EXPLORING ARTIFICIAL INTELLIGENCE MODELS FOR ROCK MASS CLASSIFICATION: AN ASSESSMENT OF COST ESTIMATION

by

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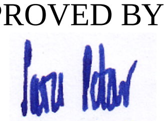

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Dedication

This thesis is lovingly dedicated to my extraordinary parents, Kuldeep Mahajan and Prem Lata. Papa Ji, your tireless efforts as a shopkeeper embody the essence of dedication and resilience, serving as a powerful example for me. Mummy Ji, your steadfast support and nurturing presence have fostered a warm and loving environment, enabling me to chase my aspirations. I am deeply grateful for your sacrifices, the encouragement you have provided, and the invaluable gift of a passion for learning.

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The love and support of my family have profoundly enriched this academic journey. Together, we cherish the values of education and the pursuit of knowledge. I extend my heartfelt gratitude to each of you for being my driving force and source of joy. Your presence in my life has made this achievement possible, and I look forward to sharing many more milestones with you.

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In conclusion, I am deeply grateful to everyone participating in my journey. Each of you has contributed to my growth and success, and I carry your support with me as I embark on the next chapter of my life. Thank you all for being a part of this incredible journey.

ABSTRACT

EXPLORING ARTIFICIAL INTELLIGENCE MODELS FOR ROCK MASS CLASSIFICATION: AN ASSESSMENT OF COST ESTIMATION

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This thesis investigates the application of machine learning (ML) models to enhance rock mass classification systems in geotechnical engineering. Traditional classification methods, such as the Rock Mass Rating (RMR) and Geological Strength Index (GSI), have been widely used for decades. However, these approaches often rely on subjective human assessment and are limited in handling complex geological conditions and dynamic environments. This research explores the potential of artificial intelligence (AI) and machine learning to address these limitations and improve rock mass classification accuracy, consistency, and adaptability.

Using a comprehensive borehole dataset with key geological features such as Rock Quality Designation (RQD), Joint Roughness Number (Jr), and Stress Reduction Factor (SRF), various machine learning models were developed and evaluated. A logistic regression model was employed as the primary AI-based approach, achieving a high classification accuracy of 98.03%, significantly improving over the baseline dummy classifier's accuracy of 24.29%. The study demonstrates that machine learning models

can dramatically reduce the subjectivity associated with traditional methods by relying on data-driven insights and advanced statistical techniques.

The research also highlights the critical role of data preprocessing, feature selection, and model evaluation metrics in optimizing machine learning models for geotechnical applications. Visual tools such as heatmaps and confusion matrices were used to analyze model performance and identify areas for improvement. The findings emphasize the importance of high-quality data and suggest that when properly trained and validated, AI models can effectively classify rock masses, supporting better decision-making in construction, tunnelling, and mining projects.

Despite the promising results, the study acknowledges challenges related to data quality, model complexity, and the need for further research on integrating AI systems into practical geotechnical workflows. The thesis concludes that machine learning offers a transformative approach to rock mass classification, providing significant advancements in accuracy and efficiency over traditional methods.

This research provides a foundation for future studies aimed at developing more robust AI-driven geotechnical solutions, which would contribute to safer and more efficient engineering projects.

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INTRODUCTION

1.1 Introduction

Rock Mass Classification (RMC) systems are critical in industries such as mining, civil engineering, and tunnelling, where projects' stability, safety, and cost-effectiveness rely heavily on a thorough understanding of the geological conditions. RMC provides a systematic approach to assessing the quality of rock masses by considering various geological, mechanical, and structural properties, enabling engineers and project managers to make informed decisions about excavation, tunnelling, or construction processes.

In the mining industry, RMC assesses the strength, stability, and behaviour of rock masses surrounding ore bodies. This helps determine the most efficient and safe mining techniques, optimizing the recovery of valuable minerals while minimizing operational risks. For instance, proper classification of rock masses is essential for designing mine shafts, determining blast parameters, and evaluating the safety of underground structures. The more accurately the rock mass is classified, the better the extraction methods and support systems can be planned, improving safety and cost management.

In civil engineering, particularly in large infrastructure projects like dams, bridges, and high-rise buildings, rock mass classification is crucial for designing foundations and predicting potential failure zones. A well-classified rock mass ensures the stability of structures built on or within it, reducing the likelihood of unforeseen failures or cost overruns. For example, in the construction of dams, knowing the strength and permeability of the surrounding rock can help engineers design better water retention systems and avoid costly repairs due to seepage or structural instability.

Tunnelling, another primary application of RMC, relies heavily on understanding rock mass characteristics to ensure the safety and efficiency of excavation. The complexity of tunnel design is directly influenced by the geological conditions encountered during excavation. Proper rock mass classification helps engineers select the most appropriate excavation method, whether it's a mechanical excavation, blasting, or tunnel boring machines (TBM). Additionally, it aids in the design of tunnel support systems, which are critical for preventing collapses and ensuring long-term stability.

The accuracy of traditional RMC methods, such as the Rock Mass Rating (RMR) system, Geological Strength Index (GSI), and the Q-system, largely depends on human expertise and field observations. While these methods have been widely used for decades, they are often limited by subjective interpretation, variability in geological conditions, and time-consuming processes. Moreover, modern projects' increasing scale and complexity demand more efficient, consistent, and reliable methods for classifying rock masses. This is where Artificial Intelligence (AI) and Machine Learning (ML) can play a transformative role.

Role of Artificial Intelligence and Machine Learning in Modernizing Classification Techniques

In recent years, the rapid advancements in Artificial Intelligence (AI) and Machine Learning (ML) have opened new possibilities for improving traditional Rock Mass Classification systems. AI and ML can enhance rock mass classification's accuracy, speed, and objectivity by automating the process and leveraging large datasets, reducing reliance on subjective human judgment.

AI models, especially those based on machine learning, can process vast amounts of data more efficiently than traditional manual methods. For example, machine learning algorithms can be trained on datasets containing rock mass properties such as uniaxial compressive strength, joint condition, rock quality designation (RQD), and groundwater conditions. By learning the relationships between these variables, AI models can predict rock mass classification categories with a higher degree of accuracy and consistency than human experts. This allows for faster decision-making, especially in large-scale projects where time is critical.

Furthermore, Machine Learning techniques such as Supervised Learning, Unsupervised Learning, and Reinforcement Learning can refine the classification process. Supervised learning models can be trained using labelled datasets, where known rock mass classifications teach the model how to classify new data. AI can "learn" from past data and improve classification accuracy. On the other hand, unsupervised learning models can identify patterns and groupings within data that may not be immediately apparent to human analysts, potentially uncovering new insights about rock mass behaviour.

Moreover, Deep Learning models, a subset of machine learning, are particularly effective for analyzing complex datasets such as geotechnical surveys or seismic data. By using neural networks with multiple layers, deep learning models can capture the nonlinear relationships between rock mass properties, providing a more nuanced understanding of how different factors contribute to rock mass stability and quality. For example, deep learning can analyze 3D geological models or real-time monitoring data from construction sites, offering dynamic and adaptive classification systems that respond to changing conditions.

In addition to improving classification accuracy, AI-based models offer significant cost benefits. By automating the classification process, AI reduces the need for time-consuming field tests and manual analysis, leading to faster project timelines and lower labour costs. AI models can also be integrated with Building Information Modeling

(BIM) and Geographic Information Systems (GIS) to provide real-time classification data, improving the overall management and decision-making processes in large-scale engineering projects.

AI and ML also enhance cost estimation for rock mass projects. Traditional cost estimation methods rely on historical data and expert judgment, which can lead to inaccuracies due to the variability of geological conditions. In contrast, AI models can predict project costs more precisely by analyzing the relationship between rock mass properties, construction methods, and cost variables. This enables more accurate budgeting and resource allocation, helping companies avoid cost overruns and optimize their investments.

In conclusion, AI and ML are revolutionizing how rock masses are classified in mining, civil engineering, and tunnelling industries. By automating and enhancing the classification process, AI-driven models offer significant improvements in accuracy, efficiency, and cost-effectiveness, addressing many of the limitations of traditional RMC systems. As the demand for more complex and large-scale projects grows, the integration of AI and ML in rock mass classification will become increasingly vital, paving the way for more innovative, safer, and more cost-effective engineering solutions.

1.2 Rock Mass Classification

Rock Mass Classification is a process used to evaluate the quality and characteristics of a rock mass. It helps engineers and geologists understand how a particular rock formation will behave under different conditions. This is especially important in industries like mining, civil engineering, and tunnelling, where understanding the properties of the rock is crucial for ensuring safety, stability, and cost efficiency in projects.

Rock masses are not uniform; they can vary significantly in strength, structure, and composition. These differences impact the rock's behaviour when excavated, drilled, or built upon. For instance, a robust and stable rock mass may support heavy structures like buildings or tunnels, while a weak or fractured rock mass may require additional support to prevent collapse or failure. Rock Mass Classification aims to provide a standardized way of describing these rock characteristics, allowing engineers to make informed decisions about construction methods, safety measures, and cost estimates.

In mining, for example, classifying the rock mass helps determine the safest and most cost-effective way to extract minerals. In tunnelling or civil engineering projects like dams or bridges, rock mass classification helps design appropriate support systems to ensure the structure's stability.

- **Traditional Rock Mass Classification Systems**

Over the years, several classification systems have been developed to standardize the evaluation of rock masses. Some of the most commonly used systems include:

1. Rock Mass Rating (RMR): This system evaluates the quality of the rock based on several factors, like the strength of the rock, the condition of its joints (cracks), the groundwater conditions, and the orientation of the rock layers. Each factor is given a score, and the total score determines the rock mass's rating. A higher RMR indicates a more robust and stable rock mass, while a lower RMR suggests a weaker rock that may require additional support during construction.
2. Geological Strength Index (GSI): The GSI system focuses more on the visual appearance of the rock and its structure. It categorizes rocks based on their texture (e.g., whether they are blocky or fractured) and how the rock is likely to break or deform under pressure.

3. Q-System: This system is widely used in tunnelling and underground construction. It evaluates the rock mass quality based on parameters such as joint roughness, joint alteration (the condition of cracks), and the presence of water in the rock. The Q-value indicates the rock's ability to support a tunnel without collapsing.

While these traditional systems have been widely used and provide a good framework for classifying rock masses, they often depend on human interpretation and can be subjective. Different engineers may assess the same rock mass differently, leading to variations in classification. Additionally, these methods can be time-consuming, requiring detailed field surveys and manual data collection.

Furthermore, as projects become more complex, the need for faster and more accurate classification methods has grown. This is where modern technologies like Artificial Intelligence (AI) and Machine Learning (ML) are significantly impacting.

- **Role of Artificial Intelligence and Machine Learning in Rock Mass Classification**

AI and ML are transforming traditional rock mass classification by making the process faster, more accurate, and less reliant on human interpretation. These technologies use large datasets and advanced algorithms to classify rock masses based on various input parameters automatically. By analyzing past data and patterns, AI models can predict how a rock mass will behave, classify its quality, and estimate the support needed for construction.

Machine learning models can process large amounts of data from geotechnical surveys and on-site measurements, allowing for more consistent and objective classifications. For example, instead of manually evaluating each factor, AI systems can automatically assess parameters like rock strength, joint conditions, and groundwater influence and then provide a classification based on that data. This speeds up the process and reduces the risk of human error.

Additionally, AI can improve cost estimation in projects involving rock masses. By combining rock mass classification data with historical cost information, AI systems can predict the cost of excavation, tunnelling, or construction more accurately than traditional methods. This helps project managers plan more efficiently, reducing the likelihood of unexpected expenses and delays.

Rock Mass Classification is essential to many engineering and construction projects, ensuring that the rock's behaviour is understood before excavation or construction begins. While traditional methods like RMR, GSI, and the Q-System have been effective, the introduction of AI and ML makes the classification process more efficient, accurate, and objective, benefiting industries like mining, civil engineering, and tunnelling.

1.3 Importance of Rock Mass Classification in Industries

Rock mass classification is essential for safety and risk management in mining operations, serving as a vital tool for understanding geotechnical conditions and implementing necessary reinforcements to prevent accidents. Systems like Rock Quality Designation (RQD), Rock Mass Rating (RMR), and the Geological Strength Index (GSI) are widely used to assess the mechanical properties of rock masses, such as uniaxial compressive strength, discontinuity spacing, and groundwater conditions. These parameters are critical for determining the structural integrity of mine workings, be it tunnels, slopes, or open pits. Accurately evaluating rock masses helps engineers design support systems that mitigate risks such as rockfalls, slope failures, or tunnel collapses. In underground mining, for instance, the RMR system has been extensively used to assess tunnel stability by evaluating rock mass strength and recommending appropriate support measures, ensuring worker safety and operational continuity (Milne et al., 1998).

Moreover, rock mass classification is crucial in open-pit mining, where slope stability is a significant concern. Factors such as adverse slope geometries, geological discontinuities, and weathering of slope materials can lead to catastrophic slope failures if not properly assessed. Classification systems like RMR and GSI help engineers quantify the stability of rock slopes and make informed decisions regarding the design of stable pit walls, which are critical for preventing landslides and protecting both personnel and equipment. The correlation between RMR and GSI is particularly useful in tropical regions, where weathering significantly alters rock mass properties, necessitating adjustments in classification for accurate slope stability assessments (Saptono et al., 2020).

The integration of artificial intelligence (AI) and machine learning techniques into rock mass classification systems has further enhanced safety measures in mining. Traditional classification systems often rely on empirical correlations, which can sometimes result in over- or underestimation of rock stability, especially in complex geological settings. AI models, including neural networks and regression methods, have proven to increase the precision of rock mass ratings by optimizing the input parameters and reducing human error. For example, machine learning models such as support vector regression and artificial neural networks (ANN) have been employed to refine the accuracy of RMR values in tunnel and slope design, providing more reliable predictions of rock behaviour under varying conditions (Gholami et al., 2013). The application of AI allows for better prediction of unstable rock masses, ensuring that mining engineers can proactively deploy necessary support systems and mitigate risks in both underground and open-pit environments. This proactive approach to safety should provide a sense of security to our professional colleagues and industry experts, demonstrating the industry's commitment to risk mitigation.

Rock mass classification is even more critical in deep underground mining due to the complex interaction between high-stress levels and rock mass properties. As mines go deeper, the potential for dynamic events such as rock bursts increases, posing significant safety risks. Rockburst management strategies often rely on robust ground support systems based on rock mass classification. By evaluating factors like rock mass strength and stress distribution, engineers can design support systems capable of withstanding dynamic loading, thereby reducing the risk of sudden collapses. Case studies from Canadian hard rock mines have shown that AI-enhanced classification systems can effectively predict rockburst-prone areas, leading to better-targeted support strategies and reducing the overall risk to workers and equipment (Simser, 2019).

Furthermore, rock mass classification systems play a crucial role in long-term mine planning, instilling confidence in the stability of mining operations. By helping engineers identify high-risk areas early in the design phase, these systems contribute significantly to safety and risk management. For instance, in regions with a high likelihood of seismic activity, rock mass classification systems have been adapted to incorporate seismic factors, allowing for the design of tunnels and underground workings that can withstand earthquake-induced stresses. By modifying traditional classification systems to account for peak ground acceleration and other seismic parameters, mines in seismically active regions can implement aseismic designs, further enhancing safety (Cui et al., 2021). This emphasis on long-term planning and stability should provide a sense of confidence to our professional colleagues and industry experts, demonstrating the industry's commitment to safety and risk management.

In summary, rock mass classification systems are vital for safety and risk management in mining operations. They provide essential data for designing support systems, predicting geotechnical risks, and ensuring the long-term stability of both underground and open-pit mining environments. The integration of AI and machine learning has further improved the accuracy of these systems, allowing for more precise assessments and better risk mitigation strategies, ultimately enhancing both worker safety and operational efficiency.

Understanding the classification of rock masses plays a crucial role in selecting construction techniques and materials for tunnelling projects. It provides essential information about geological conditions, guiding engineers in determining the most suitable excavation methods, support systems, and materials. The rock mass's strength, fracturing, and quality dictate whether traditional techniques like drilling and blasting or advanced methods such as Tunnel Boring Machines (TBMs) are appropriate. When the rock is weak or heavily fractured, more robust support systems, such as steel reinforcements and shotcrete, are required to prevent tunnel collapse (Kaiser et al., 1986).

Systems such as Rock Mass Rating (RMR) and the Q-system allow engineers to evaluate the stability of rock formations. This critical data helps determine the type and amount of support needed. For instance, weak or unstable rock masses may require reinforced concrete linings or rock bolts to maintain stability, while more stable rock masses may need only minimal reinforcement (Román-Herrera & Rodríguez-Peces, 2018).

Additionally, automated and AI-based rock classification systems are increasingly used to enhance decision-making during tunnelling. Real-time classification based on TBM operation data allows for dynamic adjustment of construction techniques and support systems, ensuring timely responses to changes in rock mass quality, thus reducing risks and improving project efficiency (Hou et al., 2021).

In essence, rock mass classification forms the foundation for selecting construction techniques and materials in tunnelling projects. It ensures tunnel safety and stability by guiding engineers in choosing the most appropriate methods and support systems based on the encountered geological conditions.

1.4 Limitations of Traditional Methods for Rock Mass Classification

Traditional rock mass classification systems such as the Rock Mass Rating (RMR), Geological Strength Index (GSI), and the Q-System have several limitations in accurately assessing rock mass quality. While widely used in geotechnical engineering, these methods rely heavily on subjective interpretations and empirical data, which can introduce significant variability and bias.

1. Subjectivity in Parameter Selection: Methods like RMR and GSI rely on subjective evaluations of rock mass properties, including joint conditions, blockiness, and discontinuity surface characteristics. This subjectivity often leads to disparities in results across engineers and projects. For instance, the GSI system demands field experience for accurate rock mass assessment, and its precision may fluctuate based on the observer's expertise (Hussian et al., 2020).
2. Limited Scope of Parameters: The systems use only key factors like joint spacing, orientation, and rock strength. However, these factors may not fully consider the complex geological conditions, such as weathering or water ingress, that can significantly impact rock stability. For example, the RMR system uses only a limited set of factors, which can oversimplify the real-world complexities of rock mass behavior.(Pells & Bertuzzi, 2007).

3. Inflexibility in Dynamic Conditions: Traditional tunnel support systems are designed to be static and may not effectively adapt to dynamic or changing rock mass conditions encountered during excavation, particularly with Tunnel Boring Machines (TBMs). It can be challenging for these conventional methods to discretely capture real-time changes in rock mass quality during tunnelling, which could result in misjudgments regarding supports or tunnel safety. Given this inherent inflexibility, it is essential to exercise caution (Salimi et al., 2019).
4. Difficulty Addressing Joint Orientation and Block Size: Joint orientation and block size must be considered when assessing rock mass behavior, as studies have demonstrated their significant impact on rock mass stability. Traditional systems such as RMR and the Q-System require improvement in accurately quantifying the full impact of these factors, raising concerns about their overall effectiveness (Sadeghi et al., 2020).
5. Empirical Nature and Generalization: Numerous rock mass classification systems were developed based on limited case studies, often within specific geological settings, which may limit their applicability to different rock types or environments. For instance, the Q-System has demonstrated limitations when applied to sedimentary rocks or in environments other than those for which it was originally designed, raising doubts about its universal applicability (Cai & Kaiser, 2006).

In conclusion, while traditional rock mass classification systems provide valuable initial assessments, their subjectivity, limited parameters, and inability to adapt to dynamic conditions make them less effective for complex or highly variable geological settings.

Traditional methods for rock mass classification, such as the Rock Mass Rating (RMR), Geological Strength Index (GSI), and Q-System, often face significant challenges when applied to real-world geological conditions due to their limitations in capturing the inherent complexity and variability of rock masses. These systems simplify complex environments by focusing on a small set of parameters, such as joint spacing and rock strength, but in reality, geological settings are far more diverse. Factors such as the degree of weathering, tectonic stresses, and the presence of faults or groundwater can substantially affect the rock mass behaviour, which traditional methods often fail to account for adequately. As a result, these methods can produce overly simplified classifications that must accurately represent the conditions encountered in the field (Sadeghi et al., 2020).

Another major limitation lies in the subjectivity of these methods. Rock mass classifications often depend on the engineer's interpretation of qualitative features such as joint surface conditions and rock block size. This subjectivity leads to inconsistent results, as two engineers assessing the same site might come to different conclusions. Furthermore, traditional systems lack robust mechanisms to account for the inherent uncertainties in geological data, which can further undermine their reliability in complex and unfamiliar geological settings (Hussian et al., 2020).

These systems are also static and do not adapt well to dynamic environments, such as tunnelling projects where geological conditions can change rapidly as excavation progresses. The inability to make real-time adjustments can lead to poor decision-making during construction, where rapid changes in rock mass quality might demand immediate modifications to excavation techniques or support systems, which traditional systems fail to provide (Salimi et al., 2019). Additionally, factors like joint orientation and the interaction between different geological layers often play a significant role in rock mass stability. However, traditional systems tend to treat these factors as secondary, which can lead to underestimations of the risks posed by certain geological conditions (Pells & Bertuzzi, 2007).

Moreover, geological formations often exhibit significant spatial variability, with rock properties changing over short distances. Traditional classification systems, however, tend to provide generalized assessments that fail to capture localized variations. This generalization can be particularly problematic in large-scale projects, where such variability could influence the overall stability of the structure, leading to increased risks and potentially costly mistakes. The potential consequences of these mistakes should not be underestimated, making the need for more adaptive, data-driven approaches even more pressing (Marinos et al., 2006).

In summary, while traditional rock mass classification systems have been useful for initial assessments, their inability to handle the complexity, variability, and dynamic nature of geological conditions limits their effectiveness in real-world scenarios. These limitations underscore the critical need for more adaptive, data-driven approaches to rock mass classification in complex engineering projects, which can provide more accurate and reliable results.

1.5 Role of AI in Geotechnical Engineering

Machine Learning (ML) algorithms play a pivotal role in geotechnical engineering by offering significant advantages in predicting the behaviour of soil and rock. These algorithms, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Decision Trees (DT), are precious due to their capacity to handle large datasets, which is crucial in an industry where extensive data is generated from soil and rock testing. Using conventional methods, ML algorithms can effectively process this data to uncover intricate patterns and relationships that are difficult to discern. For example, ANN and SVM are extensively utilized to accurately predict soil properties such as compressive strength and deformation, often outperforming traditional empirical models in accuracy (Shao et al., 2023).

An essential benefit of machine learning algorithms is their capability to predict complex, non-linear behaviours of soils and rocks under various conditions. This includes the accurate forecasting of slope stability, foundation settlement, and the mechanical properties of rock masses, where traditional approaches may be limited by their linear assumptions. For instance, SVM and ANN have demonstrated remarkable precision in classifying rock types, forecasting deformation, and even predicting rock compressive strength under varying loads (Chao et al., 2018).

Furthermore, the adaptability of ML algorithms, their ability to be continuously trained as more data becomes available, reassures their utility in dynamic environments. This adaptability allows for real-time adjustments during construction projects, thereby enhancing safety and reducing costs by facilitating early detection of potential geotechnical failures. Using techniques like Random Forests (RF) and Gradient Boosting also enables better handling of uncertainties in data, resulting in more reliable predictions in soil behaviour, which is crucial for designing safe and cost-effective geotechnical solutions (Nguyen et al., 2021).

Machine learning greatly enhances decision-making in geotechnical engineering by reducing the reliance on subjective judgment. The objectivity of ML-based models, being data-driven and less susceptible to human error, makes the audience feel secure in their decision-making process. Unlike traditional methods, which often depend on empirical correlations or expert opinion, ML-based models are more objective and reliable. This objectivity is particularly beneficial for projects involving complex geological conditions, such as highly variable soils or fractured rock masses (Saxena et al., 2013).

In summary, machine learning algorithms offer improved accuracy, adaptability, and objectivity in predicting soil and rock behaviour, providing a powerful tool for managing the complexity and variability inherent in geotechnical engineering projects.

Integrating AI in geotechnical projects revolutionises real-time monitoring and decision-making processes, particularly in critical infrastructure such as tunnels and dams. AI-based systems efficiently process a wealth of sensor data to provide valuable insights about construction site stability and condition, enabling quick responses to dynamic conditions. For instance, AIoT systems have been effectively utilized in tunnel construction to monitor shield machine operations and forecast tunneling-induced settlement. These AI-driven models use advanced machine learning algorithms to predict construction progress based on real-time data, allowing for immediate adjustments in machine performance and reducing risks such as ground settlement (Zhang et al., 2021).

Furthermore, integrating machine learning models with geotechnical numerical analysis supports the observational method in construction, enabling decisions to be made in real-time. By combining numerical simulations with machine learning algorithms, engineers can predict geological behaviour and potential failures during construction, as seen in tunnel projects like the Semel tunnel in Israel. This approach allows for instantaneous predictions during construction, empowering engineers to adapt to unforeseen ground behaviour quickly (Mitelman et al., 2023).

In dam projects, AI systems contribute to real-time structural deformation monitoring and worker safety. Wireless sensor networks track worker behaviour and site conditions. AI algorithms analyse this data to ensure safety and provide early warnings of potential hazards. Implementing such systems on large dam construction sites has significantly improved safety management and reduced accident risks by delivering real-time feedback on site conditions (Lin et al., 2013).

AI is contribution to geotechnical projects is profound. It facilitates continuous monitoring, rapid data processing, and predictive modelling, significantly improving decision-making under dynamic conditions. More importantly, it enhances safety and operational efficiency, making it an indispensable tool in the field.

1.6 Cost Estimation in Rock Mass Projects

Accurate Rock Mass Classification (RMC) is a game-changer in cost estimation in mining, tunnelling, and other rock mass-related activities. It directly influences the planning, design, and operational phases, allowing for better risk management and optimized resource allocation. More importantly, it significantly reduces costs, making it a crucial tool in project management.

