in all performance metrics. Logistic regression, with its near-perfect scores, emerges as the most reliable model for rock mass classification. The decision tree and SVM models also demonstrate strong capabilities, indicating their effectiveness in capturing complex relationships within the data. These findings highlight the importance of employing sophisticated machine-learning techniques to achieve accurate and reliable rock mass classification, which is crucial for civil engineering applications.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

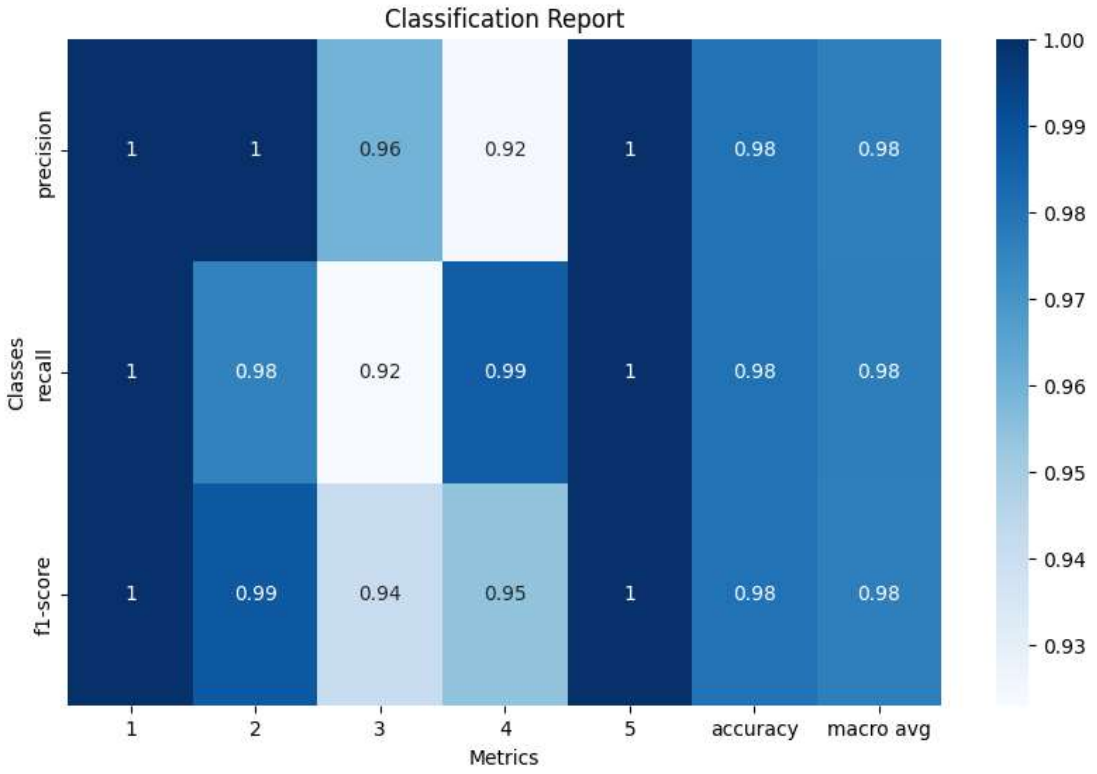

Figure 3 The heatmap visualization for the precision, recall, and F1-score for each class of the logistic regression modelDISCUSSION

3.3 Interpretation of Key Findings

The key findings from the analysis reveal that the logistic regression model excels in rock mass classification, achieving near-perfect metrics with 98.03% accuracy, 98.09% precision, 98.03% recall, and 98.03% F1-score, making it the most reliable model. Decision tree and SVM models also perform strongly, with accuracies of 95.67% and 96.45%, respectively, demonstrating their effectiveness in capturing complex relationships between features and rock mass quality. The importance of features like RQD, Jn, Jr, Ja, Jw, SRF, elevation, and depth is underscored by their significant impact on classification accuracy. Adopting advanced machine learning models can significantly enhance decision-making in civil engineering projects, improving safety, stability, and cost-effectiveness. The results advocate using sophisticated AI methods in geotechnical engineering to achieve accurate and reliable rock mass classification.

