

AN EXPLAINABLE MACHINE LEARNING FRAMEWORK FOR PREDICTING UNIAXIAL COMPRESSIVE STRENGTH OF ROCK USING INDEX PROPERTIES

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by
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CANDIDATE'S DECLARATION

I hereby declare that the thesis entitled "AN EXPLAINABLE MACHINE LEARNING FRAMEWORK FOR PREDICTING UNIAXIAL COMPRESSIVE STRENGTH OF ROCK USING INDEX PROPERTIES" submitted to Delhi Technological University for the award of the degree of Master of Technology in Geotechnical Engineering is an authentic record of my own work carried out under the guidance of Prof. Amit Kumar Srivastava.

The matter embodied in this thesis has not been submitted by me for the award of any other degree or diploma, associateship, Fellowship or other similar title or recognition.

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ABSTRACT

The uniaxial compressive strength (UCS) of rock is one of the most important engineering properties used in the design and analysis of tunnels, slopes, foundations, underground excavations, and mining projects. Although the laboratory determination of UCS provides reliable results, it is often time-consuming, expensive, and requires carefully prepared standard specimens. In many practical situations, obtaining suitable rock samples for direct UCS testing is difficult. Consequently, the prediction of UCS using easily measurable index properties has become an important area of research in rock mechanics and geotechnical engineering.

This study presents an explainable machine learning framework for predicting the UCS of rocks using four commonly measured index properties: Porosity (%), Schmidt Hammer Rebound (SHR), P-wave velocity (V_p), and Point Load Index (Is_{50}). A dataset of 584 rock specimens, compiled primarily from the open-access ROCK/10/4025 database and supplemented with specimen-level data reported by Abd El Aal (2017), was used for model development following a zero-imputation policy that retained only specimens with complete measurements. Three machine learning algorithms which are Random Forest Regression, Ridge Regression, and Huber Regression were developed and evaluated on an 80:20 train-test split using the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). The Random Forest Regression model achieved the best performance on the test partition, with an R^2 of 0.73, an RMSE of 26.19 MPa, and an MAE of 16.96 MPa, outperforming both linear alternatives.

To improve the transparency and interpretability of the predictive model, SHapley Additive exPlanations (SHAP) analysis was applied to the trained Random Forest model to quantify the contribution of each index property to the predicted UCS. The explainability analysis, consistent with the Pearson correlation trends observed in the dataset, ranked porosity as the most influential parameter, followed by P-wave velocity, Schmidt Hammer Rebound Number, and Point Load Index. Based on the trained models, an empirical equation for UCS estimation was also developed to provide a practical, rapid engineering tool.

The developed framework was further validated against ten independently tested laboratory rock specimens that were not part of the training dataset. Since the Point Load Test and the UCS Test are both destructive and cannot be performed on the same specimen, the corresponding Is_{50} values for the validation samples were estimated theoretically using established empirical correlations. The comparison between laboratory-measured and model-predicted UCS values showed close agreement, with an MAE of 3.09 MPa, an RMSE of 4.00 MPa, and a mean absolute percentage error (MAPE) of 10.32% across the ten specimens. Prediction accuracy was found to be highest for competent, low-porosity rock and comparatively lower for weaker, more porous specimens, where micro-scale heterogeneity has a greater relative influence on strength. As this validation exercise was based on a limited set of ten specimens, it should be regarded as an encouraging preliminary indication rather than conclusive proof of the framework's reliability, and broader validation on larger, independent datasets is recommended before wider adoption.

The proposed explainable machine learning framework offers an efficient, accurate, and interpretable approach for estimating the uniaxial compressive strength of rocks. It has the potential to reduce the need for extensive laboratory testing and can assist geotechnical engineers in preliminary site investigations, rock mass characterisation, and engineering design where rapid and reliable UCS estimation is required.

Keywords: Uniaxial Compressive Strength, Rock Index Properties; Machine Learning, Explainable Artificial Intelligence (XAI), SHAP Analysis, Random Forest Regression,

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
ANN	Artificial Neural Network
ASTM	American Society for Testing and Materials
BPI	Block Punch Index
BTS	Brazilian Tensile Strength
Is50	Point Load Strength Index
ISRM	International Society for Rock Mechanics
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MSE	Mean Squared Error
OLS	Ordinary Least Squares
R ²	Coefficient of Determination
RMR	Rock Mass Rating
RMSE	Root Mean Square Error
RQD	Rock Quality Designation
SHAP	SHapley Additive exPlanations
SHR	Schmidt Hammer Rebound (Number)
UCS	Uniaxial Compressive Strength
V _p	P-wave Velocity
XAI	Explainable Artificial Intelligence

CHAPTER 1

INTRODUCTION

1.1 General

Rock engineering is a specialised area of geotechnical engineering that focuses on the characterisation, analysis, design and construction of rock-based engineering structures. The mechanical behaviour of rock is essential for civil and mining projects including tunnels, dams, underground caverns, foundation work, slopes and open pits. Thus, proper property characterisation of rocks is vital in the safety, stability and durability of these structures.

The Uniaxial Compressive Strength (UCS) is one of the most important engineering properties of rock since it equals the compressive strength and load-bearing capacity of the intact rock. UCS is extensively applied in the rock mass classification systems, rock excavation design, numerical modelling and choice of appropriate rock support system. The recommended test for UCS by the International Society for Rock Mechanics (ISRM) and ASTM requires good quality cylindrical rock specimens and controlled test conditions. The preparation of specimens, however, can be a challenge, and the test may require some time, be destructive, and be somewhat costly, especially in preliminary site investigations.

Several rock index properties have been applied to the indirect estimate of UCS, with the aim to overcome these limitations. The parameters that are most commonly used include porosity, Schmidt Hammer Rebound Number (SHR), P-wave velocity (V_p), and the Point Load Strength Index (I_{s50}). These properties can be easily measured and have been shown to have strong correlation with rock strength and therefore are useful for initial engineering evaluation.

A number of traditional empirical equations have been developed based on regression analysis, which have been widely used to predict UCS. These equations, however, do not necessarily account for the complex relationships between multiple influencing factors, as there is a lot of variability in the mineral composition, grain size,

weathering, porosity and development of microcracks of natural rocks. In recent years, machine learning methods have emerged as viable alternatives to modelling such nonlinear relationships, and have performed better when it comes to predicting rock strength from many index properties.

