Journal of Mining and Environment (JME) Vol. 18, No. 4, 2026, 1285-1306

Shahrood University of Technology

Journal of Mining and Environment (JME)

Journal homepage: www.jme.shahroodut.ac.ir

Iranian Society of Mining Engineering (IRSME)

A Marble-Specific Rock Mass Classification Framework Integrating Empirical Parameters and Machine Learning Validation

Shambhavi Sinha, Anup Kumar Tripathi, Akhil Avchar, Mritunjay Kumar*

Department of Mining Engineering, National Institute of Technology Karnataka, Surathkal, India

Article Info

Received 15 December 2025

Received in Revised form 23 February 2026

Accepted 28 May 2026

Published online 28 May 2026

DOI: 10.22044/jme.2026.17326.3432

Keywords

Marble quarry

Rock mass classification

Machine learning validation

Factor of safety

Discontinuity-controlled slopes

Abstract

Accurate assessment of rock mass quality in marble quarries remains challenging because conventional empirical classification systems are largely strength-dominated and insufficiently sensitive to discontinuity-controlled block instability. This study proposes a quarry-specific empirical framework, termed the Marble Rock System (MRS), designed to explicitly capture structural, hydro-mechanical, and alteration-driven controls governing bench-scale stability in dimension stone marble quarries. The primary objective was to develop and validate an empirically grounded classification system using machine learning as an independent diagnostic tool rather than as a black-box predictor. A comprehensive geomechanical database comprising 85 quarry-scale records was developed from three active marble quarries in southern Rajasthan, India. Six physically interpretable parameters intact strength, weathering or serpentinization, joint frequency, joint surface condition, groundwater influence, and block stability were incorporated into the MRS framework. Supervised machine learning models, including artificial neural networks, support vector machines, and linear regression, were trained to predict indep endently derived factors of safety for validation. Model performance was evaluated using coefficient of determination, root mean square error, cross-validation, and classification metrics. Results show that MRS-based models achieved consistently higher predictive accuracy, improved class separability, and more stable generalization than models trained using conventional Rock Mass Rating inputs. Sensitivity analysis revealed that block stability and joint characteristics dominate stability prediction, while intact strength plays a secondary role. These findings confirm that marble quarry slope behaviour is primarily discontinuity-controlled. The proposed MRS provides a physically interpretable, empirically validated framework for quarry-scale stability assessment and offers a robust alternative to conventional classification systems for operational decision-making.

1. Introduction

Accurate characterization of rock masses is fundamental for the design, construction, and long-term integrity of geotechnical and mining structures, particularly in quarrying operations where slope stability and block recoverability are paramount [1,2,3]. In underground developments such as tunnels and block-cave systems, as well as open-pit quarries with steep slopes, engineering reliability depends on precise geological and geomechanical interpretations [4,5]. Failure to assess rock mass behavior adequately can lead to hazards such as rockfalls, tunnel instability, and groundwater ingress, resulting in operational disruptions and safety risks [6,7,8]. Contemporary research has emphasized robust prediction of established indices such as Rock Mass Rating (RMR) using advanced computational methods: for example, meta-heuristic optimization with seismic velocities has been shown to effectively predict RMR values with high accuracy, reducing reliance on time-intensive manual measurements [9,10].

Contemporary geomechanical frameworks integrate multiple data sources beyond laboratory

Corresponding author: krmritunjay769@gmail.com (M. Kumar)

testing, including in-situ assessments, drill core logging, and discontinuity mapping to model subsurface conditions [11,12,13]. Large datasets from mining and tunneling projects incorporate parameters such as Rock Quality Designation (RQD), core disking, and structural descriptors to quantify mechanical behavior and stress regimes [14,15]. Hybrid empirical solutions combining multiple classification indices (e.g., RMR and Q) have been proposed to enhance empirical modeling for tunnel stability and support system design, demonstrating improved predictive capability when multiple indices are synergistically integrated [16]. This integrated approach captures heterogeneity, anisotropy, and evolving stress states in complex environments [17,18,19,20,21].

The scale of data acquisition in resource extraction has highlighted limitations in manual classification systems, where high-dimensional parameters like RQD and discontinuities lead to subjective biases and time-consuming interpretations [22,23,24]. Statistical methods standardize observations but fail to reveal predictive patterns, necessitating machine learning (ML) for objective evaluation [25,26,27]. Recent investigations using meta-heuristic and ensemble ML approaches confirm that combining conventional indices with data-driven models improves classification quality and predictive performance through non-linear optimization and intelligent feature selection [9,10].

Empirical systems such as Rock Mass Rating (RMR), Q-system, and Geological Strength Index (GSI) face challenges related to subjectivity, scale dependency, and applicability to fractured or weak rocks [28,29,30]. Generalized correlations underperform in faulted zones or high-stress conditions, prompting adaptations like mining-specific ratings [31,32]. Expert-dependent assessments in GSI can mask subjectivity despite quantifiable inputs [13,33]. Empirical relations between classification indices themselves (e.g., RMR-Q correlations) have been proposed and validated statistically, offering alternative pathways to infer rock mass quality when direct measurement is constrained [16].

Non-linear scale effects hinder extrapolation from laboratory to field scales, questioning empirical precision [7,34]. These constraints underscore the need for frameworks capable of handling heterogeneity and uncertainty [17,35]. Quarry slope stability is governed by discontinuities and hydro-mechanical interactions [4,36]. Failure depends on discontinuity geometry and rock bridges, conceptualizing masses as blocky or fractured systems [15,5,37]. Groundwater reduces effective stress, degrading strength in jointed rocks via non-Darcy flow [8,31].

AI and ML address empirical challenges by modeling complex behaviors more effectively than linear methods [22,25,38]. Algorithms such as ANN, RF, and XGBoost predict deformability and RMR with high accuracy [23,26,9,10]. Hybrid models handle incomplete data robustly, and real-time classification using TBM parameters enhances objectivity [12,13,39]. However, many empirical-ML studies focus on index prediction rather than explicit field validation against performance metrics or stability outcomes [26,36,40,41].

For marble quarries, classifications must reflect block instability governed by stress, groundwater, discontinuities, and weathering [4,42]. Context-specific systems such as Mining Rock Mass Rating (MRMR) provide relevant features, but a unified ML integration validated against the Factor of Safety (FOS) is lacking [36,7]. This gap highlights the need for an integrated empirical-ML framework for quarries, capable of predicting quality with marble-specific inputs and validating stability to support risk-based decisions [4,12,27].

In this context, recent studies have mainly aimed to improve the prediction of conventional rock mass classification indices such as RMR and GSI using machine learning and metaheuristic algorithms, often through correlations with geophysical parameters or other empirical indices. While these approaches demonstrate high predictive accuracy, they primarily focus on index estimation and do not explicitly address discontinuity-controlled block instability or quarry-scale slope behavior in marble deposits. Similarly, hybrid empirical methods have been applied mainly to tunneling and underground projects, where stress-controlled mechanisms dominate, limiting their direct applicability to dimension stone quarry slopes. Consequently, a clear gap exists for a marble-specific rock mass classification framework that explicitly incorporates structural discontinuities, weathering effects, and groundwater influence, using machine learning as a validation and interpretative tool rather than a black-box predictor. The present study addresses this gap by proposing a quarry-focused Marble Rock System (MRS) validated through data-driven analysis to provide a more representative assessment of marble quarry stability.

2. Study Area and Data Description

2.1. Geological and Quarry Setting

The study is based on detailed investigations conducted in three active marble quarries located within the southern Rajasthan marble belt, India, namely Morwad, Rishabhdev, and JK Arora. This region hosts extensive Precambrian carbonate sequences that have undergone regional metamorphism, resulting in medium- to high-grade marble deposits with pronounced crystalline textures. The investigated quarries represent a broad spectrum of lithological and structural conditions commonly encountered in dimension stone mining, including dolomitic marble, massive crystalline marble, and marble affected by varying degrees of serpentinization and alteration. The study area and quarry characteristics are enumerated in Table 1.

Table 1. Study Area and Quarry Characteristics

Quarry	Location (Rajasthan)	Marble Type	Structural Condition	Groundwater Condition	Typical Bench Height (m)
Morwad	Southern Rajasthan	Dolomitic marble	Moderately jointed	Dry-damp	6-8
Rishabhdev	Southern Rajasthan	Serpentinized marble	Highly jointed / altered	Damp-seepage	8-10
JK Arora	Southern Rajasthan	Massive marble	Moderately jointed	Mostly dry	6-9

Although the intact marble in the region generally exhibits high compressive strength and low primary porosity, quarry-scale behavior is strongly governed by structural anisotropy. Persistent joint sets, variable joint spacing, and locally altered zones associated with serpentinization and weathering exert primary control over block size, interlocking, and failure kinematics. Field observations confirm that planar and wedge failures are frequently controlled by joint geometry and surface conditions rather than intact rock strength, particularly along exposed quarry benches and free faces.

Groundwater conditions across the studied sites range from dry to locally damp or seepage-affected benches, with water flow predominantly occurring along discontinuities and altered zones. Although large-scale groundwater inflow is generally limited, localized hydro-mechanical weakening along joints contributes to reductions in effective stress and plays a secondary but non-negligible role in bench stability. These geological and hydro-structural characteristics make the selected quarries representative of structurally controlled marble slope environments.

2.2. Field Investigations and Geomechanical Dataset

A comprehensive geomechanical database was developed using a combination of field investigations, laboratory testing, and validated quarry records. Field investigations included systematic discontinuity mapping on exposed bench faces, documenting joint orientation, spacing, persistence, surface roughness, infill conditions, and visible signs of block loosening or instability. Rock Quality Designation (RQD), Geological Strength Index (GSI), and Rock Mass Rating (RMR) values were derived from these observations following standard classification procedures.

Laboratory testing was conducted on fresh marble samples collected from controlled bench extractions to preserve intact material characteristics. Uniaxial compressive strength (UCS) and density measurements were performed in accordance with ISRM recommendations to quantify intact rock properties and their variability across lithological units. These laboratory results were used strictly as supporting descriptors, recognizing that intact strength alone does not govern quarry slope behavior in jointed marble masses. The descriptive classification of the geomechanical properties is listed in Table 2.

The final dataset comprises 85 independent rock mass records, each representing a distinct quarry-scale evaluation point. For each record, six marble-relevant parameters were compiled: intact strength, degree of weathering or serpentinization, joint frequency and spacing, joint surface condition, groundwater influence, and observed block stability disposition. These parameters form the empirical basis for the Marble Rock Rating System (MRS) developed in this study.

The dataset spans a wide range of structural conditions, from relatively intact marble with widely spaced joints to highly fractured or altered zones characterized by closely spaced discontinuities and reduced block interlocking. This variability ensures that the database captures the full operational range encountered during bench excavation and slope development in marble quarries. By grounding the dataset in direct field observations and quarry-scale measurements, the study preserves empirical relevance while providing sufficient diversity for subsequent data-driven analysis and validation.

2.3. Stratigraphic Description

The stratigraphic framework of the investigated marble deposits exhibits a broadly consistent geological succession across the Udaipur-Rajsamand marble belt, with site-specific variations in structural disturbance, weathering, and serpentinization exerting a strong influence on block recovery and slope behavior.