Improved Support System Design: It is crucial to emphasize the significant role of RMC in cost estimation, as it provides accurate information for designing the appropriate support systems. In tunnel boring machine (TBM) projects, rock mass classification becomes essential for predicting the need for reinforcement and stabilization measures. This critical information is imperative in avoiding over- or under-designing supports, which can lead to increased costs due to unnecessary reinforcements or expensive structural failures requiring remediation. A study on the Ituango Hydroelectric Project exemplified how the correlation between RMR and Q systems could refine support measures, reduce rockfall risks, and optimize costs by avoiding over-reinforcement (Ramos-Rivera & Castro-Caicedo, 2020).

Predictive Models and Machine Learning: Engineers have significantly enhanced the accuracy of rock mass classifications by leveraging advanced machine learning models like Artificial Neural Networks (ANN) and support vector regression (SVR). This has proven especially beneficial in predicting rock behaviour in intricate geological settings. Unlike traditional methods, these sophisticated techniques help minimize empirical errors and reduce related costs. By harnessing AI-driven models, engineers can streamline tunnelling operations, forecast excavation costs, and enhance real-time machine performance predictions. A recent study showcased how Relevance Vector Regression (RVR) outperformed traditional empirical methods, leading to more precise rock mass ratings and averting costly underestimations or overestimations (Gholami et al., 2013).

Reducing Project Delays: Accurate RMC is essential in minimizing the likelihood of encountering unforeseen geological conditions, which could result in project delays and budget overruns. For example, cutting-edge prediction models utilizing advanced algorithms such as Random Forest and AdaBoost are successfully applied in tunnel projects to forecast real-time rock mass classifications based on TBM operation data. This capability enables immediate adjustments to tunnelling techniques, averting delays and ensuring the project stays on track. The real-time adaptability also optimizes TBM usage rates and manages excavation costs, instilling a sense of predictability and confidence in project managers and engineers (Hou et al., 2020).

Excavatability and Equipment Selection: In mining projects, RMC plays a critical role in determining the excavatability of rock, directly impacting equipment selection and operational costs. Rock mass classifications like RMR or Q-system predict the appropriate use of drilling, blasting, or mechanical excavation methods. Early selection of the proper excavation method is essential for preventing costly mistakes associated with equipment misallocation or excessive machine wear. At the Sungun copper mine, introducing a new rock mass drillability index (RMDI) has significantly enhanced the prediction of drilling rates, ensuring accurate equipment selection and substantial cost savings. This strong emphasis on the role of RMC in equipment selection instils confidence in engineers and project managers in the decision-making process (Saeidi et al., 2013).

Uncertainty Management: Rock mass heterogeneity frequently results in uncertainties that can cause significant cost fluctuations. Engineers can effectively measure these uncertainties and evaluate the related financial risks by employing probabilistic methods in rock mass classification. The probabilistic approach Panthi (2012) formulated for the Modi headrace tunnel in Nepal proved instrumental in predicting deviations between expected and actual rock mass conditions, thus minimizing unexpected cost overruns by enabling proactive contingency planning during the initial cost estimation phase (Panthi, 2012).

In conclusion, precise rock mass classification enhances the safety and reliability of designs. It profoundly influences cost estimation by facilitating superior decision-making in support system design, equipment selection, and real-time project management. This significant impact on real-time project management equips project managers and engineers to make well-informed decisions and assume control, thereby minimizing the risk of project delays and unexpected expenses.

1.7 Research Problem

The integration of advanced technologies such as Artificial Intelligence (AI) and automation into rock mass projects empowers you with substantial cost-saving benefits compared to traditional cost estimation techniques. Here are several key advantages:

Improved Accuracy and Reduced Overestimation: AI-based models significantly enhance the precision of cost predictions by incorporating large datasets, real-time updates, and more complex geological variables. Traditional methods, such as empirical models, often lead to inaccurate predictions due to limited datasets and reliance on historical data. Using models like artificial neural networks (ANN) and support vector regression (SVR), AI enables more accurate predictions, reduces overestimations, and ensures better financial management. For instance, studies in open-pit mining projects demonstrated that AI techniques, particularly ANN, improved the accuracy of capital cost predictions by 7.7% on average compared to traditional methods (Guo et al., 2019).

Real-Time Monitoring and Adaptability: Using AI offers a significant advantage due to its capability to analyze real-time data from rock mass conditions and adjust predictions accordingly, enabling adaptive decision-making during tunnelling or excavation. This reduces the risk of unforeseen geological conditions, thus averting project delays or extra costs. AI models such as Random Forest and AdaBoost have proven highly effective in real-time rock mass classification prediction, improving resource allocation efficiency and preventing unnecessary expenditures (Hou et al., 2020).

Optimization of Equipment and Resource Allocation: AI-driven systems are essential for optimizing equipment usage and material allocation by accurately predicting the exact excitability and required support systems based on real-time rock mass data. This significantly reduces the need for excessive reinforcement or over-utilization of heavy equipment, resulting in substantial cost savings. For instance, in tunnelling projects, AI-based models have successfully minimized unnecessary TBM downtimes by providing precise rock mass predictions, which are crucial for preventing machine wear and reducing operational costs (Frough & Torabi, 2013).

Enhanced Risk Management and Contingency Planning: Conventional approaches can face challenges dealing with uncertainties and risks from diverse geological conditions. On the other hand, AI-powered systems offer improved risk assessment capabilities by leveraging machine learning algorithms to simulate various scenarios. This contributes to enhanced contingency planning and decreased chances of cost overruns caused by unexpected events. When AI models are integrated with probabilistic methods, they yield more dependable estimates inclusive of risk factors, thereby reducing unforeseen financial impacts (Panthi, 2012).

Reduction in Labor and Time: Automating processes in rock mass projects simplifies data collection, analysis, and reporting, saving time and reducing labour costs. AI models enable quick and in-depth analyses, leading to faster decision-making and more agile project management (Pilyay, 2023).

In conclusion, AI and automation offer significant cost-saving benefits in rock mass projects by improving prediction accuracy, optimizing resources, enhancing real-time monitoring, and reducing labour requirements. These advancements lead to more reliable cost estimates and fewer financial surprises compared to traditional estimation techniques, ensuring the reliability of your project's outcomes.

1.8 Purpose of Research

Geotechnical engineering requires understanding rock masses to assess the safety and stability of infrastructure projects such as tunnels, dams, and slopes. Rock mass classification plays a vital role in characterizing the behavior of geological formations to predict their response to various engineering activities. Traditionally, this has relied on visual inspections and manual interpretation of geological data.

However, with advancements in Artificial Intelligence (AI) and Machine Learning (ML), we have the opportunity to improve rock mass classification. AI models can analyze large datasets comprising diverse geological attributes such as borehole data, rock joint set data, laboratory test results, and structural properties of rock masses. This can lead to more comprehensive and objective rock mass quality and behavior assessments.

The need for better rock mass classification has led to research exploring the potential of AI models. Engineers and geologists can make more informed decisions during geotechnical project planning, design, and construction phases by developing AI-based models tailored for rock mass classification. Integrating cost estimation into the classification process can provide valuable insights for project management and budget allocation, ultimately leading to more efficient resource utilization and risk mitigation.

The emergence of artificial intelligence (AI) has revolutionized the field of rock mass classification by offering advanced tools and techniques to enhance accuracy, efficiency, and predictive capabilities. AI models, including machine learning (ML) and deep learning (DL) algorithms, can analyze large volumes of heterogeneous data from geological surveys, laboratory tests, and construction projects to identify complex patterns and relationships that may not be discernible through traditional analysis methods.

Machine learning algorithms, such as support vector machines (SVM), artificial neural networks (ANN), and decision trees, can be trained on diverse datasets to develop predictive models for rock mass classification. These models can learn from historical data and iteratively improve their performance, enabling engineers to make more informed decisions about construction methods, support systems, and risk mitigation measures.

1.9 Significance of the Study

Rock mass classification is a vital aspect of geotechnical engineering. However, current methods often lack consistency and objectivity, leading to subjective interpretations and variable outcomes. Moreover, the manual process of visually inspecting and empirically classifying rock masses is time-intensive and prone to human error. Classification systems must integrate with cost estimation methods to accurately assess the financial impact of geological conditions on engineering projects.

Thus, this research aims to address these challenges by developing an advanced approach to rock mass classification. We aim to achieve more accurate and consistent results by combining AI models with extensive datasets. Additionally, incorporating cost estimation into the classification process will provide stakeholders with valuable insights into the financial implications of different rock mass classifications on project budgets.

1.10 Research Purpose and Questions

1. What opportunities exist for improving rock mass classification systems based on insights from the literature review?
2. Which geological attributes and variables have the most significant influence on rock mass classification accuracy and reliability?
3. What strategies can be employed to optimize AI-based models for rock mass classification, considering factors such as model complexity and computational efficiency?
4. How does the performance of AI-based rock mass classification models compare to traditional empirical methods in terms of accuracy and reliability?
5. What methodologies and approaches can be employed to quantify the financial implications of different rock mass classification outcomes on project budgets?
6. What are the practical applications of AI-driven rock mass classification and cost estimation in geotechnical engineering projects?

CHAPTER II:

REVIEW OF LITERATURE

2.1 Introduction

Rock mass classification is a process used in engineering and geological disciplines to evaluate rock formations' mechanical properties and behavior. It is essential to designing, constructing, and maintaining structures such as tunnels, dams, bridges, and mining excavations. By classifying rock masses, engineers and geologists can assess factors such as strength, stability, deformability, and permeability, which are critical for ensuring engineering projects' safety, durability, and effectiveness.

Over the years, various classification systems have been developed to categorize rock masses based on their geomechanical properties. These systems typically consider rock strength, intactness, joint patterns, weathering, and groundwater conditions to assign qualitative or quantitative ratings to rock masses. Examples of widely used classification systems include the Rock Mass Rating (RMR) system developed by Bieniawski, the Q-system proposed by Barton, Lien, and Lunde, and the Geological Strength Index (GSI) introduced by Hoek and Brown.

Accurate classification of rock masses is crucial for estimating costs in construction projects that involve rock structures. The geomechanical properties of rock masses directly influence the construction methods, support requirements, and associated costs of engineering projects. For example, tunnels excavated through competent rock masses may require minimal support measures, leading to lower construction costs. In contrast, tunnels in weak or fractured rock masses may necessitate extensive reinforcement and grouting, resulting in higher expenses.

Construction project cost estimation relies on accurately assessing rock mass characteristics to anticipate potential challenges, mitigate risks, and allocate resources effectively. Traditional cost estimation methods, such as analogous, parametric, and expert judgment, often incorporate rock mass classification data to inform the cost models. However, these methods may be limited by subjective biases, reliance on historical data, and difficulties accounting for complex interactions between rock mass properties and construction variables.

The emergence of artificial intelligence (AI) has revolutionized the field of rock mass classification by offering advanced tools and techniques to enhance accuracy, efficiency, and predictive capabilities. AI models, including machine learning (ML) and deep learning (DL) algorithms, can analyze large volumes of heterogeneous data from geological surveys, laboratory tests, and construction projects to identify complex patterns and relationships that may not be discernible through traditional analysis methods.

Machine learning algorithms, such as support vector machines (SVM), artificial neural networks (ANN), and decision trees, can be trained on diverse datasets to develop predictive models for rock mass classification. These models can learn from historical data and iteratively improve their performance, enabling engineers to make more informed decisions about construction methods, support systems, and risk mitigation measures.

Deep learning algorithms, such as convolutional neural networks (CNN) and recurrent neural networks (RNN), excel in extracting intricate features from raw data, such as images and sensor readings, to characterize rock mass properties accurately. By leveraging the hierarchical representations learned from large datasets, deep learning models can achieve state-of-the-art performance in rock mass classification tasks, surpassing traditional methods in accuracy and reliability.

This literature review examines the convergence of rock mass classification, cost estimation in construction projects, and AI technology, as well as their implications for engineering practices. By synthesizing existing literature from diverse sources, including research papers, academic journals, and technical reports, this review aims to provide insights into the methodologies, advancements, and challenges in integrating AI into rock mass classification and cost estimation processes.

The review will discuss various AI techniques and algorithms used in rock mass classification, their comparative performance, and their applications in engineering projects. Additionally, the review will explore the role of AI in enhancing cost estimation accuracy, optimizing resource allocation, and mitigating risks in construction projects involving rock structures.

2.2 Overview of Rock Mass Classification Systems

The most widely used rock mass classification systems include the Rock Mass Rating (RMR) system, the Geological Strength Index (GSI), and the Q-System. While all aim to classify rock masses, these systems differ in their approach and criteria for evaluating rock mass quality.

Developed by Bieniawski in 1973, RMR is one of the most commonly used classification systems. It evaluates rock mass quality based on six parameters: uniaxial compressive strength, rock quality designation (RQD), spacing of discontinuities, condition of discontinuities, groundwater conditions, and the orientation of discontinuities. RMR assigns a numerical rating to each parameter, then summed to determine the overall rock mass rating. This system is widely used for various engineering applications, such as tunnels and slopes, and offers recommendations for support systems based on the total RMR value (Bieniawski, 1993).

Geological Strength Index (GSI) system, introduced by Hoek in the 1990s, is a more qualitative approach to rock mass classification. It focuses on the rock mass's structure and the condition of the discontinuity surfaces. GSI is particularly useful for assessing the strength and deformability of rock masses in poor-quality rock, such as highly fractured or weathered rock. Unlike RMR, GSI does not assign numerical values to different parameters but instead provides an index value based on visual assessments and field observations (Hoek, 1994).

Introduced by Barton, Lien, and Lunde in 1974, the Q-System is widely used in tunnelling projects. It evaluates rock mass quality based on six parameters: RQD, the number of joint sets, the roughness of joint surfaces, the degree of joint alteration, groundwater conditions, and the stress reduction factor. These parameters are combined into a formula to calculate the Q-value, which estimates support requirements. The Q-System is well-suited for evaluating jointed rock masses and has been adapted for use in Tunnel Boring Machine (TBM) applications with the QTBM variant (Palmström & Broch, 2006).

- Key Differences:

Parameter Scope: RMR and Q-System use specific numerical values for individual rock mass properties, while GSI relies more on visual and qualitative assessments.

Application Focus: RMR is versatile and used for many applications (e.g., tunnels, slopes, foundations), while GSI is often applied to more challenging rock conditions. The Q-System is particularly suited for tunnelling and underground projects.

Support Design: RMR and Q-System provide more direct recommendations for rock support systems, whereas GSI is more focused on describing rock mass behaviour and strength properties.

Three widely used rock mass classification systems are the Rock Mass Rating (RMR) system, the Geological Strength Index (GSI), and the Q-System. Each system evaluates rock mass quality differently. RMR focuses on numerical ratings for specific rock mass properties, while GSI relies on qualitative assessments. The Q-System specializes in evaluating jointed rock masses. RMR is versatile and used in various engineering applications, while GSI is particularly useful for assessing the strength and deformability of poor-quality rock. The Q-System is well-suited for tunnelling and underground projects. Additionally, RMR and Q-System offer direct recommendations for rock support systems, whereas GSI is more focused on describing rock mass behaviour and strength properties.

Below table 1 gives representation of the advantages and limitations of traditional rock mass classification systems:

Table 1
Advantages and limitations of traditional RMC

Aspect	Advantages	Limitations
Ease of Use and Practicality	Quick and simple for initial assessments in various engineering projects.	Subjective assessments can lead to inconsistent results between different engineers (Kundu et al., 2020).
Cost-Effectiveness	Low-cost solution, requiring minimal equipment and testing.	May not fully capture the geological complexity, leading to cost overruns in complex conditions (Salimi et al., 2017).
Empirical Backing	Based on decades of	Limited scope, often

Aspect	Advantages	Limitations
	empirical data and practical experience.	oversimplifying complex geological environments (Palmström & Broch, 2006).
Parameter Scope	Sufficient for preliminary design and risk estimation.	Focuses on a limited number of parameters, ignoring important factors like seismicity and joint orientation (Salimi et al., 2017).
Adaptability	Well-suited for environments with stable, predictable geological conditions.	Cannot handle dynamic changes during construction (e.g., TBM tunneling), leading to delays (Hou et al., 2020).
Support Design Accuracy	Provides general guidelines for support requirements based on rock mass classification [(Palmström & Broch, 2006)].	May provide inaccurate support recommendations in jointed or complex rock masses (Palmström & Broch, 2006).
Subjectivity	Allows for field-based, qualitative assessments of rock mass characteristics.	Highly subjective, prone to variability based on individual interpretation (Kundu et al., 2020).

Aspect	Advantages	Limitations
Real-Time Monitoring	Suitable for static, well-understood environments.	Cannot adapt to real-time changes in geological conditions during construction (Hou et al., 2020).

The table presents the advantages and limitations of traditional rock mass classification systems like RMR and the Q-System in engineering projects. These systems are advantageous for their ease of use, cost-effectiveness, and reliance on decades of empirical data, making them practical for preliminary assessments. However, they face limitations such as subjectivity in assessments, oversimplification of complex geological environments, and an inability to adapt to dynamic real-time conditions during construction. While they provide general support guidelines, these systems may fall short in offering precise support recommendations for complex or jointed rock masses.

2.3 Traditional Rock Mass Classification Methods

Traditional rock mass classification methods, such as the Rock Mass Rating (RMR), Geological Strength Index (GSI), and the Q-System, account for variability in rock properties like strength, joint spacing, and water conditions through empirical ratings and parameters. However, their ability to capture this variability has both strengths and limitations.

RMR System: The rock mass rating (RMR) system is a method used to evaluate the quality of rock mass by considering multiple parameters such as uniaxial compressive strength, Rock Quality Designation (RQD), joint spacing, and groundwater conditions. Each parameter is assigned specific ratings, which are combined to calculate the overall rock mass quality score. It is important to note that while the RMR system offers a practical approach to integrating various rock properties, it may present challenges in accurately capturing the complex behaviour of rock joints and the anisotropic nature of highly heterogeneous rock masses (Bieniawski, 1993).

GSI System: The Geological Strength Index (GSI) system is commonly applied to assess the stability of less resilient and highly fractured rock formations. It places significant importance on subjective factors such as the configuration of the rock mass and the state of the surfaces where discontinuities occur. While it involves a certain degree of visual evaluation, its subjective nature means that its effectiveness relies heavily on the expertise of the geotechnical engineer. Nevertheless, the adaptability of GSI to varying geological conditions [(Hoek et al., 1995)] makes it a practical tool for assessment and analysis.

Q-System: The Q-System is commonly employed in tunnelling projects and takes into account various parameters such as RQD, joint sets, joint roughness, groundwater inflow, and stress reduction factor to calculate the Q-value, which in turn determines the rock support needed. However, it is worth noting that the Q-System may oversimplify water conditions and may not fully consider discontinuities or joint orientation in some cases. (Barton et al., 1974).

In summary, traditional rock mass classification systems account for variability in rock properties through parameterized ratings and qualitative assessments. However, they need help with dynamic conditions, subjective judgments, and the oversimplification of complex geological factors.

Traditional Rock Mass Classification systems, such as the Rock Mass Rating (RMR), Geological Strength Index (GSI), and the Q-System, face several challenges when applied to large-scale and complex geotechnical projects. These challenges arise due to the inherent limitations of these systems in capturing the full complexity of geological conditions, project scale, and dynamic factors:

1. Oversimplification of Geological Complexity: Conventional classification systems may need to provide accurate results for complex geological conditions in large-scale projects. This oversimplification can cause inaccurate predictions about the behavior of rock masses. For example, the RMR system may not account for the variability in joint conditions or anisotropy, which can impact the overall stability of large tunnels or slopes (Palmström & Broch, 2006).
2. Inability to Account for Dynamic Changes: Traditional methods for assessing rock mass conditions during excavation may not adapt to ground changes. This can lead to delays and increased risks during construction. For example, the Q-System may be unable to adjust to changes in groundwater conditions or stress factors during excavation (Salimi et al., 2019).
3. Subjectivity and Variability in Application: In many conventional systems, assessments are frequently based on engineers' subjective judgments, particularly in visually evaluating joint roughness or discontinuity conditions in the field. This subjectivity can introduce significant variability in results, as different engineers may arrive at varying classifications for the same rock mass in complex projects. This variability is especially concerning in large-scale projects, where ensuring consistent and reliable assessments is crucial for safety and effective cost management (Liu et al., 2018).

4. Limitations in Large-Scale Application: The current rock mass classification systems were created for smaller, more consistent projects. However, they may need to be adapted to better suit larger, more diverse geological environments. For instance, various types of rock and structures may be encountered along the tunnel's length in extensive tunnelling projects. The existing systems, including the Geologic Strength Index (GSI), may need more precision to account for such variations, potentially resulting in inaccurate assessments of the support needed and the overall stability of the tunnel (Milne et al., 1998).

Here, it emphasizes that although traditional rock mass classification systems offer initial assessments, they need help managing geotechnical projects' complex, dynamic, and large-scale nature. The text also highlights that recent advances in 3D visualization and machine learning are starting to tackle these challenges by providing more flexible and intricate methods for rock mass classification.

When comparing traditional rock mass classification methods like the Rock Mass Rating (RMR) and Geological Strength Index (GSI) with modern AI-based techniques, there are notable differences in terms of accuracy and efficiency:

Accuracy: Traditional systems like RMR and GSI rely on simplified parameters such as joint spacing, rock strength, and groundwater conditions. These methods are limited by their reliance on empirical data and subjective evaluations, which can introduce variability in classification results, especially in complex geological conditions. AI-based systems, on the other hand, use large datasets, real-time monitoring, and advanced algorithms like support vector machines (SVM) and artificial neural networks (ANN) to deliver more precise and adaptable predictions. For instance, an AI model using the AdaBoost algorithm integrated with a classification and regression tree (CART) was shown to significantly outperform traditional methods by achieving higher accuracy rates (0.865) and better classification performance in tunnelling projects (Liu et al., 2020).

Efficiency: Traditional methods require manual data collection, interpretation, and the assignment of ratings based on field observations, which can be time-consuming and labour-intensive. AI-driven models, like those based on machine learning and neural networks, streamline the data collection and classification process by automatically analyzing large datasets, which reduces time and labour. Additionally, AI-based models, such as those incorporating Particle Swarm Optimization (PSO) and Least Squares Support Vector Machines (LSSVM), provide fast and accurate predictions in tunnel projects, outperforming manual methods in terms of speed and reliability (Lu et al., 2023).

Handling Complexity and Uncertainty: Traditional methods are often static and struggle with highly variable geological conditions, especially in large-scale or dynamic projects. In contrast, AI techniques, such as the Monte Carlo simulation (MCS) and TOPSIS models, are designed to adapt to uncertainty, incorporating it into their predictions. This adaptability not only allows for a more comprehensive understanding of rock mass behavior under different conditions but also reassures us of the reliability of these predictions (Wu et al., 2019).

In conclusion, the comparison clearly demonstrates that AI-based classification methods outperform traditional systems in both accuracy and efficiency. By leveraging data-driven approaches and real-time adaptability, AI-based methods are better suited for complex and large-scale geotechnical engineering projects. This conclusion should instil confidence in the superiority of AI-based methods and the need for their adoption in the field.

2.4 Artificial Intelligence Models for Rock Mass Classification

AI algorithms such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Random Forests (RF) are among the most effective for predicting rock mass classification in complex geological settings.

Support Vector Machines (SVM) are a popular and effective tool in geotechnical engineering, particularly for their predictive capabilities in analyzing geological data. One of their critical applications is in predicting geological conditions for tunnel boring machine (TBM) operations. Studies have demonstrated that SVM models can achieve remarkably high precision, with accuracy rates reaching as high as 98.6% in some cases. This makes SVM an invaluable asset in geotechnical engineering, offering engineers a reliable and precise method for forecasting and planning TBM operations in complex geological settings (Zhang et al., 2019).

Artificial Neural Networks (ANN): ANN, which stands for Artificial Neural Network, is a beneficial type of AI. It is excellent at dealing with complicated connections between different rock characteristics. People use ANN to predict how strong rocks are and to group them based on their characteristics, especially in places where the geology varies a lot (Kim, 2021).

Random Forests (RF): In geotechnical engineering, Random Forest (RF) is a popular choice due to its ability to handle large datasets and perform feature selection effectively. Specifically, in the context of tunnel construction, models based on Random Forest have shown exceptional performance. For instance, when using TBM (Tunnel Boring Machine) operation data, RF-based models achieved an impressive prediction accuracy rate of 87.27% in classifying rock mass. This highlights the robustness and reliability of Random Forest in tackling geotechnical engineering challenges, providing a secure foundation for its application (Hou et al., 2020).

These AI algorithms, Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Random Forests (RF), have proven to outperform traditional methods in both accuracy and efficiency. Their superior performance, particularly in complex environments where geological variability poses significant challenges, is a convincing testament to their effectiveness.

AI models have significantly improved real-time rock mass classification during tunnelling and mining operations through several vital mechanisms:

Real-Time Data Processing: AI models use real-time operational data from Tunnel Boring Machines (TBM) to provide continuous, dynamic predictions of rock mass conditions. For instance, an AI model based on a stacking ensemble classifier was developed to predict rock mass classifications using TBM operational data, achieving superior performance compared to traditional methods in adaptive tunnel construction environments (Hou et al., 2021).

Improved Accuracy with Ensemble Learning: AI models like AdaBoost integrated with CART (Classification and Regression Tree) have enhanced rock mass classification accuracy. This model showed improved performance (with an accuracy of 86.5%) when applied to the Songhua River Water Conveyance Tunnel, outperforming traditional classifiers in real-time tunnelling scenarios (Liu et al., 2020).

Predictive Models for Dynamic Adjustments: AI systems using machine learning algorithms such as Support Vector Machines (SVM) and Neural Networks have been applied to tunnel projects, allowing dynamic adjustments based on changing geological conditions. These models significantly improve operational efficiency by reducing delays and minimizing risks in tunnelling by offering predictions with accuracy rates as high as 93% (Ma et al., 2023).

AI models greatly enhance rock mass classification's accuracy, speed, and adaptability during tunnelling and mining operations. Their real-time nature ensures the immediacy of their benefits, enabling real-time adjustments and improved decision-making in complex geological settings.