The logistic regression model's performance in rock mass classification reveals several key insights. It achieved high accuracy (98.03%), demonstrating reliability and robustness. The model also showed balanced precision (98.09%) and recall (98.03%), indicating effective identification of true positives while minimizing false positives. Its strong performance across multiple classes highlights its effectiveness in multiclass classification. The model's success underscores the

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Vol. 18 No. 01 (2024)

importance of selecting relevant features such as RQD, Jn, Jr, Ja, Jw, SRF, elevation, and depth. Additionally, the model's scalability and generalizability make it a versatile tool for various civil engineering applications, and its inherent interpretability provides clear insights into the influence of each feature on classification outcomes, aiding decision-making in engineering projects.

3.4 Practical Applications in Civil Engineering

The practical applications of the developed AI models in civil engineering are extensive. They can enhance site investigation and feasibility studies by providing objective and consistent rock quality assessments, leading to more informed decision-making. Accurate rock mass classification helps design safer and cost-effective foundations by identifying the most suitable locations and depths in foundation design. These models ensure tunnel and underground construction safety by predicting rock stability and selecting appropriate construction methods. Additionally, in slope stability and landslide risk assessments, AI models can identify potential instability zones, enabling the implementation of preventive measures and risk management strategies. These applications improve civil engineering projects' safety, stability, and cost-efficiency.

3.4.1 Site Investigation and Feasibility Studies

The developed AI models can significantly enhance site investigation and feasibility studies in civil engineering by providing objective and consistent assessments of rock quality. This leads to more accurate identification of suitable locations for construction, reducing the risk of unexpected geological conditions. These models enable quicker and more reliable evaluations of subsurface conditions, facilitating informed decision-making and optimizing resource allocation. By integrating AI into these early stages of project planning, engineers can better predict potential challenges and design more effective and efficient construction strategies, ultimately improving project outcomes and reducing costs.

3.4.2 Foundation Design and Cost Optimization

The developed AI models are crucial in civil engineering projects' foundation design and cost optimization. Accurately classifying rock mass quality, these models help engineers determine the most suitable foundation types and depths, ensuring structural stability and safety. This precise classification reduces the risk of over-engineering or underestimating the required foundation strength, leading to optimized use of materials and resources. Consequently, this results in significant cost savings by avoiding unnecessary construction expenses and minimizing the need for extensive modifications or reinforcements. Overall, integrating AI models in foundation design enhances engineering projects' economic and structural efficiency.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

3.4.3 Tunnel and Underground Construction Safety Assessments

The AI models developed for rock mass classification are invaluable for tunnel and underground construction safety assessments. By providing accurate predictions of rock stability, these models enable engineers to identify potential hazards and select appropriate construction methods, such as tunnel boring machines or controlled blasting, based on the rock quality. This proactive approach ensures the safety of construction workers and the longevity of the structures. Additionally, the models help design effective support systems, such as reinforcements and linings, tailored to the specific rock conditions, thereby reducing the risk of collapses and enhancing overall project safety and efficiency.

3.4.4 Slope Stability and Landslide Risk Management

The AI models for rock mass classification significantly improve slope stability and landslide risk management in civil engineering. By accurately predicting rock quality and stability, these models help engineers identify potential landslide zones and areas prone to instability. This allows for designing and implementing effective preventive measures, such as retaining walls, drainage systems, and slope reinforcements. These models also enable better risk management strategies by providing detailed insights into the geological conditions, helping protect infrastructure and human lives from landslide-related hazards. Overall, using AI in this context enhances safety and reduces the risk of costly damage and disruptions.