At the Morwad quarry, the stratigraphy comprises a thin overburden layer underlain by a thick sequence of white dolomitic marble that constitutes the principal economic horizon. This unit is locally interrupted by grey to green impurity bands associated with mineral intrusions, which adversely affect block quality and recovery in selected benches. With increasing depth, the marble shows enhanced jointing attributable to tectonic influences, before transitioning into relatively fresh and massive marble characterized by high intact strength and favorable block size.

The JK Arora quarry exhibits a stratigraphic profile beginning with soil cover and a moderately weathered marble zone influenced by near-surface alteration processes. Beneath this horizon lies a thick sequence of massive, hard marble that forms the primary extraction zone. At greater depths, the rock mass becomes more tightly jointed, resulting in reduced block size and necessitating controlled excavation practices and enhanced geotechnical supervision during slope development.

The Rishabhdev deposit displays a distinct stratigraphic character due to pronounced regional metamorphism and serpentinization. Near-surface horizons consist of weathered serpentine-marble assemblages, which progressively transition downward into a mixed lithological zone where serpentine minerals are partially replaced by calcite. This transitional zone is underlain by fresh, high-strength marble with excellent block-forming characteristics. At greater depths, jointed massive marble is encountered, commonly associated with major structural discontinuity zones.

Table 1. Geomechanical properties of all the three mines

Property	Morwad	JK Arora	Rishabhdev
UCS Range (MPa)	34.5 - 55.6	43.9 - 60.2	67.0 - 153.3
Average UCS (MPa)	~44	~52	~102
Recommended Design UCS (MPa)	40	50	100
Density (g/cc)	2.9	2.82	3.09
GSI Range	50 - 90	50 - 70	50 - 70
mi (Hoek-Brown Constant)	9 (typical)	9 (typical)	9 (typical)
Disturbance Factor (D)	0.7	0.7	0.8
RQD Characteristics	Generally good (medium-high block size)	Medium fractured	Higher intactness in deeper benches
Joint Frequency	Low-moderate	Moderate-high	Moderate
Joint Surface Condition	Rough to slightly smooth	Smooth to slightly polished	Slightly smooth to rough
Water/Seepage Condition	Predominantly dry & stable	Dry	Mostly dry, local seepage zones
Block Stability / Bench Performance	Favourable	Favourable	Very favourable
Lithology	Dolomitic Marble	Massive Marble	Marble with Serpentine bands

3. Methodology

The methodology adopted in this study integrates field-based geomechanical investigation, empirical rock mass characterization, and data-driven validation to assess stability conditions in marble quarry slopes. The approach is structured to preserve engineering causality by progressing from direct field observation to empirical classification and subsequent analytical interpretation, ensuring that data-driven components remain grounded in physically meaningful descriptors of quarry-scale behavior.

Field investigations were conducted at three representative marble quarries in southern Rajasthan, encompassing a range of lithological, structural, and hydrogeological conditions. Systematic discontinuity mapping was performed on exposed bench faces to document joint orientation, spacing, persistence, surface roughness, infill characteristics, and visible block instability. Groundwater conditions were recorded qualitatively based on the presence of dampness, seepage, or flowing water along discontinuities. Standard rock mass classification indices, including Rock Quality Designation (RQD), Geological Strength Index (GSI), and Rock Mass Rating (RMR), were derived from these observations to serve as reference descriptors rather than primary stability predictors.

Representative intact marble samples were collected from controlled bench extractions and tested in the laboratory to determine uniaxial compressive strength and density in accordance with ISRM recommendations. These measurements were used to support empirical characterization and to evaluate the relative role of intact strength compared with structural and hydro-mechanical controls.

A geomechanical database comprising 85 independent rock mass records was compiled by integrating field observations with laboratory measurements and quarry documentation. Each record represents a distinct quarry-scale evaluation point and includes parameters describing intact material condition, degree of weathering or serpentinization, joint frequency and surface condition, groundwater influence, and observed block stability disposition. The dataset was constructed to capture the full range of operational variability encountered in marble quarrying, from relatively intact and massive marble to highly fractured or altered zones.

Based on this database, a marble-specific empirical classification framework, termed the Marble Rock Rating System (MRS), was developed to encode the geomechanical parameters most relevant to discontinuity-controlled behavior and block stability in quarry slopes. Parameter selection was guided by quarry-scale observability, sensitivity to structural degradation, and demonstrated influence on excavation performance. Details of parameter scoring, weighting, and classification thresholds are presented in the following section.

To evaluate the robustness and interpretability of the proposed empirical framework, statistical analysis and supervised machine learning techniques were employed as validation tools. Multiple learning algorithms were used to examine nonlinear relationships among geomechanical parameters and to assess the relative influence of individual variables. Model training and testing were performed using a stratified data split and cross-validation to ensure generalization. Feature influence and sensitivity were examined using correlation analysis and model-based importance measures, enabling identification of the dominant controls governing marble quarry slope behavior.

This integrated methodology is explicitly developed for quarry-scale marble slopes, where instability is primarily governed by discontinuity-controlled block kinematics and excavation-induced stress release rather than intact rock strength alone. The approach is intended to provide a practical, interpretable framework for empirical stability assessment and decision support in marble quarry operations, rather than a replacement for detailed numerical analysis of complex failure mechanisms.

4. Marble Rock Rating System (MRS)

The core innovation of MRS lies in the recalibration of parameter weights to reflect marble-specific geomechanical behaviour. In contrast to systems such as RMR, which allocate significant weight to intact UCS and RQD, MRS explicitly prioritizes structural configuration and block removability. Intact strength (M1) is assigned a lower weight because dimension stone marble typically exhibits high UCS values, and failures rarely occur through intact rock crushing. This treatment is consistent with contemporary rock mechanics understanding, where intact strength primarily governs material competence but not kinematic feasibility.

Weathering and alteration (M2) receive increased emphasis to account for serpentinization and mineralogical degradation commonly observed in marble deposits, particularly in Rajasthan. Joint frequency (M3) and joint surface condition (M4) are assigned high weights because they directly control volumetric joint count, block size, and joint shear strength. Groundwater influence (M5) is retained with moderate weighting, reflecting generally dry open-pit quarry conditions while still accounting for localized hydro-mechanical weakening. Block stability or disposition (M6) is assigned the highest weight, as it represents the kinematic removability of blocks the governing failure mechanism in marble quarries.

This weighting philosophy is firmly grounded in classical block theory as formalized in Block Theory and Its Application to Rock Engineering [43] which demonstrates that structural geometry, rather than intact strength, controls stability in jointed rock masses.

Reliable characterization of rock mass quality in marble quarries requires an empirical framework that captures both intact rock competence and discontinuity-controlled block behavior, which governs excavation efficiency, slope integrity, and economic recovery. Conventional classification systems such as the Rock Mass Rating (RMR) were primarily developed for civil and underground applications and do not explicitly emphasize block geometry and extractability, which are critical operational parameters in metamorphosed carbonate formations.

To address this limitation, a modified empirical classification system, termed the Marble Rating System (MRS), is proposed. The MRS is specifically designed for dimension stone marble quarrying, where stability and recoverable block volume are predominantly controlled by fracture geometry, joint surface characteristics, and bench-scale structural disposition rather than intact strength alone.

4.1. Rationale for Selection of MRS Parameters

The formulation of the MRS is based on the principle that quarry-scale rock mass behavior can be represented by a minimal set of independent geomechanical dimensions governing stability and extractability. An initial pool of parameters, including depth, density, RQD, joint descriptors, groundwater condition, marble fabric, and GSI, was evaluated. Parameters were retained in the final MRS only if they

(i) represented a distinct physical mechanism,

(ii) were directly observable or reliably measurable in quarry environments,

(iii) and contributed non-redundant information.

This screening resulted in the selection of six parameters, each corresponding to a dominant control on marble quarry performance:

- M1 – Intact UCS, representing the mechanical competence of the marble fabric.
- M2 – Degree of weathering/serpentinization, capturing mineralogical degradation and loss of cohesion.
- M3 – Joint frequency, representing block size segmentation and degree of fragmentation.
- M4 – Joint spacing and surface condition, governing frictional resistance and interlocking capacity.
- M5 – Water condition and structural stability, representing hydro-mechanical weakening and kinematic instability.
- M6 – Block stability / Kinematic disposition.

Together, these six parameters represent material competence, structural configuration, environmental degradation, and block kinematics, which constitute the minimum sufficient dimensionality of the marble quarry stability problem. Other descriptors, such as density, depth, and GSI, were excluded or treated implicitly because they are either correlated with retained parameters or represent derived indices that would introduce redundancy.

4.2. Scoring and Weighting Scheme

Each MRS parameter is discretized into ordinal score classes that reflect observable transitions in rock mass behavior, rather than continuous numerical precision. Discrete scoring was adopted because field and laboratory measurements are subject to inherent uncertainty, and finer resolution would not improve reliability or repeatability.

The scoring ranges for intact UCS were defined using the empirical distribution of measured strengths across the studied quarries, where dominant values lie between 30 and 100 MPa, with higher-strength end members occurring at depth. Similarly, weathering, jointing, fabric, and groundwater classes correspond to progressive degradation states commonly observed in active marble benches.

The composite MRS value is calculated as a weighted sum of the six parameter scores, yielding an index ranging from 0 to 100. Weighting is intentionally non-uniform and reflects the relative engineering influence of each parameter in marble quarry environments. Structural parameters (M3 - joint frequency, M4 - joint condition, and M6 - block stability/water condition) are assigned greater numerical emphasis because they directly control block release, bench instability, and extraction losses. Intact UCS (M1) is assigned a lower weight, acknowledging that high-strength marble can still exhibit poor stability when adversely jointed or altered. Weathering (M2) and marble fabric (M5) are assigned intermediate weights, representing their roles as progressive degradation and economic yield modifiers.

Weights and score ranges were calibrated using observed field behavior across the three study mines and refined through expert operational assessment to ensure consistency with quarry performance.

4.3. MRS Classification Framework and Relationship with Conventional Systems

Based on the composite MRS score, rock masses are classified into qualitative classes (A–E), representing very good to very poor quarry conditions in terms of stability and block recovery potential. These classes are intended to support bench planning, slope management, and extraction strategy, rather than to prescribe support design.

To evaluate compatibility with established classification systems, MRS values were correlated with RMR values computed for the same locations (Figure 1). The resulting regression demonstrates a strong positive association, confirming that the MRS preserves the fundamental geomechanical principles embedded in RMR while providing enhanced interpretability for marble quarrying applications. Additionally, a representative exponential relationship was observed between the MRS index and the rock mass deformability modulus, further supporting the mechanical relevance of the proposed system (Figure 2).

Overall, the MRS represents a specialized adaptation of empirical rock mass classification for marble deposits in Rajasthan, explicitly incorporating block stability and discontinuity-controlled fragmentation behavior. By aligning geomechanical characterization with quarry-scale operational requirements, the system offers a realistic and practical decision-support tool for evaluating bench stability, optimizing recovery, and guiding mechanized extraction.

