Prediction of Rock Mass GSI using Image Processing

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A thesis of BE degree submitted to the National University of Sciences and Technology, Islamabad,

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Supervisor: Dr. Naseer Muhammad Khan

Military College of Engineering, Risalpur

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THESIS ACCEPTANCE CERTIFICATE

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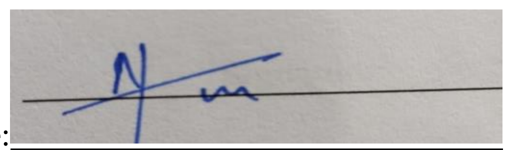
Signature: 

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No part of this thesis has been submitted anywhere else for any other degree. This thesis is submitted to the Department of Geotech & Transportation, Military College of Engineering, Risalpur in partial fulfillment of the requirements for the degree of Bachelor's in Civil Engineering.

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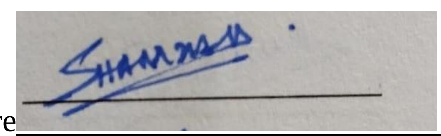
Signature 

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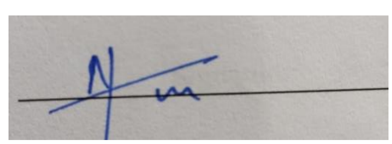
Signature: 

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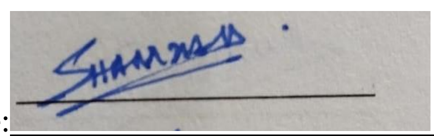
Signature: 

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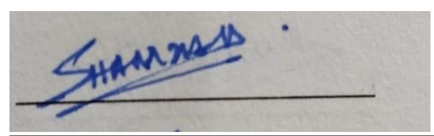
Student Signature: 

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DEDICATION

To Almighty Allah for giving us the strength to undertake this project. And to our parents, whose dedication and teachings have been a beacon of light all our lives.

ACKNOWLEDGEMENTS

We are very thankful to our affectionate and great parents because their love and prayers enabled us to achieve this goal.

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All Syndicate members

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ABSTRACT

The Geological Strength Index is a vital tool for determining the strength of rock mass including two main factors, structure of the rock mass & weathering conditions. This allows to classify the rock mass between 1-100 from the table developed by Hoek. Earlier the methods used were inefficient & incompatible since they were focused entirely on visual observation & practical expertise of the individual which was prone to many discontinuities in the results. Keeping in mind this gap, our prime objective was to develop an image processing framework for rock mass images with help of CNN, to train machine learning to predict GSI values & to validate the accuracy & reliability of the predictive models. Finally, a user-friendly tool for GSI prediction was created based on the image inputs. Following an efficient methodology in which we acquired our rock mass data from Abbottabad Motorway with help of drone DJI Mavic 3, then images taken were pre-processed to grey-scale images to control the shading & lightning conditions of rock mass. These pre-processed images were divided into two datasets, training & testing datasets. Afterwards, a CNN based framework was established in which the layers were included to teach the model only about the structure & weathering conditions which in turn gave us the GSI value from the input images. The training set was now used to train the model & remove the discrepancies. Cross validation was done to improve the accuracy & reliability of model. This tool is ready to be used on site for predicting GSI of rock mass. Nexus to above, some of the future directions regarding this research to improve the practicality & efficiency of this model will be to further refining the CNN model architecture to improve prediction accuracy. Exploring additional features or data sources that could enhance the model's performance & investigating the transferability of the model to different geological settings or rock types. Finally, carrying out detailed validation experiments to assess the real-world applicability of the model.

Keywords: GSI, Geological Strength Index, image processing, CNN, machine learning model

CHAPTER 1: INTRODUCTION

1.1 Overview

In geology, Rock is a naturally existing and clear aggregate of different kinds of minerals. The aggregates form the elementary unit of solid Earth mass and classically form familiar and map able volumes. Rocks are divided into six main classes based on their structure. (Zuo, 2020) these classes are.

- Intact Rock Mass

  A portion of rock that is undisturbed and free from any of the discontinuities such as joints, cracks, faults, or bedding planes. Essentially, a large & coherent piece of rock that has not been fragmented by natural processes (earthquakes, volcanic eruptions, etc.) or human activities (blasting, mining, etc.)

- Blocky Rock Mass

  A rock mass indicates an even higher degree of fragmentation compared to a *blocky rock mass*. In such a rock mass, the discontinuities such as joints and fractures are densely packed, creating smaller rock blocks.

- Very Blocky Mass

  A type of rock mass characterized by the presence of numerous joints that divide the rock into distinct blocks or angular pieces.

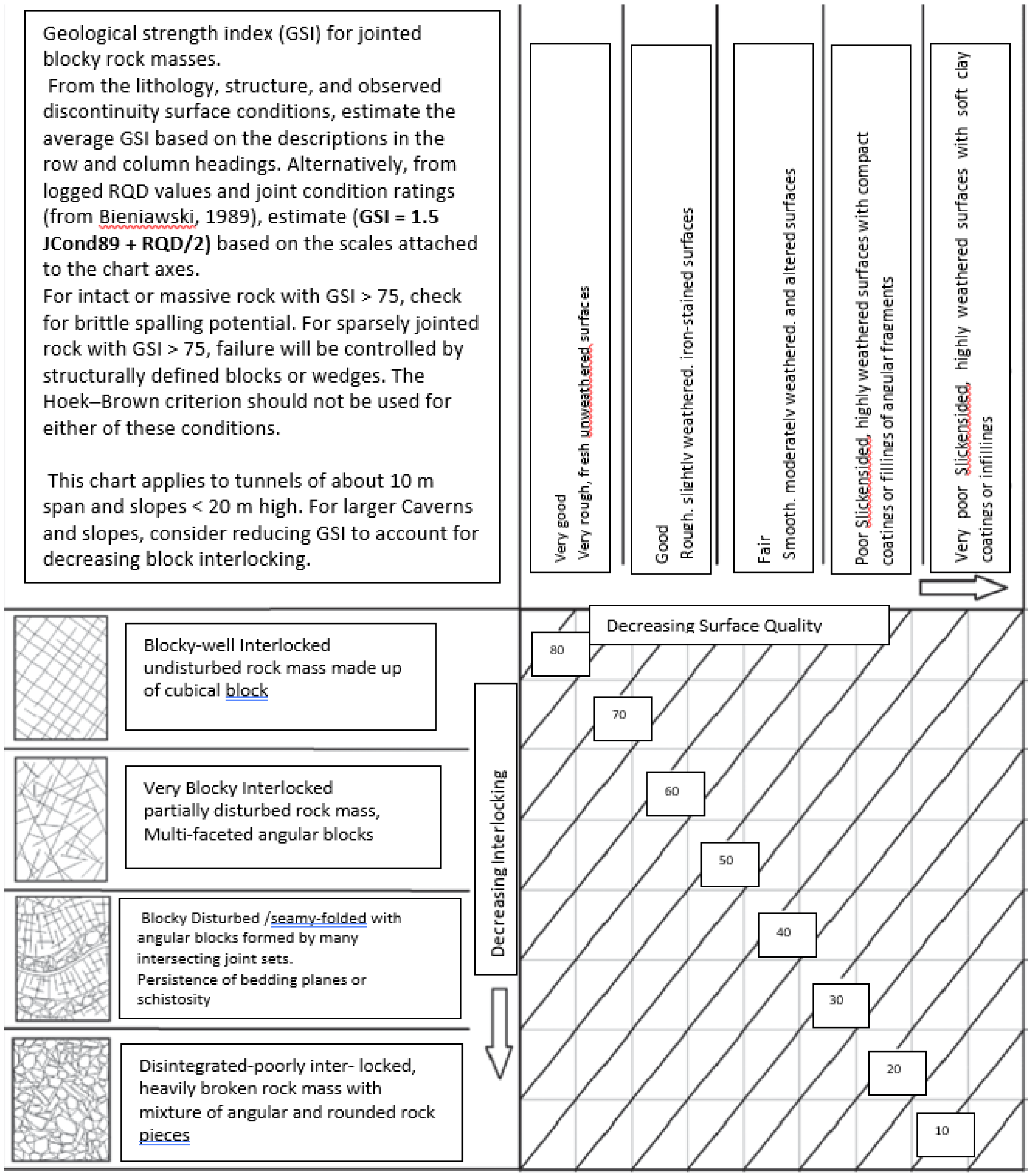
- Disturbed Mass

This rock mass refers to a type of rock structure characterized by the presence of layers or laminations, which are typically formed by sedimentary processes. These layers may vary in thickness, composition, and mechanical properties.

- Laminated Mass

A rock mass that has undergone extensive weathering or mechanical breakdown, causing it to lose cohesion and break into small particles or fragments. This type of rock mass presents challenges due to its reduced structural integrity and altered mechanical properties.

Table 1 Chart for determining GSI of jointed rock mass.



So, to assess the stability of discontinuous rock mass, it is of prime importance that we ascertain and measure the strength of the rock mass.(Abbas) Geological strength index (GSI) is one of the most remarkable methods for classifying rock mass which is related to the geo-mechanical properties *(deformation in response to changes of stress, pressure, temperature, and other parameters)* of the rock mass and includes generalized Hoek & Brown constants, deformation modulus, strength properties, and Poisson's ratio for the proper design of caves, tunnels, and other engineering works.

