A REVIEW OF INTELLIGENT ROCK MECHANICS: FROM METHODS TO APPLICATIONS CONFERENCE SUBMISSIONS

Anonymous authors
Paper under double-blind review

ABSTRACT

Intelligent rock mechanics represents the convergence of artificial intelligence (AI) and classical rock mechanics, providing new paradigms to understand, model, and predict the complex behaviors of geological materials. This review synthesizes recent progress from foundational AI methodologies to their practical applications in rock engineering. Traditional challenges—such as anisotropy, discontinuities, and multiphysics coupling—have been re-examined through data-driven and hybrid approaches that integrate learning algorithms with physical principles. The study traces the evolution of AI in this field, from early backpropagation and support vector machines to modern deep learning frameworks such as convolutional and transformer architectures, highlighting their roles in microstructure reconstruction, mechanical parameter estimation, constitutive modeling, and real-time hazard prediction. Emerging techniques, including physics-informed neural networks and graph-based learning, bridge data-driven inference with physical interpretability, while large language models are beginning to facilitate automated code generation and decision support in geotechnical analysis. Despite remarkable progress, key challenges remain in data quality, model generalization, and interpretability. Addressing these issues requires standardized datasets, interdisciplinary collaboration, and the establishment of transparent, reproducible AI workflows. The paper concludes by outlining a forward-looking perspective on developing next-generation intelligent frameworks capable of coupling physical knowledge, spatial reasoning, and adaptive learning, thereby advancing rock mechanics from empirical modeling toward fully intelligent, autonomous systems.

1 INTRODUCTION

Artificial Intelligence (AI) has evolved from an abstract computational theory into a transformative force reshaping scientific inquiry and engineering design across disciplines—including rock mechanics. The intellectual roots of AI trace back to the mathematical formalization of neural activity by McCulloch and Pitts in 1943 (McCulloch & Pitts, 1943), whose neuron model established the conceptual bridge between biological cognition and digital computation. The subsequent introduction of the backpropagation algorithm in 1986 (Rumelhart et al., 1986) revolutionized the training of multilayer neural networks and laid the groundwork for modern deep learning. By the early 1990s, researchers had begun applying these architectures to rock mechanics, where backpropagation networks were used to estimate elastic properties and optimize mining configurations (Zhang et al., 1991). The next three decades witnessed an explosion of model diversity, from convolutional neural networks (CNNs) (LeCun et al., 1989) and long short-term memory (LSTM) networks (Hochreiter & Schmidhuber, 1997) to generative adversarial networks (GANs) (Goodfellow et al., 2014) and attention-based transformers (Bahdanau et al., 2015; Vaswani et al., 2017). Each generation expanded the frontier of AI applications—CNNs improved microseismic event localization in underground mines (Huang et al., 2018), LSTMs modeled rheological behavior from early deformation histories (Qi & Fourie, 2018), and GANs synthesized realistic seismic waveforms (Wang et al., 2021). Transformers, originating in natural language processing, have now been adapted for visual classification tasks such as identifying rock fragments from post-blasting imagery (Li et al., 2025). Together, these developments reflect a long trajectory of conceptual transfer, in which core AI architectures progressively migrated from cognitive science to computational geomechanics.

A bibliometric overview of 17 journals, highlights the diffusion of AI methods into rock mechanics and related engineering fields. The literature reveals that AI has taken root most strongly in computational mechanics, owing to its dependence on high-level mathematical abstraction and algorithmic optimization. Yet, compared with other branches of civil or mechanical engineering, the research volume in rock mechanics remains modest—mirroring both the technical challenges of acquiring reliable subsurface data and the emergent stage of methodological adaptation. Nevertheless, the thematic analysis of keywords indicates rapid conceptual maturation: "machine learning" now surpasses "artificial intelligence" itself in prevalence, signifying a shift toward data-driven modeling paradigms. Among the numerous approaches, support vector machines (SVMs) (Vapnik & Chervonenkis, 1964) gained early prominence through the introduction of kernel-based nonlinear classification (Cortes & Vapnik, 1995), serving as a bridge between traditional statistical learning and modern deep architectures. More recent work extends this trajectory toward physics-informed neural networks (PINNs) (Abueidda et al., 2021), which embed governing physical laws directly into loss functions, thereby aligning data-driven inference with mechanical consistency. The increasing use of such hybrid models underscores a collective movement within geomechanics toward interpretability, robustness, and scientific grounding—attributes once viewed as outside the scope of black-box AI.

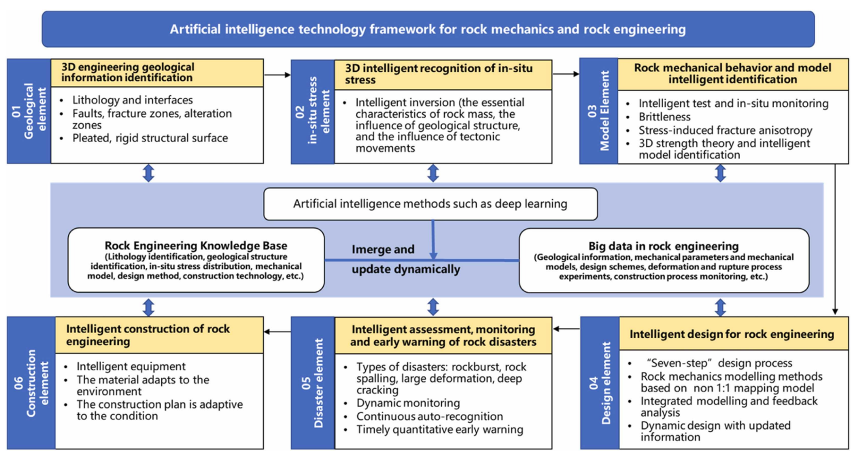

Figure 1: Collaborative development of artificial intelligence and rock mechanics (Feng et al., 2024).