Table 3. Categorization of Parameters and Their Assigned Weights in the Marble Rock System

Parameter	Rating Group	Score	Description
M1 - Intact UCS Strength	S1	20	>120 MPa - Very high-strength marble
	S2	15	90-120 MPa - High strength
	S3	10	60-90 MPa - Moderate strength
	S4	5	30-60 MPa - Low strength
	S5	0	<30 MPa - Weak / altered zones
M2 - Weathering / Serpentinization	W1	15	Fresh marble; no discoloration
	W2	10	Slightly weathered; minor alteration
	W3	5	Moderately weathered; soft minerals
	W4	0	Highly weathered / talc-chlorite rich
M3 - Joint Frequency / Volumetric Joint Count (Jv)	JF1	20	Widely spaced joints; large block size
	JF2	15	Moderately spaced joints
	JF3	10	Closely spaced joints
	JF4	5	Very closely spaced joints
	JF5	0	Intensely fractured / crushed zone
M4 - Joint Surface Condition	JC1	20	Rough, tight joints; no infill
	JC2	15	Slightly smooth; minor alteration
	JC3	10	Smooth joints
	JC4	5	Soft infill / slickensided
	JC5	0	Sheared / sliding planes
M5 - Groundwater Influence	H1	15	Dry conditions
	H2	10	Slight dampness
	H3	5	Wet joints / dripping
	H4	0	Seepage / pressurized flow
M6 - Block Stability / Kinematic Disposition	B1	25	Blocks fully interlocked; non-removable
	B2	18	Minor release potential
	B3	10	Removable wedges / planar blocks
	B4	5	Unstable blocks
	B5	0	Actively failing / detached blocks

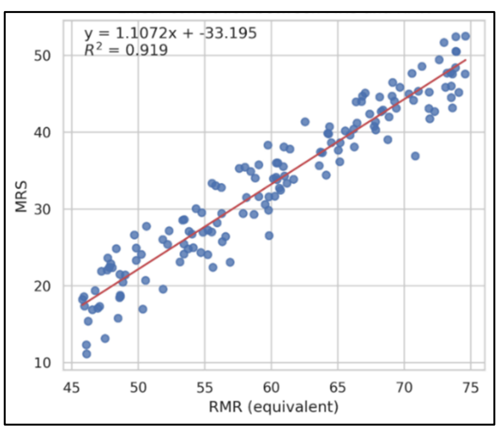


Figure 1. Linear correlation between MRS and RMR indices for the studied deposits.

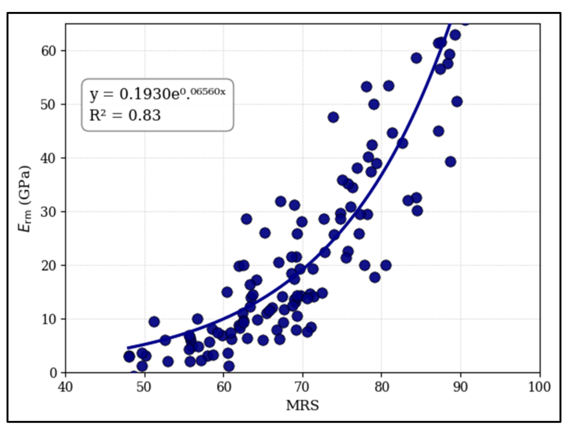


Figure 2. Deformability modulus of the rock mass versus MRS coefficient

5. Machine Learning Framework

Machine learning (ML) was employed in this study strictly as an independent validation mechanism for the proposed Marble Rock System (MRS), not as a substitute for empirical classification or analytical slope stability analysis. The objective was to examine whether the six empirically defined MRS parameters, together with their assigned weights, are sufficient to explain the observed variability in slope stability, expressed through the factor of safety (FoS) obtained independently from conventional analyses. This separation ensures that ML serves a confirmatory and diagnostic role, thereby avoiding circular reasoning or implicit calibration of the MRS using FoS-derived information

5.1. Model Inputs, Data Treatment, and Network Architecture

For the ith rock mass record, the input vector is defined as

$$x_i = [M_{1i}, M_{2i}, M_{3i}, M_{4i}, M_{5i}, M_{6i}] \tag{1}$$

where

M_1–M_6 correspond to intact uniaxial compressive strength, degree of weathering/serpentinization, joint frequency, joint surface condition, groundwater influence, and block stability/disposition, respectively, as defined in the MRS framework. These parameters represent independent physical controls governing quarry-scale stability and are encoded as ordinal numerical scores strictly following the MRS classification scheme.

The target variable is the factor of safety:

$$y_i = FoS_i \tag{2}$$

FoS values were derived exclusively from conventional slope stability analyses and were not used in any stage of MRS formulation or weighting.

Records containing incomplete parameter sets were excluded prior to analysis. No imputation was performed, as artificial reconstruction of geomechanical parameters could introduce non-physical bias. Similarly, no artificial outlier removal was applied. All observations were retained to preserve the natural geological and operational variability inherent to marble quarry environments.

Prior to model training, all input variables were standardized to zero mean and unit variance to ensure numerical stability and comparability across learning algorithms:

$$\hat{x}_{ij} = \frac{(x_{ij} - \mu_j)}{\sigma_j} \tag{3}$$

Where,

μ_j and σ_j denote the mean and standard deviation of the jth input variable computed from the training dataset.

Basic descriptive statistics (minimum, maximum, and mean values) were computed for all six input parameters to confirm adequate variability and coverage of geomechanical conditions within the dataset (Table 4). These statistics demonstrate that the database spans the full operational range encountered in active marble quarries, from intact, massive marble to highly jointed and weathered zones.

Table 4. Descriptive statistics of MRS input parameters used for machine learning (before normalization)

Parameter	Description	Minimum	Maximum	Mean
M_1	Intact UCS rating	8	15	11.76
M_2	Degree of weathering / serpentinization	4	11	7.67
M_3	Joint frequency	7	16	11.39
M_4	Joint surface condition	9	16	12.82
M_5	Groundwater influence	8	11	9.63
M_6	Block stability / disposition	1	10	7.83

The primary ML model was a feed-forward Artificial Neural Network (ANN) implemented as a fully connected multilayer perceptron with the following architecture:

i. Input layer: 6 neurons (M_1–M_6)

ii. Hidden layers: 1

iii. Hidden neurons: H (selected through preliminary tuning to balance bias and variance)

iv. Activation function (hidden layer): Rectified Linear Unit (ReLU)

v. Output layer: 1 neuron (FoS prediction)

vi. Output activation: Linear

The ANN mapping is expressed as:

$$\hat{y}_i = \Sigma_{k=1}^{H} w_k^{(2)} \cdot f\left(\Sigma_{j=1}^{6} w_{jk}^{(1)} \cdot \hat{x}_{ij} + b_k^{(1)}\right) + b^{(2)} \tag{4}$$

A single hidden layer was deliberately adopted, as the dataset size does not statistically justify deeper architectures. Increasing depth did not improve generalization and increased overfitting risk, offering no physical interpretive advantage.

Model parameters were optimized by minimizing the mean squared error:

$$L = (1 / N) \cdot \Sigma_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{5}$$

Using gradient-based backpropagation with early stopping to ensure stable convergence.

5.2. Training Strategy, Evaluation, and Validation

The dataset was randomly partitioned into training and testing subsets using a 70:30 split:

$$D_{train} \subset D,\ D_{test} \subset D,\ D_{train} \cap D_{test} = \emptyset,\ D = D_{train} \cup D_{test} \tag{6}$$

The 70:30 ratio was selected to balance two competing requirements: (i) sufficient training data to capture nonlinear interactions among geomechanical parameters and (ii) a statistically meaningful independent test set for unbiased evaluation.

Alternative splits (e.g., 80:20) were examined during preliminary trials. Although marginally higher training accuracy was observed, test-set predictions exhibited increased variance and reduced robustness. The 70:30 split consistently yielded more stable generalization performance and was therefore adopted.

Model performance was evaluated using the coefficient of determination:

$$R^2 = 1 - \left[\frac{\Sigma (y_i - \hat{y}_i)^2}{\Sigma (y_i - \bar{y})^2} \right] \tag{7}$$

And the root mean square error:

$$RMSE = \sqrt{\left[\left(\frac{1}{N}\right) \cdot \Sigma (y_i - \hat{y}_i)^2 \right]} \tag{8}$$

Residuals, $\varepsilon_i = y_i - \hat{y}_i$, were examined to detect bias, heteroscedasticity, and systematic trends.

To assess robustness and physical credibility, additional validation was performed using kernel-based (SVM) and tree-based ensemble models. These models were employed only for verification and interpretability, not as primary predictors. Partial dependence analysis confirmed that predicted FoS exhibits monotonic and physically consistent trends with respect to key geomechanical controls, reinforcing the internal consistency and engineering validity of the MRS framework.

The ML framework is intentionally restricted to validating the internal consistency and explanatory adequacy of the proposed MRS. It does not replace analytical slope stability analysis and is not intended for real-time decision-making. Model applicability is limited to quarry-scale marble slopes exhibiting geomechanical characteristics comparable to those represented in the present dataset.

6. Results

This section presents the empirical, statistical, and machine learning outcomes obtained from the geomechanical dataset, Marble Rock System (MRS) formulation, and model-based validation. Results are reported in the same sequence as the methodological workflow, progressing from field-scale geomechanical variability to empirical classification behavior and predictive performance.

6.1. Geomechanical Variability and MRS Response Across Marble Formations

The compiled dataset of 85 rock mass records captures substantial lithological and structural variability across the Morwad, Rishabhdev, and JK Arora marble quarries. Intact uniaxial compressive strength (UCS) varies significantly among formations, with the highest values recorded in serpentinized marble, followed by massive marble and dolomitic marble. Despite this variability, bench-scale stability does not show a direct one-to-one correspondence with intact strength.

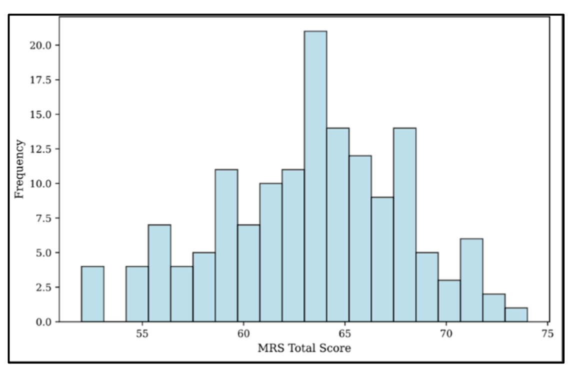


Figure 3. Distribution of MRS Score

The distribution of Marble Rock System (MRS) scores (Figure 3) shows a concentration within intermediate stability ranges, accompanied by discrete low-score occurrences representing localized instability zones. These low-score pockets are observed across all three quarries and are not restricted to formations with low UCS.