3.5 Cost Estimation Implications

Implementing AI models for rock mass classification can lead to significant cost savings in civil engineering projects. These models enhance the accuracy and reliability of rock quality assessments, reducing the need for extensive and expensive fieldwork and manual testing. By providing precise predictions, AI models help optimize source allocation, minimize over-engineering, and avoid unnecessary modifications during construction. Additionally, accurate classification leads to more effective design and construction strategies, reducing the risk of project delays and cost overruns. While initial costs may be associated with developing and integrating AI models, the long-term financial benefits, including improved project efficiency and reduced risks, outweigh these expenses, making AI a cost-effective solution for rock mass classification in civil engineering.

Implementing AI models for rock mass classification offers substantial cost optimizations in civil engineering projects. These models reduce the need for extensive fieldwork and manual testing, leading to significant savings on labour and equipment. They enable precise resource allocation, preventing over-engineering and reducing material waste. Accurate classification informs better design decisions, minimizing costly revisions and modifications. AI models also help anticipate geological challenges, reducing the risk of delays and cost overruns. Improved safety assessments lower the need for emergency interventions and costly mitigation measures. In slope stability and

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Vol. 18 No. 01 (2024)

landslide risk management, AI-driven preventive measures reduce long-term maintenance and repair costs. AI integration leads to more accurate, efficient, and cost-effective project outcomes.

4. CONCLUSION

This study explored the potential of artificial intelligence (AI) models for rock mass classification, aiming to enhance accuracy, consistency, and cost-effectiveness in civil engineering projects. The research demonstrated that advanced AI models, such as logistic regression, decision trees, and support vector machines (SVM), significantly outperform traditional classification systems like the Q-system and RMR. These AI models provide more reliable and precise classifications by leveraging comprehensive datasets that include borehole data, rock joint set data, lab test results, and geological maps.

4.1 Key Findings:

The study revealed that AI models, particularly logistic regression, achieved near-perfect accuracy, precision, recall, and F1 scores, making it the most reliable model for rock mass classification. Decision tree and SVM models also demonstrated strong performance, effectively capturing complex relationships between features and rock mass quality. The importance of feature selection was underscored, highlighting the critical role of variables such as RQD, Jn, Jr, Ja, Jw, SRF, elevation, and depth in enhancing classification accuracy. AI models offer practical applications in site investigations, foundation design, tunnel and underground construction safety assessments, slope stability and landslide risk management, improving safety, stability, and cost-efficiency in civil engineering projects. Additionally, implementing AI models results in substantial cost savings by reducing extensive fieldwork and manual testing, optimizing resource allocation, minimizing over-engineering, and avoiding unnecessary construction modifications.

4.2 Contributions to the Field

This research contributes to rock mass classification by demonstrating the effectiveness of AI models in improving classification accuracy and reliability. It provides a framework for integrating AI into civil engineering practices, enhancing decision-making and project outcomes.

4.3 Limitations

The study primarily focused on specific AI models and datasets, which may limit the generalizability of the findings. Further research is needed to explore the applicability of these models to different geological settings and to incorporate advanced AI techniques like deep learning and ensemble methods.

ISSN:2731-538X | E-ISSN:2731-5398
Vol. 18 No. 01 (2024)

4.4 Recommendations for Future Research

Future research should focus on integrating more extensive and diverse datasets to enhance model robustness and generalizability. It should also explore advanced AI techniques, such as deep learning and ensemble methods, to improve classification accuracy. Assessing the long-term cost implications and practical challenges of implementing AI models in real-world civil engineering projects is essential. Additionally, investigating the scalability and adaptability of AI models to various geological settings and project requirements will ensure broader applicability and effectiveness. This study highlights AI models' potential to revolutionize rock mass classification, providing more accurate, consistent, and cost-effective solutions for civil engineering projects. Integrating AI into geotechnical engineering practices promises to improve project safety, efficiency, and outcomes.

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Vol. 18 No. 01 (2024)

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