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Machine Learning-Based Prediction of Bearing Capacity of Shallow Foundations on Rock Masses

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Abstract

The ultimate bearing capacity of square shallow foundations resting on jointed rock masses represents one of the most complex and fundamental problems in rock mechanics and geotechnical design, primarily due to the inherent heterogeneity of the medium and the highly nonlinear nature of failure mechanisms, which are associated with significant uncertainty. In this study, a combined framework of advanced numerical modelling and machine learning algorithms is employed to develop a robust and accurate predictive approach. To this end, a comprehensive dataset comprising 150 three-dimensional finite element simulations was generated using PLAXIS 3D. The generalized Hoek-Brown failure criterion was adopted for the rock mass, while the Mohr-Coulomb criterion was applied to discontinuity surfaces. The numerical results indicated that bearing capacity is governed by a complex interaction among rock mass quality parameters, intact rock properties, discontinuity characteristics, and the geometry and orientation of joints. Failure behaviour is primarily controlled by joint planes and is characterized by stress concentration, asymmetric deformation patterns, and localized plastic zones along discontinuities. Correlation analysis identified the Geological Strength Index (GSI), the intact rock parameter m_i, and the uniaxial compressive strength (UCS) as the most influential variables affecting bearing capacity. In the machine learning phase, a comparative assessment of several models demonstrated that ensemble-based methods, particularly Gradient Boosting Regressor and Poisson Regressor, achieved the highest predictive performance, significantly outperforming conventional linear regression approaches. Feature importance analysis further confirmed the dominant roles of GSI and mi. Notably, the developed models, achieved a prediction accuracy of approximately 96% with low error levels. Overall, the results demonstrate that machine learning provides a powerful and reliable framework for modelling the highly nonlinear behaviour of shallow foundations on jointed rock masses, offering valuable support for geotechnical design and reducing epistemic uncertainty in engineering practice.

Keywords

Shallow foundations, Jointed rock mass, Bearing capacity, Machine learning predictive methods.