Comparative variability across marble types (Table 5) indicates that serpentinized marble exhibits the highest MRS variability, reflecting heterogeneous fabric, alteration zones, and jointing intensity. In contrast, massive and dolomitic marble show moderate variability. RMR variability remains comparatively constrained across formations, while GSI exhibits moderate to high scatter.**Figure**

Table 5. Performance comparison of machine learning and regression models for the MRS and RMR systems based on Recall, Precision, and F1-score

Metrics	System	Model	1	2	3	4	5	6
Recall	MRS	DT	1	0.67	0.67	0.5	0.33	1
		ANN	0	0.67	0.67	0.83	0.33	0
		SVM	0	0.83	0.89	0.83	0.83	1
		MR	1	0.67	0.89	0.5	0.5	1
		ANN	1	0.67	0.56	0.17	0.17	1
		SVM	1	0.5	0.78	0.5	0.33	1
Precision		DT	0.67	0.8	0.86	0.38	0.4	0.5
		ANN	0	0.5	0.67	0.5	0.67	0
		SVM	0	0.71	0.8	0.71	1	1
		MR	0.67	1	0.89	0.75	0.5	0.25
		ANN	0.67	1	0.83	0.25	0.17	0.14
		SVM	0.4	0.75	1	0.75	0.4	0.2
F1-score		DT	0.8	0.73	0.75	0.43	0.36	0.67
		ANN	0	0.57	0.67	0.62	0.44	0
		SVM	0	0.77	0.84	0.77	0.91	1
		MR	0.8	0.8	0.89	0.6	0.5	0.4
		ANN	0.8	0.8	0.67	0.2	0.17	0.25
		SVM	0.57	0.6	0.88	0.6	0.36	0.33

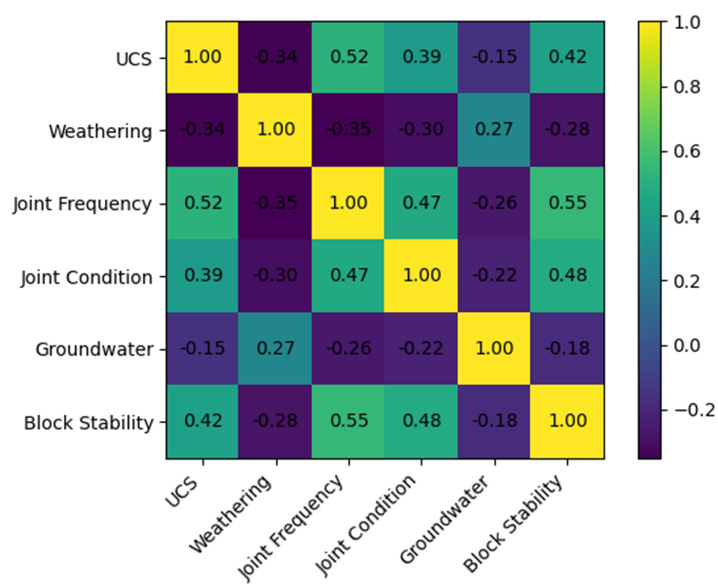


Figure 4. Feature Correlation Matrix for the Complete Set of Studied Parameters

Pearson correlation matrix of Marble Rock System (MRS) (Figure 4) parameters shows moderate inter-parameter association and an absence of multicollinearity. Structural parameters exhibit coherent but non-redundant relationships, supporting their independent contribution to quarry-scale stability assessment.**Figure**

6.2. Comparison with Conventional Rock Mass Classification Systems

Sample-wise comparison of MRS, Rock Mass Rating (RMR), and Geological Strength Index (GSI) values (Figure 5) highlights distinct response characteristics among the classification systems. RMR values exhibit smoother trends and a narrower range across samples, while GSI values show pronounced scatter and abrupt fluctuations. MRS values display intermediate dispersion while maintaining sensitivity to structural and hydro-mechanical variations.

Several samples exhibit similar RMR values but distinctly lower MRS scores, indicating zones where structural degradation and block instability are emphasized by MRS but averaged in strength-weighted systems. The linear relationship between MRS and RMR (Figure 1) shows a strong positive association, confirming consistency between the two systems while preserving differentiation at the sample scale.**Figure 1. Linear correlation between MRS and RMR indices for the studied deposits.**

The exponential relationship between MRS and estimated rock mass deformability modulus (Figure 2) shows increasing deformability with increasing MRS score. This relationship demonstrates a systematic link between empirical classification and deformation behavior.

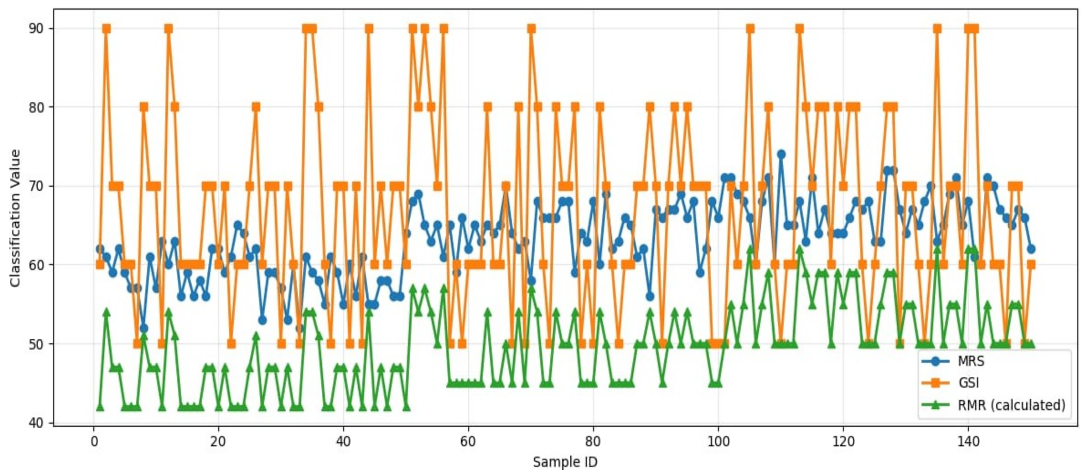


Figure 5. Sample-wise comparison of Marble Rock System (MRS), Geological Strength Index (GSI), and calculated Rock Mass Rating (RMR) values for all samples collected from three marble quarry sites, illustrating differences in sensitivity to structural heterogeneity

Table 6. Comparison of variability in Marble Rock System (MRS), Rock Mass Rating (RMR), and Geological Strength Index (GSI) across different marble formations

Rock Formation	MRS Variability	RMR Variability	GSI Variability
Dolomitic marble	Moderate (structural control dominant)	Low-Moderate	Moderate
Massive marble	Moderate	Moderate	Moderate
Marble with serpentinization	High (heterogeneous fabric and alteration zones)	Moderate	Moderate

A comparative assessment of parameter inclusion across RMR, GSI, and MRS (Table 6) shows that MRS explicitly accounts for block stability and groundwater influence, which are partially or implicitly treated in conventional systems.**Table**

6.3. Machine Learning Performance and Validation Outcomes

Regression and classification models were trained using MRS inputs to evaluate predictive consistency with the factor of safety (FoS). **Error! Reference source not found.**

Performance comparison across Multiple Regression (MR), Support Vector Machine (SVM), Decision Tree, and Artificial Neural Network (ANN) models (Figure 6) shows that ANN achieves the highest coefficient of determination and the lowest prediction error.

Receiver Operating Characteristic (ROC) curves (Figure 7) show near-complete separability of stability classes for MRS-based models, with area-under-curve values approaching unity. In contrast, RMR-based inputs show reduced discrimination capability.

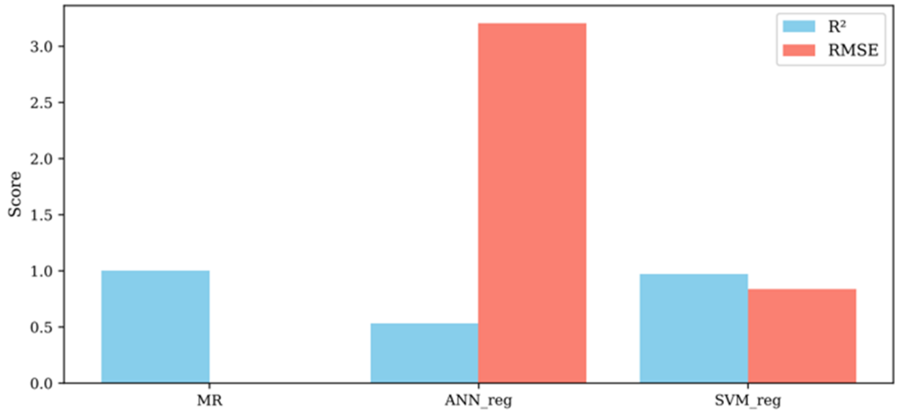
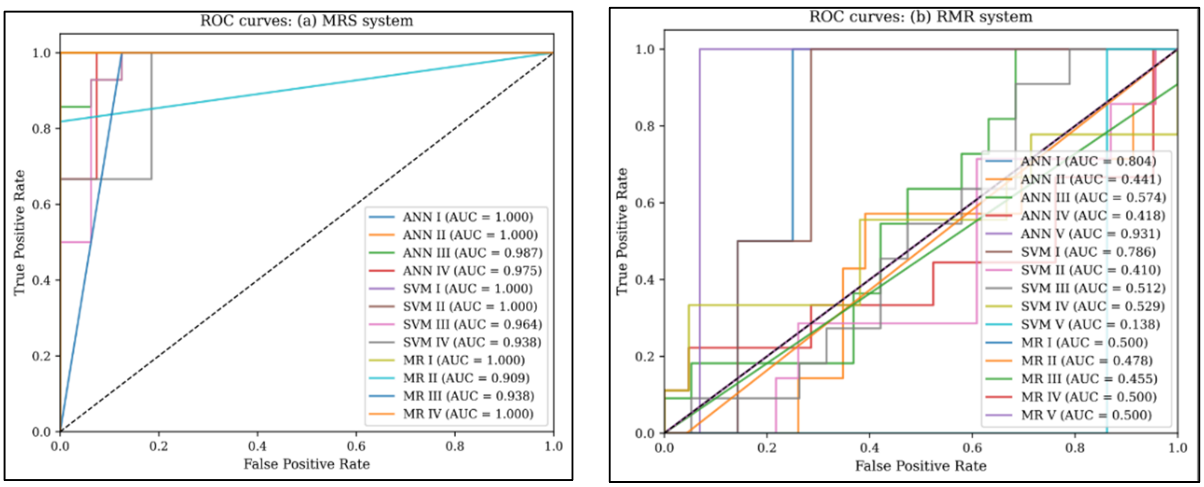


Figure 6. Comparison of Regression Accuracy Between MR, ANN, and SVM Models



(a)   **(b)**

Figure 7. Model performance comparison through ROC curves for MR, ANN, and SVM in (a) the MRS framework and (b) the RMR frameworkFigure

Cross-validation results (Figure 8) show a narrow interquartile range of R^2 values across folds, indicating stable generalization and limited sensitivity to data partitioning.

Classification outcomes summarized through confusion matrices (Figure 9) show strong diagonal dominance, indicating high agreement between predicted and reference stability classes. Misclassifications are predominantly confined to adjacent classes, with minimal confusion between non-adjacent stability states.