Much research was made to highlight how this system differs from the Q-system, the rock mass rating (RMR), and other empirical techniques(Bieniawski) It was effectively promoted as an empirical tool for the estimation of the geo-mechanical properties of rock mass required for pre-post stability of engineering structures using numerical modelling.(Marinos, (2005)) It made use of field observations, blockiness of the rock mass, and surface joint characteristics during the evaluation process of rock mass.(Hussian, 2020)

Nexus to above, our research was focused on production of a model where it is taught about the vales & will give answer specific to them when required. The broad underpinning of research method was largely exploratory. The research was carried out smoothly by studying the previous work done by researchers in similar fields and technical advice from experts.

1.2 Problem Statement

As mentioned above, traditional methods of GSI estimation often rely on time-consuming and subjective manual observations, leading to inconsistencies and potential safety hazards. Therefore, there is a pressing need for a more precise, efficient & objective approach to predict GSI. With that we come towards the aim of this research which is to explore the application of image processing techniques offering a promising solution to improve rock mass GSI prediction.

1.3 Objectives

The Objectives of our study are:

- To develop an *image processing framework* using algorithms for extracting relevant features from rock mass images
- To train *machine learning models* using the extracted features to predict GSI values.
- To validate the *accuracy & reliability* of the predictive models.
- To create a *user-friendly tool* for GSI prediction based on image inputs.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

Geotechnical engineering relies heavily on understanding the mechanical properties of rock masses to ensure the stability and safety of various civil engineering projects, such as tunnels, slopes, and excavations. One crucial parameter used in assessing the strength and behavior of rock masses is the Geological Strength Index (GSI). The GSI, first introduced by Hoek et al. (1995), is a numerical scale ranging from 0 to 100 that quantifies the rock mass quality based on geological characteristics. The GSI takes into account several factors, including rock structure, weathering, alteration, jointing, and geological discontinuities, to provide a comprehensive assessment of the rock mass strength.(Somodi, (2021).) A higher GSI value indicates better rock mass quality, characterized by fewer defects, stronger intact rock, and more favorable geological conditions for engineering purposes. Understanding the GSI is essential for engineers and geologists involved in various geotechnical projects, as it influences design decisions, construction methods, and risk assessments.(Marinos, (2005))

2.2 Traditional Methods of GSI Determination

After reviewing, following methods have been studied which are referred as traditional methods.(Bieniawski, 1993; Hong, 2017)

2.2.1 Field Mapping and Geological Observations

In this section, the authors likely discuss the conventional practice of conducting field mapping and geological observations to assess the Geological Strength Index (GSI). They may explain how geologists and engineers inspect rock outcrops, cliffs, and excavation sites to identify geological features such as joint sets, bedding planes, foliation, and weathering patterns.(Zhang, 2019)) These observations are then used to qualitatively assign GSI values based on the Rock Mass Rating (RMR) or other classification systems.

2.2.2 Core Logging and Sampling

The procedure of "core logging," which involves removing cylindrical rock cores from drill holes or other openings, would be included in this subsection. The writers might explain the process by which geologists evaluate the rock quality, roughness, discontinuity spacing, and other pertinent factors using the recovered core samples. Visual inspection and laboratory testing of core samples, such as rock strength tests, geological characterization, and mineralogical analysis, are frequently used to determine GSI values.

2.2.3 Laboratory Testing and Rock Mechanics Analysis

In this case, the paper would go into depth on the laboratory tests used to calculate GSI using an analysis of rock mechanics. This could involve point load testing, Brazilian tests, uniaxial and tri-axial compression tests, and other common laboratory techniques for determining the strength and deformation characteristics of rocks. The authors might go on how GSI computations and rock mass classification systems incorporate laboratory-derived metrics like tensile strength, Young's modulus, and Poisson's ratio.

2.2.4 Integration with Modern Techniques

The authors may quickly discuss efforts to combine contemporary technology like remote sensing, LIDAR (light detection and ranging), and GIS (geographic information systems) with conventional GSI determination methods to wrap up this section. The constraints of traditional methodologies in terms of impartiality, scalability, and automation may not be entirely addressed by new technologies, despite the opportunity they present to improve data collecting and analysis.

2.3 Image Processing Techniques in Geotechnical Engineering

2.3.1 Introduction to Image Processing

It provides a summary of how image processing methods are used in geotechnical engineering. This tool describes the roles that remote sensing, photogrammetry, and digital image processing play in the extraction of geological features and the characterization of rock masses.(Cui, 2011, December)

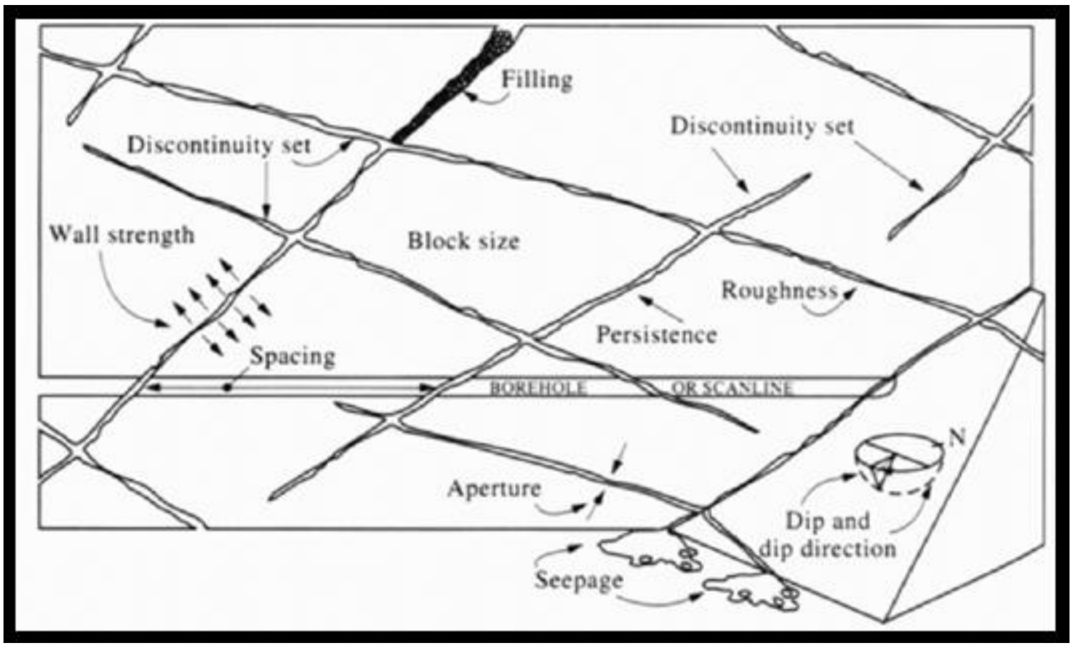


Figure 1 Schematic view of geometric properties of Discontinuities.

2.3.2 Digital Image Analysis

The method of deriving quantitative information from digital photographs is known as digital image analysis. The technique talks about popular methods for edge identification, texture analysis, and morphological operations in digital image analysis for geotechnical applications. It describes the use of digital image analysis in the classification of rock masses, mapping discontinuities, and characterization of fractures.

2.3.3 Photogrammetry

Photogrammetry is a technique that uses overlapping photos to create precise three-dimensional (3D) representations. It emphasizes the process of creating point clouds, matching features, and acquiring images using photogrammetric techniques. It describes the benefits of photogrammetry for geotechnical engineering, including its cost-effectiveness, high spatial resolution, and non-destructive data collection.

2.3.4 Integration of Image Processing Techniques

It investigates how several image processing methods might be used to provide a thorough characterization of the rock mass. This tool explains how multi-scale and multi-modal data for geotechnical study can be obtained by combining digital image processing, photogrammetry, and remote sensing. It offers illustrations of integrated image processing workflows used in geotechnical applications, including mapping subterranean and landslide detection and slope stability analysis.

2.3.5 Challenges and Considerations

It discusses the difficulties that come with using image processing techniques in geotechnical engineering, including restrictions on data collecting, distorted images, and processing artifacts. It talks about factors to consider when choosing the best image processing techniques depending on the needs of the project, the size of the area, and the availability of data. To guarantee the precision and dependability of the results, emphasize the significance of validation and quality assurance in image-based geotechnical analysis.

2.4 Local Image Descriptors in Geotechnical Engineering

2.4.1 Introduction

Local image descriptors are introduced as computational techniques designed to detect and describe key points or features within an image. These descriptors enable the extraction of relevant information from images, facilitating subsequent analysis and interpretation.**(**Tareen, 2018, March)

2.4.2 Types of Image Descriptors

This section discusses different types of local image descriptors commonly used in geotechnical engineering.

- Scale-Invariant Feature Transform (SIFT)

SIFT algorithm detects key points at various scales and orientations, making it robust to changes in scale and rotation.

- Speeded Up Robust Features (SURF)

SURF algorithm accelerates key point detection using integral images and Haar wavelets, offering computational efficiency and robustness.

- Oriented FAST and Rotated BRIEF (ORB)

ORB algorithm combines FAST key point detection with BRIEF descriptor, providing a fast and efficient method for feature extraction.

2.4.3 Application in Geotechnical Engineering

This section highlights the relevance of local image descriptors in geotechnical applications.

- Rock Mass Characterization

To help with the evaluation of the stability and quality of rock masses, local image descriptors are utilized to recognize and categorize geological characteristics inside the rock masses.