The integration of AI into rock mechanics, however, is far from a simple transplantation of algorithms. Rocks differ fundamentally from continuum materials in their heterogeneity, anisotropy, and multi-scale discontinuities—ranging from microcracks to regional fault systems. These features, coupled with strong nonlinearity, rate dependence, and multiphysics coupling, create modeling barriers that classical continuum mechanics alone cannot resolve. In this context, AI provides new tools for addressing long-standing challenges: inferring mechanical parameters from sparse data, reconstructing microstructures, identifying joint networks, and forecasting instability phenomena such as rock bursts. Yet, the field still faces limitations rooted in data scarcity, measurement uncertainty, and the difficulty of assembling large, high-quality datasets for model training and validation. As this review aims to synthesize, AI's evolution—from the McCulloch-Pitts neuron to modern transformer-based architectures—has progressively reshaped the analytical landscape of rock mechanics. Grounded in the conceptual legacy of the Turing Test (Turing, 1950), a framework is proposed to categorize AI in this field according to its cognitive resemblance and level of abstraction. By bridging theoretical advances with engineering practice, AI not only augments the predictive capacity of rock mechanics but also redefines its epistemology—transforming it from a purely empirical discipline into a data-driven, intelligence-enabled science poised for the next generation of discovery.

2 DATA-DRIVEN ESTIMATION OF ROCK PROPERTIES

In recent years, the estimation of rock mechanical properties has undergone a paradigm shift from traditional empirical correlations toward data-driven learning frameworks. Instead of relying solely on direct laboratory measurements, researchers have increasingly exploited the predictive capacity of machine learning to infer rock strength and stiffness from easily obtainable indirect indicators. Early studies demonstrated that artificial neural networks (ANNs), particularly those based on backpropagation (BP), could effectively capture the nonlinear relationship between uniaxial compressive strength (UCS) and parameters such as P-wave velocity, rebound number, or point-load index, using datasets like the 108-sample sandstone collection from the Dengkil site in Malaysia [28]. Although BP networks offer transparent and flexible implementations, their performance remains sensitive to data completeness and noise. To address these limitations, a suite of advanced algorithms—including adaptive neuro-fuzzy inference systems (ANFIS) (Yesiloglu-Gultekin et al., 2013), support vector machines (SVM) (Ceryan et al., 2013), extreme learning machines (ELM) (Liu et al., 2015), and regression trees (Tiryaki, 2008)—has been introduced. SVMs provide robust generalization in small datasets through kernel mapping, while ANFIS models integrate fuzzy logic to accommodate uncertainty in geological parameters such as porosity or density. Literature-derived databases have further expanded the scope of predictive modeling. Studies compiling 199–367 records from diverse rock types have yielded ANN and soft computing models capable of estimating UCS and other strength parameters, including triaxial and shear strength (Skentou et al., 2023; Le et al., 2022). Beyond intact rocks, data-driven frameworks have also been applied to rock-mass characterization using empirical descriptors (e.g., RMR class, Q-value, or UCS of intact rock) (Miranda et al., 2010), and to drilling data analysis through physics-informed convolutional neural networks that relate thrust force, torque, and penetration rate to UCS in jointed rock masses (He et al., 2021). Similar strategies have been extended to engineered geomaterials such as geopolymer-stabilized or cement-treated soils, demonstrating the general applicability of these methods to complex heterogeneous media (Mozumder & Laskar, 2015; Narendra et al., 2006).

Parallel advances have been achieved in predicting elastic moduli through hybrid data–model integration. Neural networks with multi-output architectures have been trained to simultaneously estimate UCS and Young's modulus by extending the output layer (Yagiz et al., 2012), while numerical databases derived from microstructural simulations have provided valuable synthetic training data. For example, fast Fourier transform–based models of the interface transition zone (ITZ) have been used to generate elastic property datasets for heterogeneous materials, subsequently mapped using multilayer BP networks (Xue et al., 2023). Hybrid learning schemes such as ANFIS have been applied to infer dynamic elastic moduli of thermally damaged rocks from UCS and Brazilian tensile strength (Waqas & Ahmed, 2020), and ensemble models such as random forest, AdaBoost, extreme gradient boosting, and CatBoost have shown excellent capability in predicting moduli of weak sedimentary rocks based on porosity, density, and durability data (Abdi et al., 2023). Multivariate regressors have also revealed the compositional dependence of granite stiffness on quartz and feldspar contents, as well as dry density and sonic velocity (Jahed Armaghani et al., 2015). Additional progress includes ANN-based correlations between P-wave velocity and field test indices (Behzadafshar et al., 2019), Bayesian frameworks that quantify prediction uncertainty for elastic constants (Feng & Jimenez, 2014), and neural-network-assisted finite element models capable of recovering the five elastic constants of transversely isotropic rocks from limited experimental orientations (Lee et al., 2022). Extending beyond rocks, support vector regression and Gaussian process regression models have been effectively used to estimate the resilient modulus of treated subgrade and clay soils from material and additive features, with polynomial kernels often outperforming RBF and linear ones (Heidaripanah et al., 2017; Hu & Solanki, 2021). Together, these developments highlight the ability of data-driven approaches to unify static and dynamic elasticity estimation under a consistent computational paradigm.

Beyond strength and stiffness, machine learning has also transformed the estimation of wave velocities and other geomechanical attributes. Recent studies have integrated artificial neural networks, fuzzy systems, and evolutionary optimization into hybrid architectures that predict sonic velocities from well-log data, achieving high accuracy on over 1,600 records from the Asmari formation through committee-based learning with weighted fusion (Asoodeh & Bagheripour, 2012). Physics-guided neural networks have further advanced velocity inversion by incorporating frequency-domain constraints into loss functions, ensuring physical plausibility and improved well-posedness of shear-wave velocity profiles from downhole signals (Ji et al., 2025). Similarly, convolutional regression models leveraging transfer learning can infer compressional velocities directly from core sample images of cement-reinforced soils, establishing a bridge between visual and mechanical domains (Kim et al., 2023). Ensemble-based architectures, such as VelProfES, combine real and synthetically generated borelog datasets—enhanced by conditional generative adversarial networks (CT-GANs)—to predict shear-wave velocity profiles across more than 10,000 synthetic and real stations (Joshi et al., 2024). The same methodological foundation has been adapted to infer diverse rock and soil properties, including fracture toughness (Afrasiabian & Eftekhari, 2022), soil-water characteristic curves (Li & Vanapalli, 2022), Poisson's ratio (Alakbari et al., 2024), and permeability (Kayabasi et al., 2015). Collectively, these studies illustrate a growing trend toward physics-aware, data-driven frameworks that enable multi-property estimation across scales—offering a coherent pathway for intelligent characterization and prediction of rock mechanical behavior from heterogeneous data sources.