1 Introduction

Shallow foundations are widely utilized to transmit heavy structural loads to near-surface rock formations in various civil engineering projects (Carter and Kulhawy 1992). The mechanical behaviour of rock masses is fundamentally different and often more complex than that of soils due to the presence of discontinuities and the non-linear nature of intact rock strength(Carter and Kulhawy 1992, Marinos, Marinos et al. 2005, Marinos, Hoek et al. 2006, Merifield, Lyamin et al. 2006). Traditional analytical methods often rely on simplifying assumptions that fail to fully capture the complex failure mechanisms of jointed rock masses (Yang and Yin 2005, Lenji, Mehmandari et al. 2025, Pradhan, Sheng et al. 2025). The mechanical response is governed by a coupled framework: the non-linear yielding of the rock mass, typically described by the generalized Hoek-Brown (HB) criterion, and the shear strength of explicit structural discontinuities, which is classically governed by the linear Mohr-Coulomb (MC) failure criterion (Chen and Drucker 1969, Ladanyi and Roy 1971, Saada, Maghous et al. 2008). Furthermore, the spatial orientation of these joints specifically their dip and dip direction introduces significant anisotropy. Consequently, numerical modelling techniques, particularly the Finite Element Method (FEM), have become indispensable, and allows for a realistic simulation of foundation-rock interaction (Griffiths, Fenton et al. 2002, Clausen 2013, Hoek and Brown 2019, Rafiei Renani and Cai 2022). Despite its importance, the characterization of bedrock is fundamentally constrained by uncertainty. This uncertainty is critical because reliable understanding of bedrock behavior directly influences the safety and performance of any design (Wei, Meng et al. 2022).Uncertainty in bedrock systems can be categorized into epistemic uncertainty, which stems from a lack of knowledge, and aleatory variability, which reflects the inherent randomness of geological processes (Mahmoodzadeh, Mohammadi et al. 2022, Lenji, Mehmandari et al. 2025). Foundation characterization is further complicated by the presence of discontinuities such as fractures, joints, and faults, which significantly influence mechanical behavior (Serrano and Olalla 1996, Zhang and Einstein 1998, Hoek, Carranza-Torres et al. 2002). Moreover, limitations in borehole sampling, geophysical surveys, and remote sensing techniques introduce additional constraints, particularly when there is a mismatch between observation scales and engineering design requirements (Waltham and Swift 2004, Yang and Yin 2005, Hoek and Brown 2019, Walton and Sinha 2022). Foundation performance may vary significantly from design expectations, necessitating conservative safety factors that can increase construction costs and lead to project delays (Mahmoodzadeh, Mohammadi et al. 2022, Wei, Meng et al. 2022, Pradhan, Sheng et al. 2025). To manage these uncertainties, engineers employ a range of methodological approaches, including probabilistic and statistical modeling techniques. Bayesian updating frameworks and integrated site investigation strategies further support decision-making by incorporating new data as it becomes available. However, current approaches are limited by persistent challenges such as data scarcity and issues of representativeness in available datasets. Deterministic models often oversimplify complex geological systems. Most importantly, epistemic uncertainty cannot be fully eliminated, as it is rooted in incomplete knowledge of subsurface conditions (Wu, Wei et al. 2021). Emerging directions in foundation engineering seek to address these limitations through advanced computational and data-driven approaches (Saadati, Hekmatnejad et al. 2026). Machine learning techniques are increasingly used to identify patterns in sparse and heterogeneous datasets, while digital twin frameworks enable dynamic representation of subsurface systems (Guo, Gao et al. 2026). Real-time sensor integration, multi-scale geological modeling, and AI-assisted uncertainty quantification are also contributing to more adaptive and responsive engineering methodologies (Al-Atroush, Aboelela et al. 2024). Rather than attempting to eliminate uncertainty, modern engineering practice focuses on its systematic management through improved data integration, modeling, and interpretation (Ma, Zhang et al. 2026). The integration of geology, engineering principles, and data science is therefore essential for advancing reliable and resilient solutions under conditions of incomplete knowledge (Sabri, Verma et al. 2025). Machine learning methods are increasingly applied in rock engineering to address prediction and estimation challenges under uncertainty in rock-based infrastructure (Dashtgoli, Narsilio et al. 2026). One of the most challenging and highly uncertain problems is the evaluation and estimation of the bearing capacity of jointed rock masses. By considering various influencing factors, it is possible to conduct an appropriate analysis and make reliable predictions of the bearing capacity of rock masses (Li, Liu et al. 2026). In this study, the bearing capacity of shallow foundations has been investigated using various machine learning methods. To address this gap, this study presents a robust, data-driven approach to investigate the ultimate bearing capacity of rock masses beneath square footings. A comprehensive dataset was generated by conducting 150 rigorous 3D numerical simulations using PLAXIS. After developing numerical models, machine learning predictive algorithms are employed to estimate the bearing

capacity, as well as to identify and understand the importance of the key features and parameters influencing its estimation.

2 Modelling

The Generalized Hoek-Brown (GHB) failure criterion was assigned to the rock mass, as it effectively captures the non-linear strength reduction caused by inherent fractures, utilizing parameters such as the Geological Strength Index (GSI). Additionally, to account for the mechanical behaviour of explicit discontinuities and joints within the rock mass, the perfectly plastic Mohr-Coulomb failure criterion was employed, defining the cohesion and friction angle of the joint interfaces (Merifield, Lyamin et al. 2006, Clausen 2013, Hoek and Brown 2019). Furthermore, three-dimensional finite element modelling was carried out to evaluate the bearing capacity of shallow foundations on rock. Finite element codes are extensively utilized in rock mechanics due to their ability to rigorously simulate complex boundary conditions, structural interactions, and the non-linear behaviour of geomaterial. A 3D computational domain with dimensions of (11 x 11 x 5 m) was constructed to model the rock mass supporting a rigid square footing of (1 x 1 m). To systematically evaluate the ultimate bearing capacity (q_u) of the jointed rock mass under the square footing, load-displacement curves were generated for each numerical model (Fig.1 & Fig.2), three distinct interpretation criteria were employed to extract (q_u) from the non-linear foundation response: the tangent intersection method, alongside the settlement-based criteria of 0.05B and 0.1B.