- Fracture Detection

Local image descriptors aid in fracture mapping and characterization by identifying and characterizing discontinuities and fractures in geological pictures.

- Discontinuity Mapping

Local image descriptors enable the mapping of geological discontinuities such as joints, faults, and bedding planes, providing valuable information for geological hazard assessment and engineering design.

2.4.4 Advantages and Limitations

Strengths include Automation, objectivity, scalability, and the ability to capture fine-scale geological features while weaknesses are sensitivity to variations in lighting conditions, image noise, and occlusions, as well as the need for parameter optimization and algorithm selection.

2.4.5 Future Directions

The article concludes by outlining potential future directions for research and development in the field of local image descriptors in geotechnical engineering, including:

- Integration with machine learning techniques for enhanced feature detection and classification.
- Further optimization of algorithms to improve performance in challenging geological environments.
- Interdisciplinary collaborations to advance the state-of-the-art in image-based geotechnical analysis.

2.5 Machine Learning Methods for GSI Prediction

Machine learning methods offer promising avenues for predicting Geological Strength Index (GSI) values based on input data such as geological images, geophysical measurements, and geotechnical parameters. This section explores various machine learning algorithms and techniques used for GSI prediction in geotechnical engineering applications.(Hong, 2017)

2.5.1 Introduction to Machine Learning in Geotechnical Engineering

In recent years, machine learning has emerged as a powerful tool in various fields, including geotechnical engineering, offering novel approaches to predictive modelling, data analysis, and decision-making. This section provides an overview of the application of machine learning techniques in geotechnical engineering and highlights their potential contributions to GSI prediction.

- Rise of Machine Learning

In recent years, there has been a notable increase in the application of machine learning techniques within the field of geotechnical engineering. This rise can be attributed to several factors. Geotechnical engineers now have enormous volumes of data at their disposal because to advancements in sensor technology, remote sensing, and geological imaging methods. Large data set processing and analysis are strengths of machine learning algorithms, which makes them ideal for gleaning insightful information from a variety of geotechnical data sources.

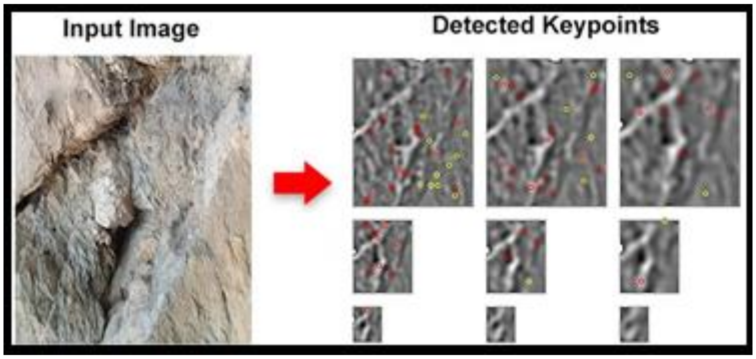


Figure 2 Application of machine learning in geotechnical engineering.

- Predictive Modelling

Using past data and identified trends, predictive modeling entails creating mathematical models that project future behavior or results. Predictive modeling in this instance is concentrated on calculating GSI values, which are important factors in determining the stability and strength of the granite mass. Regression and classification models are two examples of machine learning methods that are used to create prediction models from input characteristics including geological parameters, geophysical measurements, and image descriptors. These algorithms employ the patterns they discover from the training set of data to forecast fresh, unobserved data.

- Decision Making

In geotechnical engineering, choices are made concerning engineering projects based on the information and forecasts given by predictive models. These choices might have to do with risk mitigation techniques, tunneling, foundation design, slope stability studies, and site selection. Predictive models based on machine learning aid in decision-making by providing probabilistic estimates, pointing out important variables affecting GSI values, and evaluating the degree of prediction uncertainty. These insights can help engineers optimize design parameters, manage resources wisely, and put suitable risk control procedures in place.

- Interdisciplinary Collaboration and Knowledge Sharing

Numerous academic fields are included in geotechnical engineering, such as data science, computer science, geology, and civil engineering. Experts from these several professions collaborate to address challenging geotechnical issues. According to the publication, sophisticated predictive modeling tools for GSI prediction may be developed and applied by geotechnical engineers in conjunction with computer scientists, machine learning researchers, and data scientists through multidisciplinary collaboration. It is possible to integrate domain-specific knowledge and experience from several domains through interdisciplinary collaboration. While computer scientists and data scientists offer experience in machine learning methods, data analysis, and computational approaches, geotechnical engineers add their grasp of geological processes, rock mechanics, and engineering concepts.

2.5.2 Research Objectives and Contribution

The research objectives and contributions of the mentioned article are focused on advancing the field of geotechnical engineering through the development and application of novel methodologies for predicting Geological Strength Index (GSI) values. Here's an explanation of the research objectives and contributions.

- **Objective 1** Develop a Methodology for GSI Determination

For this, key characteristics from geological photos are extracted using algorithms and procedures, and machine learning models are then used to estimate GSI values based on these features.

- **Objective 2** Evaluate Performance and Accuracy

Comparing the performance and accuracy of the suggested technique to conventional methods for GSI value prediction is another goal. To evaluate the effectiveness, robustness, and dependability of the machine learning-based technique for GSI determination, experiments and validation studies must be carried out.

- **Objective 3** Demonstrate Practical Applications

The goal of the study is to show how the created technique may be applied in real-world geotechnical engineering settings. To evaluate how well the approach predicts GSI values for various geological formations and engineering projects, it must be applied to case studies or field trials.

- **Objective 4** Identify Opportunities for Improvement

The study also looks for ways to optimize the process and find areas for further advancement. This entails evaluating the benefits and drawbacks of the suggested methodology, seeing possible areas for improvement, and putting forward plans for further study and investigation.

2.5.3 Novel Methodology for GSI Determination

The article's main contribution is the creation of a unique GSI determination approach that makes use of machine learning techniques and local image descriptors. Through the integration of sophisticated data analytics and image processing tools, the methodology presents a novel way to evaluate the strength and quality of rock masses.

2.5.4 Improved Accuracy and Efficiency

In comparison to conventional approaches, the paper shows that the suggested methodology can increase the GSI determination's efficiency and accuracy. The approach can decrease human error, reduce subjectivity, and increase the reliability of GSI predictions through the automation of the feature extraction and analysis processes.

2.6 Introduction to Geological Strength Index (GSI)

2.6.1 Advancements in Image Processing Techniques

New avenues for GSI estimation and rock mass characterization have been made possible by recent developments in image processing methods. An effective and non-destructive method of measuring the direction, spacing, and roughness of rock joints is using digital picture analysis. Numerous areas, such as geology, civil engineering, and remote sensing, have effectively used these approaches.(Marinos, (2005))

2.6.2 Quantitative Determination of GSI

The digital rock mass rating (DRMR), created by Monte (2004), and estimates a categorization rating from digital photographs of rock masses using simple image processing techniques and computations. A discontinuity trace map's fracture data, such as length, spacing, large-scale, roughness, rock bridge percentage, and block volume, is incorporated into the rating system. In this paper, we propose a method to quantitatively determine the GSI by using image processing technology to first detect the joints in two-dimensional (2D) photographs of a rock mass surface, then fractal dimension determination and artificial neural network (ANN) prediction of the GSI. Through a stability study of coal mine operations, the applicability of the suggested technique is confirmed.

2.6.3 Previous Studies on Image- Based GSI Estimation

The application of image processing to estimate GSI from photographs of the rock surface has been studied in the past. Research has indicated that the structural properties of rock masses may be analyzed by picture segmentation, feature extraction, and pattern recognition algorithms. (Gutierrez-Corea)These methods have demonstrated encouraging outcomes in precisely measuring GSI and forecasting the behavior of rock masses.

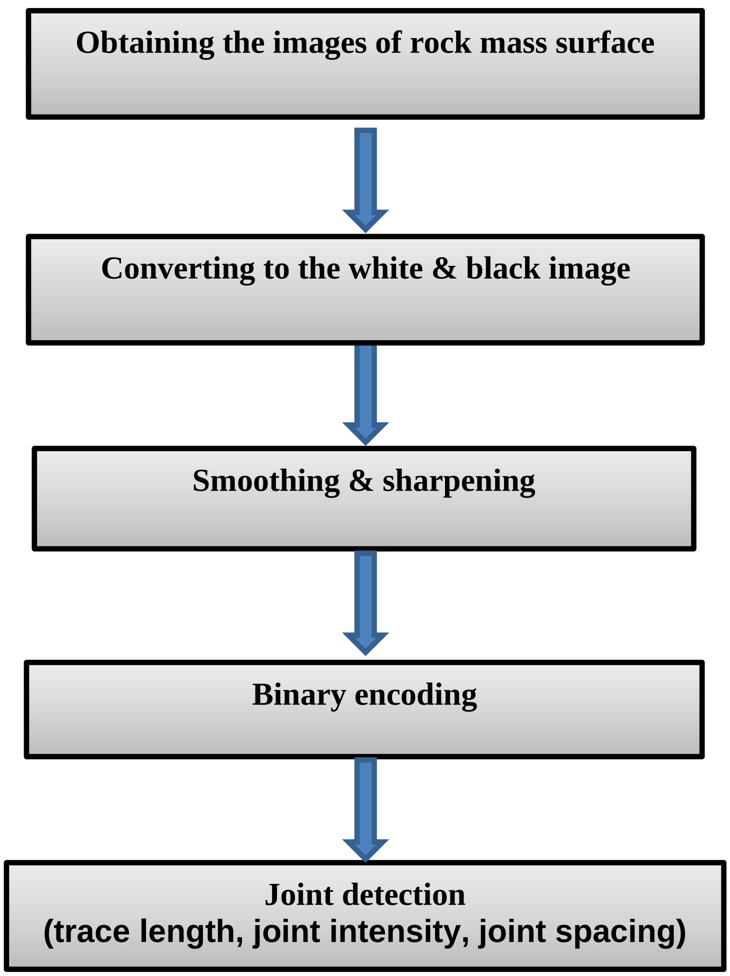


Figure 3 Conversion to White & Black Images

2.6.4 Joint Detection on Rock Mass Surface using Image Processing

Figure below shows the schematic flowchart for detecting joints on the rock mass surface via image processing. The detailed steps for joint detection on the rock mass surface are described as follows.(Hong, 2017)