This research proposes a machine learning model for predicting UCS based on porosity, Schmidt Hammer Rebound Number, P-wave velocity and Point Load Strength Index. To create predictive models from an extensive database of rock properties obtained from the literature, the following regression methods were used: Random Forest Regression, Ridge Regression, and Huber Regression. In addition, an empirical equation was produced for facilitating practical engineering applications and the proposed framework was checked with independent laboratory test results to assess its reliability and applicability in rock engineering practice.

1.2 Importance of Rock Engineering

Rock engineering is fundamental to civil and geotechnical and mining engineering, providing the basis for rock-based structures, such as dams, bridge foundations, tunnels, underground structures, rock slopes and mining excavations. Rock is a discontinuous material, the properties of which are influenced by the discontinuities (joints, faults, bedding planes) in the rock mass, as well as the properties of the material itself, which means that a rock mass can be strong in one direction and weak in another. The safety and economic importance of rock slopes and structures built on rocks has been emphasised by the loss of lives and economic disruption due to rock slope failures, rock tunnel failures, and failures of rock founded structures in the past. The selection of excavation method and support design is closely related to rock strength and deformability, especially for capital-intensive projects such as hydropower schemes and metro tunnelling, where an underestimate of strength causes unnecessary costs and an overestimate causes instability.

The strength of rocks, specifically UCS, is directly used in all major rock mass classification systems, including Bieniawski's RMR, Barton's Q-system and the Hoek-Brown criterion, so errors in its estimation cascade through all subsequent design decisions. This is significant in Indian geotechnical practice where weathering is very

complex and variable, as seen in tunnelling and hydropower projects across the Himalayas and Western Ghats, for which rapid, minimally destructive index tests have significant practical implications.

1.3 Uniaxial Compressive Strength of Rock

The maximum axial stress an intact unconfined right cylindrical specimen of the rock under uniaxial compression can withstand before failure is determined by applying axial stress to failure and following the ISRM Suggested Methods, ASTM D7012, and IS 9143, is called Uniaxial Compressive Strength (UCS) and calculated as P/A , where P is the failure load and A is the initial cross-sectional area of the specimen. UCS is a representation of mineral composition, grain size and texture, degree of interlock, porosity, density of micro-fractures and degree of weathering, and it is the starting point of rock mass strength estimation (as in the Hoek-Brown criterion) but not a representation of the strength of the rock mass. Typically, NX-size core (54 mm) right circular cylindrical specimens with a length-to-diameter ratio of 2.0 to 3.0, end faces flat within a tolerance of 0.02 mm and perpendicular to the specimen within a tolerance of 0.001 radians is standard practice.

The UCS of poorly weathered or poorly cemented sedimentary rocks can be only a few MPa, while that of dense fine-grained igneous and metamorphic rocks, such as quartzite, granite or basalt, may reach several hundred MPa. Measured strength is dependent on specimen geometry, moisture content, loading rate and the accuracy of the testing procedure and the result must be considered in relation to the controlling standard. Many indirect prediction methods are being sought as it is necessary to have a good and reliable method of determining the UCS in foundation, slope, tunnel and excavation design.

1.4 Limitations of Direct UCS Testing

Although the UCS test is the most direct way of measuring the strength of an intact rock, it has its own limitations and this has led to the development of indirect testing methods to estimate rock strength. Requirements for strict specimen preparation under ISRM, ASTM and IS standards, such as L/D ratios of 2.0 to 3.0, end-face flatness of

0.02 mm and tight perpendicular tolerances are very demanding and precision core cutting and grinding equipment is not always available during the preliminary investigation; highly fractured, weathered or friable material is excluded from testing. The test is also destructive and cannot be repeated on a single specimen of material, and the number of strength values that can be measured using boreholes with limited core recovery is limited, particularly in weak or jointed formations. The specimen preparation, curing (if necessary) and controlled-rate testing are time-consuming, require extensive laboratory resources and experience, and impose a high cost and schedule burden for large infrastructure projects that must have many determinations made across various boreholes and rock units.

Another constraint is scale dependency: the samples tested are in the laboratory size of 50 to 60 mm diameter, while the volumes of rock mass of engineering interest are much larger; a result of which heterogeneities and larger fractures are not represented. Last but not least, field fragments are frequently irregularly shaped and may not be able to be standardised into a regular geometry.

1.5 Objective of the study

1. To develop an Artificial Intelligence/Machine Learning (AI/ML) model for predicting the Uniaxial Compressive Strength (UCS) of rock specimens using their index properties.
2. To compile and preprocess a comprehensive dataset of rock physical and index properties such as Porosity, SHR, P-wave velocity, Point Load Index from published research papers for training and testing the AI/ML model.
3. To develop and evaluate the AI/ML model using appropriate performance metrics such as R^2 , RMSE, and MAE.
4. To determine the index properties of selected rock specimens through laboratory testing and obtain their corresponding UCS values.
5. To validate the developed AI/ML model by comparing the predicted UCS values with the experimentally determined UCS values of the laboratory-tested rock specimens.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

UCS estimation based on index properties has been a research topic for several decades, and there are numerous studies on different rock types, different index properties measured, different size and origin of data sets, and different techniques used to analyse the relationship between the index properties and strength. The following literature review summarizes the literature used and, in some instances, directly utilised in the development of the dataset and modelling framework employed in the current research. The review covers state of the art in UCS prediction, traditional index-based correlation studies and modern data-driven and machine learning solutions. The author's approach and contribution to each source is summarised and a statement is made regarding the differences in scope, parameters, analysis or interpretive emphasis in the present study. This treatment is not just a description of the problem, but is expected to pinpoint, source by source, the specific problem that the present study seeks to solve, and set the framework for traceability that any data-driven rock mechanics framework must provide, because the quality of any framework is dependent primarily on the quality of the data that it is based upon. The chapter ends by placing the current research into perspective with this body of research.