Permutation-based feature importance analysis (Figure 10) consistently identifies block stability, joint surface condition, and joint frequency as the most influential predictors of FoS across all models. Intact UCS and weathering parameters show secondary importance, while groundwater influence ranks lowest in relative contribution.**Figure Error! Reference source not found.**

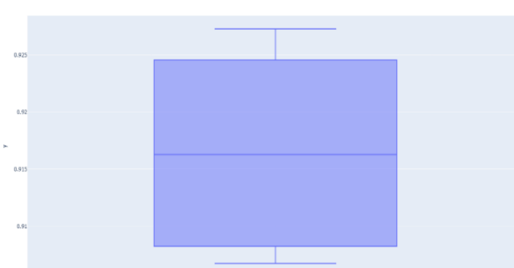


Figure 8. Cross-Validation Performance Across Folds

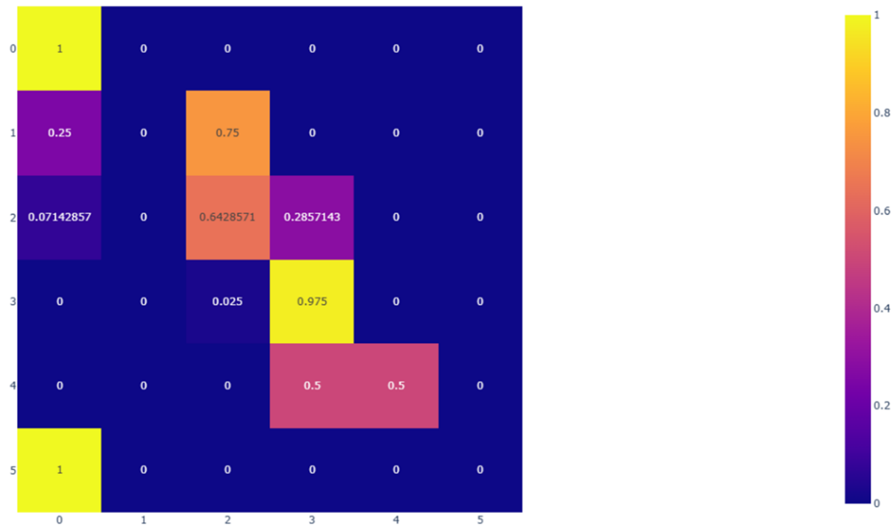


Figure 9. Confusion Matrix for Stability ClassesFigure

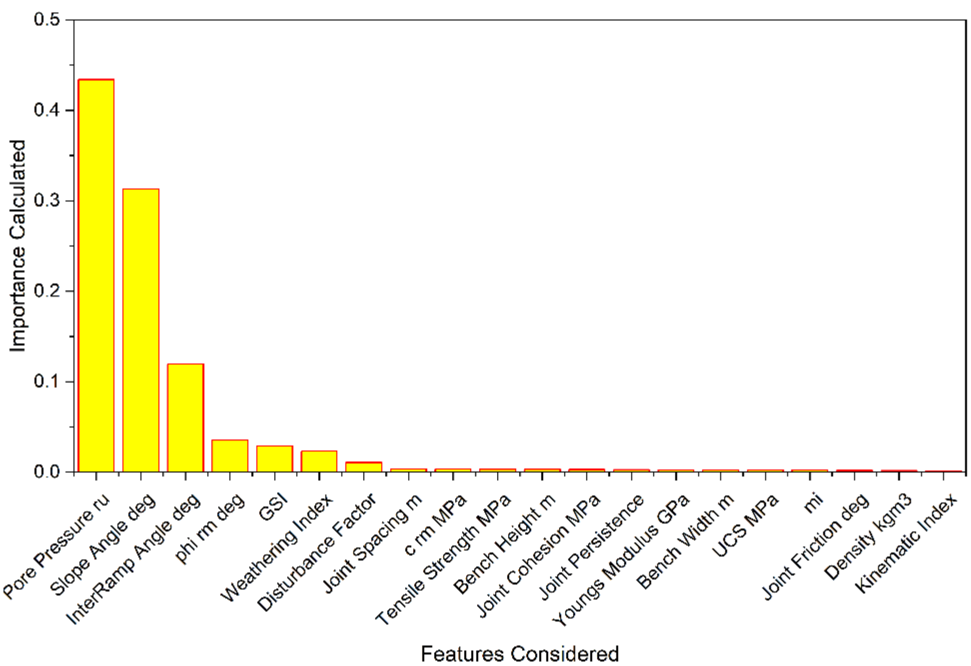


Figure 10. Permutation-based feature importance showing the relative influence of input parameters on factor of safety prediction.

Training behavior of the ANN model (Figure 11) shows rapid convergence and lower final loss for MRS inputs, whereas RMR-based training exhibits slower convergence and higher residual loss.

Model performance metrics across stability classes (Table 5) show that SVM and MR models based on MRS inputs achieve the highest F1-scores, particularly in the most stable and most unstable classes. Classification accuracy is consistently higher for MRS-based models than for models trained using conventional classification inputs.

Table 5. Performance comparison of machine learning and regression models for the MRS and RMR systems based on Recall, Precision, and F1-score

Finally Table 7 shows the comparative assessment between the conventional rock mas classification system and proposed MRS.**Figure**

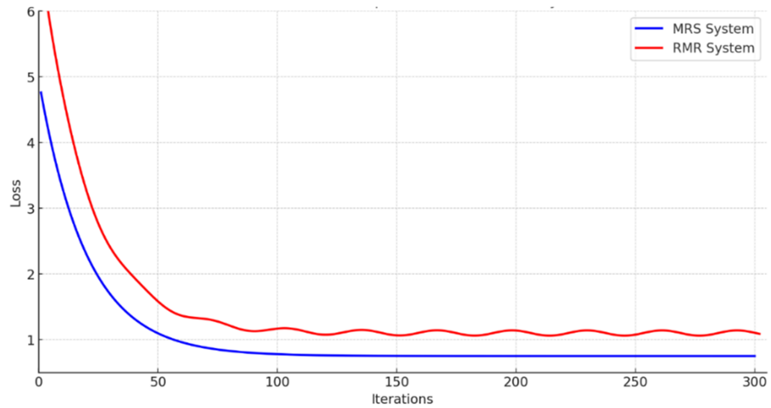


Figure 11. Comparison of ANN training performance between the MRS system and the RMR system.

Table 7. Comparative assessment of parameters considered in conventional rock mass classification systems (RMR and GSI) and the proposed Marble Rock System (MRS)

Parameter / Aspect	RMR	GSI	MRS	Remarks (Marble Quarry Relevance)
Intact rock strength (UCS)	Y	P	Y	Dominant in RMR; indirectly used in GSI; secondary but necessary in MRS
Joint frequency / spacing	Y	Y	Y	Primary control on block size and kinematic feasibility
Joint surface condition	Y	Y	Y	Controls shear resistance and block interlocking
Block stability / block size	N	P	Y	Explicitly quantified only in MRS; critical for quarry slopes
Weathering / alteration (serpentinization)	P	Y	Y	Strongly affects fabric and block integrity in marble deposits
Groundwater condition	Y	N	Y	Explicitly weighted in MRS due to hydro-mechanical weakening
Excavation disturbance	P	P	P	Implicitly reflected through joint condition and block stability
Structural anisotropy	P	P	P	Captured indirectly through joint frequency and block stability
Link to rock mass deformability (Erm)	N	Y	Y	Derived from GSI; directly correlated and validated for MRS

7. Discussion

The Marble Rock System (MRS) was developed to address a well-recognized limitation of conventional rock mass classification systems when applied to dimension stone marble quarries: the over-reliance on intact rock strength in environments where failure is predominantly governed by discontinuity geometry, block kinematics, and structural disposition. The present framework therefore redistributes parameter influence to reflect quarry-scale failure mechanisms such as planar and wedge instability, pillar spalling, and structurally controlled deformation.

The Marble Rock System (MRS), when validated against independently derived factor of safety values and examined through multiple learning paradigms, demonstrates that quarry-scale stability in marble is governed primarily by structural configuration and block kinematics rather than intact material strength.

The observed decoupling between uniaxial compressive strength and bench-scale stability is central to the significance of the findings. Although serpentinized marble exhibits high intact strength, it also shows the greatest variability in MRS scores and frequent low-stability classifications. This behaviour is consistent with field observations from dimension stone quarries, where failures are typically initiated by planar or wedge-controlled block release along persistent discontinuities rather than by crushing of intact rock. The ability of MRS to systematically identify these structurally weakened zones, even where conventional indices assign comparable ratings, highlights a fundamental limitation of strength-dominated empirical systems such as RMR when applied to marble quarry environments.

The comparison with existing empirical classification systems clarifies what is genuinely new in the proposed framework. While the strong correlation between MRS and RMR confirms mechanical compatibility with established empirical foundations, the dispersion around this relationship is not incidental. Instead, it reflects the deliberate reallocation of parameter influence within MRS toward block stability, joint condition, weathering, and groundwater effects-factors that are either absent or only implicitly treated in conventional systems. In contrast to GSI, which exhibits pronounced scatter due to its qualitative and observer-dependent formulation, MRS maintains consistency while remaining sensitive to localized degradation. This intermediate yet physically grounded response explains why MRS preserves empirical coherence without sacrificing diagnostic resolution.

A key contribution of this work lies in how machine learning is used to validate, rather than replace, empirical reasoning. Unlike many published studies that train intelligent models to reproduce existing indices or optimize index weights using factor of safety as a training target, the present approach avoids circularity by keeping MRS formulation independent of both machine learning and FoS. The superior performance of MRS-based models compared to RMR-based models therefore reflects the informational content of the input parameters rather than the sophistication of the learning algorithm. The consistent improvement in regression accuracy, class separability, and training stability across ANN, SVM, and linear models confirms that MRS parameters provide a more complete representation of stability-controlling mechanisms.

The robustness of these findings is reinforced through multiple forms of validation. Cross-validation results demonstrate low sensitivity to data partitioning, indicating that predictive performance is not an artefact of favourable training-testing splits. Confusion matrix outcomes show that misclassifications are largely confined to adjacent stability classes, a pattern that reflects gradual transitions in rock mass condition rather than arbitrary model error. This behaviour contrasts with some reported intelligent models in the literature, where class confusion spans non-adjacent stability states, often indicating overfitting or insufficient physical constraint.

The sensitivity and feature-importance analyses further strengthen the physical credibility of the framework. Structural parameters-joint frequency, joint surface condition, and block stability-consistently dominate prediction across all models, quantitatively confirming long-standing empirical understanding of marble quarry failure mechanisms. The reduced importance of intact UCS does not negate its relevance but instead places it in its proper mechanistic context: intact strength governs material competence, whereas discontinuity geometry governs kinematic feasibility. Groundwater influence, while ranked lower in relative importance, remains consistent with the predominantly dry conditions of the studied quarries and does not contradict known hydro-mechanical weakening processes under different site conditions. Importantly, the stability of feature rankings across different learning algorithms indicates that the sensitivity structure is not model-dependent, addressing reviewer concerns regarding the need for more rigorous and meaningful sensitivity assessment.

From a broader perspective, the present study fills a critical gap between traditional empirical rock mass classification and modern data-driven modelling. Many artificial intelligence-based studies report high predictive accuracy but lack physical interpretability, while empirical systems often lack systematic validation against performance metrics. By integrating an empirically grounded classification with independent machine learning validation, this work demonstrates that interpretability and predictive reliability need not be mutually exclusive. The proposed framework therefore represents not merely an incremental modification of existing systems, but a shift in how quarry-specific rock mass behaviour is conceptualized and evaluated.