- Converting to white & black images

It involves converting the colored rock image to black and white. For detection of joints in the image of jointed rock mass, the contrast of image should be analyzed. Natural color of the image is converted into black and white using gray level conversion functions. Following are the steps carried out in gray scale conversion:

a. We iterate over each pixel of the input color image.

b. For each pixel, we apply the grayscale conversion formula based on the luminosity method, which assigns different weights to the RGB components.

c. We then assign the calculated grayscale value to the corresponding pixel in the output grayscale image.

d. Finally, we return the resulting grayscale image.

- Smoothing and Sharpening

Blurring, often known as smoothing, is a technique used to take out undesired detail or noise from a picture. It reduces abrupt transitions between pixel brightness by averaging the values of nearby pixels. Using a Gaussian filter is a popular technique for smoothing. A convolution operation with a Gaussian kernel G can be used to mathematically illustrate the Gaussian smoothing process. The weights used to average the values of nearby pixels are defined by the kernel. A smooth transition is produced using the Gaussian function, which makes sure that local pixels contribute more to the smoothed value than distant pixels. The weighted sum of the nearby pixel intensities may be used to compute the smoothed intensity at each pixel position (x, y)

- Binary Encoding

To detect the emphasized joints, a binary encoding is conducted by discrimination analysis, so that the joints and background of the image are separated from each other. Because the brightness distributions of different rock masses and joints in images are varied, we perform a binary encoding by discrimination analysis to determine the threshold that rationally separates pixels into two types, based on the concentration histogram.

- Noise Removal

Noise and interference can come from a variety of causes, such as electrical sensor noise, grain noise in photos, and blast-induced fractures. Therefore, to eliminate extraneous noise that might lead to mistakes in joint detection, corrosion, and swelling operations in both automatic and manual procedures must be carried out for the binary pictures. In particular, the manual method compares the outcomes of automatic detection with those of in situ survey, eliminating the blast-induced fractures on the joint trace maps.

- Detection of Joints

We identify the joints that are still present on the binary picture after eliminating the extraneous noise. In general, the distribution of white pixels on a black backdrop makes it easy to locate edges and lines on the binary track map. First- and second-order derivatives are the two main types of edge and line detection that we employ in our solution. William goes into length in his explanation (2007). Here, we automatically gather the joint set's attributes from the discontinuity trace maps for the four sides (left and right walls, face, and roof) of an underground mine, including trace length, joint intensity, joint spacing, and roughness. However, we only gather the attributes for the left and right sides during the middle portion of the currently running, driven process.

2.6.5 Prediction of the GSI by ANN

The utilization of Artificial Neural Networks (ANNs) helps to predict the Geological Strength Index (GSI) of jointed rock masses, focusing on surface properties. ANNs, inspired by the human brain's decision-making capabilities, consist of interconnected processing nodes organized in layers. Back-propagation (BP) ANNs are specifically employed, featuring input, hidden, and output layers, with weights and biases adjusted during training to minimize error. The study employs a 3-layer BP ANN, with input neurons representing fractal dimension and surface condition index, and output neurons indicating GSI values.(Gatto) The number of neurons in the hidden layer is optimized through learning, with the most effective structure identified. The ANN model aims to accurately predict GSI based on surface conditions,

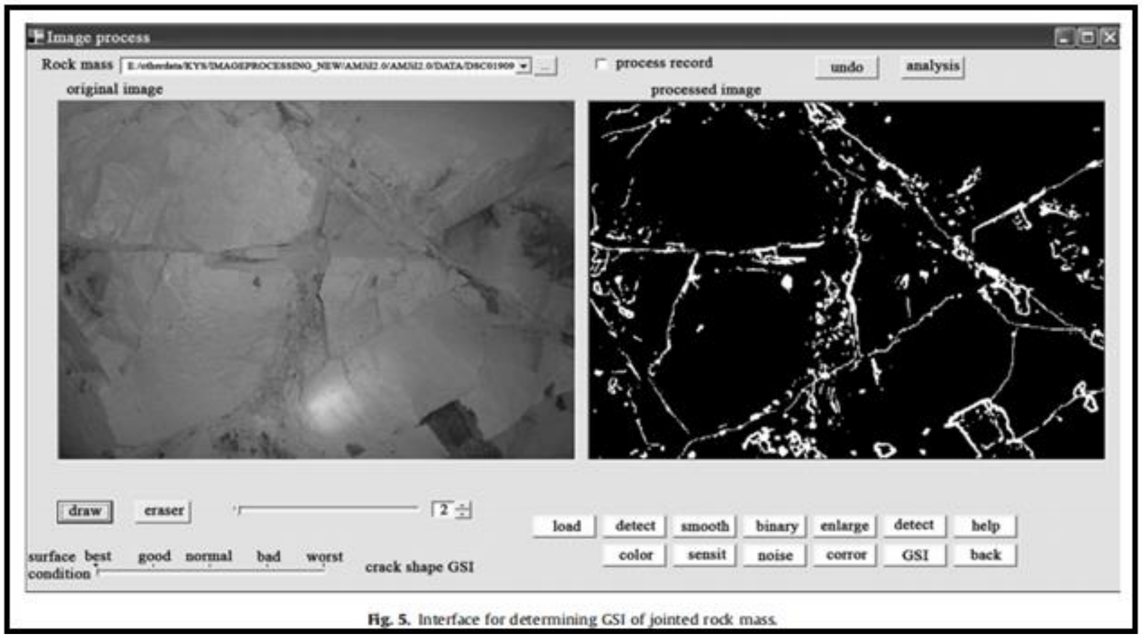


Figure 4 Interface for determining GSI of Jointed Rock Mass

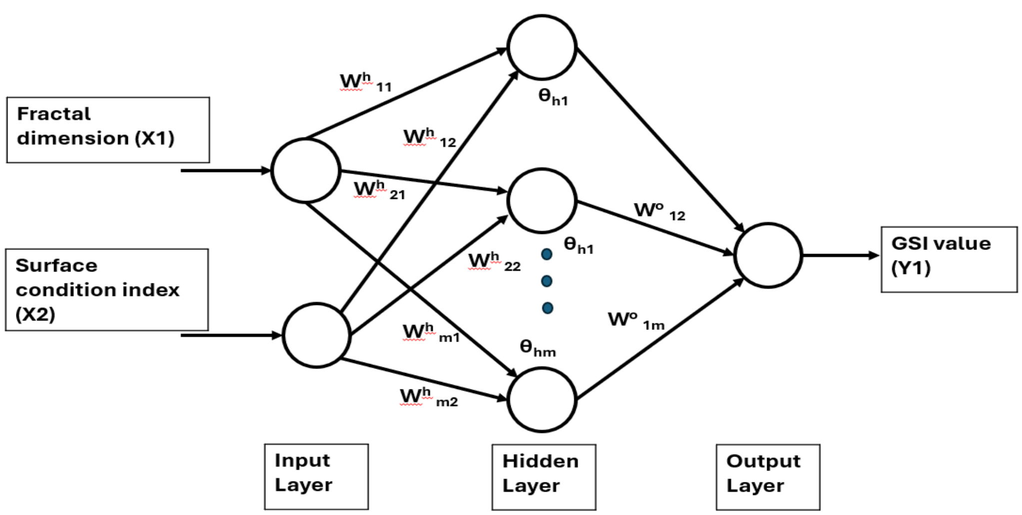


Figure 5 Conversion to White & Black Images

providing valuable insights for engineering practices dealing with jointed rock masses. Following is the image of 3-layer BP ANN used for ANN study.

After all the necessary calculations error was found which was relative error predicted by the ANN model given in the GSI chart was below 3.6%. Figure shows coding by help of built-in tools of MATLAB 7.0, such as image processing, fractal analysis and ANN, based on the proposed method.

2.7 Advancements in Geological Strength Index Determination

The Geological Strength Index (GSI), which was first presented by Hoek et al. (1995), is one of these methods that has received a lot of attention due to its ease of use and efficiency in determining the strength and deformability of rock masses.

Though GSI provides insightful information on the behavior of rock masses, its appli cability to poor and extremely poor rock masses is sometimes restricted because of their unex pected behavior and diverse character. (Miyoshi)

High degrees of discontinuities, poor interlocking between rock blocks, and notable w eathering and modification impacts are characteristics of poor and very poor rock masses, which present considerable obstacles to engineering projects including tunnelin g, slope stability, and subterranean excavations.