2.2 State of the Art

The state of the art in UCS prediction today is represented by large, open-access, multi-lithology compilations, which use specimen data from many independent studies to allow the development of generalised models. The most important such database for the present study is the ROCK/10/4025 data assembled by Muzamhindo and Ferentinou (2023), which comprises 96 source studies, representing 40 lithologies from 23 countries, for values of porosity, unit weight, Schmidt Hammer Rebound Number, Brazilian Tensile Strength, Point Load Index, P-wave velocity, Hoek–Brown material constant, Young's Modulus, and UCS. Their study introduced a generic compressive-strength prediction model that was common to this diverse collection of

studies, and showed the importance of large and pooled databases for training generalised models; it is currently the best example of scale in this field of study.

This database is used as the primary data source for the present study, but with three differences, first the data was filtered to include only those specimens that contained all four parameters non-null (porosity, Vp, SHR, Is50 and UCS), second the analysis was limited to this four-parameter subset most relevant to site investigation, and third, the present study also applies explainability analysis, regression of empirical equations, and laboratory-first external validation which were not a part of the original publication.

2.3 Conventional Prediction Methods

Predictive studies of UCS have tended to be site-specific or regional correlation studies that involved a single or two index properties which were correlated with UCS for a specified lithology, usually by simple or multiple linear regression.

Abd El Aal (2016) studied the Wajid Sandstone at Bir Askar, Najran, Saudi Arabia, and made tabulations of the sample number of the following properties: porosity, permeability, density, water absorption, void index, SHR, Vp, Is50, RQD, and UCS. A single-formation, fully parameter complete dataset was created by merging ten specimen records from this study with the ROCK/10/4025 compilation.

Sherwani et al. (2023) studied SHR for 120 specimens of sandstone, claystone and limestone from north Iraq against UCS and BTS. It was not included in this dataset because Vp and Is50 were not reported, failing the criterion for five parameters of completeness.

Jahangir and Ahmed (2013) examined the Point Load Index and UCS from 245 tests on four lithologies from the Iraqi region, which resulted in a comprehensive data set for the region under study. This data was not included because only UCS and Is50 were reported. These studies, taken together, demonstrate good internal consistency in the single-formation or regional context, but are constrained by their tightly defined nature, and do not apply to the multi-lithology data set needed here.

2.4 Modern Prediction Methods

Mishra and Basu (2013) performed a comparative analysis between the proposed approach of UCS estimation from effective porosity, P-wave velocity, Schmidt Rebound Hardness, density, Block Punch Index and Point Load Index by using the classical regression method along with a fuzzy inference system with sandstone, granite and uranium mineralised schist. They are often referred to as a comprehensive comparison of classical regression methods with soft-computing models, which sets a methodological link to modern data-driven models.

This study failed to provide direct specimen-level data to include and instead, the source is paywalled, with no public specimen table found, which is documented without imputation, as throughout. It is quite conceivable that some lithologies studied by Mishra and Basu are indirectly represented in the 96 source studies combined together in ROCK/10/4025. In terms of methodological considerations, the present study has a much larger multi-source pooled dataset (compared with a single study specimen set) and focusses on explainability (using SHAP) and laboratory-first external validation (compared with fuzzy inference), but with the same motivation of moving beyond linear regression to describe non-linear strength behaviour.

Table 2.1 Comparative summary of key literature sources evaluated for inclusion in the present dataset

Author(s)	Lithology	Sample Size	Parameters Reported	Analytical Approach	Included in Present Dataset	Basis for Decision
Mishra & Basu (2013)	Sandstone, granite, mineralised schist	Not accessible	Partial (n, V _p , SHR, BPI, Is ₅₀ , UCS reported in source)	Regression and fuzzy inference	Excluded	Source paywalled; specimen-level data unavailable
Jahangir & Ahmed (2013)	Sandstone, claystone	245 specimens	Is ₅₀ , UCS	Regression	Excluded	Missing n, V _p , and SHR;

	siltstone, limestone					fails completeness criterion
Khanlari et al. (2014)	Sandstone / sedimentary	Not specified	n, Vp, UCS (partial)	Empirical regression	Excluded	Single-lithology, partial parameter coverage; used only for early scoping
Armaghani et al. (2016)	Sandstone (Dengkil Formation, Malaysia)	108 specimens	Vp, SHR, Is50, UCS (porosity not reported)	Computational / soft-computing modelling	Excluded	Source paywalled; porosity absent, fails completeness criterion
Abd El Aal (2016)	Sandstone (Wajid Formation)	10 specimens	n, Vp, SHR, Is50, UCS (complete)	Laboratory characterisation	Included	Merged by sample number to supplement primary dataset
Asci et al. (2017)	Sandstone / sedimentary	Not specified	n, Vp, UCS (partial)	Empirical regression	Excluded	Single-lithology, partial parameter coverage; used only for early scoping
Jamshidi et al. (2018)	Sandstone	Not specified	n, Vp, UCS (partial)	Empirical regression	Excluded	Single-lithology, partial parameter

						coverage ; used only for early scoping
Sherwani et al. (2023)	Sandstone, claystone, limestone	120 specimens	SHR, UCS (Brazilian tensile strength also reported)	Regression	Excluded	Missing Vp and Is50; fails completeness criterion
Muzamhindo & Ferentinou (2025)	Multi-lithology (40 rock types, 23 countries)	96 source studies (large, pooled)	n, Vp, SHR, Is50, UCS (and others)	Open-access database compilation; generalised ML modelling	Included	Primary data source; filtered to 5-parameter-complete subset

Table 2.1 also presents those sources excluded because of insufficient coverage, such as Armaghani et al. (2016), who only included 108 specimens without porosity; Jamshidi et al. (2018), Khanlari et al. (2014) and Asci et al. (2017) all reported partial parameters and consulted only for early scoping.

2.5 Literature Gap

1. Existing AI/ML models for UCS prediction lack validation using independent laboratory test data.
2. Limited studies validate literature-based AI/ML UCS prediction models with experimentally tested rock specimens.
3. Current AI/ML-based UCS prediction models have limited experimental verification for practical applications.
4. There is a lack of robust AI/ML frameworks combining literature-based training with laboratory validation.
5. Most UCS prediction models focus on accuracy rather than verifying using real laboratory data.