3 Image-Based Modeling and Fracture Detection

The geometric complexity of rock microstructures and discontinuities has long been recognized as one of the fundamental barriers to accurate mechanical modeling. Many macroscopic behaviors—such as rate-dependent strength or nonlinear deformation—originate from processes occurring at the grain or pore scale. To overcome the limitations of traditional imaging and reconstruction approaches, recent research has increasingly adopted image-based and data-driven frameworks to recover the internal geometry of rocks from limited or indirect observations. Early numerical approaches employed simulated annealing (SA) optimization to generate three-dimensional digital rocks from limited surface or section images, reproducing statistical features of microstructures without requiring extensive datasets (Yin & Zhao, 2014; Wei et al., 2023). Although this method provided an elegant solution for small-sample reconstruction, it was hindered by heavy computational cost and low scalability when dealing with complex multiphase materials. The advent of deep learning revolutionized this domain by enabling direct 3D reconstruction from 2D imagery. Neural network–based frameworks now learn mappings between image features and volumetric structures, achieving orders-of-magnitude speedups over SA methods while retaining statistical realism (Feng et al., 2020). Generative models have further extended this paradigm: variational autoencoders (VAEs) have been trained on micro-CT datasets containing tens of thousands of sand particles to generate realistic particle geometries for discrete element modeling (Feng et al., 2020), and voxel-based 3D generative adversarial networks (GANs) have been developed to synthesize large-scale multiphase structures with anisotropic or frozen granular components (Argilaga et al., 2024). More recently, image enhancement networks such as DeblurGAN have been applied to reconstruct true-color 3D granite textures from sequential rock surface images, demonstrating the potential of combining physical imaging and data-driven restoration for microstructural realism (Zhao et al., 2025). These methods collectively signal a transition from purely statistical reconstructions toward AI-driven volumetric modeling capable of capturing the inherent heterogeneity of geomaterials.

Parallel to microstructural reconstruction, AI has become an essential tool for image-based fracture detection and geometric extraction at both laboratory and field scales. Convolutional neural networks (CNNs) have been extensively used to automate the segmentation and quantification of rock fractures, outperforming conventional image-processing pipelines in accuracy and noise suppression. The FraSegNet architecture, for example, was trained on thousands of tunnel fracture images and achieved superior fracture trace extraction performance across variable lighting and texture conditions (Chen et al., 2021). Similar CNN variants such as DeepLab V3+ and UNet3+ have been applied to high-resolution CT imagery of igneous rocks, providing microscale crack segmentation at submicron accuracy (Lei & Fan, 2024). Despite these advances, CNN-based models still suffer from limited robustness when faced with low contrast, irregular morphologies, or imbalanced datasets. Beyond 2D imagery, 3D point-cloud–based approaches have emerged as a promising alternative. Ensemble learning frameworks integrating support vector machines and random forests have been developed to identify discontinuities in laser-scanned tunnel faces, even when the surfaces were obscured by shotcrete or excavation artifacts (Peng et al., 2024). Such models achieve strong generalization by aggregating predictions from multiple learners, though they require substantial feature engineering and computational resources. The integration of transfer learning has further enhanced the adaptability of deep segmentation networks to small, domain-specific datasets, enabling stable fracture extraction and 3D reconstruction across different rock types (Pan et al., 2024). Nonetheless, the accurate restoration of the spatial topology of fracture networks remains challenging and continues to motivate research into multi-view and multimodal fusion methods.

Recent progress in combining deterministic and stochastic modeling frameworks has further improved the structural interpretation of discontinuities from image and point-cloud data. The Deterministic–Stochastic Identification and Modelling (DSIM) method represents one such approach, where discontinuity features—such as joint orientation and aperture—are statistically characterized through hybrid region-growing and Gaussian fitting strategies applied to outcrop-scale datasets (Pan et al., 2019). By integrating visual and geometric cues from both real imagery and 3D point clouds, DSIM effectively reduces uncertainty in discrete fracture network (DFN) modeling and has been successfully validated through field applications, such as the Heijing Limestone Mine in Guangxi, China. Together, these advances reflect a broader methodological convergence in rock mechanics: the fusion of imaging technologies, deep generative models, and hybrid statistical–deterministic analysis now enables more precise reconstruction and detection of fractures across scales. This image-driven perspective not only enhances our ability to simulate the mechanical response of discontinuous rock systems but also lays the groundwork for a new generation of digital twin frameworks in geomechanics—where reconstruction, detection, and prediction are integrated within unified AI-based modeling pipelines.

4 AI-Assisted Constitutive Modeling and Simulation

The development of artificial intelligence has opened a new paradigm for constitutive modeling in rock mechanics, shifting from empirically defined constitutive laws to data-driven and self-adaptive formulations. Early studies demonstrated that backpropagation (BP) neural networks could approximate complex rock strength criteria through direct learning from experimental databases rather than relying on predefined yield functions (Rafiai & Jafari, 2011; Rafiai et al., 2013). These models were trained on extensive polyaxial test datasets covering multiple rock types, allowing nonlinear failure envelopes to emerge automatically from data correlations. Beyond BP networks, ensemble and probabilistic regressors such as Gaussian process regression, random tree, and M5P models have been used to construct interpretable and uncertainty-aware strength criteria from multi-source datasets (Fathipour-Azar, 2023). More recently, sequential neural architectures—such as long short-term memory (LSTM) networks—have gained attention for capturing history-dependent constitutive responses. LSTM-based frameworks have been successfully employed to simulate stress–strain evolution in soils and other path-dependent materials (Zhang et al., 2023a; Bahtiri et al., 2023), as well as to reproduce cyclic viscoelastic–viscoplastic behaviors in heterogeneous composites. Hybrid deep models combining LSTM with temporal convolutional networks (TCN) have further demonstrated the ability to learn both monotonic and cyclic deformation mechanisms from limited data (Guan & Yang, 2023). These AI-driven constitutive models, once integrated into finite element solvers, effectively replace conventional empirical formulations and allow continuum-scale simulations to inherit the nonlinear, multiaxial, and rate-dependent behavior observed in laboratory tests.