Based on a combination of empirical and visual criteria, the Geological Strength Index (GSI) is a semi-quantitative categorization system that assesses the quality of rock masses. To determine a numerical value that represents the total strength and deformability of the rock mass, it considers many parameters, including intact rock strength, joint surface conditions, joint orientations, and the existence of geological structures. Lower values of the GSI scale, which goes from 0 to 100, indicate weaker and more pliable rock masses. The recent form of the GSI charts is on account of tunnelling in difficult ground conditions in Greece. These charts specially oriented to determination of the GSI for foliated/ laminated/sheared, heterogeneous (such as flysch) and for very weak (such as molasses) rock masses. Most recently, (Hoek,

1998) have published papers putting forward some significant suggestions related with the appropriate selection of the GSI index for a range of rock masses under various conditions.

2.7.1 Challenges in Characterizing Poor and Very Poor Rock Masses

High levels of discontinuities, such as joints, fractures, and faults, define poor and very poor rock masses and have a major impact on their engineering behavior. These rock masses are difficult to characterize and evaluate from an engineering standpoint because they frequently have poor intact rock strength, little interlocking between rock pieces, and substantial weathering and modification impacts. The varied character and complicated behavior of poor and extremely poor rock masses may not be sufficiently considered by traditional rock mass categorization methods, such as GSI**.**

2.7.2 Modified GSI for Poor and very poor Rock Masses

The study's methodology aims to improve the Geological Strength Index (GSI) by establishing a connection between quantifiable field factors and descriptive geological terminology. The study specifically highlights the usage of the Joint Condition and Blockiness-Structural Domain axes to define features of rock masses. These axes use variables including joint surface conditions, intact core recovery (ICR), and structural rating (SR) to evaluate the level of blockiness and joint conditions in the rock mass. Through five distinct stages—geological surveying, identifying the type of broken structural domain, estimating key indicators of poor rock mass, evaluating weathering conditions, and finally deriving GSI values for poor and very poor rock masses—the modified-GSI chart, represented as a 2x2 matrix, aids in this characterization process.

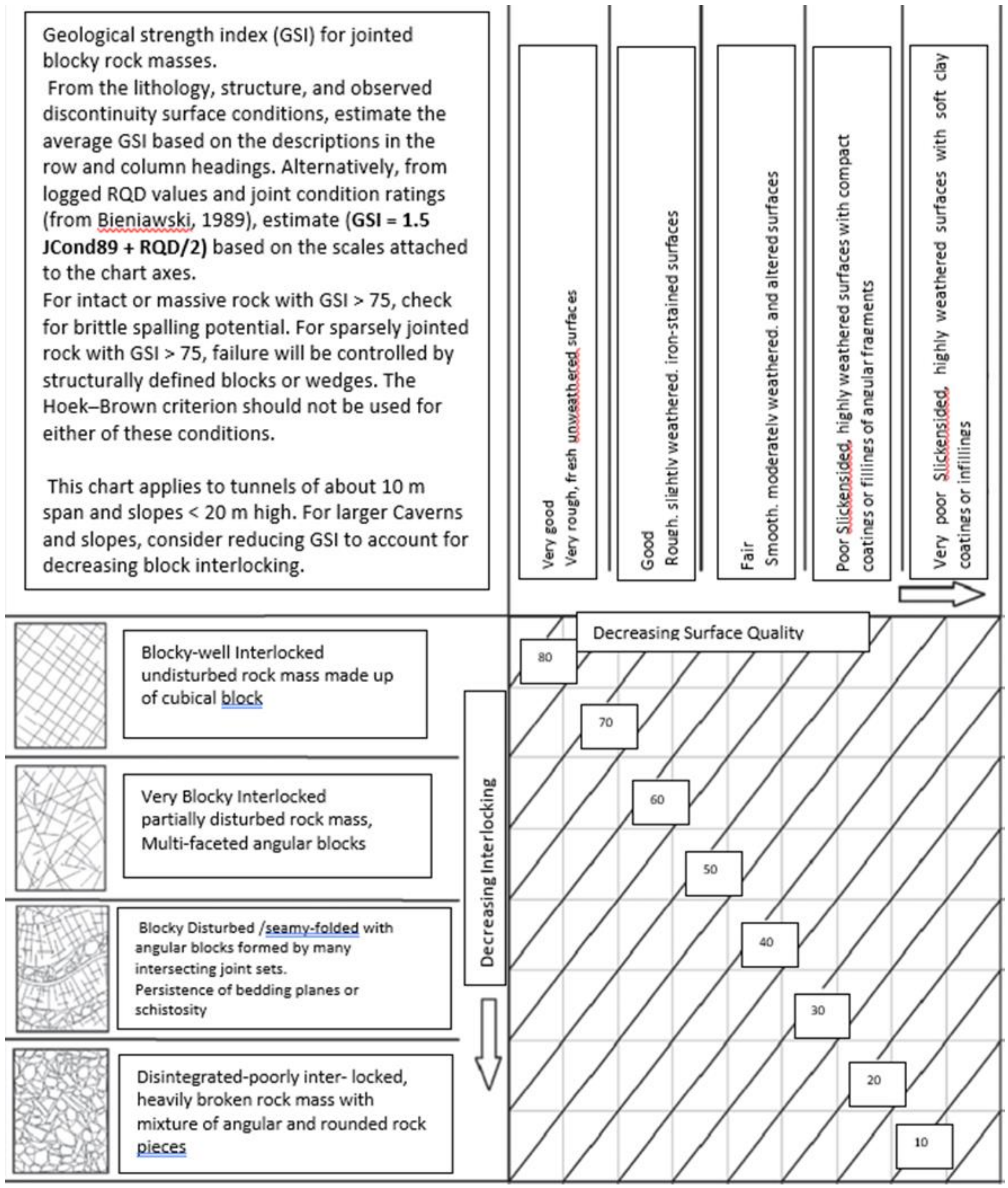


Figure 6 Geological Strength Table

2.7.3 Parameters Associated with degree of Jointing

The parameters associated with degree of jointing that is blockiness and interlocking are as follows**:**

a. Broken Structural Domain (BSTR)

b. Structure Rating (SR)

c. Volumetric Joint Count (Jv)

- Broken Structural Domain (BSTR)

Broken Structural Domain refers to a geological concept used to classify rock masses based on their structural characteristics, particularly related to the presence and distribution of fractures, faults, and other discontinuities. (Pine)Field observations, core-box logging, and structural mapping are examples of geological surveying techniques that are commonly used to locate and examine fractured structural domains within a rock mass. For characterization of the rock mass, engineering design, and risk assessment in various civil and mining projects, it is essential to comprehend the extent and characteristics of these areas.

- Structure Rating (SR)

Structure Rating (SR) is a parameter used to assess the blockiness or degree of interlocking within a rock mass. It is a quantitative measure that helps characterize the structural integrity and stability of the rock mass. The structure rating (SR) is a numerical value assigned to a rock mass to quantify its degree of blockiness or interlocking. It reflects the extent to which individual blocks of rock are tightly interlocked or separated by joints and fractures. (Yagiz)Greater structural integrity and stability are the outcome of a more densely interconnected rock mass with fewer joints and cracks, as indicated by a higher SR value. In contrast, a lower SR value may indicate a discontinuous and highly fractured rock mass with many joints, which might jeopardize its stability.

- Volumetric Joint Count (Jv)

A statistic called Volumetric Joint Count (Jv) is used to calculate how many joints or fractures there are in a chunk of rock. It contributes to the characterization of the degree of fracturing and structural discontinuities by giving an estimate of the number of joints per unit volume of rock. A statistic called Volumetric Joint Count (Jv) is used to calculate how many joints or fractures there are in a chunk of rock. When doing field surveying or core-box logging, the number of joints observed or documented inside a given volume of rock mass is counted to determine Jv. The measurements of the rock outcrop, borehole, or excavation face may be used to calculate the volume, and the number of joints found within that volume is noted. A higher Jv value denotes a more severely fractured and discontinuous geological structure because it represents a larger density of joints within the rock mass. On the other hand, a lower Jv value indicates a more cohesive and generally complete rock mass with fewer joints.