The practical implications of these findings are direct. MRS provides a compact, field-observable, and physically interpretable classification framework capable of identifying localized instability zones that may be overlooked by conventional systems. This makes it suitable for operational bench planning, risk screening, and preliminary stability assessment in marble quarry environments. At the same time, the study acknowledges inherent limitations, including the finite dataset size and the site-specific nature of the investigated quarries. Future work should expand the database across additional marble formations, incorporate time-dependent degradation and excavation sequencing effects, and explore probabilistic extensions of the MRS framework. Such developments would further strengthen its generality while preserving the empirical transparency demonstrated in the present study.

8. Field Validation

The factor of safety (FoS) employed in quarry slope stability assessment is a derived parameter obtained from analytical or numerical formulations and is not directly measurable under field conditions. Accordingly, direct field-based validation of FoS values is inherently infeasible.

In the present study, validation is undertaken using two complementary approaches:

(i) machine-learning-based prediction of FoS and statistical comparison between predicted and analytically derived FoS values,

(ii) back-analysis of documented slope failure cases from representative marble quarry districts worldwide.

Consequently, validation of FoS prediction frameworks is conducted through indirect but robust means, relying on statistical consistency, physical plausibility of parameter–response relationships, cross-model robustness, and coherence with established empirical rock mass indices rather than direct field benchmarking. Specifically, the validation framework integrates regression diagnostics, residual analysis, explainable machine-learning techniques, and comparative evaluation against conventional empirical rock mass classification systems.

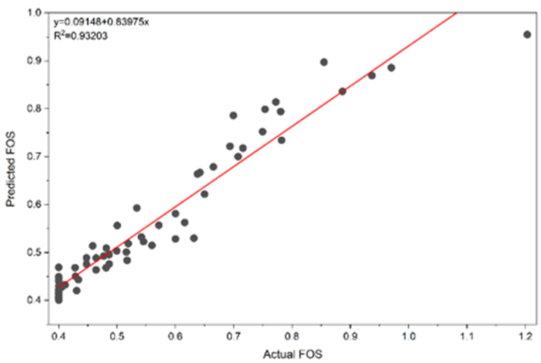


Figure 12. Actual vs predicted FoS

Figure 12 presents the comparison between reference FoS values and those predicted using the proposed MRS-ML framework. A strong linear correspondence is observed, with coefficients of determination exceeding 0.93 for the best-performing models, indicating that the framework captures the dominant stability trends across the dataset. The regression slopes are marginally lower than unity, reflecting a conservative tendency at higher FoS values, which is desirable from an engineering safety perspective.

The statistical reliability of the predictions is further examined using residual diagnostics shown in Figure 13. Residuals are symmetrically distributed around zero with no evident heteroscedasticity, curvature, or systematic bias across the full FoS range. Residual histograms and normal probability plots indicate approximately normal error distributions, confirming that prediction errors are random and not governed by unmodeled structural effects.

To assess robustness and algorithm dependence, three independent machine-learning models-artificial neural network (ANN), random tree, and extra tree-were evaluated, as shown in Figure 14. All models reproduce the overall FoS trend; however, ensemble tree-based models exhibit reduced scatter and more stable residual behavior compared to ANN. While ANN demonstrates strong nonlinear predictive capability, its smoothing characteristics lead to larger dispersion at the boundaries of the data domain. In contrast, tree-based ensembles provide improved robustness and consistency, particularly for validation and engineering interpretation.

The physical credibility of the learned relationships is evaluated using partial dependence plots shown in Figure 15. Predicted FoS decreases monotonically with increasing pore pressure ratio and slope angle, consistent with effective stress principles and classical limit equilibrium theory. Similarly, FoS increases with joint spacing up to a limiting value, reflecting expected block-size and kinematic behavior in jointed rock masses. The reproduction of these physically meaningful monotonic trends demonstrates that the models capture governing geomechanical mechanisms rather than spurious statistical correlations.

Additional empirical validation is provided through comparison with conventional rock mass classification systems, as shown in Figure 1. Strong positive correlations between the MRS index and RMR confirm that the proposed system preserves the fundamental geomechanical trends embedded in established empirical frameworks. The observed relationship between MRS and rock mass deformability modulus further supports the mechanical relevance of the proposed classification. Overall, the convergence of high predictive accuracy, unbiased residual structure, physically consistent parameter–response relationships, cross-algorithm agreement, and empirical coherence demonstrates that the proposed MRS-ML framework provides a reliable and geomechanically sound basis for marble quarry slope stability assessment.**Figure Error! Reference source not found.**