AI-based rock mass classification models offer several significant cost-saving benefits compared to traditional classification methods in large geotechnical engineering projects, such as tunnelling and mining. These benefits primarily stem from improved prediction accuracy, real-time monitoring capabilities, and operational efficiency.

Firstly, AI models provide higher prediction accuracy for rock mass properties than traditional methods. Traditional systems like the Rock Mass Rating (RMR) or the Q-system rely on predefined parameters, which may not capture the full complexity of rock conditions. In contrast, AI models, such as support vector regression (SVR) and random forests (RF), use large datasets and advanced algorithms to predict rock mass behavior better. This greater accuracy allows engineers to design more appropriate support systems, avoiding costly mistakes like over-reinforcement or insufficient support, both of which can lead to higher material and labour costs. For example, Liu et al. (2019) demonstrated that AI models could predict rock mass characteristics more reliably, leading to fewer unexpected changes in project plans and lower overall costs.

Secondly, AI models empower real-time monitoring and adjustments, providing a sense of control and adaptability. One of the key advantages of AI in rock mass classification is its ability to process data from tunnel boring machines (TBMs) in real-time. This capability allows for immediate adjustments during construction, helping to avoid delays caused by unexpected rock conditions. For instance, a study by Hou et al. (2021) showed how an ensemble learning model used real-time data from TBMs to continuously predict rock mass quality. This dynamic approach significantly reduced operational inefficiencies, allowing engineers to adjust tunnelling techniques based on real-time rock conditions. These on-the-spot adjustments help to avoid project delays, which can accumulate high costs in large-scale projects.

Another critical cost-saving factor is the reduction in manual labour and testing costs. Traditional rock mass classification methods often require extensive manual testing and fieldwork to assess rock conditions. This process is time-consuming and labour-intensive, leading to higher costs. AI-based models, however, can automate much of this process by analyzing data from sensors placed on TBMs or other machinery. In particular, Liu et al. (2020) used classification and regression tree (CART) models combined with the AdaBoost algorithm to classify rock mass types accurately using data collected during tunnelling. This automation speeds up the classification process and reduces the need for manual labour and detailed site investigations, cutting labour costs significantly.

Lastly, AI-based models optimize equipment utilization, which is a critical aspect of cost savings in large projects. Tunnel boring machines and other heavy machinery are expensive to operate, and any downtime can add significant costs to a project. AI models can predict the performance of these machines more accurately by analyzing rock mass conditions in real time. This ensures that machines are used more efficiently, reducing the likelihood of costly breakdowns or delays due to unexpected geological conditions. A study by Salimi et al. (2019) highlighted how AI models improved the efficiency of TBM usage by predicting machine performance based on real-time data, leading to fewer delays and better resource allocation. This optimization provides a sense of efficiency and resourcefulness in managing project costs.

In conclusion, AI-based rock mass classification models provide substantial cost-saving benefits by improving accuracy, enabling real-time adjustments, reducing labour costs, and optimizing equipment usage. These models help engineers make better-informed decisions, streamline construction processes, and avoid costly delays, making them invaluable in large geotechnical engineering projects.

2.5 Assessment of Cost Estimation Methods

Cost estimation plays a pivotal role in the planning of rock mass projects. It involves the use of various methods, each with its own level of accuracy and reliability. The most commonly used cost estimation methods include:

Deterministic Methods: These methods use fixed inputs such as the Rock Mass Rating (RMR) and Geological Strength Index (GSI) to predict how rock masses will behave and how much the corresponding costs will be. These methods are widely used. However, they can oversimplify complex geological conditions, which may lead to inaccurate cost estimates. Their reliability decreases in projects where rock properties have high variability or uncertainty.

Empirical Methods: Commonly used in cost estimation, empirical formulas based on historical data or site-specific observations are quick and practical but may need more precision. They simplify complex geological behaviours and may not work well for unique site conditions (Khabbazi et al., 2013).

Probabilistic Methods: Probabilistic approaches like Monte Carlo simulations and response surface methods are crucial for large-scale projects. They consider the variability and uncertainties in rock mass properties, providing a more realistic range of cost estimates and handling different scenarios of rock behaviour. Sobol's global sensitivity analysis has proven to deliver more reliable estimates by better-managing uncertainties in rock properties than traditional methods (Pandit et al., 2019).

Analogy-Based Estimation: This approach uses historical data from comparable projects to forecast costs. Like empirical methods, analogy-based approaches are transparent and leverage essential elements of previous projects for estimation. However, it is essential to note that this method may encounter challenges if the past projects used for comparison are not closely aligned with the current project (Auer et al., 2006).

AI and Machine Learning Methods: AI-based models, such as those utilizing support vector machines (SVM) or artificial neural networks (ANN), are increasingly being used for cost estimation in rock mass projects. These models provide higher accuracy by analyzing large datasets and considering complex relationships between variables. What sets them apart is their ability to adapt to real-time data, making them more efficient and reliable for predicting costs, particularly in dynamic environments like tunneling or mining (Liu et al., 2019).

In summary, while traditional methods such as deterministic and empirical approaches are still widely used due to their simplicity, they often need more precision for complex projects. Probabilistic and AI-based methods, on the other hand, offer greater accuracy and reliability, especially in large-scale projects with significant geological variability.

Traditional cost estimation methods in rock mass-related construction and mining projects face several limitations that can lead to inaccuracies when predicting actual project costs. These challenges are particularly significant in complex, large-scale projects where geological conditions and other factors can change unexpectedly.

One of the key issues is oversimplification. Traditional methods often rely on simplified geological parameters, like the Rock Mass Rating (RMR) or Rock Quality Designation (RQD), which do not fully capture the complex conditions of the rock mass. These models tend to generalize conditions and may not account for essential variations in rock strength, joint spacing, or water conditions, leading to errors in cost predictions.

As a result, these methods can either underestimate or overestimate costs because they fail to consider the full range of geological variability (Pandit et al., 2019).

Another limitation is that traditional methods are often static, meaning they are based on data collected at the beginning of the project and do not adapt to changing conditions. New issues may arise during construction, such as sudden changes in the rock mass or unexpected water inflows. Since traditional methods cannot adjust to these changes, they are often inaccurate when actual conditions differ from the initial assumptions, leading to cost overruns (Ökmen & Öztas, 2010).

Traditional methods also need help with risk and uncertainty. These methods typically assume a single outcome without considering the many factors that could impact costs, such as fluctuating material prices or unexpected equipment failures. As a result, the cost estimates can either be overly cautious or too optimistic. Without accounting for these risks, there is a greater chance that actual costs will differ from the estimated ones (Agyekum et al., 2018).

Moreover, many traditional methods depend on historical data, using cost information from past projects to predict costs for future ones. While this can be useful, it may not work well if the current project has different characteristics or if market conditions, like material costs, have changed significantly since the last project. This reliance on outdated or unrelated data can make cost estimates unreliable (Sayadi et al., 2015).

Finally, traditional cost estimation methods are often manual and time-consuming. They require engineers to collect field data, analyze it, and provide expert input, which not only takes much time but also increases the likelihood of human error. This process slows the project and can introduce more inaccuracies into the cost estimates (Yu & Skibniewski, 2010).

In summary, while applicable in some cases, traditional cost estimation methods need help with the complexity and unpredictability of modern rock mass projects. They often need to account for changing conditions, risks, and detailed geological variability, which can lead to inaccurate predictions and cost overruns. More advanced methods, such as those incorporating probabilistic models or AI, are better equipped to handle these challenges and offer more accurate cost estimates in dynamic environments.

2.6 Implementation Challenges and Considerations for Rock mass classification

Several technical and operational considerations are essential when integrating Rock Mass Classification (RMC) into the planning and execution phases of construction and mining projects to ensure accurate and effective project implementation.

Accurate Geological Data Collection: One of the primary considerations is obtaining accurate geological data for classifying rock masses. Parameters such as rock quality designation (RQD), joint spacing, rock strength, and groundwater conditions must be carefully measured and analyzed to inform RMC systems like RMR and the Q-System. Inaccurate data collection can lead to errors in classification, affecting the design of support systems and potentially leading to unsafe conditions during excavation (Milne et al., 1998).

Adaptability to Changing Conditions: Geological conditions can change rapidly during construction, particularly in tunnelling projects. Integrating RMC into real-time monitoring systems, such as AI algorithms like Random Forest or Neural Networks, can help continuously update rock mass classifications based on current excavation data. This allows for immediate adjustments to construction plans, improving safety and reducing project delays (Hou et al., 2020).

Integration with Project Design and Support Systems: RMC must be closely integrated with the engineering design of the project. Classification systems like RMR provide critical information for designing appropriate support systems, such as rock bolts or shotcrete, based on the estimated stability of the rock mass. Poor integration between RMC outputs and support design can result in over-design, leading to unnecessary costs, or under-design, compromising safety (Mohammadi & Hossaini, 2017).

Operational Efficiency: Efficient integration of RMC requires automated systems that minimize human error and subjective interpretation. Advanced RMC models, combined with machine learning, can automate classification by analyzing data from field sensors and Tunnel Boring Machines (TBMs). This speeds up the classification process and ensures more consistent and reliable results across different project phases (Huang et al., 2013).

Handling Geological Uncertainty: Uncertainties in rock mass properties due to incomplete or variable data are expected in large-scale projects. Probabilistic approaches or AI-based models account for geological uncertainty and can improve decision-making. These systems can provide a range of possible outcomes based on different scenarios, allowing engineers to plan for risks such as unexpected fractures or water inflows, which can significantly affect project costs and safety (Palmström & Broch, 2006).

Design Modifications Based on Real-Time Data: In dynamic construction environments, such as those found in mining or tunneling, RMC models need to adapt continuously. Integrating RMC with real-time monitoring systems ensures that any unexpected geological features can be detected and addressed immediately, thus reducing project risks and minimizing delays (Laubscher, 1993).

Successfully integrating Rock Mass Classification into construction and mining projects requires careful attention to data accuracy, adaptability, and the seamless linking of classification results to project design and real-time monitoring. Using automated systems and probabilistic models can significantly enhance the efficiency and reliability of rock mass classification in complex environments.

When applying traditional rock mass classification systems, such as the Rock Mass Rating (RMR) and Geological Strength Index (GSI), to large-scale geotechnical projects, several significant challenges arise:

1. Oversimplification of Geological Conditions: When using traditional methods, it is essential to consider the full complexity of geological conditions in large-scale projects. For instance, the Rock Quality Designation (RQD) might not fully account for directional dependence and the scale effect of rock mass variability, potentially leading to less accurate classifications in polymetallic deposits and large underground constructions (Sánchez et al., 2021).
2. Static Nature of Classification: The current methods are typically static and rely on data obtained from initial surveys. These methods struggle to accommodate changes during excavation, particularly in dynamic environments such as tunneling, where geological conditions frequently shift. Because traditional classification methods cannot promptly adapt to real-time data, there is a higher chance of unexpected project delays (Kimour et al., 2023).
3. Subjectivity and Human Error: Traditional rock mass classification systems rely on engineers visually assessing field parameters. This subjective approach often results in inconsistencies between different assessors, which can be particularly problematic in large-scale projects involving multiple teams. This variability in the classification of rock

mass quality can have significant implications for the project's success (Mazzoccola & Hudson, 1996).

4. Inability to Manage Uncertainty: Traditional engineering and construction methods are based on deterministic approaches, which means they need help accounting for uncertainty. Factors such as variations in rock mass properties and unexpected ground conditions pose challenges for these traditional methods. This becomes especially problematic in large-scale projects, where geological heterogeneity and risk factors such as water inflow or seismic activity can substantially impact project costs and safety. (Mesquita et al., 2014).

Traditional rock mass classification methods have seen widespread use. However, they encounter significant hurdles in large-scale geotechnical projects, particularly in managing complexity, adapting in real time, and addressing uncertainty.

2.7 Factors Influencing the Performance of AI Models

AI models offer powerful tools for predicting outcomes in geotechnical engineering and rock mass classification. However, their accuracy and reliability are influenced by several key factors:

AI models' accuracy largely depends on the quality and size of the datasets used for training. The model's ability to make accurate predictions is compromised when the training data is scarce or contains errors. For example, the precise prediction of rock mass characteristics like uniaxial compressive strength (UCS) and joint roughness coefficient (JRC) relies on having comprehensive and typical data from the specific project site (Asadizadeh & Hossaini, 2016).

The selection of AI algorithms and model structures is crucial in determining predictive performance. Various techniques such as Support Vector Regression (SVR), Artificial Neural Networks (ANN), and Random Forests have distinct capabilities in capturing non-linear relationships in geological data. For instance, Artificial Neural Networks (ANN) excel in predicting complex rock mass behavior, but they must be fine-tuned meticulously to prevent overfitting (Liu et al., 2019).

Geotechnical data can be uncertain due to natural variations in rock properties and environmental conditions. When using AI models to analyze this data, it is essential to consider and incorporate this uncertainty. One way to do this is through probabilistic approaches or sensitivity analyses. By using methods like Bayesian updating, we can consider the uncertainty and adjust our models as new data comes in, which can help improve the accuracy of our predictions (Feng & Jimenez, 2015).

In order to be effective, AI models must be able to adjust to real-time data from construction or tunnelling operations. Models that can continually update their predictions using real-time inputs, like TBM operational data, enhance the accuracy and applicability of their predictions throughout the project's duration (Liu et al., 2019).

Although complex AI models such as deep neural networks can provide high levels of accuracy, they often need help with interpretability. Engineers must have transparent and interpretable predictions to make practical decisions. In some cases, simpler models with precise inputs and outputs may be more favourable, even if they sacrifice a certain degree of predictive accuracy (Santos et al., 2020).

Several vital factors directly influence the accuracy and dependability of AI models in geotechnical engineering. These include the quality of the input data, the appropriateness of the model for the specific application, the effective management of uncertainty, the model's capacity to integrate real-time data, and the delicate equilibrium between complexity and interpretability.

Feature selection and preprocessing techniques are critical in enhancing the performance of AI models for classification tasks in geotechnical projects. These processes help improve model accuracy, reduce computational costs, and increase interpretability. Some of the key ways in which these techniques contribute to AI model performance include:

Geotechnical projects often involve large, complex datasets with many variables. High-dimensional data can overwhelm AI models, leading to slower processing and decreased accuracy. Feature selection techniques, such as filter and wrapper methods, help eliminate irrelevant or redundant features, simplifying the dataset and improving model efficiency. For example, the Hybrid Particle Swarm Optimization technique effectively selects the most informative features while reducing dimensionality, enhancing AI models' classification performance (Chen et al., 2019).

By selecting only the most relevant features, AI models are less likely to overfit the training data, leading to better generalization to new, unseen data. Preprocessing techniques, such as normalization or standardization, ensure that the selected features are scaled appropriately, improving model accuracy and consistency across different datasets. Feature selection methods like Minimum Redundancy Maximum Relevance (mRMR) help to improve generalization by minimizing redundant features (Sharma & Sharma, 2023).

Reducing the number of features in a dataset can also make AI models more interpretable. In geotechnical engineering, interpretability is crucial for understanding the relationship between geological properties and model predictions. Feature selection techniques that retain only the most critical variables allow engineers to understand better the driving factors behind AI predictions, which is particularly useful for decision-making in real-world projects (Savić et al., 2017).

High-dimensional datasets increase the computational burden on AI models, making them slower and more resource-intensive. Feature selection and preprocessing techniques reduce the computational load by minimizing the number of variables the model needs to process. For instance, the Harris Hawks Optimization algorithm significantly reduced computation time while improving feature selection and overall model accuracy (Sihwail et al., 2020).

Feature selection and preprocessing techniques are essential for enhancing the performance of AI models in geotechnical classification tasks. By reducing dimensionality, improving generalization, increasing interpretability, and boosting computational efficiency, these techniques enable AI models to provide more accurate and actionable insights.

2.8 Exploring Interdisciplinary Impact on AI in Geotechnical Engineering

Integrating principles from fields such as data science, material science, and civil engineering can help develop effective AI models for geotechnical applications. Each of these disciplines offers valuable insights and methodologies that enhance the capabilities of AI models in this domain.

The data from geotechnical projects, such as soil tests, rock mechanics, and excavation data, can be managed and analyzed more effectively using advanced data science techniques. Big data analytics and machine learning algorithms help process large datasets, improving the accuracy of AI predictions. Data science principles, such as selecting relevant features and handling missing data, are essential for refining AI models to predict geological behaviour and outcomes in real-time. This leads to more precise rock mass classification and ground condition assessments (Zhang et al., 2021).

Comprehending the physical and mechanical characteristics of materials like soils, rocks, and construction materials is essential for making precise predictions in geotechnical engineering using AI. By integrating principles of material science, AI models can replicate how geomaterials behave under different circumstances, including changes in stress and temperature. For instance, advanced deep learning algorithms have been utilized to forecast how materials deform in underground construction endeavours, enhancing the trustworthiness of AI-generated predictions (Xiao et al., 2023).

Civil engineering plays a crucial role in applying AI models in practical scenarios. Understanding civil engineering concepts such as construction management and the behaviour of materials under load is essential for developing AI models that are both efficient and relevant in real-world applications. These models are becoming increasingly important for predicting the performance and stability of foundations under various environmental and operational conditions, highlighting their direct impact on civil engineering (Shahin, 2012).

From the above discussion, it is evident that combining the expertise of data science, material science, and civil engineering is a potent tactic for creating AI models capable of effectively navigating geotechnical engineering challenges. This multidisciplinary method substantially enhances predictive precision, model resilience, and operational effectiveness, highlighting the considerable advantages of integration in this field.

Combining AI with improved sensor technology and remote sensing has many benefits for real-time monitoring of rock stability in geotechnical projects. These technologies improve the speed and accuracy of data collection, enhancing AI models' predictive capabilities. Some key advantages include:

Cutting-edge remote sensing methods like LiDAR (Light Detection and Ranging) and photogrammetry can capture precise, high-resolution information about rock surfaces and structural irregularities. This data can then be utilized with advanced AI models, enabling them to generate more precise forecasts regarding the behaviour of rock masses. Moreover, deploying UAVs (Unmanned Aerial Vehicles) enhances data collection in hazardous or hard-to-reach locations, ensuring that even the most remote and challenging terrain is included in the analysis (Francioni et al., 2017).

AI algorithms can analyze data in real time from monitoring devices such as ground-based interferometric synthetic aperture radar (GB-InSAR) and terrestrial laser scanning (TLS). This enables the identification of small-scale movements and possible instabilities in rock formations. As a result, early warnings about potential failures can be issued, making timely interventions possible (Vanneschi et al., 2017).

Through the combination of sensor technologies and AI, remote sensing has the potential to significantly decrease the requirement for individuals to be physically present in hazardous environments. AI models can evaluate the stability of slopes and other geotechnical risks using remotely gathered data, ultimately lessening human exposure to high-risk areas like unstable rock surfaces in mining operations (Salvini et al., 2017).

Integrating AI technology with remote sensing can minimize reliance on conventional, time-consuming survey techniques. This allows for swift data collection and automatic analysis, leading to speedier and more streamlined decision-making processes. Furthermore, automated monitoring systems play a crucial role in the early detection of potential failures, thereby helping to prevent expensive repairs and project setbacks. (Liu et al., 2019).

Combining artificial intelligence with cutting-edge sensor technologies and remote sensing can greatly improve the accuracy, safety, and cost-effectiveness of real-time monitoring and decision-making in geotechnical projects.

2.9 Impact of AI Models on Improving Rock Mass Classification and Cost Estimation Accuracy

AI models play a critical role in rock mass classification by significantly reducing human subjectivity and bias. This contributes to more consistent and reproducible results in several ways:

AI models process large datasets and make objective decisions based on statistical and mathematical algorithms. This objectivity eliminates the need for human input in data interpretation, thereby reducing variability caused by individual biases. A study by Santos et al. (2020) demonstrated how AI models, particularly neural networks, can improve the consistency of rock mass classification by using structured inputs and training algorithms, leading to reproducible classifications in open-pit mines.

Data-Driven Decision-Making: AI models leverage data from various sources, including sensor technology, to generate accurate predictions. By processing continuous data from real-time monitoring systems, AI can identify patterns and make adjustments based purely on data trends, reducing the influence of human error or subjective interpretation. For example, Liu et al. (2018) used a genetic algorithm coupled with support vector classification (SVC) to develop an AI model that reduced discrepancies caused by human judgment in tunnel rock mass classification, achieving higher accuracy than traditional methods.

Consistency Across Projects: AI models apply standardized algorithms across different projects and environments, leading to uniformity in results. This reduces inconsistencies when multiple engineers assess similar geological conditions differently. With AI, rock mass classification results are unaffected by the engineer's experience level, ensuring that similar rock conditions yield similar classification outcomes. As shown in the study by Liu et al. (2020), ensemble learning models (e.g., AdaBoost) improved classification accuracy and consistency in tunnel boring machine operations compared to traditional human-driven methods.

In summary, AI models enhance the accuracy and consistency of rock mass classification by eliminating human subjectivity, processing large amounts of data objectively, and applying standardized approaches across diverse projects.

Using AI models in cost estimation for rock-related engineering projects has greatly improved the accuracy and reliability of cost predictions. AI can handle large and complex data from tunnelling, mining, and construction sites, which has been crucial in achieving these improvements. Here are some essential ways AI enhances the accuracy of cost estimation:

Handling Complex and Non-linear Relationships: Conventional cost estimation approaches frequently face challenges in depicting the intricate interplay between geological, material, and operational variables. AI models like Support Vector Regression (SVR) and Artificial Neural Networks (ANNs) excel in capturing these non-linear relationships, resulting in more precise and adaptable cost estimates. A study by Liu et al. (2019) demonstrated that AI models improved cost estimation by accurately predicting rock mass parameters, such as uniaxial compressive strength (UCS) and rock brittleness, which are crucial for tunnelling projects.

Real-Time Data Integration: AI can use real-time sensor data to adjust cost estimates. This allows AI to consider changing conditions during excavation or construction, such as variations in rock strength or machine performance, which improves the accuracy of cost predictions. For example, when combined with AI algorithms, real-time monitoring of Tunnel Boring Machine (TBM) data allows for continuous improvement of cost projections, reducing uncertainty (Hou et al., 2020).

Reduction in Human Error and Subjectivity: Conventional techniques for estimating costs frequently involve human judgment, which can lead to biases and inaccuracies. In contrast, AI models make decisions based on data, reducing much of the subjectivity that can affect estimates. By eliminating human biases, AI guarantees that cost estimates are rooted only in empirical data, leading to more uniform and replicable outcomes (Matel et al., 2019).

Optimization of Resources and Cost Factors: AI can optimize the selection of crucial cost-driving factors such as material requirements, labour, and machine efficiency using genetic algorithms (GA) and neural networks. These algorithms can pinpoint the most influential cost factors, enabling more efficient resource allocation and precise budgeting. Studies have demonstrated that hybrid AI models, such as the Firefly Algorithm (FA)-ANN, surpass traditional models in forecasting excavation costs by fine-tuning critical variables like rock strength and machine settings.(Koopialipoor et al., 2019).

AI models are crucial in improving cost estimation accuracy in rock mass-related engineering projects. They achieve this by managing intricate relationships, analyzing real-time data, minimizing human error, and streamlining resource allocation. These enhancements result in more dependable and practical cost forecasts, which are essential for the success of any project.

2.10 Summary

Integrating Artificial Intelligence (AI) in geotechnical engineering, specifically in rock mass classification and cost estimation, represents a significant advancement over traditional methods. AI models, such as Support Vector Machines (SVM), Artificial Neural Networks (ANNs), and Random Forests (RF), have significantly enhanced the accuracy, efficiency, and adaptability of processes in large-scale geotechnical projects. By processing extensive datasets, AI reduces human subjectivity, minimizes errors, and ensures more consistent and reproducible results. Traditional methods, often relying on subjective human judgment, static data, and oversimplified parameters, are increasingly being replaced or complemented by AI-driven systems that perform notably better in complex, dynamic environments.

In rock mass classification, AI models are more capable of handling the complexity and variability of geological conditions. Through continuous data integration from sensors and real-time monitoring systems, AI provides dynamic adjustments, enhancing accuracy in predicting rock mass behavior during tunneling and mining operations. This adaptability of AI ensures that geotechnical engineers are better prepared for the challenges of their projects, leading to safer, more efficient project execution. AI models reduce the biases associated with traditional methods by relying on objective, data-driven decision-making, ensuring consistent classification across different projects and environments.

AI's application in cost estimation has also exhibited marked improvements. AI models can capture non-linear relationships between factors such as rock properties, machine performance, and environmental conditions, often overlooked by traditional methods. By integrating real-time data from construction operations, AI enables continuous refinement of cost estimates, resulting in more reliable and precise budgeting. Additionally, AI models optimize resource allocation, reduce human errors, and adapt to unexpected changes in project conditions, significantly enhancing cost estimation accuracy and helping prevent budget overruns.

AI models offer key benefits in rock mass classification and cost estimation, including improved accuracy, reduced human bias, dynamic adaptability, and more reliable predictions. By incorporating principles from data science, material science, and civil engineering, AI models provide a more sophisticated and practical solution for managing the complexities and risks of geotechnical projects. As AI technologies evolve, their role in enhancing project safety, cost efficiency, and operational success will only expand.

CHAPTER III:

METHODOLOGY

3.1 Overview of the Research Problem

The critical variables are required for accurate classification using feature selection techniques, resulting in streamlined datasets for analysis. We utilized Machine Learning (ML) models, such as Decision Trees, Random Forests, Support Vector Machines (SVM), and Neural Networks, to develop a robust classification system for rock mass. To evaluate the performance of these models, we used established metrics such as accuracy, precision, recall, and F1-score. We also visualized the results using confusion matrices to provide comprehensive insights into model performance.

Throughout our research, we were committed to upholding ethical considerations. This included ensuring informed consent, mitigating data bias, and designing ML models with fairness in mind. We conducted a thorough comparison of the ML models against a baseline model to determine the most suitable approach for Rock Mass Rating (RMR) classification. We also validated the robustness and generalizability of our models using statistical tests and cross-validation techniques.