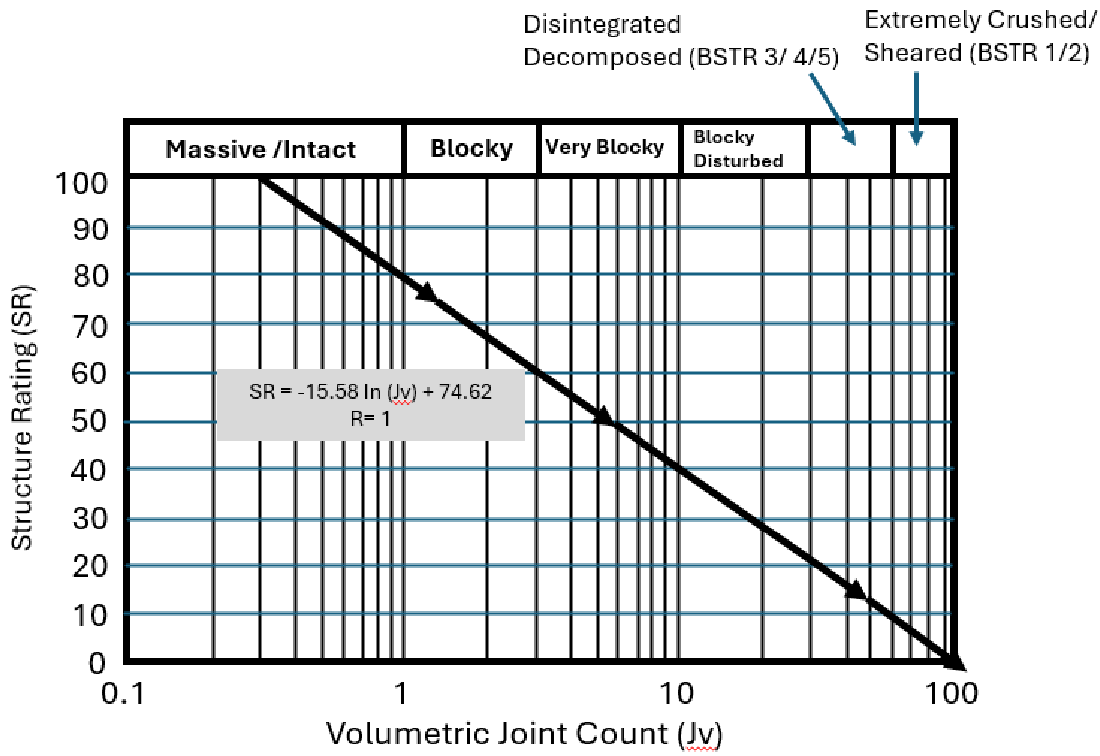


Figure 7 Comparison of Structure Rating (SR) with Volumetric Joints (Jv)

2.7.4 Conclusion

Because RQD is frequently zero, the traditional usage of rock mass categorization systems—which largely rely on criteria like the Rock Quality Designation (RQD)—proves problematic for poor and extremely poor rock masses. To improve characterization, a supplemental method has been devised to enhance the Geological Strength Index (GSI). To characterize the degree of jointing, this modified-GSI combines both qualitative and quantitative metrics, such as Blockiness-Structural Domain (BSTR) and Structure Rating (SR). Furthermore, characteristics such as weathering condition and intact core recovery (ICR) are used to characterize joint condition. The modified-GSI is intended for GSI values ranging from 6 to 27 and is appropriate for poor rock masses with homogeneous isotropic behavior. It is advised to integrate with current GSI charts for thorough characterization.

2.8 Summary

The paper describes a unique approach that makes use of machine learning techniques and local image descriptors to estimate Geological Strength Index (GSI) values in geotechnical engineering. The goal of the research is to increase the accuracy and automate the GSI determination process, which is a crucial factor in determining the stability and quality of rock masses used in engineering projects. The methodology presented in this paper uses machine learning algorithms to estimate GSI values based on relevant information extracted from geological photos using image processing techniques. The study shows via experimentation and validation tests that the suggested strategy reduces subjectivity and human error in GSI prediction while offering better accuracy and efficiency when compared to conventional approaches.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

Discontinuity plays a critical role in ascertaining the behavior of rocks, mainly at or near exposure sites such as tunnel sidewalls, slopes, and foundations. Locations where open discontinuities occur, deformation occurs due to movement along discontinuities and blocks rotation rather than through failure of the undamaged bed rock. The word ‘discontinuity’ in rock engineering explains any quantifiable disruption of a rock mass. Discontinuity is referred to more often than geologically more suitable terms like bedding plane, lamination, fault and joint, just to accentuate the significance of the presence of discontinuities in governing the engineering behavior of rock masses, instead of their genesis.

The Geological Strength Index is an innovative tool to determine the strength of the jointed rock mass. The difference between the joints and faults is crucial which tells about the movement along the plane of the bed. With help of visual observation, by determine the structure which the rock mass is exhibiting, in which certain classes are available (from being intact till disintegrated rock mass) & consequently determining the weathering conditions (from very good till poor) will help to assess the correct strength of rock mass.

Rock mass must be finalized by taking the average of GSI values. A preferable way is to give the range of GSI instead of giving a fixed value. It will be more precise to give range in which the GSI of the rock mass lies. This method to determine the value of GSI poses a lot of discrepancies. To address the issue, development of model in which for a set of input images, an output value can be obtained will make the process easier.

Nexus to above, our research was focused on production of a model where it is taught about the vales & will give answer specific to them when required. The broad underpinning of research method was largely exploratory. The research was carried out smoothly by studying the previous work done by researchers in similar fields and technical advice from experts.

Throughout the research, an effort was made to conduct the research free of assumptions to make it more practical.

3.2 Research Methodology

The study started with literature review of the research carried by researchers, scholars, students on the Rocks, discontinuity in rocks, the presence & orientation of joint set, their importance for Engineers, current practices to determine them, grey areas in current practices and visual observation of already accomplished works. This led to clarification of goals to achieve in the research.

The next step was to observe the GSI table & check its preference on other empirical methods which allowed us to follow object-oriented approach towards our research. We also studied the contents of GSI table in detail having separate classes as intactness of rock mass, the weathering conditions & combining them both to have an average GSI range which can help in determination and correction of data to be used for research.

The next step was acquisition of relevant data for area of study, the relevant data which included the drone pictures taken from the site. In actual, there was a need of a great range of images to train the model. So, we aimed to include the rock mass from some classes of the table for less complexity & greater accuracy. It included weathering classes from very good till very poor covering the following structure in them. This will be clearer if we observe the GSI table,

- Intact or Massive
- Blocky
- Very Blocky
- Blocky/ Disturbed/ Seamy

- Disintegrated
- Laminated/ Sheared

This is followed by development of an image processing model precisely described as:

- Data Acquisition
- Image Pre-processing
- Dataset Splitting
- Model Compilation
- Model Evaluation
- Model Deployment

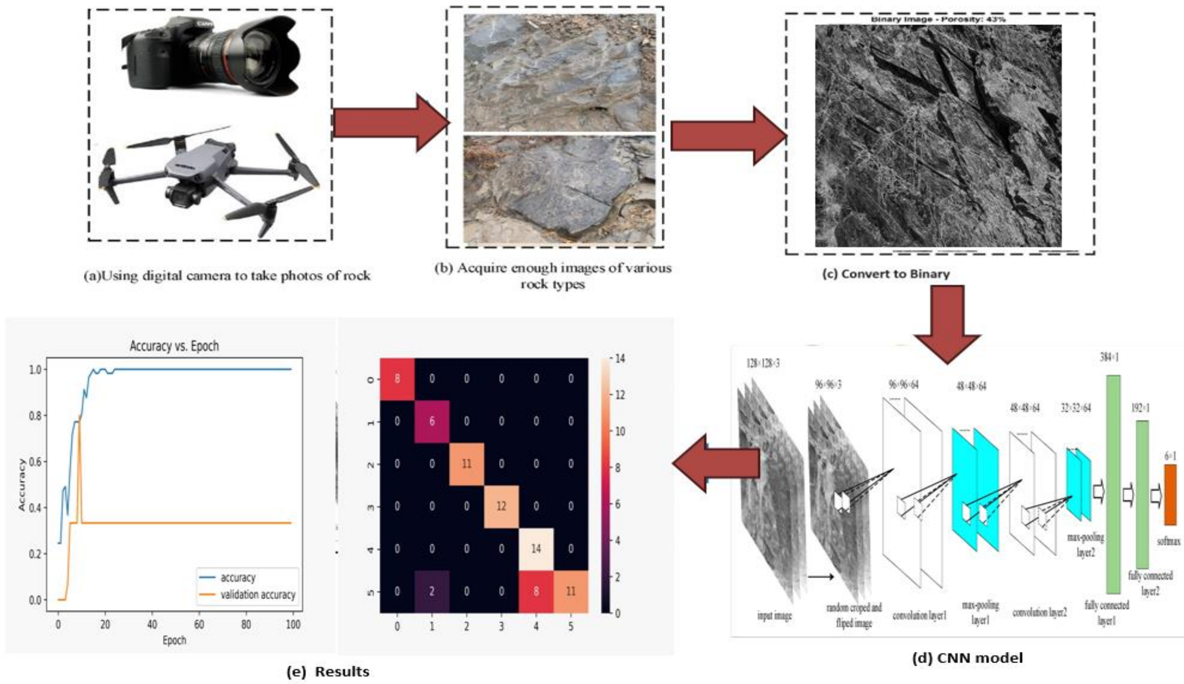


Figure 8 Overview of Methodology

After the development, to get the information we require, model has to be trained to extract only the relevant features. The features form the data set are divided in Image based, geological & statistical features. By extracting relevant features from rock mass images and geological data, you can capture meaningful information conducive to predicting Rock Mass GSI using artificial intelligence models. These extracted features serve as informative input variables for training predictive models, facilitating accurate and robust predictions of rock mass properties and behavior.

3.2.1 Data Acquisition

The initial stage is meticulously gathering pertinent information and taking excellent pictures of rock samples. To gather representative rock specimens from the many geological formations in our research region, we went on fieldwork.

We took close-up photos of these rock samples using a drone (DJI Mavic 3) and a mobile camera with a macro lens under regulated lighting.(Zuo, 2020) In order to capture the minute details of the rock surfaces, such as their textures, hues, and structural elements, the best focus and resolution had to be guaranteed. We were able to get incredibly detailed and comprehensive aerial photos of the rock outcrops and geological formations in our research region thanks to the drone. To guarantee thorough coverage of the region while preserving the ideal height and camera settings for images, we meticulously plotted our flight patterns.