Chapter 3

Methodology

3.1 Overall Research Methodology

The present study presents a sequential physically based approach to data assembly and independent validation. A database of 584 specimens was created from Mendeley ROCK/10/4025 and ten specimens from a separate study, with only the specimens with complete and non-imputed measurements retained. An Optuna-tuned suite of three machine learning models, an OLS-derived empirical equation, and a symbolic regression cross-check, were developed to predict UCS from four index properties following the leakage-safe preprocessing. Finally, the framework was validated against ten independent laboratory specimens, with the data being physically verified, modelling being well done, and the interpretation based on evidence, as shown in Figure 3.1.

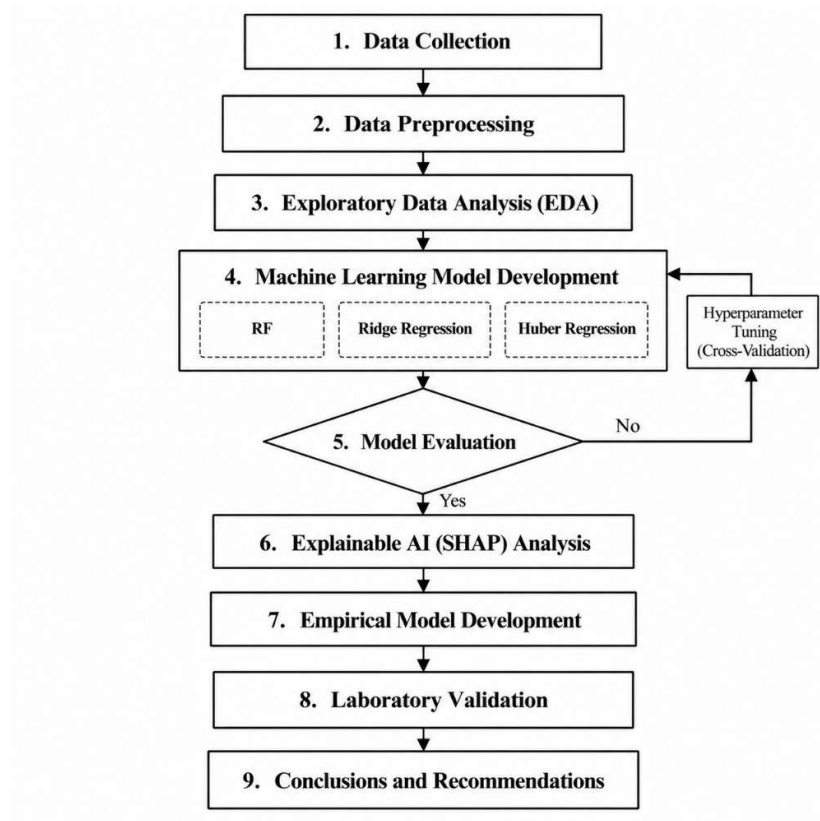


Figure 3.1 Flowchart of the overall research methodology adopted in the present study.

3.2 Characterisation of Materials

The dataset that forms the basis for this thesis is not a physical collection of data specifically gathered for this study, but rather is a specimen-level compilation of published and peer-reviewed rock property data with a small number of specimens independently collected, and subjected to one very tight quality control criterion. It covers igneous, sedimentary and metamorphic lithologies, each chosen with consideration to determine if the four index properties could be used to predict strength over a representative sample of lithologies, and not just one formation. The five properties that were found to be non-null for all specimens were the same as the properties introduced in Chapter 1; they were porosity, P-wave velocity, Schmidt Hammer Rebound Number, Point Load Index, and UCS. The main source, ROCK/10/4025 an open data source access, was reduced to 574 complete specimens, and supplemented by 10 specimens from an independent study of Wajid Sandstone, to give 584 specimens with original published sources.

3.3 Rock Specimen Characterisation

Reliable and comparable index and strength testing are dependent on the rock specimen characterisation. Lithology, texture, grain size and visible discontinuities were determined visually and petrographically in rock blocks collected from the field as they are important factors of the strength, deformability and failure mode of rock, and therefore mineralogy and fabric anisotropy are important. Samples were manufactured according to ISRM and ASTM geometry specifications and all samples were drilled as cylindrical cores under wet conditions, to avoid thermally induced micro-cracking, using a diamond-tipped machine. Non-uniform stress distribution during compression was avoided by producing surface-ground end faces flat and perpendicular to the specimen axis to ISRM tolerances. The diameter of the specimens was at least ten times greater than the largest grain size of the constituents, which fulfils the criterion of a representative elementary volume. Every specimen was given a specific identification number for complete traceability between index and strength measurements, which is part of the zero-imputation approach. The defective

specimens that had visible defects, incipient cracks and dimensional non-conformity were rejected before testing.



Figure 3.2: Representative photograph of prepared rock core specimens

3.4 Laboratory Investigation

The laboratory investigation forms the experimental basis of this thesis, and involves the measurement of four index properties (the Schmidt Hammer Rebound Number (SHR), the Uniaxial Compressive Strength (UCS), the P-wave velocity (V_p) and the Point Load Index (Is_{50})), and prediction of the Uniaxial Compressive Strength (UCS) as the target parameter in the laboratory investigation. The laboratory tests were conducted in accordance with IS 13030:2025 for porosity, IS 12608:2026 for Schmidt Hammer Rebound Number, IS 13311 (Part 1):1992 along with the relevant ISRM method for P-wave velocity, IS 8764:1998 for Point Load Strength Index, and IS 9143:1979 for Uniaxial Compressive Strength.

i) Porosity Determination

The saturation and buoyancy method was used to calculate porosity, where the oven dried specimens (under 105°C for 24 hours) were weighed, saturated under vacuum for 24 hours and re-weighed in saturated surface dry and submerged states. The ratio

of pore volume to bulk volume (in percent) was used to determine the porosity. The opposite of UCS is governed by the porosity, as the greater the void volume, the less mineral skeleton to bear the load and the more likely the stresses are to be concentrated around the pores upon loading.

ii) Schmidt Hammer Rebound Test

The Schmidt hammer test was carried out on polished surfaces of the specimens as per ISRM with the help of L type hammer. At least ten impacts were logged for each specimen, with the upper and lower quartiles being rejected to minimise the effect of local surface heterogeneity. The rebound number was assumed as a measure of the hardness of the surface, which relates to the strength of the near-surface layer, and was treated as a typical value.