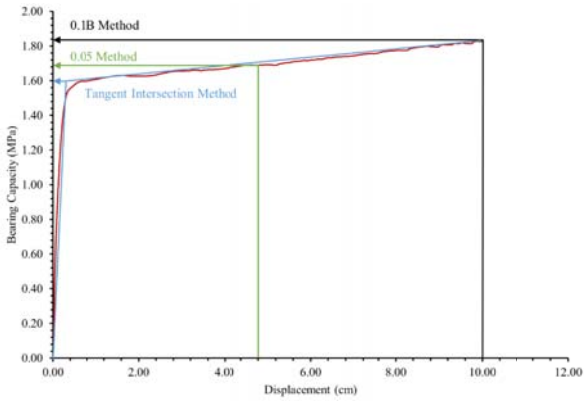


Fig. 1 Bearing Capacity Calculation.

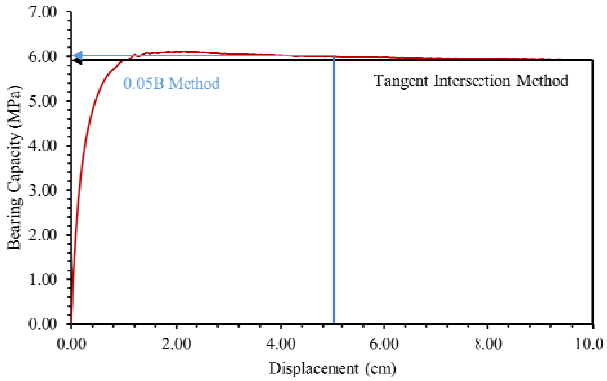


Fig. 2 Bearing Capacity Calculation.

The rock mass properties include Young's modulus, Poisson's ratio, uniaxial compressive strength, the rock mass parameters m and GSI, the disturbance factor, normal and shear stiffness, cohesion and friction angle, as well as joint orientation angles and direction, which are considered for calculating the bearing capacity of shallow foundations. The sample dataset used for the calculations is presented in Table 1(see Table 1). A representative subset of these simulations has been carefully selected to illustrate the varied bearing capacity and displacement responses (see Fig.3).

Table 1. Dataset used for model development.

Run	E_{rm} (Mpa)	ν	σc_i (Mpa)	m_i	GSI	D	K_n (Gpa/m)	K_s (Gpa/m)	C_j	φ_j	Dip Angle (degree)	Dip Direction (degree)
1	1645	0.35	10.0	14.9	30	0	10.0	0.8	0.0	0.7	23.6	14.5
2	5495	0.33	15.1	3.8	50	0	11.9	0.6	0.3	20.0	73.7	54.5
3	5636	0.33	19.7	9.3	52	0	11.1	0.5	0.3	24.8	58.0	36.9
4	5706	0.33	19.3	10.9	53	0	10.5	0.7	0.3	28.2	77.3	55.9
5	4375	0.34	14.0	8.8	33	0	10.8	0.3	0.1	30.3	10.8	33.0
6	4725	0.34	15.0	14.1	38	0	11.7	0.2	0.2	28.0	11.9	41.5
7	7736	0.32	16.2	10.8	48	0	11.8	0.4	0.1	31.4	49.5	47.2
8	7386	0.32	15.2	9.9	27	0	11.3	0.5	0.1	31.2	79.7	31.6