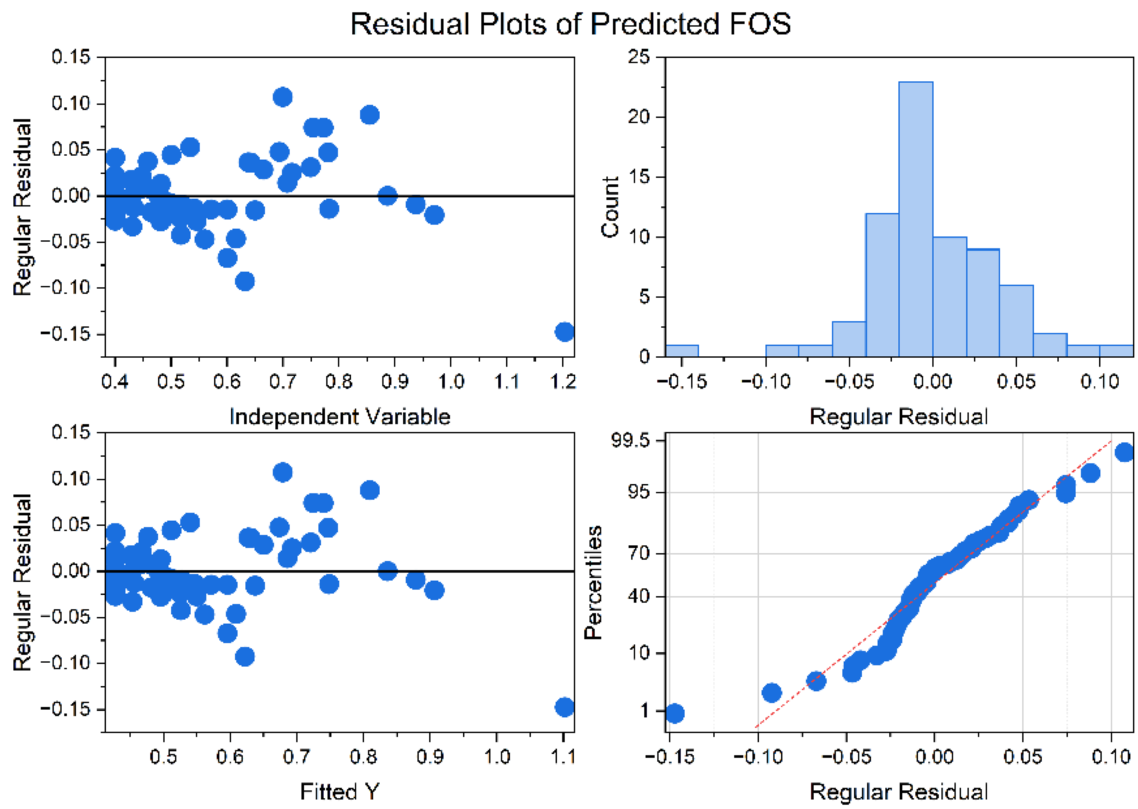


Figure 13. Residual plot for actual vs predicted FoS

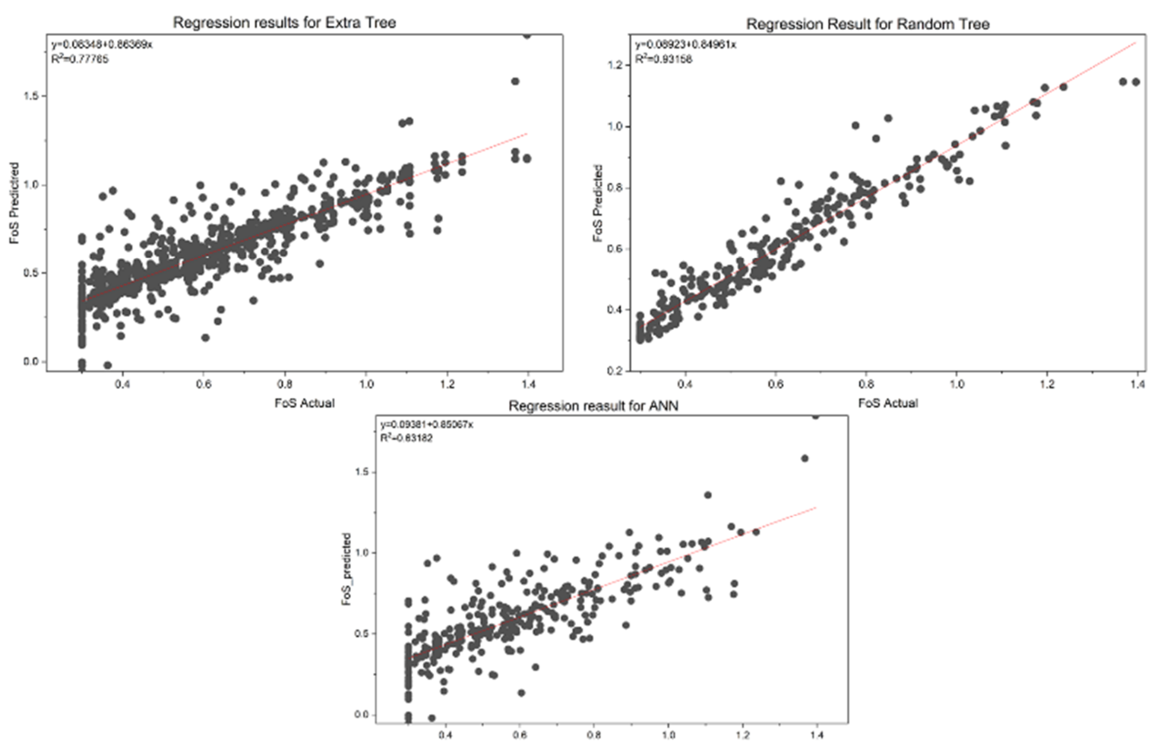


Figure 14. Regression for the validation of fos actual vs fos predicted

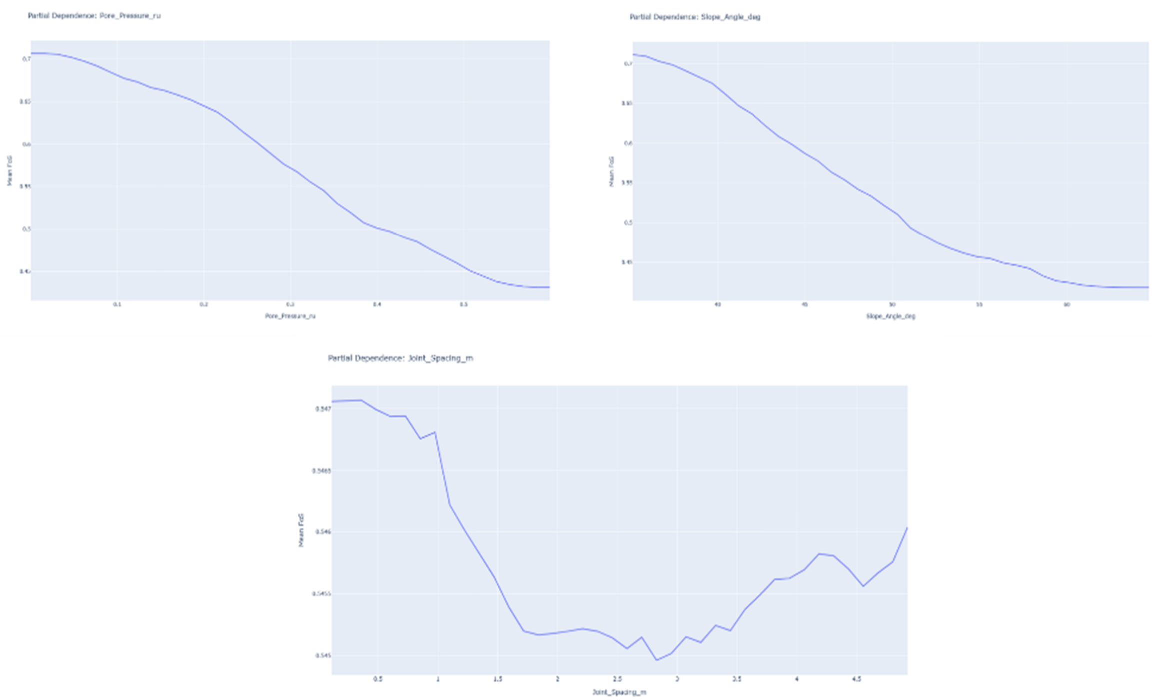


Figure 15. Partial dependency plot for all three regression

8.1. Validation against Global Benchmark Cases

To demonstrate that the MRS framework is grounded in physical reality rather than statistical correlation alone, the system was used to back-analyze documented failure cases from global marble districts. These cases represent benchmarks where conventional systems often provide misleading safety ratings.

At the Neyriz Marble Mine in Iran, deep bench excavation in high-quality marble (UCS > 120 MPa) resulted in brittle toe spalling and localized instability under elevated in-situ stress conditions. Conventional RMR classification rated the rock mass as "very good," yet failure occurred. When mapped into the MRS framework, the rock mass is penalized through the block stability parameter (M6), yielding a lower overall rating that correctly reflects observed instability. This case demonstrates that MRS identifies structural risk masked by strength-dominated systems.

A complementary benchmark is provided by failures in the ancient Parian underground marble quarries in Greece, where instability occurred through the collapse of isolated tetrahedral wedges formed by intersecting joint sets. Back-analysis of these failures showed that joint frequency, persistence, and surface condition were the dominant controls, with intact strength playing a secondary role. When evaluated under MRS, these conditions result in strong penalties to M3 and M4, producing low stability classes that are fully consistent with calculated factors of safety below unity. This alignment directly validates the structural emphasis embedded in the MRS weighting scheme.

Further support is drawn from the marble basins of the Apuan Alps (Carrara District, Italy), including Fantiscritti and Macchietta quarries, where documented pillar spalling and rock spur deformation were shown to be structurally controlled by fault intersections and excavation geometry. Monitoring-based change detection revealed displacement localization along structurally constrained rock masses, reinforcing the dominant role of block disposition. These observations are consistent with the strong sensitivity of stability to M6 identified in the present study.

Similarly, investigations in the Itaoca marble district of Brazil identified discontinuities as the most influential factor controlling planar and wedge failures, with joint persistence exceeding critical thresholds posing the highest risk. This directly corroborates the MRS philosophy of prioritizing joint condition and structural configuration over intact rock properties for quarry-scale assessment.

Collectively, these benchmark cases demonstrate that the failure mechanisms emphasized by MRS-block stability, joint geometry, and surface condition-are not site-specific artifacts but globally observed controls governing marble quarry instability.

The following table summarizes how the specific geomechanical parameters of the MRS framework capture the failure drivers observed in internationally documented marble quarries.

Table 8. Comparative Mapping of Failure Mechanisms

Case Study & Location	Observed Failure Mechanism	Standard RMR/GSI Bias	MRS Sensitivity & Response	Reference
Neyriz Marble Mine (Iran)	Brittle toe spalling and instability in deep benches.	Overestimates Safety: High UCS (>120 MPa) masks structural risk.	Rectified: Penalizes M6 (Block Stability) due to stress-induced disposition.	Doghozlou et al. (2016)
Ancient Parian Quarries (Greece)	Collapse of tetrahedral wedges (FoS < 1.0).	Underestimates Risk: Fails to weight joint intersection geometry.	Rectified: Strong penalties to M3 (Freq) and M4 (Condition) reflect block release.	Marinos & Farmakis (2025)
Carrara District (Fantiscritti) (Italy)	Rock spur deformation and pillar spalling.	Insensitive: Does not prioritize structural "Key Blocks."	Rectified: Validates the high 25% weight of M6 (Block Disposition).	Giani et al. (2004)
Itaoca District (Brazil)	Planar and wedge failure along weathered dikes.	Broad Categorization: Misses localized mineralogical decay.	Rectified: Specifically captures hydro-mechanical risk through M2 (Weathering).	Jordt-Evangelista & Viana (2000)

The back-analysis reveals a consistent trend: in every failure case, the dominant driver was a structural or block-scale parameter (M3, M4, or M6) rather than intact rock strength (M1). As shown in Table 7, the MRS framework correctly identifies these risks by allocating 65% of its total weight to structural and joint parameters. This explains the high predictive accuracy ($R^2 = 0.93$) achieved in our Artificial Neural Network validation, as the machine learning model recognized the same physical dependencies observed in these global field benchmarks.

9. Limitations and Future Scope

Despite the encouraging empirical and computational outcomes, certain limitations of the present study must be acknowledged to ensure objective interpretation and to guide future research. First, the dataset is derived from three marble quarry sites, and while it captures a wide range of lithological, structural, and alteration conditions, it may not fully represent the variability encountered across all marble deposits or quarrying practices. Consequently, direct extrapolation of the Marble Rock System (MRS) beyond geologically comparable settings should be undertaken with caution.

Second, the proposed framework focuses on bench-scale stability under predominantly static loading conditions. Dynamic influences such as blasting-induced damage, time-dependent degradation, and stress redistribution associated with progressive excavation were not explicitly incorporated. Although some of these effects are implicitly reflected through joint condition and block stability parameters, their direct representation could further improve predictive fidelity.

Third, validation of the MRS was performed using analytically derived factor of safety values rather than direct measurements of slope performance. While this approach is consistent with standard geotechnical practice and supported by strong agreement with field observations and physical trends, the absence of long-term displacement monitoring or failure back-analysis limits direct calibration against observed instability events.

From a modelling perspective, machine learning was intentionally employed as a validation tool rather than as a predictive engine. While this ensures interpretability and avoids circular reasoning, it also restricts exploration of advanced adaptive or real-time learning frameworks that could potentially enhance operational decision-making.

Future research should therefore focus on expanding the database to include additional quarry sites, marble types, and excavation geometries, enabling broader validation and potential regional calibration of the MRS. Incorporation of time-dependent factors, such as weathering progression and excavation sequencing, would allow assessment of stability evolution rather than static conditions alone. Integration of displacement monitoring data and documented failure cases would further strengthen empirical validation. Finally, probabilistic extensions and hybrid physics-informed machine learning approaches could be explored to quantify uncertainty and enhance robustness while preserving the physical transparency demonstrated in the present study.

10. Conclusions

This study addressed a fundamental limitation in marble quarry slope assessment: the inability of conventional rock mass classification systems and many data-driven models to adequately represent discontinuity-controlled block instability at the quarry scale. To bridge this gap, an empirically grounded, quarry-specific classification framework-the Marble Rock System (MRS)-was developed and independently validated using analytical stability outcomes and machine learning diagnostics.

The results demonstrate that bench-scale stability in marble quarries is governed primarily by structural configuration, block stability, and alteration-related degradation rather than intact rock strength alone. The proposed MRS consistently captured localized instability zones that were smoothed or overlooked by strength-dominated systems, while remaining mechanically compatible with established empirical frameworks. Machine learning validation confirmed that the six physically interpretable MRS parameters contain sufficient information to explain variability in the factor of safety, yielding higher predictive accuracy, improved class separability, and more stable generalization than models based on conventional indices. Sensitivity analyses further established that block stability and joint characteristics dominate stability response, quantitatively reinforcing long-standing empirical understanding of marble quarry failure mechanisms.

The principal contribution of this work lies in redefining quarry rock mass classification around block-scale mechanics and demonstrating a rigorous pathway for empirical system validation without circular dependence on artificial intelligence. Practically, the MRS offers a transparent, field-applicable tool for identifying structurally vulnerable zones and supporting risk-informed bench planning in marble quarry operations. More broadly, the study illustrates how empirical rock mechanics and machine learning can be integrated in a complementary manner, advancing both interpretability and predictive reliability. As such, the proposed framework represents a meaningful step toward more physically grounded and operationally relevant stability assessment in dimension stone quarrying.

References

[1]. Bieniawski, Z. T. (1993). Engineering rock mass classification: A textbook for geologists and mining engineers. In J. A. Hudson (Ed.), *Comprehensive rock engineering (Vol. 2, pp. 97-106)*.

[2]. Bustos, N. (2022). An integrated approach for design and construction of drawbells in block cave mines. PhD thesis, Curtin University, Kalgoorlie, Australia.

[3]. Hoek, E., Carranza-Torres, C., & Corkum, B. (2002). Hoek-Brown failure criterion-2002 edition. *In Proceedings of the 5th North American Rock Mechanics Symposium (pp. 267-273)*.

[4]. Price, L. (2016). The interaction of groundwater with rock masses and the implications for slope stability. *In Proceedings of the 14th International Conference of the International Association for Computer Methods and Advances in Geomechanics (IACMAG).*

[5]. Villaescusa, E. (2014). Geotechnical design for sublevel open stoping. *Taylor & Francis*.

[6]. Dyke, C. G. (1988). In situ stress indicators for rock at great depth. PhD thesis, Imperial College London, UK.

[7]. Scavia, C., Giani, G. P., & Semprich, S. (2009). The Randa rockslides: An investigation of the discontinuity network influence on rock slope stability. *Landslides, 6*(3), 267-279.

[8]. Rana, M. J., Mussa, S. M., Ahmed, K. A., & Buniya, M. K. (2024). Geomechanical characterization and stability analysis of rock for optimizing slope design in open pit mines. *Mining, 4*(1), Article 11.

[9]. Davoodi, P. K., Hajizadeh, F., & Rezaei, M. (2025). Application of the metaheuristic algorithms to quantify the GSI based on the RMR classification. *Scientific Reports, 15*(1), 28950.

[10]. Davoodi, P. K., Hajizadeh, F., & Rezaei, M. (2025). Evaluating the RMR correlation with the rock mass wave velocity using meta-heuristic algorithms. *Scientific Reports, 15*(1), 17716.

[11]. Drover, C. (2019). Logging of core disking in diamond drill holes using the database of photographs. Western Australian School of Mines, Curtin University.

[12]. Liu, Q., Wang, H., Tan, Y., Lu, H., Huang, R., & Wu, X. (2024). Real-time prediction and reliability analysis of surrounding rock classification based on improved hybrid random forest models during TBM tunneling. *Buildings, 15*(2), 47.