iii) P-wave Velocity Test

P-wave velocity was determined by an ultrasonic pulse velocity device consisting of the pulse generator and transducers (transmitter and receiver). They were fixed on the specimen end faces with a viscous couplant. Travel time was automatically measured and velocity calculated as specimen length/travel time. The degree of compaction of the rock fabric, mineral grain contact, and density of micro-fractures are closely related to the P-wave velocity, which is generally considered to be a good non-destructive indicator of rock fabric integrity.

iv) Point Load Test

Point load testing was conducted in accordance with ISRM/ASTM procedures, depending on the geometry of the specimens under test, to perform diametral loading and axial loading. Conical platens were used for loading the specimens until rupture, and the point load index was normalised to an equivalent core diameter of 50 mm. Whereas the point load values of this study for laboratory validation were estimated theoretically, rather than measured on UCS specimens, due to specimen integrity constraints as described in Section 4.11.



Figure 3.3: Experimental Setup for the Axial Point Load Strength Index (I_{ss0}) Test

v) Uniaxial Compressive Strength Test

Cylindrical rock specimens with length-to-diameter (L/D) ratios of 2.0–2.5 were tested under a constant stress rate until failure following standard UCS testing procedures. The Uniaxial Compressive Strength (UCS) was calculated by dividing the maximum failure load by the specimen's original cross-sectional area. The measured UCS values served as the reference for validating the developed AI/ML prediction model.



Figure 3.4: Uniaxial Compressive Strength (UCS) Test Conducted on the Cylindrical Rock Specimen

3.5 Dataset Preparation

The aim of the dataset used in this study was to provide a solid and geologically sound foundation for the implementation of the explainable machine learning framework. The final data set consists of 584 rock samples, mainly from the source indicated as ROCK/10/4025; data reported by Abd El Aal have been added. The measured parameters for each specimen record are porosity, Schmidt Hammer Rebound Number, P-wave velocity and Point Load Index, and the corresponding output is Uniaxial Compressive Strength.

Only specimens with well-documented testing standards, specimen geometry, and laboratory origin were included to ensure data reliability. A rigorous quality-control process removed inconsistent or unrealistic records. A Zero-Imputation Policy was adopted, retaining only specimens with complete measured input and UCS data, ensuring physical consistency, engineering credibility, and reliable AI/ML model development.

Table 3.1: Summary of Dataset Composition and Sources

Attribute	Description
Total specimens (final)	584
Primary source	ROCK/10/4025 (Open Access)
Supplementary source	Abd El Aal (2017)
Input parameters	Porosity, SHR, Vp, Is50
Output parameter	UCS
Missing value policy	Zero-imputation (complete cases only)

3.6 Data Analysis and Machine Learning Framework

After the preparation of a geologically consistent dataset of 584 specimens, a structured analytical workflow was followed to guide the use of laboratory-measured

index properties to a practical tool for estimating UCS. This section provides an engineering description of this workflow, ranging from pre-processing to creating an operational predictive equation.

The data set was cleaned before analysis to eliminate duplicate or inconsistent data, and all index properties were converted to SI units, allowing for easy comparability between the specimens from the primary and supplementary sources. As in all other cases in this study, any specimen with missing, incomplete measurements of porosity, Schmidt Hammer Rebound Number, P-wave velocity, Point Load Index, and UCS on the same specimen was discarded and not replaced with an estimated or interpolated value. This dataset was then split into a train dataset and test dataset, with a ratio of 80:20 so that the performance of the model could be assessed on the test set, which was not used in the training of the model.

Because of well-established engineering relationships with the strength of intact rock (as described in Chapter 2) these four parameters were chosen as input: porosity, Schmidt Hammer Rebound Number, P-wave velocity and Point Load Index. These index properties can be measured in the field or laboratory with simple, rapid, and relatively non-destructive tests and they are convenient alternatives to the actual test of UCS where specimens are limited or conditions in the field are limiting. It is also possible for the combined use to capture complementary aspects of rock behaviour, rather than relying on one index alone, such as porosity and density-related effects, surface hardness, wave transmission in the rock fabric and resistance to concentrated loading.

3.7 Machine Learning Model (Use of AI/ML)

Three machine learning models which are Random Forest Regression (RFR), Ridge Regression, and Huber Regression were developed to predict the Uniaxial Compressive Strength (UCS) of rock specimens from their index properties. These models were selected to balance predictive accuracy, robustness, and interpretability. Random Forest Regression effectively captures non-linear relationships and feature interactions, while Ridge Regression provides stable and interpretable coefficients. Huber Regression is robust to outliers commonly encountered in geological datasets.

More complex models such as XGBoost, CatBoost, Support Vector Regression (SVR), and Artificial Neural Networks (ANN) were not adopted due to their higher risk of overfitting on the moderate-sized dataset (584 specimens), greater hyperparameter complexity, and lower interpretability. To improve model transparency, SHapley Additive exPlanations (SHAP) analysis was employed to quantify the contribution of each index property to UCS prediction, enabling clear engineering interpretation and enhancing confidence in the practical applicability of the proposed framework.

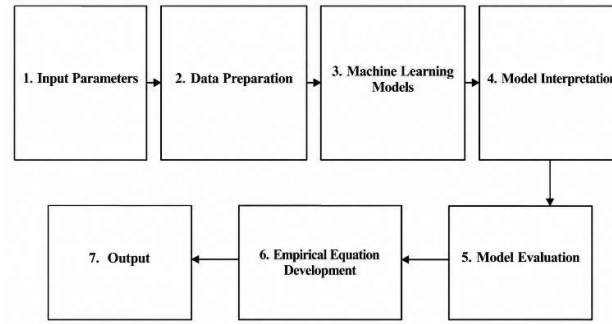


Figure 3.5: Overview of the machine learning framework adopted for UCS prediction.