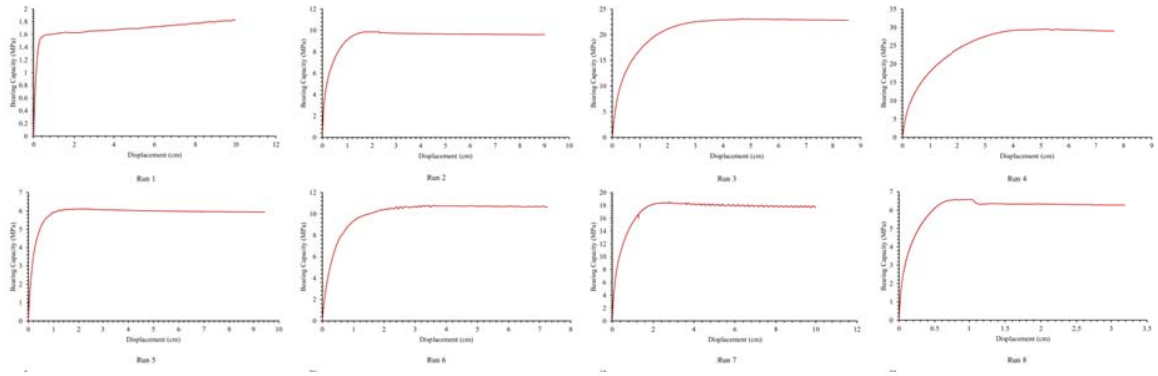


Fig. 3 Figures of conducted simulations after completion.

The application of advanced Machine Learning techniques is justified as an effective means of modeling the underlying relationships between the governing parameters and bearing capacity.

3 Machine Learning Modelling

Figure 4 shows the shift in AI from rule-based, knowledge-driven systems to data-driven models that learn patterns directly from data (Yang, Zuo et al. 2024). In the data-driven AI domain, machine learning, deep learning, and neural networks enable layered learning methods and advanced applications such as NLP, computer vision, and autonomous systems (Lenji, Mehmandari et al. 2025). In rock engineering, this hierarchy reflects the shift from physics-based and expert-driven methods to data-driven approaches for modeling complex rock mass behavior and geo-mechanical uncertainty(Park and Yoon 2026).In this context, machine learning provides a disruptive framework that enhances predictive capability and decision-making in geotechnical applications.

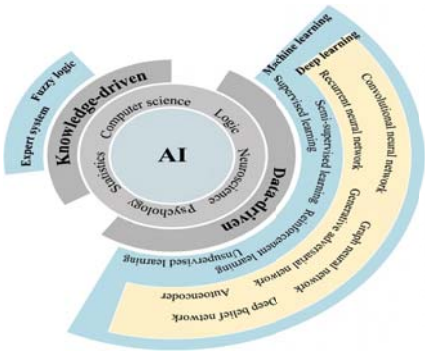


Fig. 4 Structure of Artificial Intelligence (Yang, Zuo et al. 2024).

Traditional rock engineering methods are constrained by geological heterogeneity, nonlinearity, and data uncertainty, which limits the reliability of empirical and analytical approaches (Lenji, Mehmandari et al. 2025, Guo, Gao et al. 2026, Park and Yoon 2026, Saadati, Hekmatnejad et al. 2026). Machine learning models effectively capture nonlinear relationships in high-dimensional geotechnical data with greater robustness than conventional methods (Lenji, Mehmandari et al. 2025). Machine learning is widely used in rock engineering for classification, stability prediction, deformation analysis, support design, and fracture characterization. (Xiao, Tao et al. 2026).Traditional models are interpretable but limited in complex systems, while machine learning offers higher accuracy, with hybrid approaches combining both providing the most effective solutions (Morgenroth, Khan et al. 2019, Mahmoodzadeh, Mohammadi et al. 2022). Machine learning improves rock engineering by enabling better nonlinear prediction, data integration, and real-time adaptive monitoring under uncertainty (Lenji, Mehmandari et al. 2025, Pradhan, Sheng et al. 2025). Despite its advantages, machine learning in rock engineering is limited by data scarcity, overfitting risks, poor generalization across sites, and low interpretability due to its “black box” nature (Chen, Gui et al. 2026). The integration of digital twins, IoT-enabled monitoring systems, and continuously learning frameworks is expected to further enhance predictive capabilities (Lenji, Mehmandari et al. 2025, Park and Yoon 2026, Saadati, Hekmatnejad et al. 2026, Zhang, Nie et al. 2026). Machine learning enhances rock engineering by improving prediction, risk assessment, and design under uncertainty while