[13]. Wang, L., Ma, S., Lu, H., & Tian, G. (2023). Discussion on the quantification of the Geological Strength Index (GSI) and its application in rock engineering: A perspective review. *Sustainability, 15*(14), 11233.

[14]. Matsuki, K., Kaga, N., Yokoyama, T., & Tsuda, N. (2004). Determination of three-dimensional in situ stress from core discing based on analysis of principal tensile stress. *International Journal of Rock Mechanics and Mining Sciences, 41*(7), 1167-1190.

[15]. Dershowitz, W. S., Finnila, A., Rogers, S., Hamdi, P., & Moffitt, K. M. (2017). Step path rock bridge percentage for analysis of slope stability. *In Proceedings of the 51st US Rock Mechanics/Geomechanics Symposium*.

[16]. Rezaei, M., & Habibi, A. (2023). Predicting the production of dimension stone quarries using a modified rock mass classification system. *Journal of Mining and Environment, 14*(1), 125-142.

[17]. Palmstrom, A., & Broch, E. (2008). Use and misuse of rock mass classification systems. *Tunnelling and Underground Space Technology, 23*(6), 575-593.

[18]. Wei, D., Li, Z., & Yang, B. (2024). Comprehensive evaluation of rock mass classification systems. *Rock Mechanics and Rock Engineering, 57*(3), 1897-1915.

[19]. Kumar, M., Avchar, A., Sinha, S., & Swamy, S. V. (2026). Integrated approaches for pillar design and stability assessment in underground hard rock mining: From empirical models to machine learning. *Physics and Chemistry of the Earth, Parts A/B/C, 142, 104235*.

[20]. Kumar, M., Avchar, A., & Sinha, S. (2026). A hybrid empirical-numerical framework for pillar stability and reinforcement in deep underground marble mines: A case study. *International Journal of Mining and Geo-Engineering, 60*(1), 25-33.

[21]. Sinha, S., Tripathi, A. K., Avchar, A., Kumar, M., & Swamy, S. V. (2026). Influence of angle of internal friction and slope face angle on kinematic failures in marble mines: A predictive approach. *Indian Geotechnical Journal, 56*, 1581-1589.

[22]. Ma, J., He, P., & Zhang, D. (2018). Challenges in applying machine learning to geotechnical engineering: A review. *Computers and Geotechnics, 95*, 103-114.

[23]. Raghuvanshi, C., Mishra, V., Prakash, P., & Tiwari, A. (2022). Predictive modeling of rock mass deformation modulus using artificial intelligence techniques. *Sustainability, 14*(22), 15225.

[24]. Miranda, T., Sousa, L. R., Roggenthen, W., & Sousa, R. L. (2013). Application of data mining techniques for the development of new rock mechanics constitutive models. *In Springer Series in Geomechanics and Geoengineering (pp. 735-740)*.

[25]. Han, M., & Yang, B. (2024). Prediction of slope stability based on five machine learning techniques: A comparative study. *Multiscale and Multidisciplinary Modeling, Experiments and Design, 7*(2), 1521-1535.

[26]. Rahimi, M., & Mirmozaffari, M. (2024). Deep learning-powered rock mass classification: Predicting RMR from Q-system parameters with high accuracy. *Rock Mechanics Bulletin, 3*(3), 100152.

[27]. Niu, L., Feng, Y., Liu, H., & Zhang, X. (2024). Deep learning-based rockburst prediction in tunneling: A review. *Tunnelling and Underground Space Technology, 145*, 105583.

[28]. Bieniawski, Z. T. (1989). Engineering rock mass classifications. *John Wiley & Sons*.

[29]. Barton, N. (2000). TBM tunnelling in jointed and faulted rock. A.A. Balkema.

[30]. Hong, Y., Zhang, Y., He, C., & Zhang, H. (2024). A study on the correlation between rock mass rating (RMR) and Q-system for faulted and weak rock masses in South Korea. *PLOS ONE, 19*(5), e0301985.

[31]. Sun, Z., Wang, B., & Zhang, Q. (2024). Research on the applicability of rock mass classification system in deep-buried hard rock tunnels. *Frontiers in Earth Science, 12*, 1453912.

[32]. Yang, J., Rong, G., Hou, D., Peng, J., & Zhou, C. (2022). Application of mining rock mass rating (MRMR) in underground mining engineering. *Rock Mechanics and Rock Engineering, 55*(8), 4523-4541.

[33]. El-Naqa, A. (1996). Assessment of geotechnical characterization of a proposed dam site using geophysical and geotechnical data. *Geotechnical and Geological Engineering, 14*(1), 35-57.

[34]. Ghorbani, M., Sharifzadeh, M., Masoudi, R., & Noaslati, A. (2025). Investigating scale effects on the mechanical properties of rock joints using a lower bound limit analysis. *Rock Mechanics and Rock Engineering, 58*(3), 1123-1145.

[35]. Wu, Q., Weng, L., & Zhao, Y. (2023). Anisotropic time-dependent modeling of basic creep of weak sandstone considering crack deformation. *International Journal of Rock Mechanics and Mining Sciences, 162*, 105305.

[36]. Zhao, H., Li, T., & Liu, Q. (2019). Integration of machine learning with traditional geomechanical models for enhanced prediction accuracy. *International Journal of Rock Mechanics and Mining Sciences, 123*, 104092.

[37]. Heidarzadeh, S., Saeidi, A., & Rouleau, A. (2021). Evaluation of the effect of geometrical parameters of rock joints on the stability of underground excavations. *Geotechnical and Geological Engineering, 39*(3), 2197-2215.

[38]. Yang, B., Liu, Y., Liu, Z., Zhu, Q., & Li, D. (2024). A novel hybrid optimization XGBoost model for rock mass quality classification using incomplete dataset. *Applied Sciences, 14*(16), 7074.

[39]. Miranda, T., Sousa, L. R., Gomes, A. T., Tinoco, J., & Ferreira, C. (2018). Geomechanical characterization of volcanic rocks using empirical systems and data mining techniques. *Journal of Rock Mechanics and Geotechnical Engineering, 10*(1), 138-150.

[40]. Singh, R., Umrao, R. K., & Singh, T. N. (2023). Probabilistic stability analysis of failed rock slope using machine learning algorithms. *Geomechanics and Engineering, 32*(5), 513-524.

[41]. Garg, A., Garg, A., Tai, K., & Sreedeep, S. (2014). An integrated SRM-multi-gene genetic programming approach for prediction of factor of safety of 3-D soil nailed slopes. *Engineering Applications of Artificial Intelligence, 30*, 30-40.

[42]. Gulli, D., Greco, R., Lo Presti, D. C. L., Squeglia, N., & Vessia, G. (2013). A laboratory study on serpentinized ultrabasic rocks from Valmalenco (Central Alps, N. Italy). *Procedia Earth and Planetary Science, 7*, 322-325.

[43]. Goodman, R. E., & Shi, G. H. (1985). Block theory and its application to rock engineering. *Prentice-Hall.*

انجمن مهندسی معدن ایران
نشریه مهندسی معدن و محیط زیست
نشانی نشریه: www.jme.shahroodut.ac.ir
دانشگاه صنعتی شاهرود

یک چارچوب طبقه‌بندی توده سنگ مخصوص سنگ مرمر با ادغام پارامترهای تجربی و اعتبارسنجی یادگیری ماشینی

شامباوی سینها، آنوپ کومار تریپاتی، آخیل آوچار، و مریتونجی کومار*

گروه مهندسی معدن، موسسه ملی فناوری کارناتاکا، سوراتکال، هند

اطلاعات مقاله

تاریخ ارسال: ۲۰۲۵/۱۲/۱۵
تاریخ داوری: ۲۰۲۶/۰۲/۲۳
تاریخ پذیرش: ۲۰۲۶/۰۵/۲۸

DOI: 10.22044/jme.2026.17326.3432

کلمات کلیدی

معدن سنگ مرمر
طبقه‌بندی توده سنگ
اعتبارسنجی یادگیری ماشین
ضریب ایمنی
شیب‌های کنترل‌شده با ناپیوستگی

چکیده

ارزیابی دقیق کیفیت توده سنگ در معادن سنگ مرمر همچنان چالش برانگیز است زیرا سیستم‌های طبقه‌بندی تجربی مرسوم تا حد زیادی تحت سلطه مقاومت هستند و به ناپایداری بلوک کنترل‌شده توسط ناپیوستگی حساسیت کافی ندارند. این مطالعه یک چارچوب تجربی خاص معدن به نام سیستم سنگ مرمر (MRS) را پیشنهاد می‌کند که برای ثبت صریح کنترل‌های ساختاری، هیدرومکانیکی و دگرسانی حاکم بر پایداری در مقیاس آزمایشگاهی در معادن سنگ مرمر با ابعاد بزرگ طراحی شده است. هدف اصلی توسعه و اعتبارسنجی یک سیستم طبقه‌بندی مبتنی بر تجربی با استفاده از یادگیری ماشین به عنوان یک ابزار تشخیصی مستقل به جای یک پیش‌بینی‌کننده جعبه سیاه بود. یک پایگاه داده ژئومکانیکی جامع شامل ۸۵ رکورد در مقیاس معدنی از سه معدن سنگ مرمر فعال در جنوب راجستان هند توسعه داده شد. شش پارامتر قابل تفسیر فیزیکی شامل مقاومت سالم، هوازدگی یا سرپانتینی شدن، فرکانس درزه، وضعیت سطح درزه، تأثیر آب‌های زیرزمینی و پایداری بلوک در چارچوب MRS گنجانده شدند. مدل‌های یادگیری ماشین تحت نظارت، از جمله شبکه‌های عصبی مصنوعی، ماشین‌های بردار پشتیبان و رگرسیون خطی، برای پیش‌بینی عوامل ایمنی مشتق‌شده مستقل برای اعتبارسنجی آموزش داده شدند. عملکرد مدل با استفاده از ضریب تعیین، جذر میانگین مربعات خطا، اعتبارسنجی متقابل و معیارهای طبقه‌بندی ارزیابی شد. نتایج نشان می‌دهد که مدل‌های مبتنی بر MRS به طور مداوم دقت پیش‌بینی بالاتری، تفکیک‌پذیری بهبود یافته کلاس‌ها و تعمیم پایدارتری نسبت به مدل‌های آموزش دیده با استفاده از ورودی‌های مرسوم رتبه‌بندی توده سنگ به دست آورده‌اند. تجزیه و تحلیل حساسیت نشان داد که پایداری بلوک و ویژگی‌های درزه بر پیش‌بینی پایداری غالب هستند، در حالی که مقاومت دست نخورده نقش ثانویه‌ای ایفا می‌کند. این یافته‌ها تأیید می‌کنند که رفتار شیب معدن سنگ مرمر در درجه اول تحت کنترل ناپیوستگی است. MRS پیشنهادی یک چارچوب فیزیکی قابل تفسیر و از نظر تجربی معتبر برای ارزیابی پایداری در مقیاس معدن ارائه می‌دهد و جایگزینی قوی برای سیستم‌های طبقه‌بندی مرسوم برای تصمیم‌گیری عملیاتی ارائه می‌دهد.

نویسنده مسئول مکاتبات: krmritunjay769@gmail.com (م. کومار)