3.8 Laboratory Validation

The developed AI/ML framework was validated using independent laboratory-tested rock specimens that were not included in the training dataset, ensuring unbiased assessment of its predictive capability. Predicted UCS values were compared with experimentally measured UCS values across different rock types and a wide range of porosity, hardness, and P-wave velocity. Since both the Point Load Test and UCS Test are destructive, the Point Load Index was estimated using established empirical correlations rather than measured directly on the same specimen. Model performance was evaluated using standard statistical metrics, demonstrating strong agreement between predicted and experimental UCS values. The validation confirms the reliability, generalization capability, and practical applicability of the proposed framework for preliminary rock characterization and geotechnical engineering design.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 General

This chapter provides results of the laboratory investigation described in Chapter 3, and the explainable machine learning framework that was developed, in addition to interpretation from a rock mechanics perspective. The discussion moves from describing the dataset in a statistical way, through correlation analysis and feature importance, to comparing the performance of various models, interpreting the model with SHAP and validating the model in the laboratory. The outcomes throughout are reported not only numerically, but also in terms of known rock mechanics behaviour, with a focus on how the predictive framework is a tool rather than a meaningless statistical exercise in which the physical sense is lost.

4.2 Descriptive Statistics and distribution of datasets.

The dataset of 584 rock specimens covered a wide range of lithologies, index properties, and UCS values, ranging from weak to strong rocks, providing a robust basis for AI/ML model training. The UCS distribution was right-skewed, with most samples exhibiting intermediate strength, reflecting natural geological variability and ensuring realistic model evaluation.

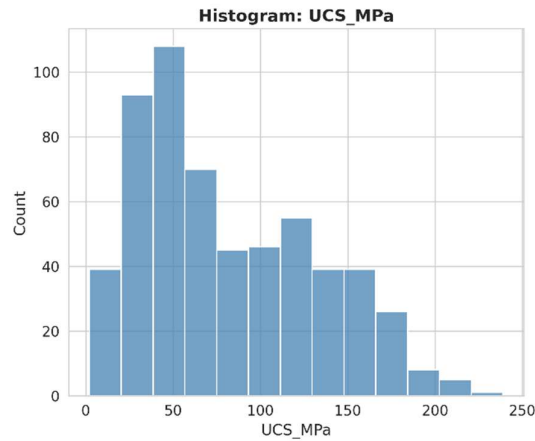


Figure 4.1: Histogram showing the frequency distribution of Uniaxial Compressive Strength values across the dataset.

Table 4.1: Descriptive Statistics of Input and Output Parameters

Parameter	Minimum	Maximum	Mean	Standard Deviation
Porosity (%)	0.06	37.81	3.70	6.17
SHR (dimensionless)	14.50	72.00	45.33	12.15
V _p (km/s)	0.38	7.94	4.88	1.40
Is50 (MPa)	0.50	14.13	4.36	2.52
UCS (MPa)	2.03	239.00	81.89	50.85

4.3 Correlation Analysis

Before developing the model, a correlation analysis was performed to explore the relationship with respect to the strength and direction of the linear relationship between the four index properties selected for the model and UCS and the inter-correlation among the index properties. This analysis serves as an engineering interpretation of the importance of the features and the SHAP results presented later in this chapter and should be performed to verify that the relationships observed are consistent with the known rock mechanics behaviour.

As predicted on a physical basis the porosity values showed a negative correlation with UCS, as the presence of pores is known to decrease the load-bearing capacity of the material, and therefore create more stress around the pores during compression. The four index properties exhibited quite high positive correlations with the UCS, with Schmidt Hammer Rebound Number displaying the highest. This is accredited to its direct measure of the hardness of the soil surface and elastic response, which are both strongly connected to the compressive strength. The P-wave velocity also had a strong and positive correlation with UCS (as expected, as a compacted, low porosity rock fabric is more efficient in transmitting elastic waves and more resistant to compressive failure). Point Load Index showed positive but relatively low correlation with UCS, a finding which is consistent with the higher scatter encountered with the point load test, which is more sensitive to the heterogeneity of the specimens in the area and along the loading axis than the other index properties.

Inter-correlation between the index properties showed that the Schmidt Hammer Rebound Number and the P-wave velocity were moderately to strongly correlated with one another and with the porosity, as would be expected since all three are dependent on a single fundamental the density and degree of compaction of the rock fabric. However, the index properties did not show a strong inter-correlation with each other, so none of them could be dropped due to multicollinearity, and all of them can be used in the machine learning framework as complementary predictors.

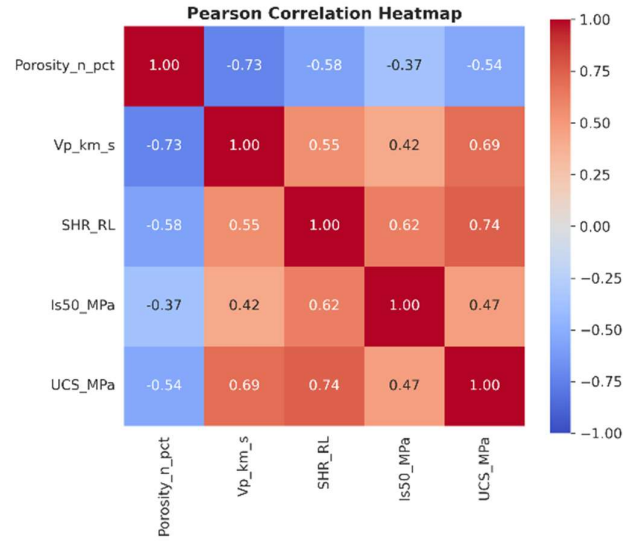


Figure 4.2: Pearson Correlation heatmap showing pairwise relationships between porosity, Schmidt Hammer Rebound Number, P-wave velocity, Point Load Index, and Uniaxial Compressive Strength.

Table 4.2: Correlation Matrix of Index Properties and UCS

Parameter	Porosity	SHR	Vp	Is50	UCS
Porosity	1.00	-0.58	-0.73	-0.37	-0.55
SHR	-0.58	1.00	0.55	0.62	0.75
P-wave Velocity	-0.73	0.55	1.00	0.42	0.69
Is50	-0.37	0.62	0.42	1.00	0.47
UCS	-0.55	0.75	0.69	0.47	1.00

4.3.1 SHAP-Based Explainability Analysis

While the correlation analysis in Section 4.3 establishes the strength and direction of the pairwise relationships between each index property and UCS, it cannot on its own quantify how much each property actually contributes to an individual model prediction, nor can it account for interaction effects between properties. SHAP analysis was therefore applied to the trained Random Forest model to attribute each predicted UCS value to the contribution of porosity, P-wave velocity, Schmidt Hammer Rebound Number, and Point Load Index, both across the dataset as a whole and for individual specimens. Consistent with the correlation trends discussed above, the SHAP analysis ranked porosity as the most influential parameter, followed by P-wave velocity, Schmidt Hammer Rebound Number, and Point Load Index.