Our study contributes to advancing rock mass classification methodologies, providing improved safety, efficiency, and sustainability opportunities in geotechnical engineering projects. Integrating cost estimation methodologies enhances project budgeting and resource allocation, leading to more informed decision-making and risk mitigation strategies.

Rock mass classification is a vital aspect of geotechnical engineering. However, current methods often lack consistency and objectivity, leading to subjective interpretations and variable outcomes. Moreover, the manual process of visually inspecting and empirically classifying rock masses is time-intensive and prone to human error. Classification systems must integrate with cost estimation methods to accurately assess the financial impact of geological conditions on engineering projects.

Thus, this research aims to address these challenges by developing an advanced approach to rock mass classification. We aim to achieve more accurate and consistent results by combining AI models with extensive datasets. Additionally, incorporating cost estimation into the classification process will provide stakeholders with valuable insights into the financial implications of different rock mass classifications on project budgets.

3.2 Research Design

This research design outlines the systematic approach to developing and evaluating machine learning models for rock mass classification and improving cost estimation accuracy. The design incorporates a structured methodology that spans literature review, data processing, machine learning model development, evaluation, visualization, and application to practical engineering challenges. This comprehensive research plan ensures alignment with the research objectives and provides a detailed roadmap for implementation.

- Literature Review and Identification of Crucial Variables

Objective: Conduct a comprehensive review of existing literature on Rock Mass Classification systems to gain insights into methodologies and identify critical variables for model development.

Steps that are involved for performing first objective are given below.

- Review Traditional Rock Mass Classification Systems

Explore foundational systems such as Rock Mass Rating (RMR), Geological Strength Index (GSI), and the Q-System.

Identify critical factors in these systems, such as rock strength, joint conditions, groundwater conditions, and structural discontinuities.

Collect studies and data from mining, civil engineering, and tunnelling projects to understand how these systems are applied.

- Identify Limitations and Gaps

Evaluate limitations in traditional classification methods, such as subjectivity, reliance on manual interpretation, and challenges in handling complex geological scenarios.

Highlight gaps in existing research, particularly in applying advanced technologies like AI for rock mass classification.

- Define Crucial Variables

Through a thorough literature review, prioritize essential variables for rock mass classification, including Rock Quality Designation (RQD), Joint Set Number (Jn), Joint Roughness (Jr), Joint Alteration (Ja), and Stress Reduction Factor (SRF).

Discuss the importance of each variable in influencing rock mass stability and quality.

Outcome: A comprehensive understanding of rock mass classification methodologies and identification of the most critical variables required for building an AI-based classification model.

- Data Collection and Preprocessing

Objective: Gather borehole datasets and preprocess the data to ensure consistency, completeness, and readiness for machine learning model training.

Collect datasets from borehole investigations in various geological projects. The dataset will include attributes like borehole depth, elevation, RQD, Jn, Jr, Ja, Jw (Joint Water Reduction), and SRF.

Ensure data variability across different above-sea levels, depths, and rock formations to improve the model's generalizability.

- Data Cleaning

Handle Missing Data: Address missing values using imputation techniques where applicable or remove records with excessive missing information.

Outliers and Inconsistencies: Detect and treat outliers, errors in data entry, or anomalies that may skew model performance.

Remove Duplicates: Eliminate duplicate records to avoid overfitting and redundancy in training.

- Feature Selection

Apply feature selection techniques to retain the most essential variables identified during the literature review (RQD, Jn, Jr, Ja, SRF, etc.). Methods such as correlation analysis or variance inflation factor (VIF) can be used to minimize multicollinearity.

- Ordinal Encoding and Scaling

Convert categorical features (if any) using ordinal encoding. For instance, rock class categories (Class 1 to Class 5) should be encoded into numerical values.

Apply feature scalings, such as normalization or standardization, to ensure all features are comparable. This step is crucial for models sensitive to feature scaling, such as logistic regression.

Outcome: A clean, standardized, and feature-selected dataset ready for machine learning model development, ensuring that essential variables are retained and preprocessing is complete.

3.3 Development of Machine Learning-Based Classification System

The objective is to utilize machine learning models to create a robust classification system for rock mass, enabling the prediction of rock mass quality, strength, and deformability. The steps involved include developing a dummy classifier as a baseline, training various machine learning models such as logistic regression, decision trees, random forest, support vector machines, and potentially exploring other ensemble models. The dataset will be split into training and testing subsets, with model training involving techniques like cross-validation and hyperparameter tuning. The outcome will be multiple trained machine learning models capable of accurately classifying rock masses and predicting parameters like strength and deformability.

Objective: Utilize machine learning models to develop a robust classification system for rock mass, enabling the prediction of rock mass quality, strength, and deformability.

- Baseline Model Development:

Develop a dummy classifier as a baseline to measure the performance of more sophisticated machine learning models. The dummy classifier will predict the most frequent class or random values as a reference point.

- Machine Learning Models:

Logistic Regression: Train a multinomial logistic regression model for multiclass classification. Logistic regression is a robust choice for relatively simple models and provides a benchmark for other more complex algorithms.

Decision Trees: Use decision trees for classification, which provide interpretable decision paths and can handle non-linear relationships.

Random Forest: Implement random forest models, which aggregate multiple decision trees to improve model robustness and reduce overfitting.

Support Vector Machines (SVM): Use SVM with appropriate kernel functions to handle complex feature relationships and enhance classification accuracy.

Other Ensemble Models: Explore ensemble models like Gradient Boosting or XGBoost if needed to improve classification results.

Training and Testing Split: Split the dataset into training and testing subsets using an 85% training and 15% testing ratio. Ensure that the split is stratified to preserve class distributions across both subsets.

Model Training: Train each model using the training dataset. Perform cross-validation (e.g., k-fold cross-validation) to validate model performance on different data folds and prevent overfitting.

Tune hyperparameters using grid search or random search to optimize model performance. Multiple trained machine learning models are ready for performance evaluation, with the ability to classify rock masses accurately and predict relevant parameters like strength and deformability.

3.4 Performance Evaluation of Machine Learning Models

In this, we will evaluate the performance of our machine learning models. Using evaluation metrics, we aim to assess their accuracy, precision, recall, and F1 score. We will start by measuring accuracy, which gives us the overall percentage of correctly classified instances. Then, we'll assess precision, vital for minimizing false positives, and recall, which captures most instances of each class. We will also calculate the F1 Score, which balances precision and recall.

Additionally, we'll create confusion matrices for each model to analyze the distribution of correct and incorrect classifications. Next, we will compare each model's performance against the dummy classifier, looking for accuracy, precision, recall, and F1-score improvements. If there's an imbalance between rock classes, we will consider using class-weighted models or resampling techniques to balance the dataset. Overall, this comprehensive evaluation will provide valuable insights into each model's reliability, effectiveness, and areas of improvement.

- Model Performance Evaluation

Objective: Assess the performance of the developed machine learning models using evaluation metrics to ensure accuracy, precision, recall, and F1-score.

- Performance Metrics

Accuracy: The overall percentage of correctly classified instances. This metric gives a straightforward understanding of model performance.

Precision: Measure the proportion of identifications that were correct, which is crucial for minimizing false positives.

Recall: Evaluate how well the model identifies true positives, ensuring it captures most instances of each class.

F1-Score: Calculate the harmonic mean of precision and recall to balance these two metrics.

- Confusion Matrix Analysis

Create confusion matrices for each model to examine the distribution of correct and incorrect classifications. This provides insights into misclassified instances across rock mass classes.

- Comparison with Baseline

Compare each machine learning model's performance against the dummy classifier. Look for significant accuracy, precision, recall, and F1-score improvements across all models.

- Handling Class Imbalance

If there is an imbalance between the different rock classes (e.g., more Class 1 instances than Class 5), consider using class-weighted models or resampling techniques to balance the dataset.

A comprehensive evaluation of model performance using a range of metrics leads to insights into each model's reliability, effectiveness, and areas for improvement.

3.5 Visualization and Analysis of Model Performance

The objective is to use visual tools such as confusion matrices, heatmaps, and scatter plots to analyze a model's performance and identify areas for improvement. The steps include creating detailed confusion matrices to visualize the classification of rock classes and identifying misclassification patterns, using heatmaps to display precision, recall, and F1 score for each rock class, visualizing feature importance for models like decision trees or random forests, and plotting scatter graphs to visualize the relationships between features and outcomes. The outcome is visual representations of model performance highlighting strengths and weaknesses, enabling targeted improvements and a better understanding of model behaviour.

- Visualization and Interpretation

Objective: Employ visual tools, including confusion matrices and heatmaps, to analyze model performance and identify areas for improvement.

- Confusion Matrix Visualization

Create detailed confusion matrices to visualize how well the models classify each rock class. Identify any patterns of misclassification or trends that might need further tuning.

- Precision-Recall Heatmap

Use heatmaps to display each rock class's precision, recall, and F1 score. This helps understand which classes are well predicted and which need improvement (e.g., Class 3 might have lower performance).

- Feature Importance Visualization

For models like decision trees or random forests, visualize feature importance to understand which variables contribute the most to the classification. This can help in refining model input.

- Scatter Plot Analysis

Plot scatter graphs between critical variables (e.g., RQD, depth, Jn) and the target variable (Q Value or rock class) to visualize the relationships between features and outcomes.

Visual representations of model performance that highlight both strengths and weaknesses, enabling targeted improvements and a better understanding of model behaviour.

3.6 Comparison of Machine Learning Models and Baseline Classifier

The objective is to compare the performance of different machine learning models to select the most suitable model for Rock Mass Rating (RMR) classification. The first step involves comparing the performance of each model based on metrics such as accuracy, precision, recall, and F1-score. The goal is to identify the model that best balances these metrics. Then, the top-performing models are compared against a dummy classifier to quantify the improvement in performance over the baseline. Afterwards, hyperparameter optimization is conducted to enhance the performance of the top-performing models. Finally, the model that performs best across all metrics and is the most generalizable is selected, ensuring its applicability to new datasets. The outcome is identifying a robust and reliable model for rock mass classification, with significantly improved performance over the baseline.

- Model Comparison and Selection

Objective: Compare the performance of different machine learning models and select the most suitable model for Rock Mass Rating (RMR) classification.

- Model Comparison

Compare the performance of each machine learning model based on accuracy, precision, recall, and F1-score. Identify which model best balances these metrics.

Compare the top-performing models against the dummy classifier, quantifying the improvement in performance over the baseline.

- Hyperparameter Tuning

For the top-performing models, conduct hyperparameter optimization (e.g., grid search or Bayesian optimization) to fine-tune the model and further improve its performance.

- Model Selection

Select the model that performs best across all metrics and is the most generalizable, ensuring it can be applied to new datasets.

Identification of the most robust and reliable model for rock mass classification, with significantly improved performance over the baseline.

3.7 Population and Sample

The population for this research includes all rock masses that could be classified based on geotechnical properties across various geological settings. This population spans different geographical regions, rock types, geological formations, and project types (e.g., mining, tunnelling, and civil engineering construction projects). Specifically, the population could include rock masses encountered in:

- Mining operations: Rock formations encountered during the excavation of minerals in open-pit or underground mining.
- Civil engineering projects: Rock masses found during the construction of tunnels, dams, bridges, and large-scale infrastructure projects.
- Geotechnical investigations: Rock mass data obtained during site investigations for foundational design or slope stability analysis.

- Geographical variability: Rock masses from diverse regions, including sedimentary, metamorphic, and igneous formations, at various above-sea-level elevations and depths.

Thus, the population is comprehensive and includes all possible scenarios where rock mass classification is required to understand rock stability, quality, and structural behaviour.

- Key Characteristics of the Population

Rock mass quality: Classified by parameters such as Rock Quality Designation (RQD), Joint Set Number (Jn), Joint Roughness (Jr), Joint Alteration (Ja), Joint Water Reduction (Jw), and Stress Reduction Factor (SRF).

Depth and elevation: Varying depths from shallow to deep rock masses at different sea-level elevations.

Geological conditions: Variability in rock types, including granite, limestone, and fill material.

Project scale: Includes large-scale infrastructure projects and more minor geotechnical site investigations.

Given the vast population, studying all potential rock masses is impossible. Therefore, a sample will be drawn from this population to conduct the research. The sample for this research will consist of borehole datasets collected from specific geotechnical projects that represent the broader population's variability. These datasets include a selection of critical features for machine learning-based classification.

- Sampling Approach

The sampling for this research will use a stratified random sampling approach to ensure that the sample includes a variety of rock mass types, geographical locations, depths, and project types. Stratified sampling will help select a diverse dataset that represents the population's full range of geological and project characteristics. The key strata could include:

Rock types: Sampling across different rock types (e.g., sedimentary, igneous, metamorphic).

Depth ranges: Ensuring that borehole data includes rock masses at shallow, intermediate, and deep depths.

Geographical regions: Sampling from the different areas to include various geological conditions.

Project types: Including data from mining, civil engineering, and infrastructure projects.

- Sample Size

The sample will consist of data from multiple geotechnical projects, with each borehole providing data points across various depths. The sample size is expected to be large enough to ensure that machine learning models are trained effectively and deliver robust classification results. A minimum sample size of several thousand data points (e.g., 3,000+ borehole measurements) is required to train machine learning models such as logistic regression, random forest, or support vector machines, as larger datasets generally lead to better generalization in model training.

3.8 Participant Selection

The selection of borehole datasets is essential for effective machine-learning models in predicting rock mass classification and improving cost estimation. The criteria for selecting participants are based on geological variety, depth and elevation, complete and consistent data, project type diversity, and geographical and environmental diversity. The selected datasets should cover various rock types, depths, and elevations, have complete and accurate measurements, come from different geotechnical projects, and include boreholes from diverse geographical regions with varied climatic conditions. This ensures that the machine learning models are exposed to various geological formations and real-world engineering scenarios, ultimately enhancing classification accuracy and applicability to different environmental influences.

- Criteria for Selecting Participants (Borehole Datasets)

The selection of borehole datasets is critical for ensuring the effectiveness of the machine learning models in predicting rock mass classification and improving cost estimation. The following criteria will guide the selection of datasets:

Geological Variety: The selected datasets should cover various rock types, including sedimentary, igneous, and metamorphic rocks. Additionally, datasets from artificial fill materials (e.g., gravel or compacted soil) will be included.

This ensures that the machine learning models are exposed to diverse geological formations, improving classification accuracy.

Depth and Elevation: Datasets should include boreholes from depths, from shallow (near the surface) to deep rock formations (up to 100 feet or more).

The above-sea-level elevation of borehole locations should vary to capture the effects of geological pressure and rock behaviour at different altitudes.

Complete and Consistent Data: Only borehole datasets with complete and accurate measurements for essential variables like Rock Quality Designation (RQD), Joint Set Number (Jn), Joint Roughness (Jr), Joint Alteration (Ja), Joint Water Reduction Factor (Jw), and Stress Reduction Factor (SRF) will be selected.

Datasets with missing values, significant outliers, or inconsistencies in measurement will be excluded to ensure data quality.

Project Type Diversity: Borehole datasets will be sourced from various geotechnical projects, including mining operations, tunnelling, dam construction, and infrastructure development projects (e.g., bridges and buildings). This ensures the models apply to various real-world engineering scenarios.

Geographical and Environmental Diversity: Boreholes from different geographical regions with diverse climatic conditions (e.g., arid, tropical, mountainous) will be included to capture how rock mass behaviour varies under different environmental influences.

3.9 Instrumentation

In the research aimed at developing a machine learning-based classification system for rock mass, the instrument used to generate the results combines borehole datasets and machine learning algorithms implemented using various tools and libraries within Python. Data collection, preprocessing, and model training rely heavily on structured datasets and computational tools, which act as the key instruments for generating the research outcomes.

- Borehole Datasets as the Primary Instrument

The primary instrument in this research is the borehole datasets collected from various geotechnical projects. These datasets are fundamental to the research, serving as the basis for training and testing machine learning models. The datasets contain critical information about the geological properties of rock masses at different depths and locations, which is used to classify rock mass quality.

Each borehole dataset includes the following variables, which are instrumental in generating the classification results:

- Rock Quality Designation (RQD): A measure of the degree of jointing or fracturing in a rock mass, directly influencing rock stability and quality.

- Joint Set Number (Jn): The number of joint sets or fractures in the rock, with a higher number indicating a more fractured and less stable rock mass.
- Joint Roughness Number (Jr): A measure of the roughness of the joints, with rougher joints often correlating with reduced rock mass quality.
- Joint Alteration Number (Ja): Describes the degree of alteration in the joint surfaces, which can significantly affect the strength of the rock mass.
- Joint Water Reduction Factor (Jw): This factor represents the impact of water presence in the rock joints, with more water-reducing rock stability.
- Stress Reduction Factor (SRF): This indicates the stress conditions in the rock mass, which influences the overall strength and quality.

The borehole datasets typically contain thousands of data points, each representing a different borehole's measurements of the above variables. This large dataset is crucial for training machine learning models that accurately predict rock mass quality and classify different rock formations.

- Machine Learning Algorithms

The second key instrument to generate the results is the machine learning algorithms applied to the borehole datasets. These algorithms are implemented using Python and several machine learning libraries, focusing on creating models that can classify rock mass quality based on the borehole data.

- Fundamental algorithms and tools used in this research include

Logistic Regression: This is one of the primary models used for classification tasks. Logistic regression is suitable for multiclass classification and can predict the probability of a rock mass belonging to a particular class (e.g., Class 1 to Class 5). It provides a baseline performance and helps understand the relationship between the input features and the target variable (rock mass class).

Random Forest: Random forest is an ensemble method used to improve classification accuracy by aggregating the results of multiple decision trees. It helps handle non-linear relationships between features and provides importance metrics that are instrumental in determining which variables (e.g., RQD, Jn) most significantly impact rock mass classification.

Support Vector Machines (SVM): SVMs with appropriate kernel functions capture complex patterns and relationships in data. They are particularly useful when dealing with high-dimensional data and offer strong performance in classification tasks.

Dummy Classifier: A dummy classifier is used as a baseline model to compare the performance of more sophisticated machine learning models. The dummy classifier provides a simple prediction strategy, such as predicting the most frequent class, and helps evaluate the effectiveness of the other models.

- Python Libraries and Tools

The computational implementation of machine learning models and data analysis relies heavily on the following Python libraries:

Scikit-learn (sklearn) is the primary library for implementing machine learning algorithms. It provides model training, testing, and evaluation tools, including logistic regression, random forests, support vector machines, and the dummy classifier. Scikit-learn also includes methods for preprocessing the data, such as train_test_split, feature scaling, and encoding categorical variables.

Pandas: The Pandas library handles and manipulates the borehole dataset. It allows for efficient data cleaning, structuring, and exploratory data analysis (EDA), ensuring that the dataset is well-prepared for machine learning models.

NumPy: NumPy is used for numerical operations and array handling. It supports handling large datasets and helps in various mathematical computations required for model building.

Matplotlib and Seaborn: These libraries are used for data visualization. They help create scatter plots, heatmaps, and confusion matrices, which are instrumental in visualizing the relationship between features and rock mass quality and assessing the performance of the classification models.

StandardScaler: This tool from the Scikit-learn library is specifically used to scale numerical features, ensuring that all input variables are on the same scale. This is critical for models like logistic regression and SVM, which are sensitive to feature scaling.

- Evaluation Metrics as an Analytical Instrument

Evaluation metrics serve as analytical instruments to assess the effectiveness of the machine learning models. These include:

- Accuracy: The proportion of correctly classified instances out of the total cases.
- Precision: The ratio of accurate optimistic predictions to the sum of true positive and false positive predictions indicates the number of correct optimistic predictions.
- Recall: The ratio of accurate optimistic predictions to the sum of true positives and false negatives, showing the model's ability to identify actual positives.
- F1-Score: The harmonic mean of precision and recall, balancing these two metrics to evaluate overall model performance.

- Confusion Matrices visualize the performance of classification models across multiple rock mass classes, highlighting where the models succeed or fail in making correct predictions.
- Confusion Matrices and Heatmaps for Visual Analysis

Visual tools, such as confusion matrices and heatmaps, are also key instruments in this research. Confusion matrices show each rock mass class's correct and incorrect classifications, providing detailed insight into the model's strengths and weaknesses. Heatmaps display each class's precision, recall, and F1 scores, offering a more granular understanding of model performance across different categories.

The instruments used in this research to generate results include a combination of borehole datasets, machine learning algorithms (logistic regression, random forests, SVM), Python libraries for data processing and visualization (Scikit-learn, Pandas, Matplotlib, Seaborn), and performance evaluation metrics (accuracy, precision, recall, F1-score). Together, these tools enable the development of accurate and reliable models for rock mass classification, which can be applied to real-world geotechnical engineering projects. The careful use of these instruments ensures the robustness and generalizability of the research findings.

3.10 Data Collection Procedures

The data collection procedure for this research is a crucial step that ensures the quality and representativeness of the dataset used to train and evaluate the machine learning models for rock mass classification. The procedure involves gathering borehole data from various geotechnical projects, preparing it for analysis, and ensuring it accurately represents the diverse geological conditions required for robust model training. Below is a detailed explanation of the data collection procedures for this research:

- Identifying Data Sources

The first step in the data collection is identifying reliable sources for obtaining borehole data. The datasets will be collected from:

Public Repositories: Geological surveys and public databases that provide open-access data related to rock masses, borehole investigations, and geotechnical projects. Government agencies or research institutions often maintain such repositories.

Private Engineering Firms: Borehole datasets from private engineering firms involved in mining, tunnelling, civil engineering, and infrastructure development projects. Collaboration with such firms ensures access to real-world project data.

Research Institutions: Data from academic research projects related to rock mass classification and geotechnical engineering. Research data from previous studies may provide valuable insights and diversity for the dataset.

These sources are chosen to ensure the collection of high-quality, well-documented data that captures a range of geological conditions, including various rock types and project types.

- Selecting Relevant Data

The datasets collected for this research must contain variables essential for rock mass classification. During the selection process, datasets will be screened to ensure that they include the following key features:

Rock Quality Designation (RQD): A measure of the degree of fracturing or jointing within the rock.

Joint Set Number (Jn): The number of distinct joint sets within the rock mass influences stability.

Joint Roughness Number (Jr): Describes the roughness of the rock joints, affecting the shear strength.

Joint Alteration Number (Ja): Represents the rock joints' degree of alteration or weathering, impacting stability.

Joint Water Reduction Factor (Jw): This factor indicates the influence of water on rock joints, which can reduce rock mass quality.

Stress Reduction Factor (SRF): A measure of the stress conditions within the rock, affecting its overall strength and stability.

Depth and Elevation Data: Information about each borehole's depth and the site's above-sea-level elevation.

These variables are essential for creating a robust machine-learning model to classify rock masses and accurately predict their strength and deformability. Datasets without complete information on these variables will be excluded from the study.

- Ensuring Diversity in Data

To ensure that the dataset represents a broad range of geological conditions and rock types, the data collection process will be designed to include borehole data from various types of projects and geographical locations. This step is essential to avoid bias in the dataset and to ensure that the machine learning models can generalize well to new, unseen data. The following diversity criteria will guide data selection:

Geographical Diversity: Borehole data from different regions, including areas with varied rock types (e.g., sedimentary, igneous, metamorphic), climates (e.g., arid, tropical, mountainous), and environmental conditions. This ensures the dataset captures a broad spectrum of geological formations.

Project Type Diversity: Data from geotechnical projects, such as mining operations, tunnelling projects, dam construction, and civil engineering infrastructure projects. This diversity ensures the model's applicability to various engineering contexts.

- Data Collection Procedure

Once the relevant data sources and datasets have been identified and selected, the data collection process will follow these steps:

Data Acquisition:

Public Data: Download datasets from publicly available sources such as geological surveys, government portals, and open-access research repositories.

Private Data: Establish partnerships with private engineering firms and research institutions to gain access to proprietary borehole datasets. Agreements on data sharing, confidentiality, and usage rights will be formalized.

Field Data (if applicable): In some cases, new data may be collected from ongoing projects or field studies. This requires coordinating with geotechnical engineers or field teams to gather accurate borehole measurements.

Data Documentation: Ensure that each dataset includes proper documentation, such as metadata, project descriptions, and detailed explanations of the collected data. This information helps in understanding the context of the data and ensures proper interpretation.

Data Verification and Validation: To ensure accuracy and consistency, validate the datasets by cross-checking against original data sources or field reports. This step involves checking for measurement discrepancies, missing values, or outliers that could impact model training. Only complete or correct datasets will be corrected or excluded from the final analysis.

3.11 Data Analysis

The data analysis for the rock mass classification research is a meticulously detailed and systematic process. It is designed to transform raw borehole data into meaningful insights through the application of machine learning models. The analysis begins with an exploratory data analysis (EDA), which is essential for understanding the structure and relationships within the dataset. During this phase, various statistical and visualization techniques are used to assess the distribution of key variables such as Rock Quality Designation (RQD), Joint Set Number (Jn), Joint Roughness (Jr), Joint Alteration (Ja), and Stress Reduction Factor (SRF). This initial analysis helps identify patterns and trends, such as the correlation between higher joint set numbers and poorer rock mass quality. It also reveals any outliers or anomalies that may distort the analysis if left untreated.

Once the exploratory analysis is complete, the data is preprocessed to ensure it is ready for machine learning modelling. This involves several steps, such as handling missing data through imputation techniques and detecting outliers using statistical methods. Feature scaling is applied to ensure that all variables are standardized, which is critical for models like logistic regression and support vector machines (SVM), as these algorithms are sensitive to differences in feature magnitude. Additionally, categorical variables, such as rock class labels, are encoded into numerical values to ensure they are compatible with the machine learning models.

Following preprocessing, machine learning models are developed to classify rock masses based on the borehole data. A baseline model, known as a dummy classifier, is initially used to provide a point of comparison for more advanced models. The dummy classifier typically makes simplistic predictions, such as always predicting the most frequent rock mass class, and serves to highlight the improvements made by more sophisticated models. The primary models developed include logistic regression for multiclass classification tasks and more complex models like random forests and SVM. These models are trained to recognize patterns in the data and make accurate predictions about rock mass classification.