complementing traditional methods and supporting AI-assisted decision-making systems (Morgenroth, Khan et al. 2019, Al-Atroush, Aboelela et al. 2024, Yang, Zuo et al. 2024, Lenji, Mehmandari et al. 2025, Saadati, Hekmatnejad et al. 2026).The correlation analysis shows that rock mass quality (GSI, mi) and strength parameters (σci, qu) are strongly interrelated, while deformation modulus (Erm) is perfectly collinear with Poisson's ratio (ν), indicating redundancy. Overall, GSI, σci, qu, and Erm are the dominant variables, whereas weak or redundant parameters should be removed to enhance model robustness and reduce overparameterization.

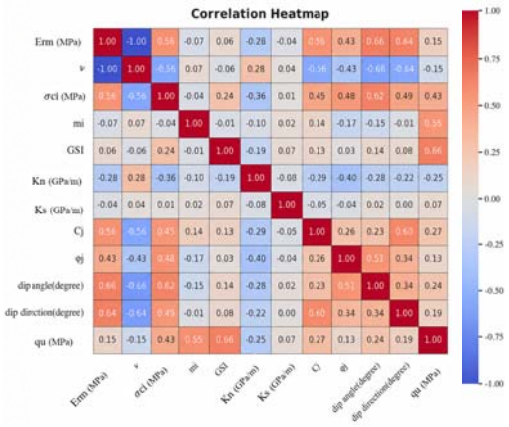


Fig. 5 Matrix of Interactions Among Parameters.

The correlation analysis shows that ultimate strength (q_u) is primarily controlled by GSI and mi, with a secondary influence from σci, emphasizing the dominant role of rock mass quality. A perfect negative correlation between Erm and Poisson's ratio (ν) indicates a deterministic relationship, while Erm is also strongly affected by joint orientation. In contrast, Ks shows negligible correlation with other variables, indicating minimal interaction within the dataset. Model performance in this study was evaluated using three standard regression metrics: R^2, MSE, and MAE. R^2 measures the proportion of variance explained by the model, indicating predictive strength, while MSE and MAE quantify prediction errors, with MSE being more sensitive to large deviations and MAE providing a more robust average error measure. A range of machine learning models was assessed for predicting the bearing capacity of shallow foundations, with ensemble methods significantly outperforming linear and regularized approaches. The Poisson Regressor and Gradient Boosting achieved the highest accuracy ($R^2 \approx 0.96$) with the lowest RMSE, indicating strong predictive capability. Overall, the results show that bearing capacity is governed by nonlinear and interacting geo-mechanical factors, which are best captured by ensemble learning models, while also demonstrating good generalization with limited overfitting.

Table 2. Specifications of the developed models.

Model	**Adjusted R-Squared**	**R-Squared**	**RMSE**
AdaBoostRegressor	0.716992	0.858496	2.57045
BaggingRegressor	0.824532	0.912266	2.02399
BayesianRidge	0.760721	0.88036	2.363535
ElasticNetCV	0.7545	0.87725	2.39406
ExtraTreesRegressor	0.854975	0.927487	1.840057
GradientBoostingRegressor	0.925727	0.962863	1.31682
HistGradientBoostingRegressor	0.772765	0.886383	2.303281
HuberRegressor	0.712094	0.856047	2.592595
LGBMRegressor	0.806763	0.903382	2.124
Lars	0.762773	0.881387	2.353377
LarsCV	0.759568	0.879784	2.369223
LassoCV	0.759553	0.879776	2.369297
LassoLars	0.531604	0.765802	3.306863
LassoLarsCV	0.759568	0.879784	2.369223