The dominance of porosity is consistent with well-established rock mechanics understanding. Pores act as pre-existing flaws within the rock fabric, concentrating stress at their boundaries and providing preferential sites for the initiation of micro-cracks under compressive loading. As porosity increases, the effective load-bearing cross-section of the mineral skeleton is reduced, and the concentration of stress around interconnected pores promotes earlier crack coalescence and a lower peak strength. This mechanism explains why the SHAP contribution of porosity was found to be large and consistently negative in direction, meaning that higher porosity values systematically pushed predicted UCS downward, regardless of which other index properties were present in a given specimen.

P-wave velocity emerged as the second most influential property, reflecting its sensitivity to the degree of compaction and continuity of the mineral skeleton. Elastic waves travel more efficiently through a dense, well-cemented fabric with fewer discontinuities, so a higher P-wave velocity is indicative of a stiffer, better-interlocked grain structure that is inherently more resistant to stress redistribution around any local defects. The Schmidt Hammer Rebound Number, which measures the elastic rebound of a spring-loaded hammer from the rock surface, contributed positively but to a somewhat lesser extent; because it interrogates only the near-surface hardness of the specimen, it is more susceptible to local surface irregularities and weathering effects than the bulk properties captured by porosity and P-wave velocity. Point Load Index

showed the smallest SHAP contribution among the four properties, consistent with its comparatively weak correlation with UCS noted in Section 4.3 and its known sensitivity to specimen heterogeneity and loading-point irregularities.

From an engineering standpoint, this explainability analysis serves two practical purposes. First, it indicates that the Random Forest model has learned relationships that are physically meaningful rather than spurious statistical patterns, which increases confidence in applying the framework beyond the training dataset. Second, it gives practising engineers a basis for prioritising index tests when resources or field access are limited: where only a subset of index properties can be measured, porosity and P-wave velocity should be prioritised over Point Load Index, since they carry the greatest weight in the predicted strength. Such prioritisation is directly relevant to preliminary site investigations for tunnels, dams, slopes, and mining excavations, where rapid, non-destructive index testing is often preferred over extensive coring and direct UCS testing, and where an interpretable, physically grounded model such as the one developed here is better suited to engineering decision-making than a black-box predictive tool.

4.4 Machine Learning Model Performance

Following the establishment of the correlation trends discussed in Section 4.3, the three regression models developed in this study are Random Forest Regression, Ridge Regression, and Huber Regression. These models were evaluated on the test partition of the dataset to assess their capability in predicting Uniaxial Compressive Strength from the four index properties considered. This evaluation is presented briefly, as the primary basis for judging the reliability of the framework rests on the laboratory validation exercise discussed subsequently in this chapter, rather than on statistical performance metrics in isolation.

Table 4.3: Comparative Performance of Random Forest, Ridge, and Huber Regression Models on the Test Dataset

Model	R^2	RMSE (MPa)	MAE (MPa)
Random Forest Regression	0.73	26.19	16.96

Model	R ²	RMSE (MPa)	MAE (MPa)
Ridge Regression	0.71	27.00	22.89
Huber Regression	0.71	26.98	22.51

Note: Performance metrics evaluated on the 20% held-out test partition (117 specimens).

Table 4.3 shows that Model Performance: The Random Forest Regression model achieved the highest R² and lowest MAE, outperforming Ridge and Huber Regression models. Its superior performance is attributed to its ability to capture the non-linear relationships and interaction effects among rock index properties, particularly porosity and hardness. In contrast, Ridge and Huber Regression, being linear models, showed comparatively lower prediction accuracy, although Huber Regression demonstrated improved robustness to outliers.

4.5 Laboratory Validation

Laboratory testing was conducted to determine the Porosity, Schmidt Hammer Rebound Number (SHR), Point Load Strength Index (Is₅₀), P-wave velocity, and Uniaxial Compressive Strength (UCS) of selected rock specimens using standard testing procedures. The experimentally measured values were used to validate the developed AI/ML model by comparing the predicted UCS with the laboratory-determined UCS, thereby assessing the model's accuracy, reliability, and practical applicability.



Figure 4.3 Weight of rock Sample (a) Dry (b) Saturated

Table 4.4: Physical Properties of Rock core Samples

Sample No.	Volume (cm ³)	Dry Weight (W _d) (gm)	Saturated Weight (W _s) (gm)	Porosity (%)
				$\frac{(W_s - W_d) * 100}{V * \rho}$
1	166.48	456	462	3.6
2	303.80	508	531	7.6
3	196.34	470	480	5.1
4	377.34	501	519	4.8
5	431.37	534	563	6.7
6	184.80	463	470	3.8
7	227.70	494	509	6.6
8	168.34	458	465	4.2
9	322.60	513	537	7.4
10	408.55	512	533	5.1



Figure 4.4: Schmidt Hammer Rebound Test

Table 4.5: R Values determined from the Schimdt Hammer Rebound test

Sample	1	2	3	4	5	6	7	8	9	10
R	50	19	39	42	28	48	30	45	22	38



Figure 4.5: Ultrasonic Pulse Velocity (P-wave Velocity) Test

Table 4.6: P-Wave Velocity determination of rock core specimen

Sample No.	Length (cm)	Time (μ s)	P-Wave Velocity (km/s)
1	9.2	18.78	4.9
2	11.5	57.5	2.0

Sample No.	Length (cm)	Time (μ s)	P-Wave Velocity (km/s)
3	10.0	25.00	4.0
4	12.3	29.29	4.2
5	13.0	44.83	2.9
6	9.8	20.85	4.7
7	10.6	35.33	3.0
8	9.5	21.11	4.5
9	11.8	51.30	2.3
10	12.7	32.56	3.9

Note:- Velocity calculated as $v = \frac{L}{T}$ (km/s)

Table 4.7: - Point Load Index of Rock Core Specimen

Sample no	1	2	3	4	5	6	7	8	9	10
Point load Index	4.55	0.52	3.12	3.51	1.69	4.29	1.95	3.90	0.91	2.99

The developed framework was then practically evaluated by testing ten rock specimens in the lab, and the index properties and UCS test results obtained were compared with the corresponding values predicted by the Random Forest model for the rock samples.