Parallel progress has been achieved in embedding AI directly into the numerical solution of governing equations. Traditional partial differential equations describing elasticity, diffusion, and multiphysics coupling have been reformulated through machine learning surrogates that blend physical constraints with data-driven inference. BP neural networks have been inserted at Gauss integration points within finite element meshes to emulate representative volume elements (RVE) derived from discrete element simulations, enabling a hybrid FEM–DEM framework capable of resolving anisotropy and microscale interactions in granular materials (Guan et al., 2024). Building on this concept, physics-informed neural networks (PINNs) emerged as a general framework for solving nonlinear PDEs by incorporating governing equations into loss functions. However, challenges in convergence and stability have led to refined architectures such as the physics-informed radial basis network (PIRBN), which introduces localized basis functions to better capture diffusion and viscoelastic flow behavior (Bai et al., 2023a). Similarly, the physics-informed temporal convolutional network (PI-TCN) has been integrated with variational formulations of finite element analysis to efficiently simulate transient thermoelastic problems while reducing differentiability and memory constraints (Abueidda & Mobasher, 2024). These methods have also been extended to poromechanical systems, addressing coupled flow–deformation equations for both single- and multiphase media through dimensionless reformulation and stress-split training schemes that stabilize optimization (Haghighat et al., 2022). In addition to PINN variants, alternative architectures such as multi-fidelity graph neural networks (MFGNNs) (Black & Najafi, 2022), recurrent networks (RNNs, LSTMs, GRUs) (Hu et al., 2022), and convolutional-peridynamic hybrids (Mavi et al., 2023) have been explored for solving elasticity, phase-field, and nonlocal fracture problems with improved accuracy–efficiency trade-offs.

Collectively, these developments mark a convergence between machine learning and computational mechanics, where AI serves not merely as a surrogate but as an active component of the constitutive and governing framework. By coupling data-driven learning with physical priors, AI-assisted models can reveal hidden structure–property relationships that transcend empirical formulations and extend predictive capability across scales—from grain-level anisotropy to continuum-scale deformation. Yet, the application of such techniques in rock mechanics remains nascent compared to other material domains. Future research will likely emphasize hybrid physics–data architectures, multi-scale transfer learning, and uncertainty quantification, integrating neural constitutive laws with numerical solvers to form self-evolving simulation systems. These intelligent frameworks have the potential not only to reproduce observed mechanical responses but also to uncover emergent behaviors, offering a pathway toward autonomous, knowledge-guided constitutive modeling and simulation in rock and geomaterial mechanics.

5 Model Generalization in Rock Mechanics AI

6 Applications in Rock Engineering

The ultimate value of intelligent rock mechanics lies in solving real-world engineering problems more effectively than before. Across various sub-disciplines of rock engineering, AI and ML techniques have begun to yield tangible improvements in analysis, design, and decision-making. Here we survey several key application areas where these intelligent methods are making a difference.

6.1 Rock Mass Classification and Characterization

Rock mass classification plays a foundational role in the design and stability assessment of tunnels, slopes, and other rock engineering projects, yet traditional systems such as RMR and Q remain constrained by empirical formulations and regional calibration, often requiring expert judgment for parameter interpretation. Artificial intelligence (AI) introduces a paradigm shift in this field by enabling data-driven classification and automated feature extraction that transcend site-specific empirical dependence. Recent reviews have summarized substantial progress in AI-powered methodologies for rock mass evaluation (Saadati et al., 2024), where machine learning models are employed to infer classification indices directly from measurable or visual inputs. For example, hybrid frameworks combining support vector classification (SVC) and backpropagation neural networks (BPNN) have been trained on multi-site tunnel databases to refine basic quality (BQ) predictions, with SVC outperforming BPNN due to its superior capability to identify nonlinear decision boundaries in heterogeneous geological data (Liu et al., 2019). Similarly, regression-based algorithms such as relevance vector regression (RVR) and support vector regression (SVR) have demonstrated significant improvements in estimating Rock Mass Rating (RMR) values compared to conventional empirical conversions, reducing systematic over- and underestimation errors through probabilistic inference (Gholami et al., 2013). AI also enables a transition from manual to image-based rock mass characterization: neural networks can derive the Geological Strength Index (GSI) from three-dimensional point cloud data captured via photogrammetry or unmanned aerial vehicle (UAV) surveys, automatically quantifying geometrical attributes such as trace length, orientation density, and intersection frequency (Zeni et al., 2021). Convolutional neural networks (CNNs) extend this capacity by directly learning visual patterns from thousands of core images, achieving high accuracy in predicting Rock Quality Designation (RQD) across lithologies while eliminating the need for manual labeling (Alzubaidi et al., 2022). Moreover, hybrid neuro-fuzzy systems such as the Adaptive Neuro-Fuzzy Inference System (ANFIS) have integrated mechanical and geological indicators—uniaxial compressive strength (UCS), RQD, joint spacing (JS), joint condition (JC), and groundwater (GW)—to estimate RMR in diverse field environments, combining the interpretability of fuzzy logic with the adaptivity of neural learning (Jalalifar et al., 2011). Collectively, these AI-based approaches transform rock mass classification from an experience-dependent process into a quantitative, reproducible, and scalable framework, capable of integrating image analysis, field sensing, and machine learning to deliver consistent, objective, and high-resolution characterization of geological materials.