LassoLarsIC	0.758533	0.879266	2.374317
LinearRegression	0.762773	0.881387	2.353377
OrthogonalMatchingPursuitCV	0.776219	0.88811	2.285708
PoissonRegressor	0.928083	0.964042	1.295758
RandomForestRegressor	0.862874	0.931437	1.789242
Ridge	0.762006	0.881003	2.35718
RidgeCV	0.762006	0.881003	2.35718
SGDRegressor	0.761663	0.880831	2.358879
TransformedTargetRegressor	0.762773	0.881387	2.353377
XGBRegressor	0.828346	0.914173	2.001875

The comparison of fifteen regression models shows that ensemble methods (e.g., Poisson Regressor, Gradient Boosting, Random Forest, XGBoost) significantly outperform traditional linear models, achieving higher R^2 values (up to ~0.96). This indicates that the geo-mechanical system is strongly nonlinear and best captured by ensemble learning, though careful validation is required to avoid overfitting and ensure robust generalization.

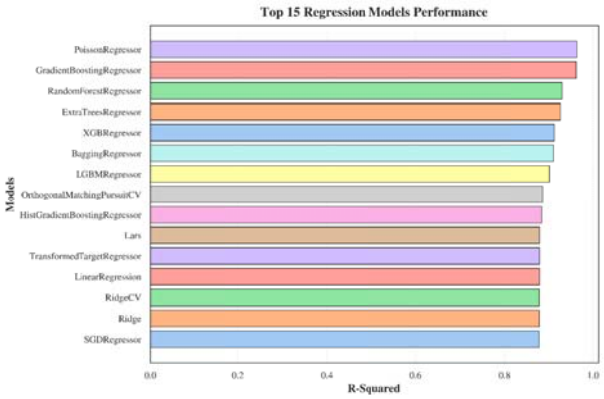


Fig. 6 Comparative evaluation of the predictive performance of the fifteen best-performing regression algorithms.

Random Forest analysis shows that rock mass behaviour is mainly controlled by GSI and mi, which together explain most model importance, indicating a strength-dominated system where accurate estimation of key strength parameters is crucial for reliable geo-mechanical prediction.

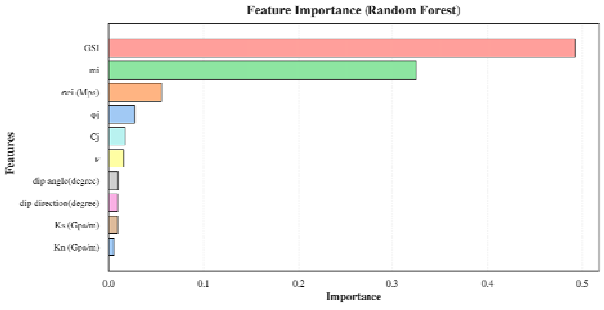


Fig. 7 Feature-importance.

4 Conclusion

This study investigates the ultimate bearing capacity of shallow square foundations on jointed rock masses using 3D finite element modelling (PLAXIS 3D) combined with machine learning techniques. The results show that bearing capacity is governed by complex interactions among rock mass quality, intact rock properties, and joint characteristics, with failure mainly controlled by discontinuity behaviour. Among the tested variables, GSI, mi, and UCS were identified as the most influential parameters. Ensemble learning models, particularly Poisson Regressor and Gradient Boosting, achieved the highest predictive accuracy (up to 96%), outperforming conventional regression methods.

Overall, the findings confirm that machine learning provides a robust framework for capturing nonlinear geo-mechanical behaviour and improving the reliability of foundation design in jointed rock masses.

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