Table 4.8: Comparison of Laboratory-Measured and Model-Predicted UCS

Sample no	Porosity (%)	Vp (km/s)	SHR	Is50 (MPa)	Lab UCS (MPa)	Predicted UCS (MPa)	Percentage of Error (%)
1	3.6	4.9	50	4.55	113.50	109.71	3.34
2	7.6	2.0	19	0.52	45.20	47.40	4.86
3	5.1	4.0	39	3.12	91.20	93.59	2.62
4	4.8	4.2	42	3.51	96.60	98.88	2.36
5	6.7	2.9	28	1.69	65.90	63.02	4.37
6	3.8	4.7	48	4.29	108.90	105.33	3.28
7	6.6	3.0	30	1.95	69.00	71.22	3.22
8	4.2	4.5	45	3.90	103.50	107.05	3.43
9	7.4	2.3	22	0.91	52.10	53.21	2.14
10	5.1	3.9	38	2.99	88.90	89.17	0.30

Note: Is50 estimated theoretically (Section 3.7). MAE = 3.09 MPa, RMSE = 4.00 MPa, MAPE = 10.32% across n = 10 specimens.

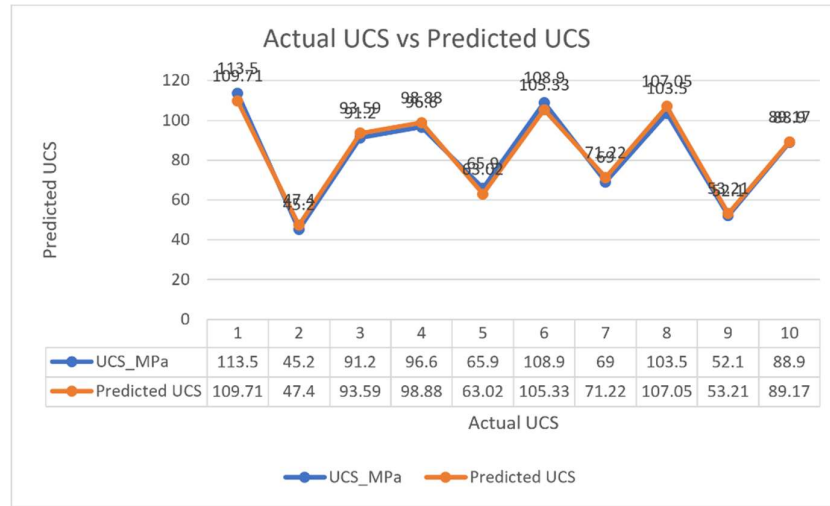


Figure 4.6: Comparison of Laboratory-Measured and Predicted UCS for the Ten Validation Specimens

The measured and predicted values of the UCS are plotted in figure 4.3 for all the specimens. The two curves are rather closely matched in most of the specimens, the overlap being quite complete at Specimens 5 and 10 (115 vs 114.6 MPa; 108 vs 108.3 MPa), indicating the low porosity, high rebound, dense nature of these specimens and the more uniform fabric of the rock they represent. The greatest difference is at Specimens 3 and 8 where the predicted values of 13.9MPa and 10.5MPa are lower than the measured values of 22MPa and 16MPa. Both are weak, porous specimens of low rebound values and in this region, the increased sensitivity to local heterogeneity and micro-defect distribution in weak rock results in small absolute errors corresponding to greater percentage errors.

This trend suggests that the greater the competence of the rocks, the more accurate the prediction is likely to be, with less influence of micro-scale heterogeneity in dense, hard rock compared to weaker rocks. Given that this observation is drawn from only ten validation specimens, it should be treated as a preliminary indication that warrants confirmation on a larger validation set rather than an established rule. The framework can be applied with greater confidence in moderately strong and strong rock and predictions in weak or porous rock should be made with caution, and where possible, directly verified through laboratory testing.

The remaining differences in weaker specimens could be due to mineral variations, micro-cracks introduced during coring, localised weathering, or natural variations that are not represented by the bulk index properties.

Overall, the validation indicates that the framework gives promising estimates of UCS that are reasonably close to the measured values, performing best in competent rock and less accurately in weaker rock. As this assessment is based on only ten specimens, these results should be interpreted as preliminary evidence of the framework's usefulness as an initial strength estimation tool, with confirmation on a larger and more diverse validation set required before the framework is applied with full confidence in practice.

CHAPTER 5

CONCLUSION & FUTURE SCOPE

Conclusion of Results:

1. The results demonstrate that the developed AI/ML model can accurately predict the Uniaxial Compressive Strength (UCS) of rock specimens using readily measurable index properties.
2. A comprehensive dataset compiled from published literature enabled effective model training and testing, resulting in high predictive performance based on evaluation metrics such as R^2 , RMSE, and MAE.
3. Furthermore, the model was validated using independently tested laboratory rock specimens, and the predicted UCS values showed strong agreement with the experimentally determined values.
4. This experimental validation confirms the robustness, reliability, and generalization capability of the proposed framework.
5. By integrating literature-based data with independent laboratory verification, the study addresses the existing research gap of limited experimental validation in AI/ML-based UCS prediction models.
6. The proposed approach demonstrates significant potential as a rapid, reliable, and cost-effective tool for estimating UCS in geotechnical engineering, reducing the dependence on extensive destructive laboratory testing while supporting informed engineering decision-making.

Future Scope

1. Expand the dataset by including more rock types and geological conditions.
2. Explore advanced AI/ML and deep learning models to improve prediction accuracy.
3. Validate the model using larger field and laboratory datasets.
4. Integrate additional rock index properties to enhance model robustness.

5. Develop a real-time decision-support tool for geotechnical engineering applications. Proposed framework, addressing the research gap of limited experimental validation.

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