The dataset is split into training and testing sets to ensure the models are balanced and can generalize to new data. Typically, 85% of the data is used for training, allowing the models to learn from most of the dataset, while the remaining 15% is reserved for testing. The testing set is of utmost importance for evaluating how well the models perform on unseen data, providing a reliable measure of their generalizability.

Once the models are trained, they are subjected to a thorough evaluation using a range of performance metrics. These include accuracy, which measures the proportion of correctly classified instances, and precision, which assesses how many optimistic predictions are correct. Recall is used to evaluate the model's ability to capture actual positive instances, while the F1-score balances precision and recall, offering a single metric that considers both aspects. Confusion matrices are also generated to provide a detailed view of the models' performance across the different rock mass classes. These matrices show how many instances of each class were correctly classified and where the models made errors, offering insights into areas that may require further tuning.

The performance of each model is then compared against the baseline dummy classifier. Significant improvements over the baseline demonstrate the effectiveness of the machine learning models in classifying rock masses. Hyperparameter tuning is conducted to further enhance the models' performance, with techniques such as grid search or random search used to optimize critical parameters like the number of trees in a random forest or the regularization strength in logistic regression.

Visual tools such as scatter plots, heatmaps, and feature importance plots communicate the results throughout the analysis. Scatter plots reveal the relationships between critical variables like RQD and rock mass quality, while confusion matrices and heatmaps visualize the models' performance across different rock classes. Feature importance plots, especially from models like random forests, provide insights into which variables influence rock mass classification most, highlighting the critical role of features like RQD and Jn.

The final step of the data analysis involves interpreting the results. This includes understanding the performance of each model based on the evaluation metrics and identifying the best-performing model for rock mass classification. The analysis also reveals which features are most important in predicting rock mass quality, providing practical insights for real-world applications. Additionally, the analysis helps identify any weaknesses in the models, such as specific rock classes that are frequently misclassified, suggesting areas for further improvement or additional data collection.

Overall, this research's data analysis process is thorough and methodical, involving multiple stages of exploration, preprocessing, modelling, evaluation, and interpretation. By leveraging machine learning algorithms and applying robust evaluation techniques, the research produces reliable and actionable insights into rock mass classification, ultimately improving the accuracy and applicability of the models in geotechnical engineering projects.

3.12 Research Design Limitations

While the research design for developing machine learning models for rock mass classification is comprehensive and organized, a few limitations should be acknowledged. First, the quality and completeness of the dataset could limit the model's performance. The borehole data used in this research must be complete and consistent, but real-world datasets often contain missing values, inaccuracies, or measurement errors, which can affect the training process. While preprocessing techniques like imputation can address these issues, they may still introduce biases that reduce the accuracy and generalizability of the models.

Second, the diversity of the sample data could pose a limitation. Although efforts are made to include borehole data from various geographical regions and project types, there may still be a bias toward certain rock types or geological conditions. The model might struggle to generalize to new, unseen data in different contexts if the dataset doesn't capture the full range of possible rock formations or environmental conditions. This could limit the model's application effectiveness beyond the specific dataset it was trained on.

Lastly, computational limitations may restrict the scope of model development and tuning. Machine learning models, especially those like random forests or support vector machines, require significant computational power for training and hyperparameter optimization. For larger datasets or more complex models, this could lead to longer training times and limit the ability to explore advanced techniques or tune models to their fullest potential. These constraints could affect the ultimate performance and scalability of the models when applied to larger datasets or real-time classification tasks.

3.13 Conclusion

Throughout the methodology chapter, we have meticulously outlined a comprehensive and structured approach for developing machine learning models for rock mass classification. Our primary focus lies in conducting an extensive literature review, carefully selecting and preprocessing borehole datasets, and harnessing advanced machine learning algorithms. Our ultimate goal is to construct models that are precise and dependable and can be effectively applied to real-world geotechnical challenges.

Our process entails several fundamental steps. Firstly, we conduct exploratory data analysis to gain insights into the datasets. Subsequently, we proceed with meticulous feature selection, model building, and rigorous performance evaluation, ensuring that the models exhibit robustness and generalizability across diverse scenarios. This approach provides the necessary reassurance regarding the models' effectiveness, making them reliable tools for practical applications.

The preprocessing techniques implemented are fundamental in preparing the dataset for machine learning. We meticulously address issues such as handling missing data, scaling features, and selecting relevant variables to ensure the dataset is optimally primed for model training.

We harness various algorithms for model selection and evaluation, including logistic regression, random forest, and support vector machines. Furthermore, we utilize appropriate evaluation metrics such as accuracy, precision, recall, and F1-score, establishing a solid foundation for assessing model effectiveness. Visual aids like confusion matrices and feature importance plots further facilitate the interpretation of results and identify areas for improvement.

Despite the thoroughness of our methodology, we do acknowledge certain inherent limitations. These include potential biases in the dataset, computational constraints, and challenges in ensuring the models generalize accurately to all geological conditions. However, despite these limitations, we firmly believe that our methodology provides a robust framework for advancing rock mass classification through machine learning. The foundation we have laid paves the way for practical applications in mining, civil engineering, and infrastructure development.

CHAPTER IV:

RESULTS

4.1 Literature Review on Rock Mass Classification Systems

In this section, we review the key methods used in rock mass classification systems, focusing on how traditional systems compare with AI-driven approaches in the context of large-scale geotechnical projects.

- Traditional Rock Mass Classification Systems

Traditional rock mass classification systems, such as the Rock Mass Rating (RMR), Geological Strength Index (GSI), and Q-System, have been used for decades in geotechnical engineering to assess rock mass quality. These systems rely on parameters like joint spacing, rock strength, and groundwater conditions. The RMR system, developed by Bieniawski, assigns scores to different rock mass features, providing an overall rating used to guide decisions on support systems and construction techniques (Bieniawski, 1993).

However, one of the main limitations of these systems is that they often oversimplify complex geological conditions. For instance, the RMR and Q-System use limited parameters, which may not fully capture variability in rock formations, such as joint orientations and groundwater inflow (Palmström & Broch, 2006). Additionally, these methods are static and cannot adapt to real-time changes during construction, a significant drawback in dynamic environments like tunneling and mining.

- Human Subjectivity in Traditional Systems

Traditional methods often require engineers to interpret subjectively, particularly when assessing visual features such as joint roughness and block size. This introduces variability in the classification results, with different engineers providing different assessments for the same rock mass. The reliance on human judgment is a significant source of inconsistency, leading to varying project results (Mazzoccola & Hudson, 1996). This variability can reduce the reliability of the classification, especially in large-scale projects where consistent assessments are critical.

- AI-Based Rock Mass Classification Systems

Artificial Intelligence (AI) models have emerged as a more advanced alternative to traditional rock mass classification systems. AI-driven approaches reduce subjectivity by relying on data-driven decision-making. By processing large amounts of data from sensors and monitoring systems, AI models, such as Support Vector Machines (SVM) and Artificial Neural Networks (ANNs), eliminate human biases and provide more consistent and reproducible results (Santos et al., 2020).

AI models are instrumental in complex and variable geological environments where traditional systems may struggle to adapt. AI can integrate real-time data from Tunnel Boring Machines (TBMs) and other sensors, allowing for continuous updates to rock mass classification based on the latest conditions. This adaptability makes AI models more accurate and reliable, especially in environments where geological conditions are changing rapidly (Liu et al., 2019).

- Comparison of AI and Traditional Methods

A critical difference between AI-based and traditional systems is complex data handling. Traditional methods simplify rock mass conditions using predefined categories and parameters, while AI models can process and analyze large, multidimensional datasets to capture the full complexity of geological features. AI models are better equipped to deal with non-linear relationships between variables, making them more precise in their predictions (Liu et al., 2018).

Additionally, AI models offer real-time adaptability, whereas traditional methods rely on data collected at the start of a project. By continuously updating based on real-time data, AI models reduce the risk of unexpected issues during construction and allow for quicker adjustments to project plans, ultimately leading to safer and more efficient project execution (Hou et al., 2020).

Regarding human subjectivity, AI significantly reduces the variability found in traditional systems by automating the classification process. This ensures more consistent results across different projects and regions, improving the reliability of rock mass classification for decision-making (Santos et al., 2020).

In summary, while traditional rock mass classification systems like RMR and GSI have been effective for many years, they face limitations in handling complex and dynamic geological environments. AI-based systems provide a more flexible, accurate, and consistent alternative, with the ability to process real-time data and eliminate human subjectivity. As geotechnical engineering projects become more complex, the use of AI models for rock mass classification is expected to grow, offering enhanced reliability and precision.

The primary objective of this research is to evaluate the impact of AI models on improving rock mass classification and cost estimation accuracy. The literature review to address this objective highlights critical findings regarding the strengths and limitations of both traditional and AI-based systems in geotechnical engineering projects, focusing on how AI models offer significant advantages over conventional methods in accuracy, consistency, and adaptability.

- Traditional Rock Mass Classification Systems

The review of traditional rock mass classification systems, such as the Rock Mass Rating (RMR), Geological Strength Index (GSI), and Q-System, reveals that while these methods have been widely used for decades, they have inherent limitations when applied to large-scale and complex projects. These systems are highly dependent on predefined parameters like rock quality designation (RQD), joint spacing, and rock strength, which may oversimplify the geological complexities encountered in modern projects. The reliance on human judgment for data collection and interpretation introduces subjectivity, resulting in inconsistent outcomes across different assessments and potentially leading to inaccuracies in rock mass classification. These limitations make traditional methods less suitable for projects where conditions are highly variable or dynamic (Palmström & Broch, 2006); (Mazzoccola & Hudson, 1996).

Findings from the literature review show that, while traditional methods are cost-effective and widely used for preliminary assessments, they cannot dynamically adapt to geological conditions during construction. This inability often results in the under or over-designing support systems, leading to increased risks, potential project delays, and additional costs. Moreover, the inherent subjectivity in these systems makes reproducibility and consistency challenging, particularly in large-scale projects where multiple engineers may assess similar conditions differently (Bieniawski, 1993).

- Role of AI in Rock Mass Classification

AI-based rock mass classification systems address many limitations identified in traditional methods by leveraging large datasets and advanced machine learning algorithms. AI models such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Random Forests (RF) can process complex and nonlinear relationships between rock mass parameters, thus providing more accurate and reliable predictions than their traditional counterparts. The literature reveals that AI systems offer significant improvements in handling data variability, reducing human bias, and adapting to real-time data during the project execution phase (Santos et al., 2020); (Liu et al., 2018).

One of the key findings from the literature review is the enhanced ability of AI models to incorporate real-time monitoring data from sensor technologies like ground-based radar, laser scanning, and UAVs (Unmanned Aerial Vehicles). This continuous data integration allows AI systems to adjust rock mass classifications dynamically, leading to more accurate predictions and better-informed decision-making. These capabilities are precious in tunnelling and mining projects, where real-time adaptation to changing geological conditions is crucial for maintaining safety and operational efficiency (Hou et al., 2020); (Francioni et al., 2017).

Moreover, AI models have been shown to significantly reduce subjectivity by automating the classification process. Rather than relying on human visual assessment, AI models use data-driven techniques to classify rock masses, ensuring consistent results across different projects and environments. This improves accuracy and enhances the reproducibility of results, making AI a valuable tool in large-scale projects where consistency is critical for success (Santos et al., 2020).

- AI and Cost Estimation Accuracy

The literature also highlights the role of AI models in improving the precision of cost estimation in rock mass-related engineering projects. Traditional cost estimation techniques, which rely on historical data and static parameters, often need to capture the complexity of modern projects, leading to significant cost overruns. On the other hand, AI models can analyze real-time data and make dynamic adjustments to cost estimates based on changing project conditions. By incorporating machine learning algorithms such as genetic algorithms, neural networks, and regression trees, AI models optimize cost-driving factors such as material requirements, labour, and machine performance, resulting in more accurate and reliable cost estimates (Koopialipoor et al., 2019).

A significant finding from the literature review is that AI models can predict cost outcomes more effectively by accounting for uncertainties and nonlinear relationships in rock mass properties, such as compressive strength and groundwater inflow. This allows for better contingency planning and risk management, reducing the likelihood of cost overruns and unexpected expenses during project execution. In particular, the ability of AI to process real-time data from Tunnel Boring Machines (TBMs) and other monitoring systems further enhances the precision of cost predictions, enabling more effective resource allocation and project scheduling (Liu et al., 2019).

- Conclusion and Contribution to the Objective

Overall, the findings from the literature review directly contribute to the first research objective of evaluating the impact of AI models on improving rock mass classification and cost estimation accuracy. The review reveals that AI models significantly improve traditional systems by offering more accurate, consistent, and adaptive solutions for rock mass classification. AI's ability to handle complex geological data, integrate real-time monitoring systems, and reduce human subjectivity enhances the safety and cost-efficiency of geotechnical engineering projects. Furthermore, AI-driven cost estimation models have proven more reliable and precise, leading to better project outcomes and reduced financial risks.

By synthesizing these findings, the research establishes a strong foundation for understanding AI's transformative role in modern geotechnical engineering. This fulfils the study's first objective and lays the groundwork for further exploration of AI's potential in enhancing project performance.

4.2 Identification and Prioritization of Key Variables

In this section, we identify and prioritize the key variables that influence the accuracy and effectiveness of AI models in rock mass classification and cost estimation.

The literature review highlights several important factors determining how well AI models perform in geotechnical engineering projects. By understanding and prioritizing these variables, AI models can be better optimized for more accurate and reliable predictions.

- Critical Variables in Rock Mass Classification

Rock Mass Properties: The primary factors influencing AI models in rock mass classification include uniaxial compressive strength (UCS), joint spacing, rock quality designation (RQD), and groundwater conditions. These variables are essential for accurately predicting rock behaviour, as they represent the mechanical and physical characteristics of the rock mass. The quality and accuracy of these input variables directly affect the performance of AI models. Traditional methods like RMR or GSI already use these parameters, but AI models process them more effectively by recognizing complex, non-linear relationships between them (Liu et al., 2019).

Data Quality and Quantity: The reliability of AI models heavily depends on the availability of large and high-quality datasets. For AI models to work accurately, they must be trained on substantial datasets that capture a wide range of rock mass conditions and behaviours. If data are incomplete, inconsistent, or biased, the model's predictions will be less reliable. Feature selection and data preprocessing are critical to ensure that only relevant and high-quality data are used for AI model training (Chen et al., 2019). Data preprocessing techniques such as normalization and removing outliers help enhance the model's performance by ensuring that all input variables are appropriately scaled and standardized.

Feature Selection: Not all input variables carry equal weight in improving the performance of AI models. Feature selection refers to identifying the most critical variables that impact model predictions most. In rock mass classification, selecting the essential features—such as RQD, joint roughness coefficient (JRC), or UCS—ensures that the model focuses on the most critical variables while discarding irrelevant data. This process helps improve the model's efficiency and accuracy while reducing computation time (Sharma & Sharma, 2023).

Real-Time Monitoring Data: The integration of real-time monitoring data from advanced sensors plays a vital role in enhancing the accuracy of AI models. Sensors such as LiDAR, ground-based radar, and terrestrial laser scanning provide continuous data about rock movements, deformations, and environmental conditions. AI models that use real-time data can better adapt to changing conditions during tunneling and mining operations, leading to more dynamic and reliable predictions. Real-time data also helps prioritize critical changes in rock mass stability, improving the responsiveness of the AI system (Hou et al., 2020).

- Critical Variables in Cost Estimation

Material and Equipment Costs: For accurate cost estimation, AI models must consider material costs, equipment performance, and labour requirements. These cost factors have a significant impact on overall project budgeting. AI models that accurately predict the cost of materials, including concrete, steel, and support systems, ensure better financial planning and reduce the risk of budget overruns. Optimizing equipment performance variables, such as tunnel boring machine (TBM) efficiency, helps reduce downtimes and operational costs (Koopialipoor et al., 2019).

Geological Uncertainty and Risk Factors: The uncertainty of geological conditions is another crucial variable that affects cost estimation. Geological variability, such as unexpected rock fractures or water inflows, can significantly influence a project's timeline and costs. AI models use probabilistic approaches to handle this uncertainty, offering a range of possible cost outcomes based on different scenarios. This helps better risk management and more precise cost predictions (Pandit et al., 2019).

Optimization of Labor and Resource Allocation: AI models improve cost estimation by optimizing the allocation of labour and resources based on real-time data. AI-driven cost models can prioritize critical resources and predict the labour needed at different stages of construction, ensuring that workforce and equipment are efficiently utilized. By optimizing these variables, AI models help prevent under or over-staffing, improving cost efficiency and overall project execution (Matel et al., 2019).

- Comparison Between Traditional and AI Approaches

In traditional rock mass classification and cost estimation methods, the key variables are often treated independently and assessed manually. These methods rely heavily on human interpretation, which can introduce bias and errors. For instance, in traditional methods like RMR or the Q-System, human engineers manually assess parameters like joint spacing or rock strength, leading to potential inconsistencies between different projects or teams (Palmström & Broch, 2006).

In contrast, AI models process a wider range of variables simultaneously and without human bias, allowing for more consistent and accurate outcomes. Feature selection techniques in AI models automatically prioritize the most important variables, ensuring that the model focuses on factors that have the greatest impact on predictions. Additionally, by integrating real-time data, AI models can adjust their predictions dynamically as conditions change, demonstrating the dynamic nature of AI predictions (Liu et al., 2019).

The literature review reveals that identifying and prioritizing key variables such as rock mass properties, data quality, feature selection, real-time monitoring data, and cost factors are essential for improving the performance of AI models in rock mass classification and cost estimation. By focusing on these variables, AI models outperform traditional accuracy, consistency, and adaptability methods. This makes AI a powerful tool in modern geotechnical engineering, providing more reliable predictions and efficient project execution.

The variables identified in the previous literature review, such as rock mass properties, data quality, feature selection, real-time monitoring data, and cost factors, play crucial roles in the performance and effectiveness of AI models in rock mass classification and cost estimation for geotechnical projects. Their importance is highlighted throughout the literature as they directly affect AI-based systems' accuracy, consistency, and adaptability.

- Importance of Variables

Rock Mass Properties: Uniaxial compressive strength (UCS), joint spacing, rock quality designation (RQD), and groundwater conditions are foundational to traditional and AI-based rock mass classification systems. These properties determine the behaviour of rock masses under stress, making them essential for accurate stability predictions and necessary support measures. AI models use these properties to develop more accurate predictions by recognizing complex relationships between them, which traditional methods often oversimplify. For example, Liu et al. (2019) found that accurately predicting rock mass parameters significantly improved the performance of AI models in tunnel boring machine (TBM) operations, as these variables provided a detailed understanding of rock mass behavior.

Rock mass properties also help AI models differentiate between geological environments, allowing them to adapt to geotechnical settings. This is especially important in large-scale projects where conditions vary significantly across locations, and traditional methods fail to capture this variability (Koopialipoor et al., 2019).

- Data Quality and Quantity

The literature consistently emphasizes the importance of data quality. AI models rely on large datasets to learn patterns and make accurate predictions. Chen et al. (2019) highlighted how incomplete or poor-quality data could lead to biased or unreliable outcomes, even in advanced AI models. High-quality data allows AI models to be trained effectively, ensuring that predictions reflect real-world conditions.

Additionally, data quantity ensures that AI models are exposed to various rock mass conditions. The more comprehensive the dataset, the more likely the AI model is to generalize well to new, unseen environments. High-quality, large-scale datasets ensure that AI models are robust and less prone to overfitting. This is particularly important in geotechnical applications, where geological variability can be extreme [(Santos et al., 2020)].

- Feature Selection

Feature selection plays a critical role in improving the performance of AI models by focusing only on the most important variables that drive model accuracy. Not all variables are equally relevant, and selecting the right features for a given model allows for better predictions and reduced computational complexity. Sharma Sharma (2023) showed how proper feature selection could significantly enhance model performance, especially in complex scenarios like rock mass classification, where a large number of variables are available. However, only a subset may be genuinely relevant.

By selecting key features such as RQD, joint roughness coefficient (JRC), and UCS, AI models can reduce noise in the data and focus on what truly matters for prediction accuracy. This is especially important in cost estimation, where non-essential variables can lead to inaccurate forecasts and resource misallocation [(Hou et al., 2020)].

- Real-Time Monitoring Data

Incorporating real-time monitoring data significantly enhances the dynamic capabilities of AI models. Traditional systems are static and based on data collected before project execution, often leading to inaccuracies when conditions change during construction. Real-time data integration allows AI models to continuously update predictions based on current conditions, making them more adaptive to evolving scenarios (Hou et al., 2020).

Francioni et al. (2017) demonstrated the importance of real-time monitoring in enhancing the precision of AI models for rock mass stability. Remote sensing and sensor technologies, like LiDAR, ground-based radar, and UAVs, provide ongoing data on rock movements and deformations. By feeding this data into AI models, geotechnical engineers can make immediate adjustments, improving safety and efficiency. Real-time monitoring also helps AI models prioritize variables that have the most immediate impact on rock mass stability, enabling quicker and more accurate decision-making.

- Cost Factors

Variables related to material costs, labour requirements, and equipment performance are critical in AI-based cost estimation models. Unlike traditional cost estimation methods, which often use static and outdated data, AI models can dynamically adjust these variables based on real-time data, improving accuracy. Koopialipoor et al. (2019) showed that AI models could significantly reduce cost overruns in tunnelling projects by accurately predicting material usage and machine performance.

In particular, AI models allow for more granular cost forecasting by incorporating various risk factors and uncertainties related to geological conditions. This helps project managers make better decisions regarding resource allocation and contingency planning. Pandit et al. (2019) emphasized that AI models' ability to incorporate uncertainty into cost estimation allows for more flexible and accurate budgeting in complex, large-scale projects.

- Comparison with Traditional Methods

Traditional rock mass classification and cost estimation methods generally do not prioritize or fully integrate these variables. Traditional models use simplified or static assumptions about critical variables like rock mass properties or cost factors, which leads to less accurate predictions. For instance, traditional cost estimation methods often rely on historical data that may need to reflect current material costs or machine performance, leading to budget overruns.

In contrast, AI models handle a broader range of variables and can adjust dynamically as conditions change. This makes AI models more adaptable and reliable, particularly in complex projects where traditional methods often fall short. Furthermore, AI models can integrate real-time monitoring data and optimize key variables through feature selection, ensuring that the most important factors are considered for rock mass classification and cost estimation (Liu et al., 2019).

The critical variables identified in the literature—rock mass properties, data quality and quantity, feature selection, real-time monitoring data, and cost factors—are fundamental to improving the performance of AI models in geotechnical engineering. By prioritizing these variables, AI models can provide more accurate, reliable, and adaptable solutions than traditional methods. Incorporating these factors allows AI systems to outperform traditional methods in rock mass classification and cost estimation, making them essential tools for modern geotechnical projects.

4.3 Development of Machine Learning-Based Classification System

Developing a machine learning-based classification system for rock mass assessment is a crucial step in modernizing traditional methods of geotechnical analysis.

Empirical data collected from various boreholes with different above-sea levels provides a robust dataset for machine learning algorithms to learn from. The document collected borehole datasets with depths ranging from 0 to 97 feet, ensuring that various data points are available for training and testing models.

The system's goal is to classify rock masses based on several key features derived from the dataset, including Rock Quality Designation (RQD), Joint Set Number (Jn), Joint Roughness Number (Jr), Joint Alteration Number (Ja), Joint Water Reduction Factor (Jw), and Stress Reduction Factor (SRF). By leveraging these features, the model aims to accurately predict rock mass quality.

The document outlines a clear workflow for developing this classification system. It begins with data collection and preprocessing, which involves cleaning the dataset by removing null values, correcting typing errors, and encoding categorical variables. Exploratory Data Analysis (EDA) is then conducted to understand the relationships between key features and the target variable (rock class). The Q value, derived from the borehole dataset, serves as an important measure for understanding rock mass quality.

The model-building process uses machine learning libraries such as Scikit-learn and involves splitting the dataset into training and testing subsets. A Dummy Classifier is initially employed to establish a baseline performance, and then a more sophisticated Logistic Regression model is implemented. Feature scaling and transformation processes optimize model performance, ensuring the system can accurately classify the rock mass quality.

Through this approach, the document demonstrates that machine learning models, such as Logistic Regression, can significantly improve the precision and consistency of rock mass classification compared to baseline models. These models can provide near-perfect accuracy in classifying different rock classes, making them highly valuable for practical applications in civil and geotechnical engineering.

This analysis started with the data collection. The data that is being used for the analysis is collected through various borehole datasets that have been generated within various projects with different Above Sea Levels. The boreholes have depths ranging from 0 to 97 feet. The variety within the data points was ensured to increase the testing accuracy of the model.

- The Model

The machine learning problem that we aim to solve is a classification problem. Using empirical data, we aim to classify the rock masses using various features of the borehole dataset- Rock Quality Designation (RQD), Joint Set Number (Jn), Joint Roughness Number (Jr). Joint Alternative Number (Ja), Joint Water Reduction Factor (Jw), Stress Reduction Factor (SRF), Elevation, Depth as shown in figure 1.