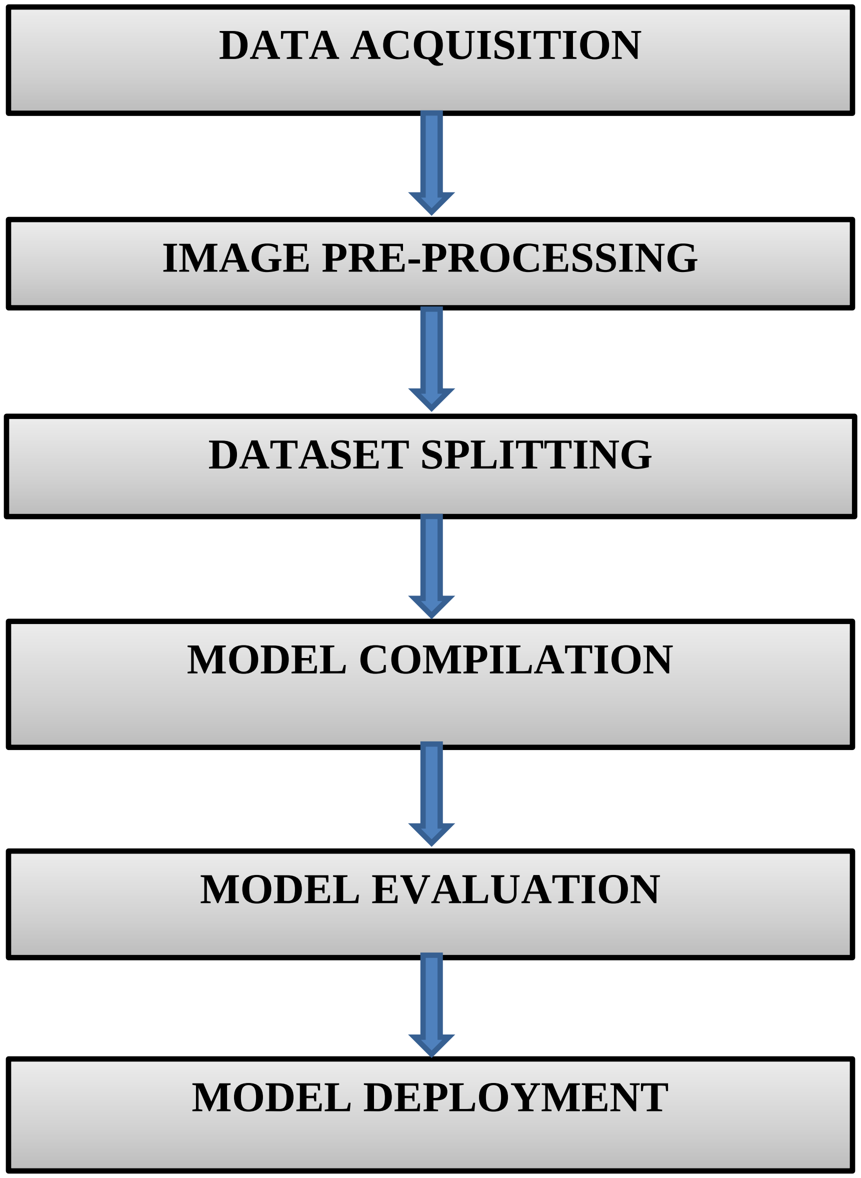


Figure 9 Methodology Adopted During the Research

Due to the sophisticated visual capabilities of the DJI Mavic 3, we were able to take pictures of complex geological characteristics, such as surface textures, structures, and

Figure 10 DJI Mavic 3

different types of rock, from unusual angles that would have been difficult to obtain on foot. Our dataset was enhanced by the drone-acquired photographs, which added useful aerial perspectives to complement the observations made from the ground. The diversity and richness of our data were improved by this integrated method, which also helped to provide a more thorough examination of the properties of the rock mass and the determination of the GSI.

3.2.2 Image Pre-processing

Resizing images to a consistent size is essential for CNN models to process them efficiently. This ensures that all input images have the same dimensions, preventing issues during trainin***g.*** Normalizing pixel values to a common scale (usually between 0 and 1 or -1 and 1) helps stabilize and accelerate the training process. It ensures that different features contribute equally to the model's learning, regardless of their original scale. Image augmentation involves applying transformations such as rotation, flipping, scaling, or shifting to artificially increase the diversity of the training dataset. (Cui, 2011, December)This helps improve the model's robustness and generalization ability by exposing it to a wider range of variations in the input data. Removing noise from images helps improve their quality and enhances the model's ability to extract meaningful features. Techniques like Gaussian blur, median filtering, or denoising autoencoders can be used for noise reduction. Enhancing the contrast of images increases the visual separation between different features and makes them more distinguishable. Techniques like histogram equalization or adaptive histogram equalization can be used to improve contrast. Cropping images to focus on the most relevant regions of interest helps reduce computational complexity and improves the model's ability to capture important features. This can be particularly useful when dealing with large images or when the region of interest is small. Applying filters like Gaussian blur, edge detection, or sharpening can help highlight specific features in the images or smooth out noise. Filters are often used as ***pre-processing*** steps to enhance the quality of input data before feeding it into the CNN model.

3.2.3 Dataset Splitting

Main Classes Distribution:

A = Intact or Massive

B = Blocky

C = Very Blocky

D = Disturbed/Seamy

E = Disintegrated

F = Laminated/Sheared

Subset Distribution:

Based on Surface Conditions of Rock Mass

S1 = Very Good

S2 = Good

S3 = Fair

S4 = Poor

S5 = Very poor

3.2.4 Model Compilation

Specifying the metrics to monitor during training and evaluation (e.g., accuracy, precision, recall). Combining the selected loss function, optimizer, and evaluation metrics into the model and prepare it for training.

Given below is the summary of the parameters included in the model developed for Predicting GSI values.

Table 2 Summary of Parameters included in Model Development

Model : "sequential"		
Layer (type)	**Output Shape**	**Param #**
convd (Conv2D)	(None, 222, 222, 16)	160
max_pooling2d (Maxpooling2D)	(None, 111, 111, 16)	0
convd_1 (Conv2D)	(None, 109, 109, 32)	4640
max_pooling2d_1 (MaxPooling2)	(None, 54, 54 32)	0
conv2d_2D (Conv2D)	(None, 52, 52, 64)	18496
max_pooling2d (Maxpooling2D)	(None, 26, 26, 64)	0
flatten (Flatten)	None, 43264)	0
dense (Dense)	(None, 512)	22151680
dense_1 (Dense)	(None, 6)	3078
Total param: 22,178,054 **Trainable param: 22,178,054** **Non-trainable params: 0**		

3.2.5 Model Evaluation

In CNN model evaluation, after training, we assess its performance. We make predictions on a separate test set, calculating these metrics to gauge its accuracy. Visualizing results through plots like scatter plots or regression plots helps interpret the model's performance and understand any patterns or outliers. Iteration involves refining the model based on evaluation results, tweaking hyperparameters, or gathering more data for better generalization. Finally, comparison against baseline models or previous iterations validates improvements and guides further iterations for model enhancement.

Table 3 Comparison done for model validation.

Classification report:				
	Precision	Recall	F1-score	support
0	1.00	1.00	1.00	8
1	0.75	1.00	0.86	6
2	1.00	1.00	1.00	11
3	1.00	1.00	1.00	12
4	0.64	1.00	0.78	14
5	1.00	0.52	0.69	21
Accuracy			0.86	72
Macro avg	0,90	0,92	0.89	72
Weighted avg	0.91	0.86	0.85	72

3.2.6 Model Deployment

Model is ready to be used for prediction of rock mass GSI of images gathered from site.

3.3 Software

a. MATLAB

b. Visual Studio

c. Image J

d. Lobe AI

3.4 Results

Accuracy is achieved when the model is run on the training dataset. Validation accuracy is achieved when model is run on a dataset other than training dataset.

It can be seen in the graph that the model has been trained with almost one accuracy but when the dataset is changed for validation, the accuracy changes considerably. This may be a result of lack of considerable amount of data in training dataset. Increasing the training dataset may bring the validation accuracy to more acceptable range.