6.2 Rockburst and Geohazard Prediction

Rockburst represents one of the most complex and hazardous manifestations of rock mass instability, where the abrupt release of stored elastic energy under high stress leads to violent ejection and catastrophic damage in deep tunnels, mines, and hydropower caverns. The nonlinear coupling among geological heterogeneity, in-situ stress distribution, and excavation-induced perturbations makes its prediction extremely challenging for conventional empirical or analytical models. Artificial intelligence (AI) has therefore emerged as a transformative tool for rockburst and geohazard prediction, providing a data-driven framework capable of learning the intrinsic relationships between precursor signals and failure intensity. Early AI applications employed fuzzy inference systems (FIS) to manage uncertainty and incomplete knowledge in geological datasets, yet their predictive capacity remained limited, as shown by (Adoko et al., 2013), whose model explained only 45.8% of the variance. By integrating neural learning, the adaptive neuro-fuzzy inference system (ANFIS) achieved substantial improvements, with 95.6% successful prediction accuracy and reduced error metrics, demonstrating the potential of hybrid logic–learning architectures in handling nonlinearity and fuzziness. Support vector machines (SVMs), often combined with regression splines or deep ensemble algorithms, have proven effective in modeling high-dimensional rockburst parameters, enabling multivariate decision boundaries that improve classification robustness (Guo et al., 2022). Neural networks—ranging from feedforward and convolutional (CNN) to extreme learning machines (ELMs)—have been extensively applied to identify rockburst precursors from monitoring data such as microseismic activity, stress ratios, or acoustic emissions, often enhanced through optimization strategies like particle swarm algorithms (Xue et al., 2020; Zhang et al., 2021). Ensemble learning methods further elevate prediction stability and precision: (Jia et al., 2024) demonstrated that integrating seven classifiers in a voting-ensemble framework increased accuracy by 4.4%, while (Liang et al., 2021) showed that multi-learner ensembles combining SVMs, logistic regression, and decision trees outperform individual models across precision and recall metrics. For time-dependent hazard forecasting, deep recurrent architectures—particularly long short-term memory (LSTM) networks—enable dynamic early-warning models that capture temporal dependencies in microseismic or stress evolution data. Hu et al. (Hu et al., 2023) established an LSTM-based framework that predicted rockburst intensity and timing across blasting cycles with accuracies exceeding 70%, marking a key step toward continuous temporal risk monitoring. The reliability of these AI systems relies heavily on robust datasets integrating geological, geomechanical, and microseismic indicators, such as maximum tangential stress, uniaxial compressive strength, brittleness index, elastic energy, and event frequency. Effective preprocessing—including noise filtering, missing-value imputation, and class-balancing—is crucial; for instance, (Liu et al., 2023) employed K-means–based synthetic minority oversampling (KM-SMOTE) to mitigate imbalance in rockburst datasets, significantly enhancing predictive performance. Cross-validation procedures, such as k-fold optimization, ensure model generalization, as shown by (Zhang et al., 2020), who achieved over 15% improvement in accuracy after hyperparameter tuning. Collectively, these advancements demonstrate that AI has transcended empirical prediction, establishing an intelligent, adaptive, and interpretable framework for rockburst and geohazard forecasting—one capable of fusing multi-source data, uncovering latent physical patterns, and supporting real-time early warning in complex underground environments.

6.3 Tunneling and Boring Operations

Within the operational context of tunneling and boring, AI/ML has evolved from post-hoc curve fitting to an integrated decision engine that links geodata ingestion, physics-aware representation, and real-time control of construction variables in rock mechanics. Classic supervised learners remain valuable when aligned with mechanistic priors: multi-layer backpropagation networks map geometry–soil/rock–method descriptors to settlement metrics for construction planning and monitoring (Neaupane & Adhikari, 2006), and when trained on numerical experiments they can invert rheological parameters in soft rock so that calibrated long-horizon deformation forecasts feed maintenance scheduling and support retuning (Kovacevic et al., 2021); replacing sigmoids with wavelet activations, Wavenet improves learning efficiency and generalization for maximum ground-surface settlement estimation during advance, making it attractive for data streams with nonstationary spectral content (Pourtaghi & Lotfollahi-Yaghin, 2012). Hybridizing data-driven inference with structural geology, a Gray BP framework coupled to a DFN uncovers a linear link between P-wave velocity and structural plane density, enabling data-assisted optimization of prestressed anchor layouts while revealing burial depth and cable length as primary drivers of surrounding-rock response (Li et al., 2023). For squeezing risk under weak or highly stressed rock, meta-heuristic optimization and probabilistic learning complement deterministic heuristics: a WOA-tuned SVM leverages multi-site case histories to classify squeezing from depth, stiffness, RTQI, diameter and strain inputs (Zhou et al., 2022), whereas a Naïve Bayes formulation provides robust prediction with incomplete evidence and low error across 10-fold validations and external cases (Feng & Jimenez, 2015). Ensemble and time-series architectures strengthen proactive control at the face: PSO-optimized XGBoost scores deformation risk in fault-fractured zones to prioritize countermeasures (Bo et al., 2024), and adaptive chaotic sparrow-search–enhanced ELM/AMLSTM pipelines anticipate short-term deformation trajectories for construction pacing and support staging (Dong et al., 2024). Blending physics constraints with data yields further gains in data-scarce, noisy settings critical to subsurface operations: a DPNN jointly infers geological parameters and ground-loss while outperforming SVM/BP under 20% noise, thus stabilizing settlement and volume-loss estimates needed for shield guidance and risk buffers (Liu et al., 2024); more generally, PINN formulations embed equilibrium and compatibility into displacement-field learning for shield tunneling, curbing extrapolation error and improving interpretability for engineers (Zhang et al., 2023b). Finally, sequence models close the loop on machine–ground interaction in EPB operations: LSTM predictors maintain posture accuracy and anomaly sensitivity despite delayed events and disturbances, outperforming ML ensembles and supporting on-the-fly set-point adjustments for torque, thrust, and chamber pressure (Bai et al., 2023b). Collectively, these advances position AI not as a black box but as a physics-constrained, data-efficient co-pilot for tunneling and boring operations—transforming rock-mechanics inference into actionable control for design, construction, and lifecycle risk management.

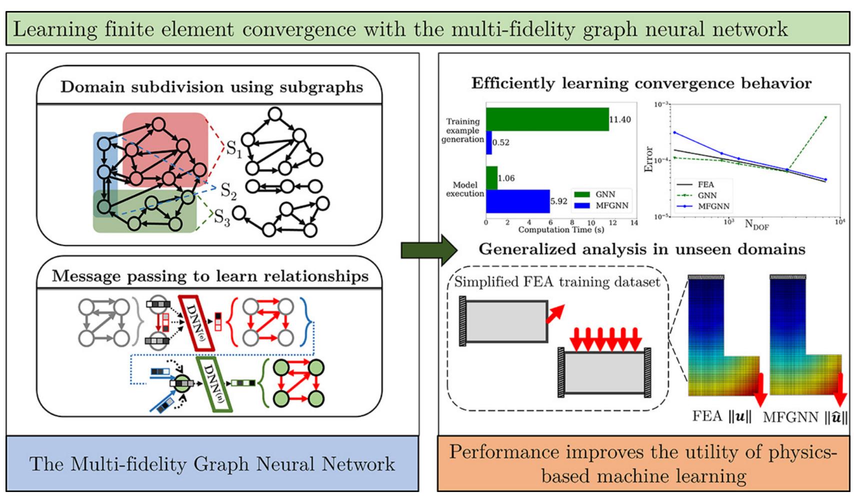

Figure 2: Machine learning methods for solving FEM problems(Black & Najafi, 2022).