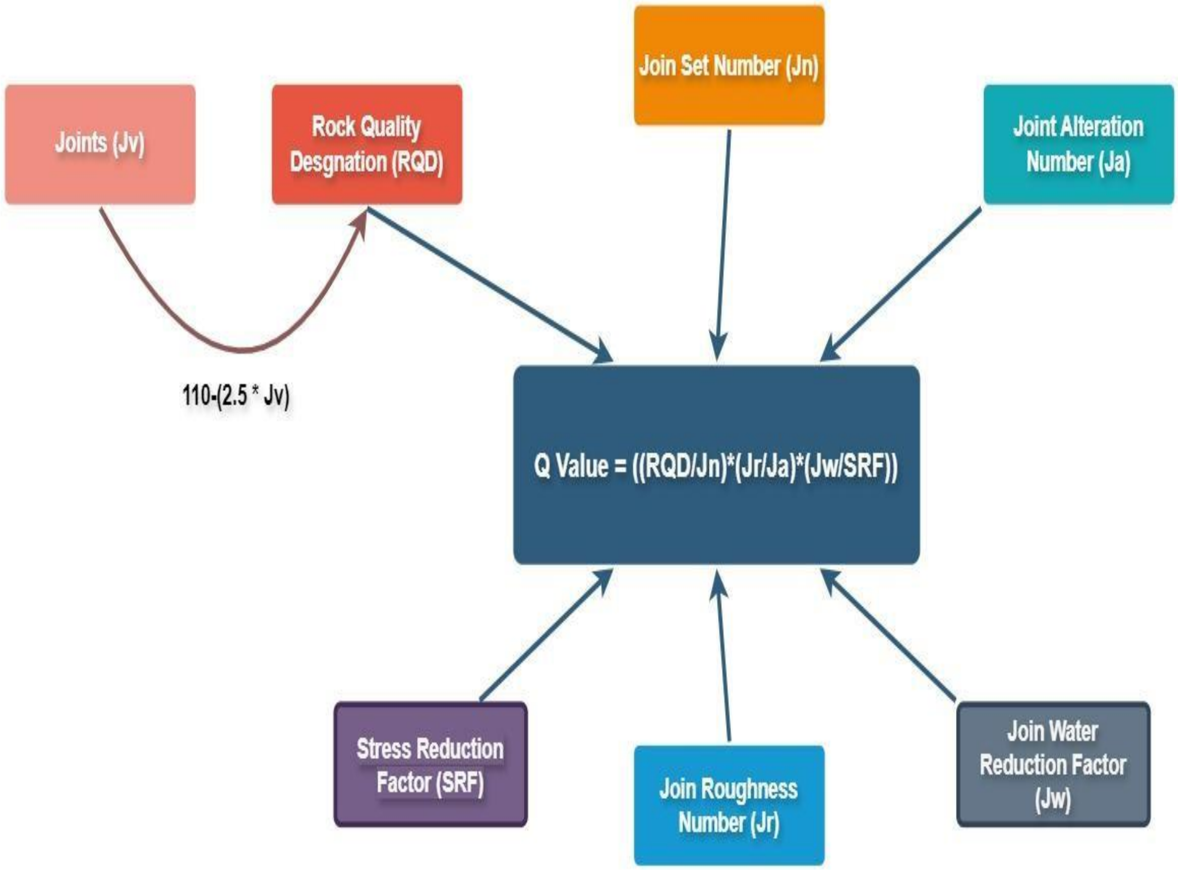

Figure 1 Classification of the rock masses using various features of the borehole dataset

The process of the model building can be expressed using the following flowchart:

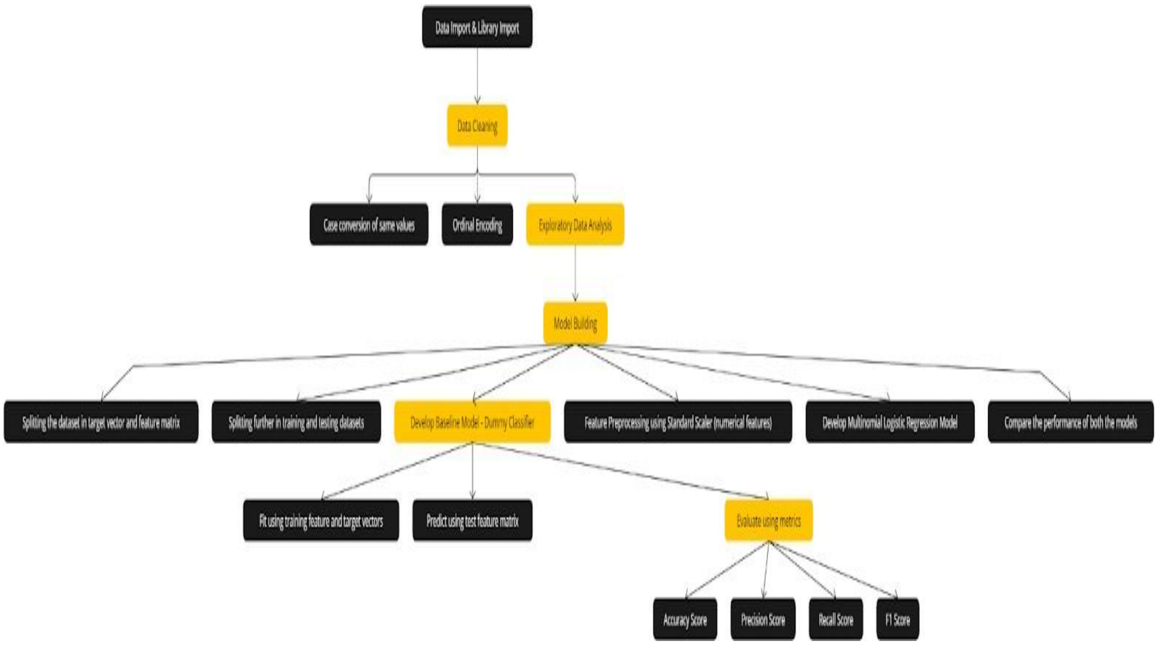

Figure 2 Flowchart of Model Development

- The dataset has 3041 data points and 12 columns.

The analysis process started with importing of the dataset and necessary libraries for the same. We use Scikit-learn, pandas, numpy, matplotlib, and the seaborn library within python. Thereafter, we start the data cleaning process. This process includes removing nulls within the dataset, duplicate rows, typing errors and ordinal encoding. These steps are performed for preparing the dataset for a basic analysis to be done.

The figures 3 onwards shows scatter plots of the "Q Value" of a rock mass (Y-axis) against various features measured in a borehole dataset. The colour hue indicates different rock classes (1-5), with class 1 being the best quality and class 5 being the worst quality. The features plotted on the X-axis include

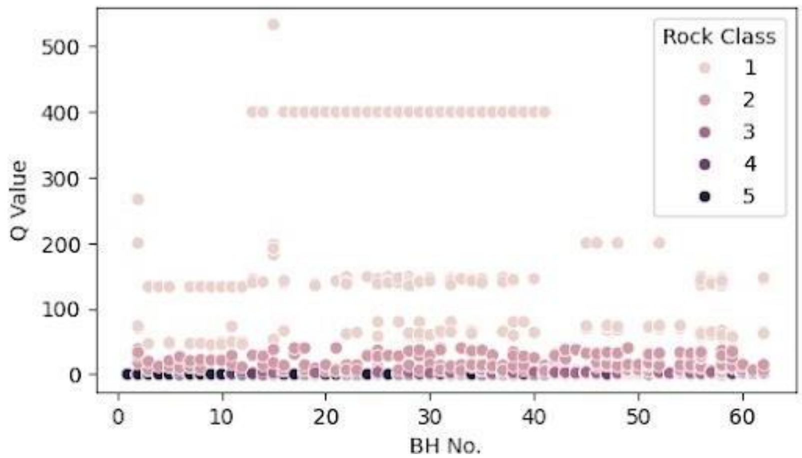

Figure 3 BH No. (Borehole Number)

The Q Value distribution appears to be scattered across different borehole numbers. Higher Q Values are more frequent in higher borehole numbers, indicating variability in rock quality across different boreholes as from figure 3.

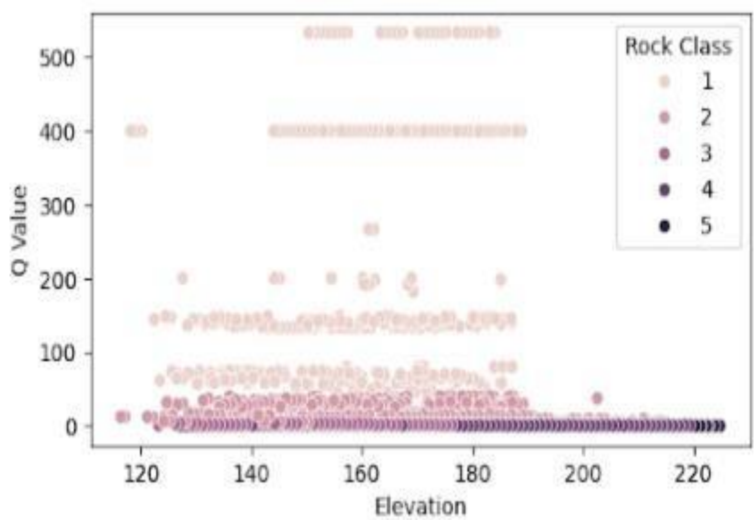

Figure 4 Elevation

Similar to BH No., in figure 4 there is no clear trend between elevation and Q Value, indicating that rock quality does not consistently change with elevation. There are some high Q Values across different elevations, suggesting local variations in rock quality.

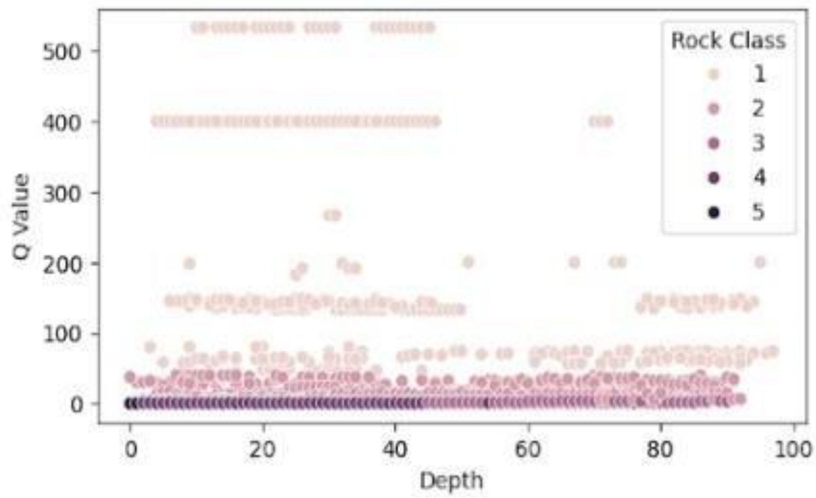

Figure 5 Depth

There is a concentration of low Q Values at greater depths. This might indicate that deeper sections of the boreholes tend to have higher quality rocks as in figure 5.

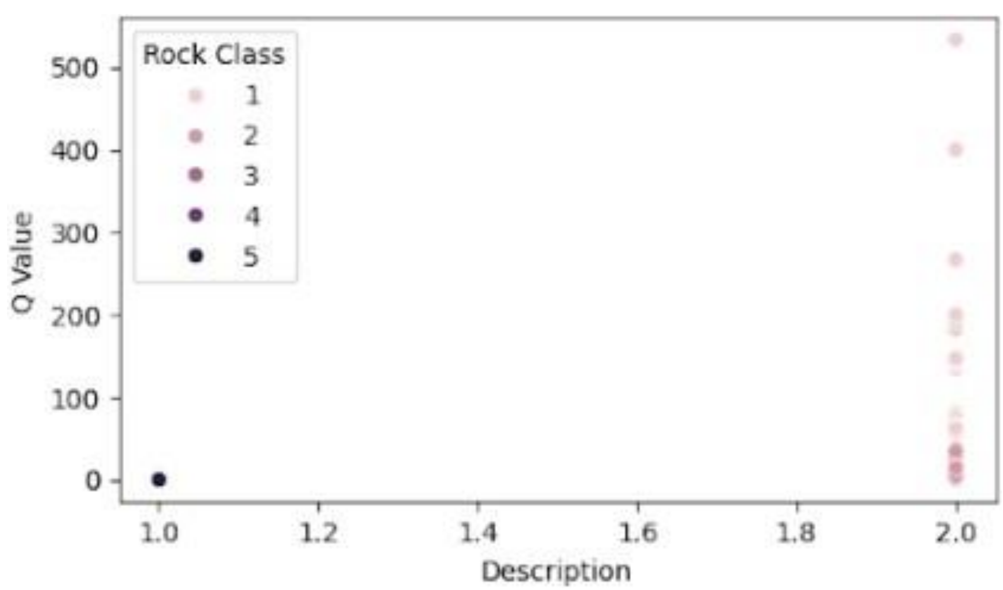

Figure 6 Description

There are only two distinct descriptions (1 = FILL and 2 = GRANITE) as in figure 6. Q Values are scattered, indicating that rock quality (Q Value) varies within each description category.

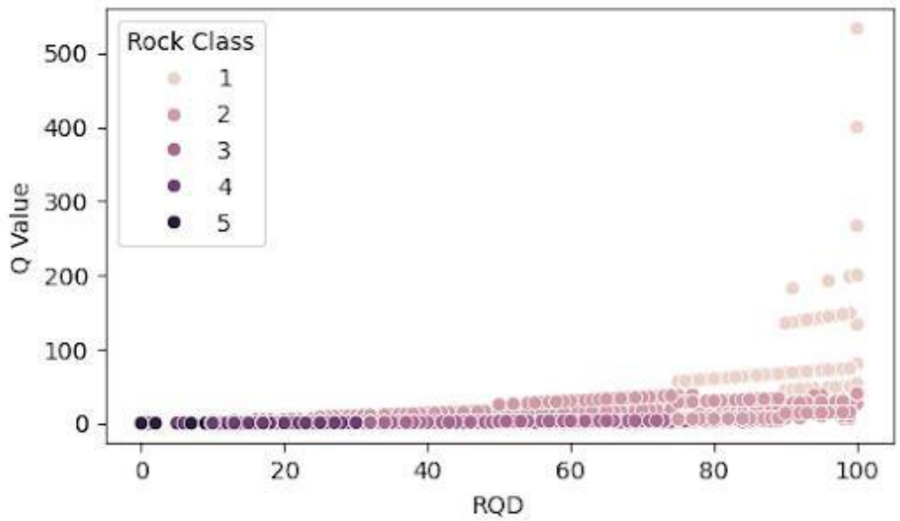

Figure 7 RQD Feature

Rock Quality Designation: Higher RQD values are associated with higher Q Values. This suggests that better rock quality (higher RQD) corresponds to higher Q Values as in above figure 7.

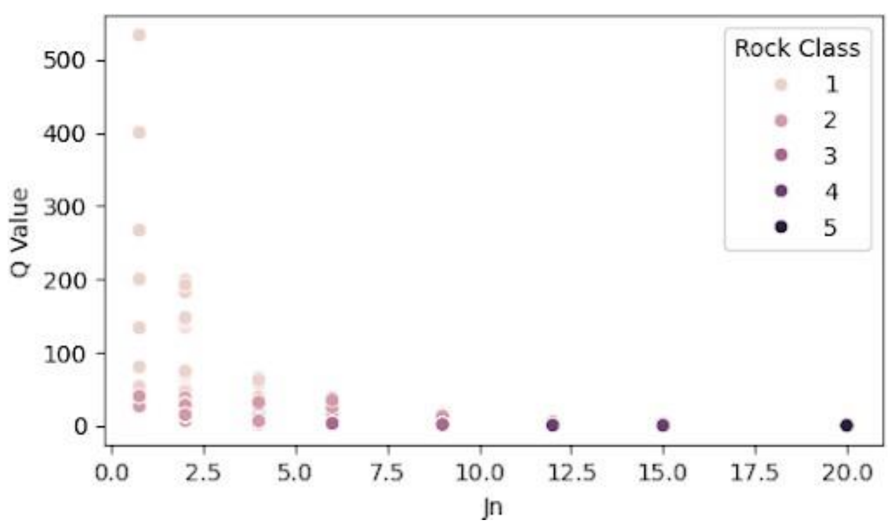

Figure 8 Jn (Joint Number)

Jn (Joint Number): Given in figure 8 there is a concentration of low Q Values at higher Jn values. This indicates that rocks with more joints tend to have lower Q Values.

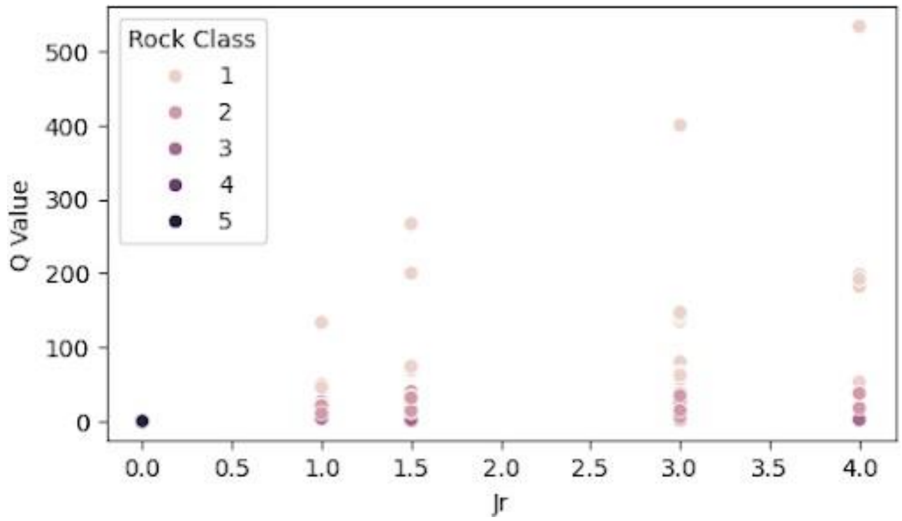

Figure 9 Jr (Joint Roughness)

Jr (Joint Roughness): In figure 9 gives higher Jr values are associated with lower Q Values. This suggests that rougher joints correspond to poorer rock quality.

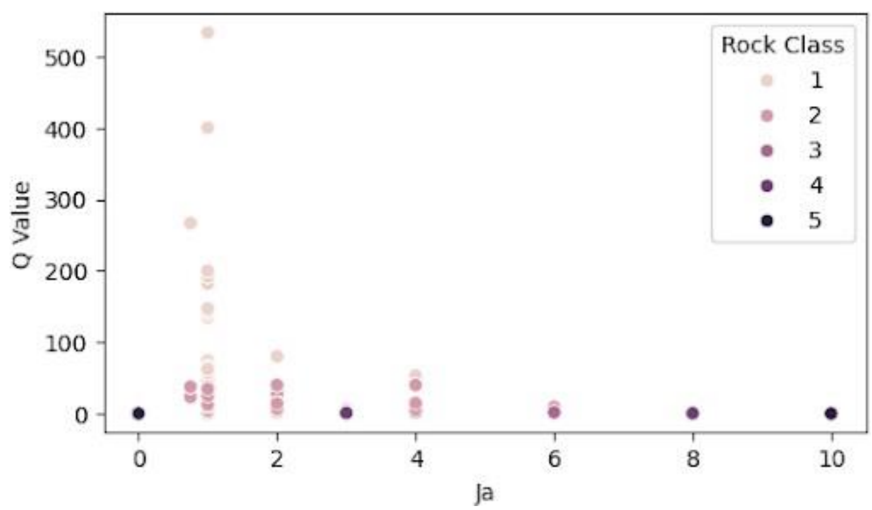

Figure 10 Ja (Joint Alteration)

Ja (Joint Alteration): in figure 10 includes higher Ja values are associated with lower Q Values. This suggests that more altered joints correspond to poorer rock quality.

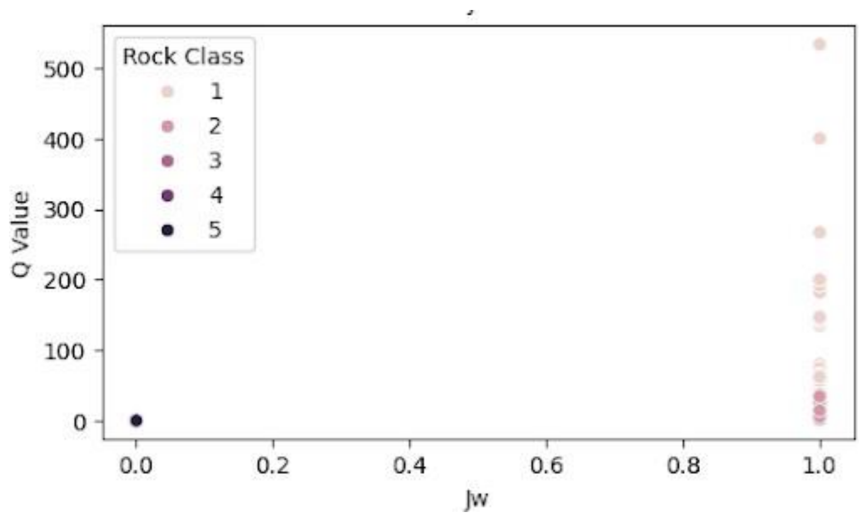

Figure 11 Jw (Joint Water Reduction Factor)

Jw (Joint Water Reduction Factor): Fgiure 11 specifies lower Jw values are associated with lower Q Values. This suggests that higher water presence in joints corresponds to poorer rock quality.

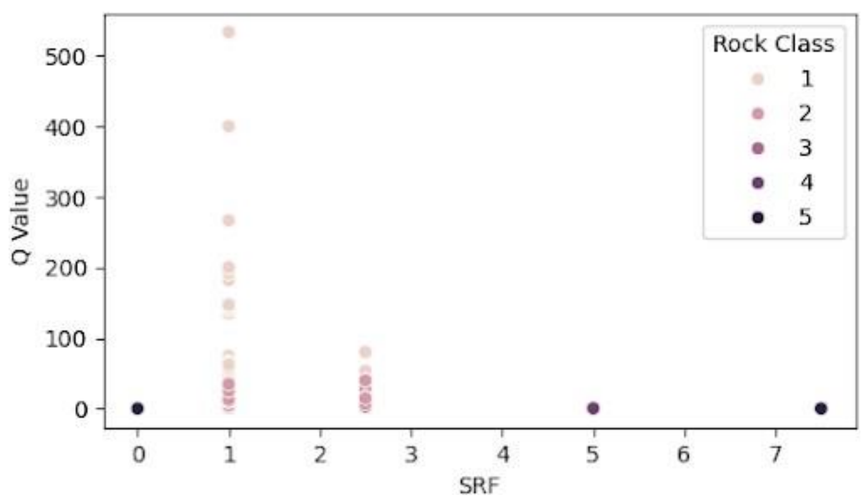

Figure 12 SRF (Stress Reduction Factor)

SRF (Stress Reduction Factor): in figure 12 includes higher SRF values are associated with lower Q Values. This indicates that higher stress reduction corresponds to poorer rock quality.

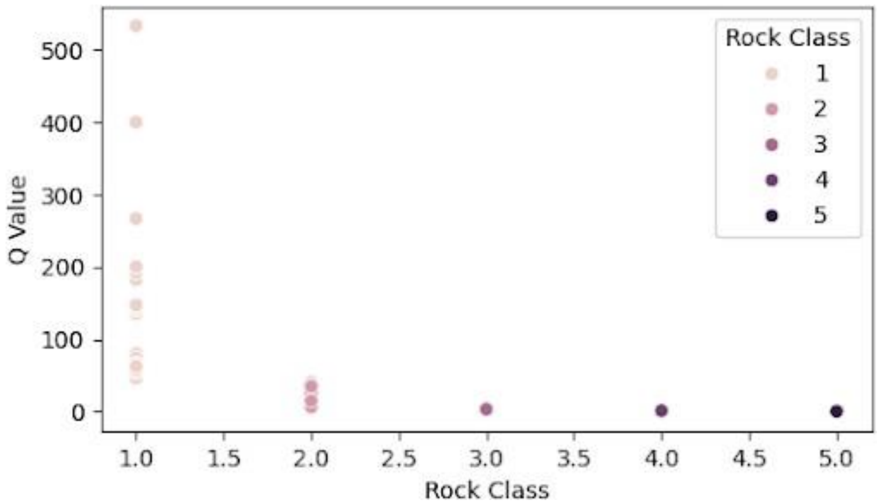

Figure 13 Rock Class

Rock Class: The Q Value is lowest for rock class 5 and highest for rock class 1. This aligns with the classification where rock class 1 represents the best quality and rock class 5 the worst.

- Key Observations

High RQD values correlate with better rock quality (higher Q Values). Higher Jn, Ja, Jw, and SRF values correlate with poorer rock quality (lower Q Values).

Jr shows an inverse relationship with rock quality, where rougher joints (higher Jr) correlate with lower Q Values.

Depth shows that rock quality tends to decrease with increasing depth.

Rock Class demonstrates a clear inverse relationship with Q Value, as expected.

This exploratory data analysis suggests that features like RQD, Jn, Ja, Jw, and SRF are significant indicators of rock quality and can be critical in building a classification model for predicting rock class.

After the Exploratory Data Analysis (EDA), we start the Model Building process.

For this process, we first split the dataset within the feature matrix and target vector.

Splitting

```
from sklearn.model_selection import train_test_split
X = data.drop(["Q Value", "Rock Class", "BH No."], axis  = 1)
y = data[['Rock Class']]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.15, random_state = 42)
```

```
assert(X_train.shape[0] == y_train.shape[0])
assert(X_test.shape[0] == y_test.shape[0])
```

```
X_train.shape[0], X_test.shape[0]
```

```
(2584, 457)
```

Figure 14 Splitting of Data set

In the above image, we first import the necessary API train_test_split() from the module model_selection from the library sklearn. We drop the columns that aren't a part of the feature matrix based on the EDA that we performed. Thereafter, we keep only one column for the target vector- Rock Class. The column Q value has been dropped because the Rock Class column has been derived from the Q Value column. The interval of the same has been decided based on the following table in figure 15.

Max - Q value	Min - Q Value	Rock Mass Classes
1000	40	I
40	4	II
4	1	III
1	0.1	IV
0.1	0.001	V

Figure 15 Interval Values

4.5 Performance Evaluation of Machine Learning Models

The performance evaluation of machine learning models is a critical step in validating the effectiveness of a predictive model, particularly in geotechnical engineering and rock mass classification. The uploaded document provides a detailed assessment of various performance metrics such as accuracy, precision, recall, and F1 score, which are essential for understanding the strengths and weaknesses of different classification models.