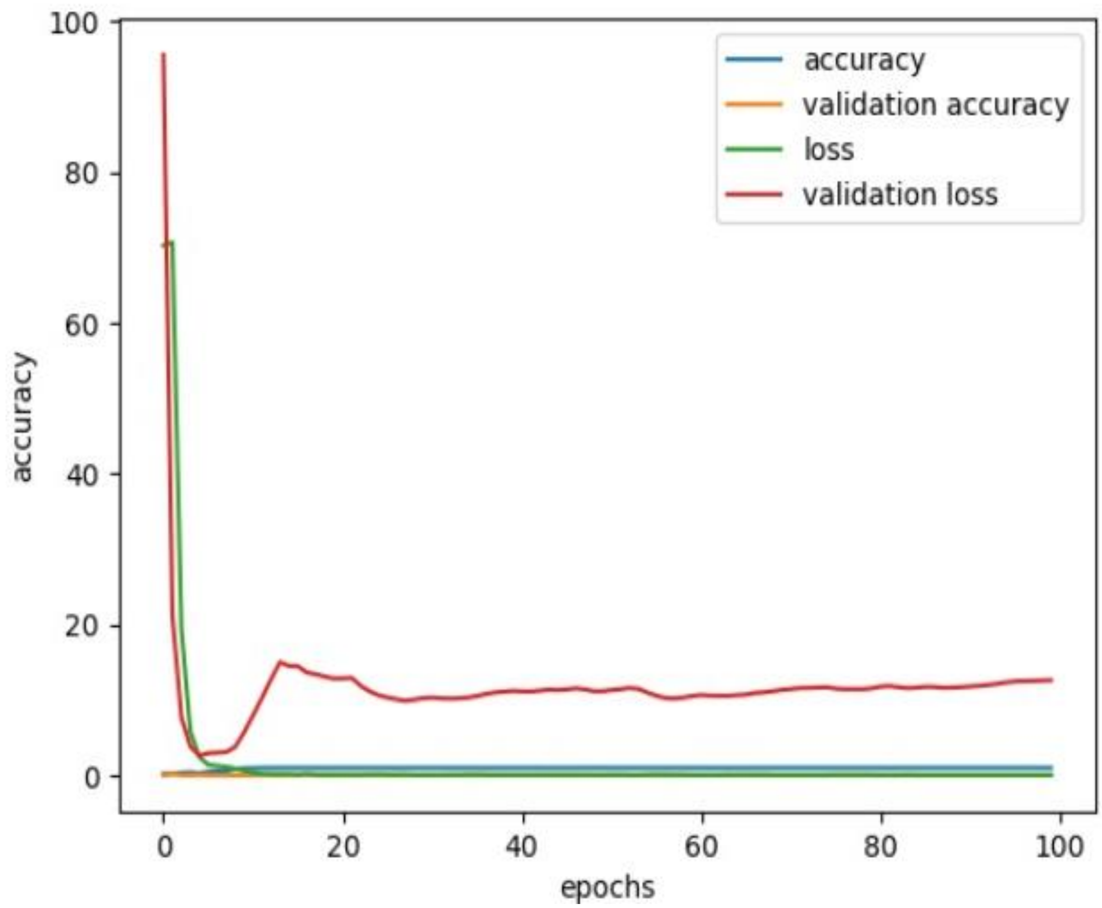


Figure 11 Figure Validation Loss vs Accuracy.

It can be seen in this graph that the model keeps on improving more and more when the model trains. In the beginning, losses are more, and accuracy is less. But after a few runs, the losses decrease and stabilize.

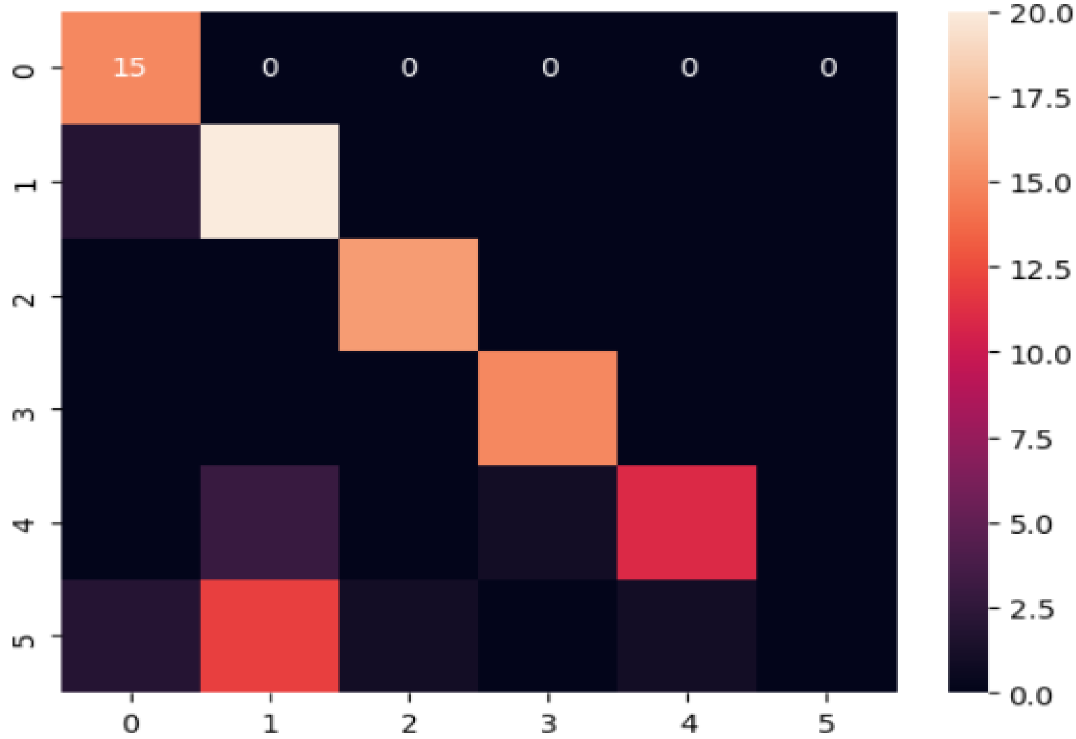


Figure 12 Heat Map representing Accuracy of the Model

This Heat Maps shows an example the validation run that was performed to check the accuracy of the Model. It can be clearly seen that out of the six main classes, data consisted of the first few classes. The model accurately identified the images for first 5 classes whereas the model showed confusion in the last class. This inaccuracy may be due to lack of diversity in training dataset of the last class. The more diverse the training dataset is, the more accurate the model is. As stated in the limitations of this model, diversity is the main restraining factor.

CHAPTER 3: CONCLUSIONS, RECOMMENDATIONS & LIMITATIONS

4.1 Conclusions

Our findings demonstrate the effectiveness of the CNN model in predicting GSI values based on visual features extracted from rock mass images. One of the key contributions of our work lies in leveraging deep learning techniques to automate the prediction of GSI values, which traditionally relies on manual interpretation and subjective assessment. By harnessing the power of CNNs, we have introduced a data-driven approach that offers potential benefits in terms of efficiency, accuracy, and objectivity in GSI estimation. In conclusion, our study represents a step forward in the integration of deep learning methods into geotechnical engineering practice. By providing a framework for automated GSI prediction, we hope to contribute to more efficient decision-making processes in rock mechanics and related fields.

4.2 Recommendations

a. Further refining the CNN model architecture to improve prediction accuracy.

b. Exploring additional features or data sources that could enhance the model's performance.

c. Investigating the transferability of the model to different geological settings or rock types.

d. Conducting field studies or validation experiments to assess the real-world applicability of the model.

4.3 Limitations

- Data Quality and Quantity:

  The dataset used for training the CNN model may be small or may not adequately represent the diversity of geological conditions and rock types.

- Model Performance:

The CNN model may have learned to memorize patterns specific to the training dataset without generalizing well to new, unseen data.

- Feature Representation:

The CNN model may not have access to all relevant information about the rock mass, such as structural characteristics, geological history, or weathering conditions, which could impact GSI prediction accuracy.

- Model Interpretability:

CNN models are often regarded as "black box" models, making it challenging to interpret how the model arrives at its predictions. Understanding the underlying factors influencing GSI prediction may be difficult.

- Computational Resources:

Training and evaluating CNN models require significant computational resources, including processing power and memory, which may be limiting factors.(Hoek, 1998)

- Generalization:

The CNN model may have been trained and evaluated on a specific dataset or geological setting, limiting its applicability to other regions or rock types with different characteristics.(Marinos, (2005))

- External Factors:

Factors such as weathering, stress conditions, or anthropogenic activities that are not captured in the dataset may influence GSI values but are not accounted for in the model.

PROS	CONS
Further refining the CNN model architecture to improve prediction accuracy.	Inaccurate or inconsistent labeling of GSI values in the dataset could introduce noise and affect the model's performance.
Exploring additional features or data sources that could enhance the model's performance.	The model may not have captured the complexity of the relationship between image features and GSI values, resulting in poor predictive performance.
Investigating the transferability of the model to different geological settings or rock types.	Potential lack of generalizability across diverse geological settings due to varying compositions, structures, and data availability.
Conducting field studies or validation experiments to assess the real-world applicability of the model.	Potential cost and time-intensive nature of conducting field studies or validation experiments, which may limit scalability and accessibility.
Developing a user-friendly model so it can replace conventional GSI methods.	Time consuming and requires firm knowledge on CNN model with expertise in specific software.

SUMMARY OF RESEARCH WORK

Our research aimed on the objectives addressed above which included the development of an image processing framework through algorithms, the training of model & its validation for a user-friendly model helping to solve the issue of time-taking manual methods.

To ascertain the Geological Strength Index (GSI) of rock masses using image processing techniques, a variety of geological formations from the research region were sampled. We acquired airborne data using a DJI Mavic 3 drone, which allowed us to take high-resolution pictures of difficult rock outcrops. To improve quality and usability, preprocessing was applied to the obtained photos. To normalize the dataset, we used scaling, noise reduction, and grayscale conversion. Texture, form, and color traits were among the pertinent elements that were retrieved from photographs of rock samples. Subsequently, image analysis techniques were used to measure geological features. Next, we used machine learning techniques to continue building a predictive model. Creation of associations between known values from the GSI table and characteristics taken from the extracted picture. For model training and validation, the dataset was split into training and testing sets. Interpretation of model outcomes in relation to GSI values was performed & Generation of comprehensive reports documenting the methodology, results, and interpretations. Provided visual representations (maps, graphs, annotated images) to communicate research findings effectively.

This integrated methodology combined fieldwork, drone technology, image processing, and machine learning to advance the understanding of rock mass characteristics and their correlation with GSI. The research outcomes contribute to the broader field of geotechnical engineering and provide valuable insights for rock engineering applications.

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