6.4 Slope Stability Analysis

Framed within slope stability analysis and geomechanical hazard management, recent AI advances have shifted from ad-hoc predictors to rigorously validated surrogates and physics-aware learners that compress computational cost while preserving reliability: back-propagation neural networks and support vector machines accelerate Monte Carlo reliability by orders of magnitude with sub-percent bias, enabling probabilistic assessment under heterogeneity and anisotropy using only sparse training subsets (Aminpour et al., 2023a;b); data-centric toolchains extend to 3D effects through efficient ANN implementations (Meng et al., 2021) and to more interpretable and robust surrogates via monotonicity constraints and augmentation strategies that enforce geotechnical priors (Pei & Qiu, 2024). Classic BP paradigms have also been embedded in landslide hazard formulations—either coupled with interaction matrix theory (Ferentinou & Sakellariou, 2007) or distilled into open-pit operational indices such as the MSII for mine slopes (Zare Naghadehi et al., 2013) while deep learning fused with GIS and pseudo-static analyses yields high-fidelity susceptibility mapping at territory scale (Pradhan & Kim, 2021). Convolutional architectures further streamline mechanics-based workflows: pre-trained CNNs deliver near-instant estimates of safety factors and slip-surface geometry for design screening (Hsiao et al., 2022); CNN-enabled nonintrusive SRFEM resolves random-field variability without succumbing to dimensionality growth (Liu et al., 2023); and CNN metamodels substitute for random-field FEM in reliability calculations with superior accuracy–efficiency trade-offs (Wang et al., 2021). For forecasting, spatiotemporal CNN pipelines outperform rainfall–landslide correlations in operational nowcasting of engineered slopes (Xiao et al., 2022), and disciplined augmentation helps control overfitting on limited labeled cases (Soranzo et al., 2023). Beyond ANNs, kernel and gradient-boosting surrogates support scenario-specific risk evaluation: SVR/XGBoost frameworks quantify failure probability of reservoir slopes under rapid drawdown by ingesting geomechanical descriptors (Guardiani et al., 2022); rare-event seismic reliability is tractably resolved by marrying subset simulation with SVM classifiers in a collaborative conditioning scheme (Xu et al., 2023); and learning systems based on XGBoost (leveraging NGA-West2), subset simulation, K-fold validation, RVM-FORM hybrids, and related boosters provide competitive estimates of rainfall-induced failure probabilities while retaining statistical rigor (Li et al., 2017; Wang et al., 2020; Świtała et al., 2023). At the interface of deterministic modeling and statistical learning, an uncoupled FEM–LEM pipeline supplies numerical labels to calibrate a random-forest surrogate that classifies reservoir-slope responses with probabilistic consistency (Li & Vanapalli, 2022). Finally, hybrid ensembles consolidate complementary inductive biases from multiple learners: meta-stacking with bio-inspired search identifies performant base/meta-classifiers from FEA-generated training corpora and generalizes to field cases with strong AUC while quantifying variable importance (Kardani et al., 2021); genetic-algorithm–tuned mixtures of Gaussian processes, SVMs, and boosted trees achieve further gains under cross-validation (Qi & Fourie, 2018); stacked ensembles spanning AdaBoost/GBM families highlight the primacy of material parameters in predictive stability (Lin et al., 2022); and combined RF–XGBoost models surpass SVM/logistic baselines in regional landslide catalogs while ranking profile geometry among the dominant controls (Zhang et al., 2022). Collectively, these contributions delineate an AI-enabled slope engineering workflow in which data-efficient surrogates, physics-informed learning, and ensemble uncertainty quantification cohere into fast, scalable, and decision-relevant tools for design screening, reliability assessment, and operational forecasting across the rock-mechanics spectrum.

6.5 Other Emerging Applications

Positioned within rock mechanics and adjacent geotechnical practice, recent studies exemplify how AI serves as a surrogate, predictor, and design aide across load-carrying assessment, ground response forecasting, support optimization, and seismic detailing: trained on FLAC simulations governed by the Hoek–Brown criterion, an ANN replaces cumbersome empirical or fully numerical workflows to estimate shallow-foundation bearing capacity on rock masses using compact descriptors such as lithology and uniaxial compressive strength, reproducing numerical trends with far lower computational burden (Millán et al., 2021); spatiotemporal sequence modeling further elevates predictive fidelity for metro excavation environments, where a convolutional–recurrent hybrid (STdeep) captures spatial gradients and temporal memory in settlement records to yield stable, high-accuracy forecasts for foundation-pit influence zones (Zhang et al., 2024); in support design for soft-rock tunnels, a BP-driven dynamic framework couples with numerical simulations to tune active–passive support parameters under evolving ground conditions (Liu et al., 2025), while an expanded optimization scheme that integrates P-wave velocity and geological context with a neural surrogate isolates structural plane density and anchor cable length—together with burial depth—as dominant drivers of surrounding-rock deformation, thereby sharpening design targets and improving deployment efficiency (Li et al., 2023); and for fault-crossing bridges, explainable ML pipelines trained on large synthetic–empirical databases deliver rapid seismic classification/regression tools to size cable restrainers, yielding transparent formulae suitable for preliminary and parametric design loops (Zhang et al., 2024). Collectively, these AI instruments demonstrate tangible gains in efficiency and accuracy across the rock-mechanics workflow; nevertheless, truly mature, field-proven, and routinely adopted AI applications in rock engineering remain relatively scarce, underscoring the need for physics-aware generalization, uncertainty quantification, and standardized validation before widespread practice integration.

7 Challenges and Future Discussions

Despite the impressive progress in intelligent rock mechanics, several challenges must be addressed for these technologies to reach their full potential in practice:

Data Limitations: High-quality, representative data are the fuel for AI models, yet in rock mechanics such data can be scarce or hard to share(see Appendix A.1). Many AI models discussed are trained on relatively small datasets or data from specific sites, which raises concerns about overfitting and generalizability. A concerted effort is needed to develop open, standardized databases for rock mechanical properties, case histories, and monitoring data (Xiao et al., 2022). Collaborative data repositories and industry-academia partnerships could help accumulate the large datasets necessary for robust model training and validation. Additionally, methods to augment data – such as using physics-based simulations or generative networks to create plausible synthetic data – will be valuable in overcoming data scarcity.