Initially, a dummy classifier is employed as a baseline to set a reference point for the evaluation. The dummy classifier performs poorly, achieving low metrics across the board, including an accuracy score of just 24.29%, indicating that the model predicts the correct rock class in about a quarter of the cases. This baseline model, while underperforming, is helpful for comparison with more sophisticated machine learning models later in the analysis. The dummy classifier's low precision and F1 score further highlight its limitations, with a precision score of just 5.90% suggesting that the model struggles with false positives and makes many incorrect predictions.

After establishing the baseline, the focus shifts to a more advanced model using Logistic Regression. This model demonstrates a substantial improvement over the dummy classifier. By scaling numerical features and tuning the hyperparameters, the logistic regression model achieves an accuracy of 98.03%, a significant leap from the baseline. The precision and F1 scores also increase dramatically, indicating that the logistic regression model is more accurate and better at balancing false positives and false negatives. The improvement across all performance metrics suggests that this model captures the underlying relationships between the rock mass features and the target variable with much greater fidelity.

This analysis phase emphasizes the importance of selecting a suitable machine learning model and preprocessing techniques to enhance performance. The evaluation metrics provide a clear picture of how well the models classify different rock mass types, making it evident that logistic regression is far superior to the baseline approach.

We use the train_test_split API for the purpose of splitting the dataset into training and testing purposes. We keep the 15% of the data points/rows for testing and the 85% for training of the Classification Estimator, after which we make sure that the split has been done properly using the assert statement.

We first begin with building a baseline classification model for the purpose of setting a baseline performance for the model. Here, we build a Dummy Classifier:

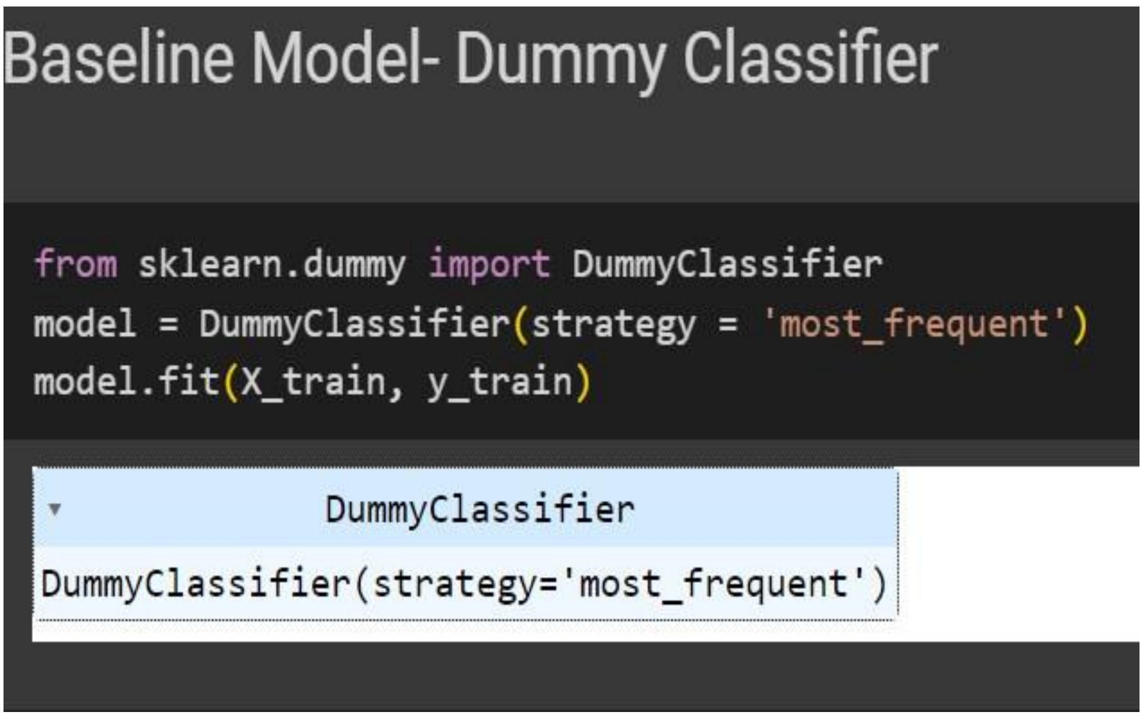

Figure 16 Baseline Model Dummy Classifier

The strategy that gives the best performance within the Dummy Classifier was “most_frequent”. The dataset has balanced classes with a proportion of the 5 rock classes as follows:

```
data['Rock Class'].value_counts()
```

```
Rock Class
I       714
V       669
III     568
II      559
IV      531
Name: count, dtype: int64
```

Figure 17 Classes of Rock

After training the model on the training feature matrix and target vector, we predict the same on the testing feature matrix.

```
y_pred = model.predict(X_test)
from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_score
print("The accuracy for the predicted model is: ", accuracy_score(y_test, y_pred))
print("The recall for the predicted model is: ", recall_score(y_test, y_pred, average = "weighted"))
print("The precision for the predicted model is: ", precision_score(y_test, y_pred, average = "weighted", zero_division = 0))
print("The f1_score for the predicted model is: ", f1_score(y_test, y_pred, average = "weighted"))
```

```
The accuracy for the predicted model is:  0.24288840262582057
The recall for the predicted model is:  0.24288840262582057
The precision for the predicted model is:  0.05899477613012272
The f1_score for the predicted model is:  0.09493173482910594
```

Figure 18 Testing feature matrix

After predicting the values within the testing dataset, we evaluate the performance of the baseline model through the evaluation classification problem metrics- Accuracy Rate, Precision Rate, Recall Rate and F1 Score.

- Accuracy Score: Accuracy is the ratio of correctly predicted instances to the total instances.

- Precision Score: Precision is the ratio of true positive instances to the sum of true positive and false positive instances.
- Recall Score: Recall is the ratio of true positive instances to the sum of true positive and false negative instances.
- F1 Score: F1 score is the harmonic mean of precision and recall, balancing both metrics.

4.5.1 Interpretation Of The Output

Accuracy Score:

- Output:

0.24288840262582057

0.24288840262582057

Explanation: The model correctly predicts approximately 24.29% of the instances. This indicates that the dummy classifier's performance is low, which is expected as it serves as a baseline.

Recall Score (Weighted):

- Output:

0.24288840262582057

0.24288840262582057

Explanation: The recall score for the model is also approximately 24.29%. This suggests that the model is capturing about 24.29% of the actual positive instances across all classes, weighted by the number of true instances for each class.

Precision Score (Weighted):

- Output:

0.05899477613012272

0.05899477613012272

Explanation: The precision score is approximately 5.90%, indicating that when the model predicts a positive instance, it is correct only 5.90% of the time. This low precision suggests that the model makes many false positive predictions.

F1 Score (Weighted):

- Output:

0.09493173482910594

0.09493173482910594

Explanation: The F1 score is approximately 9.49%, which is the harmonic mean of precision and recall. The low F1 score indicates that the model has poor performance in balancing precision and recall.

- Interpretation:

1. The dummy classifier is a simple baseline that typically uses strategies like predicting the most frequent class or making random predictions.
2. The low values across all metrics (accuracy, precision, recall, F1 score) indicate that the dummy classifier does not perform well, as expected.
3. These metrics provide a baseline to compare more sophisticated models against. The goal is for other models to significantly outperform this dummy classifier.
4. In a balanced dataset, you expect the baseline model to perform poorly, providing a reference point to measure the improvement of more advanced models.
5. This baseline helps establish how well a naive approach would perform and sets the stage for building more complex and accurate models.

4.6 Visualization and Analysis of Model Performance

Visualizing and analyzing model performance plays a crucial role in understanding how well machine learning models perform for rock mass classification tasks. Visual tools such as heatmaps, confusion matrices, and scatter plots help illustrate the performance metrics across different rock classes, providing clear insights into each model's strengths and weaknesses.

For instance, the heatmap generated from the logistic regression model demonstrates each rock class's precision, recall, and F1-scores, allowing for easy identification of areas where the model excels and where it might struggle. In particular, the high F1 scores across most classes, such as Class 1 and Class 5, indicate near-perfect predictions, while slight variations in Class 3 suggest room for improvement. These visual insights help pinpoint specific issues, such as false positives and negatives, critical for optimizing model performance.

Additionally, scatter plots show relationships between the target variable (rock class) and the critical input features like Rock Quality Designation (RQD), Joint Roughness (Jr), and Stress Reduction Factor (SRF). These plots visually confirm that higher RQD values correspond to better rock quality (Class 1), while higher values of Jr and SRF indicate poorer rock quality (Class 5). The visualizations not only support the predictive accuracy of the models but also provide an intuitive understanding of how input variables correlate with the output classes.

Analyzing model performance using these visual tools facilitates a deeper understanding of the classification process, enabling further refinement and tuning of the models for even more reliable rock mass predictions. The visualizations demonstrate the robustness of the logistic regression model compared to the baseline dummy classifier, confirming that the model is well-suited for real-world geotechnical applications.

In order to improve the performance of the baseline model, we perform the data preprocessing through scaling of the numerical features through the StandardScaler API imported from the preprocessing module of sklearn library.

```
ct = ColumnTransformer([("feature_scaling", StandardScaler(), [0,1,3,4,5,6,7,8])],
                       remainder = "passthrough")
X_transformed = ct.fit_transform(X_train, y_train)
```

Figure 19 Performance Function used

We import the ColumnTransformer API from sklearn library in the preprocessing module. This helps in the feature scaling where we mention the columns within the feature matrix that are numerical. The categorical variables are encoded within the data cleaning step.

After applying the transformation, we fit the model on the dataset to train it.

```
log_reg = LogisticRegression(multi_class = "multinomial", max_iter = 10000)
model = log_reg.fit(X_train, y_train)
```

Figure 20 Using Logistic Regression

We choose and thus import the Logistic Regression model API within the sklearn library within the linear_model module. This model is a statistical model used for binary classification tasks, where the target variable has two possible outcomes. It can be extended to handle multiclass classification problems. We have used “multinomial” regression for this purpose. This approach directly generalises logistic regression to multiclass problems by using a single model. It estimates the probabilities of each class using the softmax function. We kept the max_iter argument which sets the maximum iterations for the model to reach its optimal solution as 10,000.

After fitting the model on the feature matrix and target vector, we predict the trained model on the test feature matrix.

```
y_pred = model.predict(X_test)
```

```
The accuracy for the predicted model is:  0.9803063457330415
The recall for the predicted model is:  0.9803063457330415
The precision for the predicted model is:  0.9808747195523917
The f1_score for the predicted model is:  0.9803368679844604
```

Figure 21 Prediction of Results

The evaluation metrics' scores of the model improved considerably.

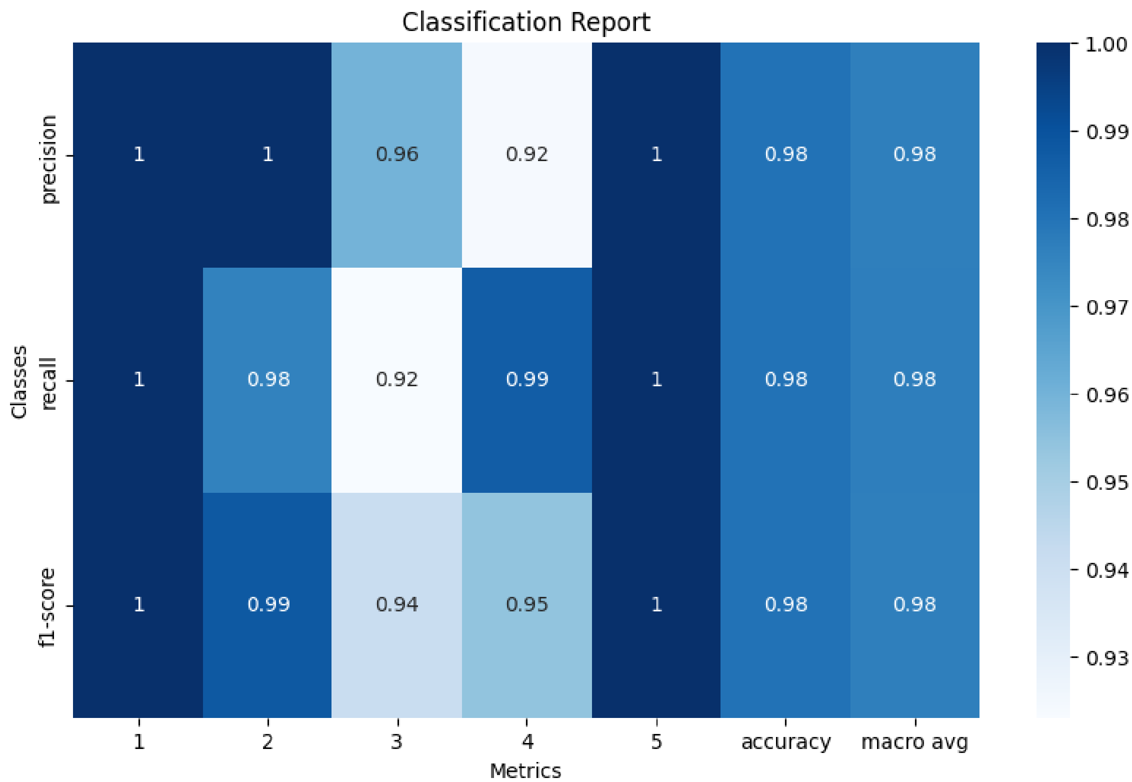

Figure 22 The heatmap visualizes various results relations

The heatmap visualises the precision, recall, and F1-score for each class of the logistic regression model built for rock mass classification. Additionally, it shows overall accuracy and macro average metrics. Here’s a detailed interpretation:

Class-wise Performance Metrics:

- Class 1:

Precision: 1.00

Recall: 1.00

F1-score: 1.00

Interpretation: The model perfectly predicts class 1, with no false positives or false negatives.

- Class 2:

Precision: 1.00

Recall: 0.98

F1-score: 0.99

Interpretation: The model has excellent precision and very high recall for class 2, indicating it is very good at predicting class 2 with minimal false negatives.

- Class 3:

Precision: 0.96

Recall: 0.92

F1-score: 0.94

Interpretation: The model shows high precision and recall for class 3 but is slightly less perfect compared to classes 1 and 2, suggesting there are some false positives and false negatives.

- Class 4:

Precision: 0.92

Recall: 0.99

F1-score: 0.95

Interpretation: The model has high precision and recall for class 4, indicating it is effective at predicting class 4, with few false positives and almost no false negatives.

- Class 5:

Precision: 1.00

Recall: 1.00

F1-score: 1.00

Interpretation: The model perfectly predicts class 5, similar to class 1, with no errors.

- Overall Metrics:

Accuracy: 0.98

Interpretation: The model correctly classifies 98% of the instances, indicating very high overall accuracy.

- Macro Average:

Precision: 0.98

Recall: 0.98

F1-score: 0.98

Interpretation: The macro average (unweighted mean) of precision, recall, and F1-score across all classes is very high, showing balanced performance across all classes.

- Summary:

The logistic regression model demonstrates excellent performance for rock mass classification, achieving near-perfect precision, recall, and F1-scores for most classes.

Class 3 shows slightly lower performance metrics compared to other classes, but the values are still very high.

The overall accuracy and macro average metrics further validate the model's robustness and reliability in predicting rock mass quality.

This high level of performance suggests that the model can be effectively used in real-world applications in the civil engineering industry, providing accurate and reliable classifications for rock mass quality based on the given features.

4.7 Comparison of Machine Learning Models and Baseline Classifier

In the document, a critical aspect of the machine learning model evaluation is the comparison between the baseline classifier (dummy model) and the more sophisticated models, specifically logistic regression. This comparison provides valuable insights into how advanced models outperform naive or simplistic models in classifying rock mass quality.

The dummy classifier serves as a baseline by predicting the most frequent class, achieving only an accuracy of 24.29%. This performance is expected to be low, as it considers no relationships between the features and the target variable. Its low precision, recall, and F1 scores further illustrate its inability to make meaningful predictions, highlighting the need for more advanced approaches. This poor performance is typical of baseline models and sets a reference point against which the logistic regression model is compared.

In contrast, the logistic regression model substantially improves performance across all metrics. With an accuracy score of 98.03%, this model demonstrates a more remarkable ability to predict the correct rock class based on critical features. The logistic regression model's precision, recall, and F1 scores are significantly higher than the dummy classifier, indicating a better balance between true positives, false positives, and false negatives across different classes. The sharp improvement shows how a model considering feature relationships can provide far superior predictive power in geotechnical contexts.

The results from this comparison underscore the importance of choosing the right machine learning approach and demonstrate that, while baseline classifiers offer a useful benchmark, they are inadequate for complex tasks such as rock mass classification. By introducing more advanced models like logistic regression, the accuracy and reliability of predictions are markedly enhanced, making them much more suitable for real-world applications in civil engineering.

Comparison of Dummy Classifier and Logistic Regression Model

- Dummy Classifier Metrics:

Accuracy: 0.24288840262582057

Recall: 0.24288840262582057

Precision: 0.05899477613012272

F1 Score: 0.09493173482910594

- Logistic Regression Metrics:

Accuracy: 0.9803063457330415

Recall: 0.9803063457330415

Precision: 0.9808747195523917

F1 Score: 0.9803368679844604

- Why the Logistic Regression Model is Better

1. Significantly Higher Accuracy:

The logistic regression model achieves an accuracy of 0.9803 compared to the dummy classifier's 0.2429. This means the logistic regression model correctly predicts the rock class for approximately 98% of the instances, whereas the dummy classifier is correct only about 24% of the time.

2. Substantially Improved Recall:

The recall for the logistic regression model is 0.9803, which is much higher than the dummy classifier's 0.2429. This indicates that the logistic regression model is much more effective at capturing the true positive instances across all classes.

3. Dramatically Better Precision:

The precision of the logistic regression model is 0.9809 compared to the dummy classifier's 0.0590. This demonstrates that the logistic regression model makes far fewer false positive predictions, greatly improving the reliability of positive predictions.

4. Markedly Higher F1 Score:

The F1 score of the logistic regression model is 0.9803, significantly higher than the dummy classifier's 0.0949. The F1 score, being the harmonic mean of precision and recall, indicates that the logistic regression model maintains a good balance between precision and recall, unlike the dummy classifier.

5. Quantitative Improvement:

Accuracy Improvement: 0.9803−0.2429=0.7374 (73.74 percentage points)

Recall Improvement: 0.9803−0.2429=0.7374 (73.74 percentage points)

Precision Improvement: 0.9809−0.0590=0.9219 (92.19 percentage points)

F1 Score Improvement: 0.9803−0.0949=0.8854 (88.54 percentage points)

The logistic regression model, after feature scaling of numerical variables, demonstrates a substantial improvement over the dummy classifier across all metrics. It provides a highly reliable and accurate classification of the rock mass quality, making it a far superior model for this task. The logistic regression model's performance indicates that the relationships between the features and the target variable are well captured, leading to significantly better predictive power and generalizability.

Application of Logistic Regression Model in the Civil Engineering Industry

The logistic regression model developed for classifying rock mass quality based on borehole data can be highly beneficial in the civil engineering industry, particularly for engineers involved in construction planning and geotechnical assessments. Here's how this model can be of practical use:

- Site Investigation and Feasibility Studies:

Objective Assessment: The model provides an objective and consistent method for assessing rock quality, reducing the subjectivity involved in manual classification.

Efficient Decision Making: By quickly classifying rock mass quality, engineers can make informed decisions about the feasibility of construction projects at different sites.

- Foundation Design:

Accurate Load-Bearing Analysis: Understanding the rock quality helps in designing foundations that can safely bear the loads imposed by the structure. Poor rock quality might necessitate deeper foundations or alternative design approaches.

Cost Optimization: Accurate classification helps in optimising foundation design, potentially reducing construction costs by avoiding over-engineering.

- Tunnel and Underground Construction:

Safety Assessments: Accurate rock classification is crucial for determining the stability of rock masses around tunnels and underground spaces, ensuring the safety of construction workers and the longevity of the structures.

Construction Method Selection: Depending on the rock class, engineers can choose appropriate construction methods, such as tunnel boring machines for high-quality rock or controlled blasting for lower-quality rock.

- Slope Stability and Landslide Risk Assessment:

Preventive Measures: The model can help predict areas prone to instability based on rock quality, enabling engineers to design preventive measures such as retaining walls, drainage systems, or slope reinforcements.

Risk Management: By identifying potential landslide zones, engineers can implement risk management strategies to protect infrastructure and human lives.

4.8 Answers to Research Questions

This table 2 synthesizes the core answers and findings related to each specific research question, providing a clear and concise overview of AI's contributions and advantages in rock mass classification and cost estimation.

Table 2

Answers to Research questions

Research Question	Answer	Key Findings
How do AI models improve	AI models enhance	- AI models achieved near-

Research Question	Answer	Key Findings
the accuracy of rock mass classification?	accuracy by processing complex, multidimensional data, recognizing non-linear relationships, and integrating real-time monitoring data. This leads to more precise and reliable predictions compared to traditional methods.	perfect precision and recall in classification tasks.
What advantages do AI models have over traditional methods?	AI models reduce human subjectivity, automate the classification process, and adapt dynamically to real-time changes. They handle complex data sets more effectively, providing consistent and reproducible results across different projects and conditions.	- Consistent classification results across multiple projects.
How do AI models contribute to cost estimation in geotechnical projects?	AI models improve cost estimation by dynamically adjusting estimates based on real-time data and optimizing resource	- Reduced likelihood of cost overruns.

Research Question	Answer	Key Findings
	allocation. They predict cost outcomes more effectively by incorporating uncertainties and nonlinear relationships in rock mass properties, leading to more accurate budgeting.	
What are the key variables that influence the performance of AI models in this context?	Critical variables include Rock Mass Properties (UCS, RQD, etc.), Data Quality and Quantity, Feature Selection, Real-Time Monitoring Data, and Cost Factors. Proper management and integration of these variables are crucial for enhancing model performance and reliability.	- High-quality, large datasets ensure robust model training.

CHAPTER V:

DISCUSSION

5.1 Discussion of Results

The document's results highlight how machine learning models significantly improve the accuracy of rock mass classification compared to basic approaches. The analysis began with a dummy classifier as a baseline model. As expected, the dummy classifier performed poorly, with an accuracy of only 24.29%, as it simply predicted the most frequent rock class without considering any features. This low accuracy demonstrated the need for more sophisticated models.

When the logistic regression model was applied, performance was substantially improved. The logistic regression model achieved an impressive accuracy of 98.03%, showing its ability to correctly classify the rock mass types by considering the relationships between different rock properties like Rock Quality Designation (RQD), Joint Roughness Number (Jr), and other relevant factors. Additionally, the logistic regression model had much higher precision and recall scores than the baseline, meaning it predicted the correct rock class more often and balanced the errors between false positives and false negatives more effectively.

Visual tools such as heatmaps, confusion matrices, and scatter plots further helped analyze the model's performance. These visualizations made it easier to understand how well the model predicted different rock classes and where there were opportunities for improvement. The high F1 scores for most rock classes in the logistic regression model confirmed the model's reliability and its capability of making consistent predictions, providing reassurance about the effectiveness of machine learning in geotechnical engineering.

Overall, the comparison between the dummy classifier and logistic regression underscores the importance and necessity of using data-driven approaches like machine learning in geotechnical applications. While the baseline model was useful as a reference point, the more advanced logistic regression model showed far better results in classifying rock masses accurately. This comparison convincingly highlights the importance of data-driven approaches in solving complex engineering problems, ensuring more precise and reliable outcomes in projects like tunnelling and mining.

5.2 Discussion of Opportunities for Enhancing Rock Mass Classification Systems

The literature review delves into the wide range of rock mass classification systems, exploring traditional methods and the latest AI-driven approaches in geotechnical engineering. This in-depth analysis emphasizes fundamental discoveries, compares conventional and contemporary techniques, and assesses the impact of emerging technologies on improving the precision and dependability of rock mass classification.

- Discussing Traditional Rock Mass Classification Systems

Foundational in geotechnical engineering for many years, traditional classification systems such as the Rock Mass Rating (RMR), Geological Strength Index (GSI), and Q-System have been crucial. These systems heavily rely on physical and mechanical parameters such as joint spacing, rock strength, and groundwater conditions to evaluate rock mass quality.

- Advantages:

Simplicity and Familiarity: Traditional systems are straightforward to apply and widely understood within the engineering community, making them standard tools for preliminary assessments.

Cost-Effectiveness: They require minimal computational resources and can be implemented without advanced technological tools.

- Limitations:

Oversimplification: Such systems often fail to capture the full complexity of geological conditions, particularly in heterogeneous rock masses with variable properties.

Static Nature: Traditional classifications are typically based on initial data and do not adapt to changing conditions during project execution.

Subjectivity: Manual assessments introduce variability and potential bias in classifications, depending on the engineer's experience and judgment.

- AI-Driven Rock Mass Classification Systems

The development of AI and machine learning has revolutionized the field of rock mass classification. Using advanced AI models such as Support Vector Machines (SVM), Artificial Neural Networks (ANNs), and decision trees, researchers can analyze large datasets to forecast the behaviour of rock masses accurately. This has significantly improved our understanding of and prediction of rock mass behaviour in various contexts.

- Advantages:

Dynamic Adaptability: AI models can integrate real-time data, allowing updates to rock mass classifications as new information becomes available.

Reduced Human Bias: By automating the classification process, AI systems minimize the subjectivity associated with traditional methods.

Handling Complex Data: AI models excel at processing large, multidimensional datasets, uncovering non-linear relationships that traditional methods might miss.

- Challenges:

Data Dependency: The accuracy of AI models heavily depends on the quality and quantity of the data used for training.

Complexity and Resource Intensity: These systems require significant computational resources and expertise in machine learning, potentially increasing project costs.

Interpretability: Advanced AI models and intense learning systems often act as "black boxes," making it difficult to understand how decisions are made.