Model Interpretability and Trust: Engineering fields demand that models not only perform well, but also be interpretable and trustworthy for high-consequence decisions. Many AI models (e.g. deep neural networks) are often criticized as "black boxes." Improving interpretability is thus a key frontier. This could involve using simpler surrogate models to approximate the behavior of complex networks or integrating explainable AI techniques that highlight which input features most influence the predictions (for instance, identifying which combination of joint orientation and strength led an ML model to flag a slope as unstable). The development of models that incorporate physical laws (such as PINNs or hybrid models) is another way to boost trust, since they are constrained by known behavior and less likely to predict nonsensical outcomes (Soranzo et al., 2023). Ultimately, increasing transparency and providing uncertainty estimates with predictions will be essential for convincing engineers to adopt AI tools widely.

Computational Efficiency: While many AI models can run predictions in milliseconds once trained, the training process or the integration with large-scale simulations can be computationally demanding. Physics-informed models, for example, often require significant computational resources to converge on a solution for complex 3D problems. Future research will likely explore more efficient training algorithms, model compression, and the use of high-performance computing (including GPUs and cloud platforms) to make training and deploying intelligent models more accessible. Additionally, intelligent algorithms might be used to accelerate each other – for example, using one neural network to intelligently sample or reduce the input space for another, thereby cutting down computation without sacrificing accuracy.

Integration with Domain Workflows: For AI to truly revolutionize rock engineering, it must be integrated into existing engineering workflows and software. This means AI models should be packaged into user-friendly tools, possibly as add-ons to popular rock engineering software or as stand-alone decision support systems. There is ongoing work on frameworks to guide practitioners in selecting appropriate AI methods for a given problem (Guardiani et al., 2022). Such frameworks help in demystifying AI for engineers by linking problem types (e.g. "classification problem with small dataset") to recommended techniques (e.g. "SVM or decision tree ensemble") (Xu et al., 2023). Education and training of rock engineers in data science fundamentals will also facilitate smoother adoption – the next generation of geotechnical professionals will likely need to be as comfortable using a machine learning model as they are using a Mohr-Coulomb failure criterion.

Maintenance of AI Systems: Unlike physical laws, data-driven models may need periodic retraining or calibration as new data come in. For instance, as an operation progresses and more monitoring data are collected, initial predictive models for deformation or seismicity might need updating to maintain accuracy. Establishing protocols for model maintenance, validation, and update is important so that AI models remain reliable over the lifespan of a project. In addition, ensuring reproducibility of AI-based research is a community challenge – sharing code, model parameters, and test datasets openly can help validate findings and prevent situations where a published model cannot be reproduced or trusted in a different context.

Looking forward, the future of intelligent rock mechanics appears bright. We anticipate far greater use of hybrid models that combine data-driven learning with explicit physics and domain expertise – this could mean widespread adoption of physics-informed neural networks for routine design problems, or real-time digital twins of underground constructions that marry sensor data with adaptive

AI predictions. Advances in related fields such as computer vision, natural language processing, and robotics will also influence rock mechanics. For example, large language models (LLMs) might be harnessed to quickly parse and summarize vast geotechnical reports or to assist in generating computer code for simulations(see Appendix A.3), although their direct role in core rock mechanics analysis remains to be defined. Meanwhile, spatial intelligence – AI that understands spatial and geometric information – will be crucial for interpreting geological models and integrating multi-scale data (from microscopic images to GIS-based regional data) into a coherent predictive framework (Li et al., 2017).

8 Conclusion

In conclusion, intelligent rock mechanics is moving from a niche research topic toward mainstream application. The methods reviewed here, from predicting rock properties with simple tests to automating the mapping of fractures and optimizing tunnel operations, showcase a paradigm shift in how we handle the uncertainty and complexity of rock engineering. By addressing current challenges and fostering interdisciplinary collaboration between AI experts and rock mechanics specialists, the next decade should see these intelligent methods mature into standard tools – making rock engineering safer, more efficient, and more innovative than ever before.

A Appendix

A.1 Datasets of Intelligent Rock Mechanics

This appendix summarizes the major publications, research subjects, and available datasets or codes that were reviewed or referenced in this study. Table 1 provides an overview of representative works across microstructure reconstruction, fracture modeling, mechanical property estimation, and rock engineering applications, along with links to open-source repositories and supplementary materials.

Table 1: Summary of publications, subjects, and available datasets or codes.

Publications	Subject	Data set
(Argilaga et al., 2024)	Microstructure Reconstruction	DOI Link
(Lei & Fan, 2024)	Fracture Reconstruction	GitHub Link
(Kim et al., 2023)	Fracture Reconstruction	GitHub Link
(Abdi et al., 2023)	Mechanical Properties	Appendix A
(Afrasiabian & Eftekhari, 2022)	Mechanical Properties	Table 1
(Heidaripanah et al., 2017)	Mechanical Properties	Table 1, Table 2
(Hu et al., 2023)	Mechanical Properties	Appendix A
(Moussas & Diamantis, 2021)	Mechanical Properties	Table 1
(Mozumder & Laskar, 2015)	Mechanical Properties	Appendix B
(Narendra et al., 2006)	Mechanical Properties	Table 3, Table 4
(Tiryaki, 2008)	Mechanical Properties	Table 1
(Abueidda & Mobasher, 2024)	Governing Equations	GitHub Link
(Behzadafshar et al., 2019)	Governing Equations	GitHub Link
(Bai et al., 2023a)	Governing Equations	GitHub Link
(Black & Najafi, 2022)	Governing Equations	GitHub Link
(Lee et al., 2022)	Rock Mass Classification	GitHub Link
(Adoko et al., 2013)	Rockburst	Table 1
(Feng & Jimenez, 2015)	Tunnel Squeezing	Online Link
(Ferentinou & Sakellariou, 2007)	Slope	Table 3, Table 5
(Kayabasi et al., 2015)	Slope	Appendix A
(Kovacevic et al., 2021)	Tunnelling Deformation	Appendix A
(Liang et al., 2021)	Slope	Appendix
(Bahtiri et al., 2023)	Coal Mining	Appendix A
(Neaupane & Adhikari, 2006)	Tunneling-induced Ground Movement	Table 2, Table 3