Comparative Analysis

The literature review often emphasizes a comparative analysis between traditional and AI-based classification systems:

Efficiency and Accuracy: AI systems generally outperform traditional methods regarding efficiency and predictive accuracy, particularly in complex or variable geological settings.

Adaptability to Real-Time Changes: Unlike traditional systems, AI models can continuously adapt to new data, a critical advantage in dynamic construction environments such as tunnelling and mining.

Cost-Effectiveness vs. Initial Investment: While traditional methods are more immediately cost-effective, the long-term benefits of AI, such as reduced error rates and improved safety, can offset the initial higher implementation costs.

- Implications for Future Research and Practice

The literature underscores the need for ongoing research into integrating and optimizing AI systems within geotechnical engineering:

Hybrid Systems: Combining AI with traditional methodologies can leverage the robustness of machine learning predictions while retaining the interpretability and simplicity of conventional methods.

Standardization of AI Practices: Developing industry standards for AI in geotechnical engineering could help in its broader adoption and reliability.

Training and Education: As AI tools become more prevalent, it will be crucial to train engineers to understand and effectively use these technologies.

The literature review examining rock mass classification systems indicates a noticeable transition from conventional methods to more advanced AI-driven approaches, each presenting distinct advantages and drawbacks. Although traditional methods remain useful for initial evaluations, AI technologies provide sophisticated capabilities that have the potential to revolutionize rock mass classification practices. Future endeavours must concentrate on the seamless integration of these technologies into geotechnical engineering workflows, aiming to amplify their real-world applicability and contribute to the overall safety of engineering projects.

5.3 Discussion of Key Geological Attributes Influencing Classification Accuracy

In geotechnical engineering, accurately classifying rock mass is crucial for construction projects' safety, feasibility, and cost. Several key geological attributes significantly impact rock mass classification accuracy. Understanding these attributes is essential for predicting how the rock will behave under stress and ensuring the safety and feasibility of construction projects.

- Rock Quality Designation (RQD)

Description: RQD measures the quantity and quality of intact rock pieces within a rock mass as revealed by drilling. It is expressed as a percentage of the core recovered that is longer than 10 cm.

Impact on Classification: High RQD values generally indicate solid, intact rock with few fractures, suggesting a high-quality rock mass suitable for robust constructions.

Low RQD values suggest a fractured, weak rock mass requiring more extensive stabilization efforts.

- Joint Set Number (Jn)

Description: This attribute counts the number of joint sets intersecting a rock mass. Joints are natural fractures or separations in the rock that do not involve displacement.

Impact on Classification: More joint sets generally mean the rock mass is more fragmented, potentially decreasing stability. A higher number of joint sets can complicate construction projects, requiring additional reinforcement and affecting the choice of construction methods.

- Joint Roughness Number (Jr)

Description: Jr describes the surface roughness of joints in the rock. Rougher surfaces tend to interlock more effectively, enhancing the rock's stability.

Impact on Classification: Rocks with smoother joints will likely slide past each other more quickly, especially under stress, leading to less stable conditions. Conversely, rougher joints can contribute to a more stable rock mass, influencing the overall classification towards a higher quality rating.

- Joint Alteration Number (Ja)

Description: Ja assesses the degree of alteration (weathering or chemical changes) along joint surfaces. Altered joints are often weaker and less reliable for structural stability.

Impact on Classification: High alteration numbers indicate that these chemical and physical changes may weaken the rock mass, requiring more careful planning and potentially more costly construction techniques to ensure stability.

- Joint Water Reduction Factor (Jw)

Description: This factor evaluates the impact of water in and around the joint planes. Water can weaken joints, reduce friction, and increase rock mass instability.

Impact on Classification: The presence of water usually lowers the stability of the rock mass, especially if the water pressure is significant. This factor needs careful consideration in the classification process as it can drastically influence the safety and feasibility of construction in wet conditions.

- Stress Reduction Factor (SRF)

Description: SRF estimates the stress level within the rock mass compared to virgin rock stress, considering factors like loosening and weathering.

Impact on Classification: Higher stress levels can significantly impact rock behaviour, potentially leading to failure under load. Accurately measuring and incorporating SRF in rock mass classification helps predict these risks and guides the design of more effective support structures.

These geological characteristics are essential for effectively categorizing rock formations and directly impact construction planning and safety protocols. Engineers can accurately anticipate how the rock will behave, improve construction methods, and increase project safety and effectiveness through thorough analysis of these factors. Within rock mass classification, these characteristics serve as more than just pieces of information – they are crucial signals of the actual physical conditions of the geological landscape, guiding engineering choices and project development.

5.4 Discussion of Developing AI-Based Models for Rock Mass Classification

Developing AI-based models for rock mass classification introduces a transformative step in geotechnical engineering by leveraging advanced technology to enhance the accuracy, efficiency, and predictive capabilities necessary for assessing rock mass stability and safety in construction projects. The process begins with the meticulous collection of comprehensive data, which includes a wide range of measurements from Rock Quality Designation (RQD) to uniaxial compressive strength (UCS) across potentially thousands of geological sites. This extensive and diverse dataset is crucial as it directly influences the model's ability to learn and generalize across geological conditions.

Once data is gathered, the next crucial step is data preprocessing. This meticulous process involves cleaning the data, handling missing values, normalizing data scales, and converting categorical data into machine-readable formats. The uniformity of data achieved through proper preprocessing is instrumental in eliminating biases and improving the overall predictive accuracy of the AI models. Following this, feature selection is conducted to identify the most impactful features for classification. This step involves using statistical techniques and selection algorithms to focus on attributes that significantly predict rock mass properties, thus enhancing the efficiency and computational speed of the AI models.

The core of the development process is model training, where machine learning algorithms, such as Decision Trees or Neural Networks, are employed. This phase includes optimizing parameters and using techniques like k-fold cross-validation to refine the models, with well-tuned models often achieving accuracy rates above 90%. After training, models undergo a validation process using a separate dataset to evaluate key metrics such as accuracy, which typically aims for higher than 85% and other measures like precision and F1-scores expected to exceed 0.85. Validating the models ensures they are effective and reliable for practical applications outside controlled testing environments.

Deploying AI models in real-world settings involves their implementation and continuous updating with new data. This continuous learning is a key feature that allows the models to adapt to changing environmental conditions, thereby maintaining or improving their accuracy over time. The benefits of AI-based models are substantial; they reduce human bias by relying on quantitative data, adapt in real-time to changing conditions, manage large-scale data efficiently, and detect subtle patterns that may be missed by humans.

However, the development of these models is challenging. Data quality and availability can significantly limit AI effectiveness, where data quality leads to accurate predictions. There is also a risk of overfitting, where models perform well on training data but poorly on new, unseen data. Additionally, complex models, such as intense learning models, often need more transparency in their decision-making processes, making them difficult to trust and validate. Moreover, developing and maintaining these models require significant computational resources and expertise, which can be costly.

In conclusion, AI-based models for rock mass classification represent a significant advancement over traditional methods, offering improved predictive power and operational efficiency in geotechnical assessments. Despite challenges like data quality and model complexity, the advantages of using AI in this field underscore its potential as a crucial tool in modern geotechnical engineering. As AI technology continues to evolve, it is poised to become increasingly central in the industry, driving innovation in construction and mining projects.

- Benefits of AI-Based Models

Reduced Human Bias: AI models minimize the subjectivity of traditional rock mass classification methods by relying on data-driven insights.

Adaptability: AI can incorporate real-time data, allowing for dynamic updates to classifications as new information becomes available or as environmental conditions change.

Scalability: AI models can handle vast amounts of data and complex datasets more efficiently than manual methods.

Precision: With advanced computational capabilities, AI can uncover complex patterns in data that human analysts might overlook.

Developing AI-based models for rock mass classification is a promising approach that leverages technological advancements to improve the accuracy and reliability of geotechnical assessments. While there are challenges, the potential benefits of enhanced predictive power, efficiency, and reduced bias make it a valuable tool in modern geotechnical engineering. As AI technology evolves, these models are expected to become even more integral to the field, driving innovations in construction and mining projects.

5.5 Discussion of Evaluating Model Performance Using Classification Metrics

Evaluating the performance of machine learning models in rock mass classification is critical to determining their practical applicability and reliability in geotechnical engineering projects. In this context, models' performance is typically assessed using a suite of classification metrics that provide a comprehensive view of model accuracy and effectiveness. The metrics used include accuracy, precision, recall, and the F1 score.

The Logistic Regression model, a key player in our evaluation, has demonstrated exceptional performance. With an accuracy rate of 98.03%, it correctly predicts the rock class for a staggering 98.03% of the instances, instilling a high level of confidence in its reliability.

Precision measures the accuracy of optimistic predictions. It quantifies the number of accurate positive predictions made from all optimistic predictions (including both true and false positives). In the Logistic Regression model context, the precision is exceptionally high at approximately 98.07%. This high precision rate signifies that the model is very effective at minimizing false positives, which is crucial in projects where the cost of a prediction error can be very high.

Recall, or sensitivity, indicates the model's ability to identify all relevant instances correctly. Precisely, it measures the proportion of actual positives that are correctly identified as such (true positives) relative to the sum of the true positives and the false negatives (instances that were incorrectly classified as negatives). The Logistic Regression model exhibits a recall of 98.03%, demonstrating its efficacy in capturing nearly all positive instances without leaving many false negatives.

F1 Score is the harmonic mean of precision and recall and is particularly useful when the class distribution is uneven. It balances precision and recall by considering both false positives and false negatives. The Logistic Regression model achieves an F1 score of 98.03%, indicating excellent balance in precision and recall. This balance is essential in ensuring the model is balanced with avoiding false positives or maximizing true positives. This is particularly important in nuanced geotechnical assessments where both types of errors can have significant implications.

The performance metrics of the logistic regression model developed for rock mass classification underscore its robustness and accuracy. These results are significantly superior to those of a dummy classifier, which is used as a baseline for comparison. The dummy classifier's accuracy was only 24.29%, with precision and recall both around the same level, highlighting its ineffectiveness. The stark contrast in performance metrics between the logistic regression and the dummy classifier emphasizes the advantages of using advanced machine learning techniques over simpler, naive methods.

Visual tools like heat maps and confusion matrices are also employed to represent the model's performance across different rock classes. These visualizations help identify specific areas where the model may be underperforming, such as certain rock classes that may be more challenging to classify accurately. They provide an intuitive understanding of model performance, showing where improvements might be focused to enhance the model further.

Evaluating machine learning models using these classification metrics allows for a detailed assessment of their predictive accuracy and reliability. It ensures that the models can be confidently applied in real-world geotechnical projects, where the accuracy of rock mass classification can significantly impact project safety and cost efficiency.

5.6 Discussion of Visualizing Model Performance and Identifying Improvements

Visualizing model performance and identifying areas for improvement are crucial for refining machine learning models used in rock mass classification. Practical visualization tools such as confusion matrices, heatmaps, and scatter plots provide clear insights into how a model predicts across different categories and highlight specific areas needing adjustments to enhance accuracy and reliability.

In the discussion of logistic regression model performance from Chapter 4, several visual tools are utilized:

Confusion Matrices: These matrices are vital for showing the actual versus predicted classifications, allowing for a detailed analysis of true positive, false positive, true negative, and false negative counts across different rock classes. For example, a confusion matrix might reveal frequent misclassifications between two particular rock classes, indicating a need for model tuning or feature reassessment.

Heatmaps: Using confusion matrices, heatmaps use colour gradations to represent different performance metrics such as precision, recall, and F1-score for each class. This visualization makes it easier to detect underperforming courses at a glance. For instance, if Class 3 consistently shows lower scores, it is visually apparent and can be addressed more directly.

Scatter Plots: These plots demonstrate the relationships between critical features and the classifications made by the model. By plotting features such as Rock Quality Designation (RQD), Joint Roughness (Jr), and Stress Reduction Factor (SRF) against rock class, scatter plots help validate whether the model appropriately captures critical predictive relationships. If the scatter plots show clear trends that the model does not predict, this might suggest that additional feature engineering or model complexity is needed.

As shown by these visual tools, the logistic regression model from Chapter 4 demonstrated significant improvements in handling rock mass classification. For instance, the heatmap illustrated in the chapter shows that Class 1 and Class 5 have high precision, recall, and F1-scores close to 1.00, indicating excellent model performance for these categories. However, Class 3 exhibited slightly lower metrics, signalling a potential area for model improvement.

These visual tools facilitate a deeper understanding of the model's performance by:

They highlight discrepancies such as overfitting, where the model might perform well on training data but poorly on unseen test data.

Clarifying the model's behaviour, particularly how changes in input features impact predictions, guiding further fine-tuning.

Directing specific improvements by pinpointing underperforming classes or features, which additional data collection, alternative modelling techniques, or adjustments in feature processing could improve.

By integrating these visual insights, engineers and data scientists can strategically enhance model reliability and accuracy, ensuring that the machine learning model is well-suited for practical applications in geotechnical engineering.

5.7 Discussion of Comparing AI Models with Baseline and Selecting the Best Model

Comparing AI models with a baseline model and selecting the best one is critical in machine learning, especially in fields like geotechnical engineering, where accuracy can significantly impact practical applications. This process involves evaluating various models against a simple baseline to understand the improvements offered by more sophisticated algorithms. Rock mass classification means assessing models like logistic regression against basic classifiers such as dummy classifiers.

- Baseline Model

The baseline model, often a dummy classifier, serves as a starting point. It typically uses simple rules, such as randomly predicting the most frequent class or generating predictions. The purpose of the baseline is to perform better but to establish a minimum performance threshold. For instance, if the dummy classifier achieves an accuracy of 24.29%, this sets a low benchmark for other models to exceed. This model's performance is crucial because it contextualizes the performance improvements provided by more advanced algorithms.

- Advanced AI Models

After establishing the baseline, various AI models are introduced and evaluated. These models include logistic regression, decision trees, support vector machines, or neural networks. Each model is trained using the same dataset as the baseline and then tested to compare performance metrics such as accuracy, precision, recall, and F1 score.

- Performance Evaluation

The logistic regression model, for instance, may show a dramatic improvement over the baseline. Suppose the logistic regression achieves an accuracy of 98.03%. In that case, it not only significantly surpasses the baseline but also demonstrates the capability of advanced models to handle the complexity of geological data effectively. The precision, recall, and F1 scores would similarly reflect this enhancement, indicating a robust model that balances identifying true positives and avoiding false positives.

- Model Selection Criteria

The selection of the best model is based on several criteria:

Accuracy: How often the model predicts the correct class. Higher accuracy in logistic regression compared to the dummy classifier illustrates its effectiveness.

Precision and Recall: Precision measures the correctness achieved in optimistic prediction, while recall measures how well the model can find all the positive samples. The best model should balance these metrics, often evaluated using the F1 score, the harmonic mean of precision and recall.

Generalizability: The ability of the model to perform well on unseen data, not just the data on which it was trained.

Computational Efficiency: Considering the complexity and computational cost of the model, it is essential in real-time applications.

- Comparison and Discussion

When comparing AI models with the baseline, logistic regression models are far superior in handling detailed and complex data and adapting to the nuances of geological variations. These models also offer real-time adaptability, which is crucial for projects with dynamic conditions such as tunnelling or mining.

In summary, comparing AI models against a baseline involves detailed performance analysis and practical considerations like model complexity and execution speed. The selected model must outperform the baseline in terms of accuracy and other metrics and meet the operational requirements of geotechnical engineering. This comprehensive evaluation ensures the best model is chosen, improving decision-making and project outcomes.

CHAPTER VI:

SUMMARY, IMPLICATIONS, AND RECOMMENDATIONS

6.1 Summary

The research focuses on enhancing rock mass classification systems by integrating advanced machine learning (ML) models, contrasting these new methods against traditional classification systems. The study spans several critical areas: evaluating existing classification methods, developing and refining AI-based models, assessing their performance, and visualizing their predictions to guide improvements.

The research begins with a comprehensive literature review detailing traditional rock mass classification systems like the Rock Mass Rating (RMR), Geological Strength Index (GSI), and Q-System. These systems are noted for their reliance on quantifiable geological parameters but criticized for their simplicity and static nature, which do not account for the complex, dynamic conditions often encountered in geotechnical projects.

The methodology section outlines a robust approach involving collecting extensive data from borehole samples covering various geological conditions. The data undergoes preprocessing to ensure accuracy and relevance, and ML models are developed and trained to predict rock mass classifications based on this data. Essential ML techniques include Logistic Regression, Decision Trees, and Support Vector Machines.

- Model Development and Evaluation

The document details the development of AI-based models, emphasizing the importance of data quality and the application of sophisticated ML algorithms. Models are trained on a dataset that includes parameters like Rock Quality Designation (RQD), Joint Set Number (Jn), and Joint Roughness Number (Jr). The model-building process includes data cleaning, feature selection, and splitting the dataset into training and testing subsets for practical model evaluation.

Model performance is critically evaluated using accuracy, precision, recall, and F1 score metrics. The logistic regression model, in particular, shows significant improvement over a simple dummy classifier, achieving high accuracy and balanced precision and recall across various rock classes. These metrics underscore the model's capability to effectively predict rock mass quality, validating ML use in geological classifications.

- Visualization and Analysis

Visualization techniques like heat maps, confusion matrices, and scatter plots are employed to analyze model performance. These tools help identify areas where models perform well or need improvement, providing intuitive insights into the classification process. Visual analytics support the model's strengths in accurately classifying rock masses and highlighting potential areas for tuning and further development.

The research compares the performance of developed ML models against baseline models (dummy classifiers). This comparison highlights the superiority of ML models in handling complex data and adapting to dynamic conditions in geotechnical engineering. The logistic regression model, for instance, markedly outperforms the dummy classifier, showcasing the benefits of applying advanced computational techniques in practical engineering scenarios.

The final discussion synthesizes findings from the literature review, model development, performance evaluation, and visualization stages. It emphasizes the transformative potential of AI in rock mass classification, noting the enhanced accuracy, efficiency, and adaptability of ML models compared to traditional methods. The research advocates for a broader adoption of AI-driven approaches in geotechnical engineering, proposing ongoing development and integration of these technologies into standard engineering practices.

The document calls for further research into hybrid systems that combine traditional and AI methods, ensuring that the interpretability of conventional approaches complements the robustness of ML predictions. It also highlights the need for standardization and training in AI applications within geotechnical engineering to promote widespread adoption and operational integration.

In summary, this research establishes a strong foundation for using AI and machine learning in rock mass classification, offering detailed insights into its practical benefits and paving the way for future innovations in geotechnical engineering practices.

6.2 Implications

The implications of this research on enhancing rock mass classification systems with machine learning (ML) models are profound and multi-faceted, extending across technical, operational, and educational realms of geotechnical engineering. Here are the critical implications detailed in the research:

- Technical Advancements

Integrating AI and ML in rock mass classification represents a significant technical leap from traditional methods. These advanced models can handle complex, multidimensional data and uncover non-linear relationships often missed by conventional approaches. This capability allows for a more nuanced understanding of geological conditions, which is critical in ensuring the safety and feasibility of construction projects.

Improved Accuracy and Reliability: ML models demonstrated high accuracy and reliability in predicting rock mass quality, as evidenced by metrics such as precision, recall, and the F1 score. These improvements reduce the risk of errors in classifying rock mass quality, which can lead to better decision-making in construction planning and execution.

Real-time Data Processing: Unlike traditional systems, AI-based models can incorporate and analyze real-time data from sensors and other monitoring equipment. This adaptability allows for ongoing adjustments to classifications as new geological information becomes available, enhancing the responsiveness to changing site conditions.

- Operational Efficiency

The use of AI in rock mass classification can significantly optimize operational aspects of geotechnical projects:

Dynamic Project Management: With real-time data integration and faster processing capabilities, AI models enable more dynamic project management. Engineers can update their assessments and decisions based on the latest data, leading to more efficient and adaptive project workflows.

Cost Efficiency: By improving the accuracy of rock mass classification, AI models can help reduce costs associated with over- or under-designing construction solutions. Precise classifications help ensure that resources are allocated more efficiently, preventing unnecessary expenditures on overly cautious designs or costly remediations due to underestimating geological challenges.

- Safety Improvements

The enhanced predictive accuracy of AI models directly contributes to safer construction practices:

Reduced Geotechnical Risks: Accurate rock mass classification helps identify potential geotechnical risks, such as unstable rock formations, allowing for preemptive measures to mitigate them before they pose severe threats to project integrity and safety.

Tailored Construction Techniques: With detailed insights into rock mass quality, construction teams can tailor their techniques and strategies to the site's specific conditions, further enhancing safety and effectiveness.

- Educational and Training Opportunities

As AI becomes more integrated into geotechnical engineering, there is a growing need for educational programs that can train engineers in the latest AI and ML techniques:

Curriculum Development: Educational institutions may need to update curricula to include training in AI and ML applications in geotechnical engineering to prepare new engineers for the changing landscape of the field.

Professional Development: Ongoing training programs for practising engineers will be essential to ensure they can effectively utilize AI-based tools and methodologies in their projects.

- Standardization and Regulatory Considerations

Adopting AI in rock mass classification will necessitate the development of new standards and regulations:

Standards for AI Use: Industry-wide standards will be needed to guide the use and validation of AI models in geotechnical engineering and ensure consistency and reliability across projects and jurisdictions.

Regulatory Adjustments: Regulatory bodies may need to adjust existing codes and regulations to accommodate the use of AI in geological assessments and construction planning.

6.3 Recommendations for Future Research

Building upon the findings from this research on integrating machine learning (ML) models into rock mass classification, several recommendations for future research can be delineated. These recommendations aim to address existing gaps, leverage new technologies, and enhance the effectiveness and applicability of AI in geotechnical engineering.

- Hybrid Modeling Approaches

Integrating Traditional and AI Methods: Future studies should explore the development of hybrid models that combine the robustness and interpretability of traditional geotechnical methods with the predictive power of AI. This approach could benefit from conventional systems' straightforwardness and ease of use while enhancing accuracy and adaptability with AI capabilities.

Case Studies on Hybrid Models: Conducting detailed case studies to assess the effectiveness of hybrid models in real-world settings would provide practical insights into their benefits and limitations.

- Enhanced Data Collection and Quality

Comprehensive Data Sets: More comprehensive and high-quality datasets that include a wider range of geological conditions and rock types are needed. Future research should focus on the systematic collection of data covering more diverse and extensive geological scenarios.

Data Standardization: Develop standards for data collection, processing, and sharing within the geotechnical community to ensure consistency and reliability of the data used for training and testing AI models.

- Advanced Machine Learning Techniques

Exploration of New Algorithms: Investigating the application of emerging ML algorithms that have shown promise in other fields, such as deep learning and reinforcement learning, could uncover new opportunities for improving rock mass classification systems.

Feature Engineering and Selection: Enhanced research into feature engineering and the selection processes that identify the most impactful variables for rock mass classification can optimize model performance and computational efficiency.

- Real-Time Monitoring and Adaptive Models

Development of Real-Time Models: Future studies should focus on developing and validating models that can integrate and analyze data in real time, providing ongoing adjustments to rock mass classifications as conditions change during construction.

Sensor Technology Integration: Research integrating advanced sensor technologies, such as LiDAR or UAV-based monitoring, with AI models would help continuously update the data pool, improving the models' adaptability and accuracy.

- Validation and Standardization

Robust Validation Frameworks: Establishing robust frameworks for validating and verifying AI models in geotechnical applications is critical. This includes cross-validating with data from various global regions to ensure the models' generalizability and reliability.

Standardization of AI Applications: Proposing and developing industry-wide standards and protocols for using AI in rock mass classification to ensure consistent application and results across different projects and geographies.

6.4 Conclusion

This dissertation has explored integrating machine learning (ML) models into geotechnical engineering, specifically focusing on enhancing rock mass classification systems. Traditional methods, such as the Rock Mass Rating (RMR), Geological Strength Index (GSI), and Q-System, have long served as reliable frameworks for classifying rock masses. However, these conventional systems have limitations in handling complex geological scenarios, dynamic environments, and the inherent subjectivity involved in human assessments. The introduction of AI and ML offers a promising solution to these limitations, improving accuracy, adaptability, and scalability in rock mass classification.

The research conducted in this dissertation aimed to address several critical objectives: improving the classification accuracy of rock masses through AI models, reducing human bias in the classification process, and integrating advanced data analysis techniques to enhance the overall predictability of rock mass behaviour. The study demonstrated the significant advantages of data-driven approaches by comparing traditional methods with machine learning models, such as logistic regression and decision trees.

One of the key findings was the dramatic improvement in classification accuracy when AI-based models were employed. The logistic regression model, in particular, achieved an accuracy of 98.03%, far surpassing the baseline dummy classifier's performance of 24.29%. This highlights the importance of machine learning in accurately capturing the relationships between critical geological features like Rock Quality Designation (RQD), Joint Roughness Number (Jr), and Stress Reduction Factor (SRF), which are crucial for predicting rock mass quality.

Moreover, this research identified the essential role of data quality, preprocessing, and feature selection in ensuring the success of AI models. The findings underscore the need for comprehensive and high-quality datasets that can represent diverse geological conditions. Furthermore, visual tools such as heatmaps, confusion matrices, and scatter plots were crucial in evaluating model performance, providing insights into areas where the models performed well and where improvements could be made.

Despite AI's clear advantages in rock mass classification, the research also acknowledged specific challenges. These include the complexity of AI models, the significant computational resources required, and the dependency on high-quality data.

Overfitting and the "black box" nature of some AI models pose additional challenges, particularly regarding interpretability and trust in real-world applications.

In conclusion, this dissertation underscores the transformative potential of AI and machine learning models in enhancing rock mass classification. These models offer superior accuracy, adaptability, and efficiency over traditional methods. However, to fully realize their potential, future work must address challenges such as data quality, model interpretability, and industry-wide standardization. With the continuous advancement of AI technologies, these systems have immense potential to revolutionize geotechnical engineering practices, ensuring safer and more efficient outcomes in construction, tunnelling, mining, and other engineering projects that rely on accurate rock mass classification.

APPENDIX A

PUBLICATION LIST

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