A.2 Case Study of Deep Learning in Rockburst

A representative real-world application of deep learning in rockburst prediction was demonstrated by (Zhang et al., 2021), who developed a time-series prediction framework using convolutional neural networks (CNNs) and long short-term memory (LSTM) models to analyze microseismic multi-parameters collected from deep tunnels. Their case study, conducted in a deeply buried tunnel excavation project, employed continuous microseismic monitoring data—including event counts, cumulative energy, apparent volume, and energy index—to capture the temporal evolution preceding rockburst events. The proposed multivariate and multi-step CNN–LSTM hybrid model successfully predicted the future trends of these parameters, achieving strong agreement between predicted and observed evolution curves, as illustrated in Figure 3. Notably, the predicted increase in cumulative apparent volume and decrease in energy index consistently preceded actual rockburst occurrences, demonstrating the model's ability to serve as an early-warning tool. Compared with traditional methods focusing only on instantaneous risk indices, this deep learning–based approach provided time-tagged forecasts of rockburst probability and offered a more interpretable understanding of precursor evolution. The model's integration of field monitoring data, temporal learning, and early-warning interpretation represents a concrete example of how deep learning can be embedded into practical geotechnical risk management workflows, bridging theory and engineering application in intelligent rock mechanics.

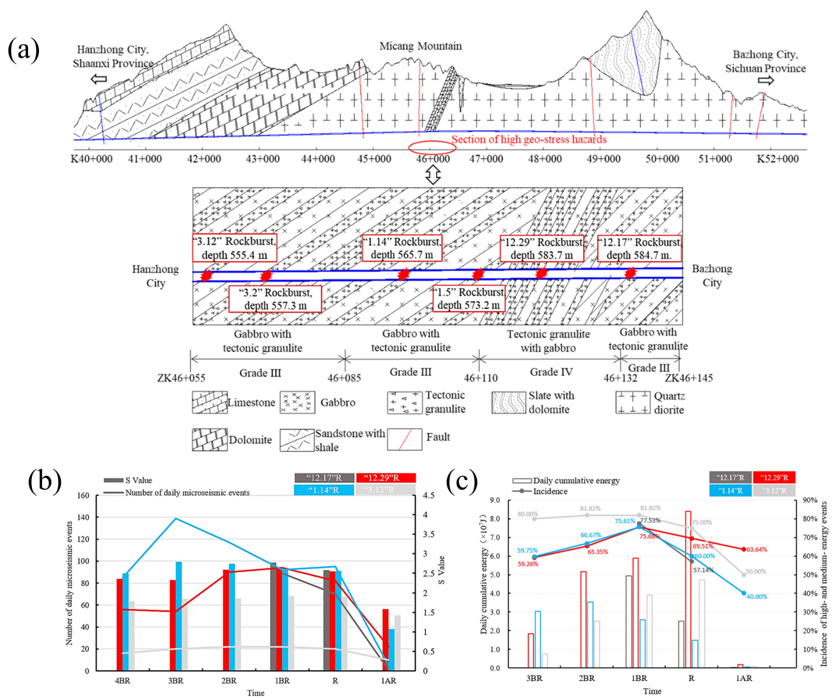

Figure 3: (a)Geological cross-section along the Micangshan tunnel(Zhang et al., 2021);(b) Number of daily microseismic events and S value before and after rockburst occurrence. The processes of four typical rockbursts, namely "12.17," "12.29," "1.14," and "3.12," are illustrated. "4BR" denotes 4 days before the rockburst; "R" denotes the day of rockburst occurrence; "1AR" denotes 1 day after rockburst(Zhang et al., 2021).(c)Daily cumulative seismic energy and incidences of high- and medium-energy events during the rockburst process(Zhang et al., 2021).

A.3 LLMs for rock mechanics

A PYTHON script based on the finite difference method (FDM) was developed to solve the steady-state seepage equation with fixed-head boundaries and an impermeable sheet pile. The program iteratively computes the hydraulic head distribution until convergence. This code was generated and refined with assistance from a LLM (ChatGPT). The full script is available in the Supplementary Materials.

Listing 1: Seepage Flow Analysis using Finite Difference Method

```
#!/usr/bin/env python3
# -*- coding: utf-8 -*-

import numpy as np
import matplotlib.pyplot as plt

# --------------------------
# Seepage Flow Analysis (FDM)
# --------------------------

# Geometric Information
H1 = 10.0 # Left water level (m)
H2 = 0.0 # Right water level (m)
W = 25.0 # Width of soil layer (m)
H_soil = 10.0 # Depth of soil layer (m)
W_pile = 1.0 # Width of sheet pile (m)
D = 5.0 # Depth of sheet pile penetration (m)

# FDM Settings
dx = 0.1 # Grid size in x-direction (m)
dy = 0.1 # Grid size in y-direction (m)
threshold = 1e-4 # Convergence threshold

# Grid Points
nx = int(W / dx) + 1 # number of grid points in x
ny = int(H_soil / dy) + 1 # number of grid points in y

# Initialize Water Head Matrix (H): ny rows (y), nx cols (x)
H = np.ones((ny, nx)) * ((H1 + H2) / 2.0)

# Apply Boundary Conditions
H[:, 0] = H1 # Left boundary
H[:, -1] = H2 # Right boundary
H[0, :] = H1 # Top boundary
H[-1, :] = H2 # Bottom boundary

# Sheet pile (no-flow through the pile): keep values fixed in that x-band
pile_start = int(round((W/2.0 - W_pile/2.0) / dx)) # zero-based index
pile_end = int(round((W/2.0 + W_pile/2.0) / dx)) # inclusive in MATLAB
    sense
H[:, pile_start:pile_end+1] = (H1 + H2) / 2.0

# Iterative Finite Difference (Laplace: 5-point average with dx=dy)
converged = False
iteration = 0
while not converged:
   H_old = H.copy()

   for j in range(1, ny - 1): # y-direction (rows)
      for i in range(1, nx - 1): # x-direction (cols)
         if not (pile_start <= i <= pile_end):
            H[j, i] = 0.25 * (H_old[j+1, i] + H_old[j-1, i] +
                              H_old[j, i+1] + H_old[j, i-1])

   H[:, 0] = H1
   H[:, -1] = H2
   H[0, :] = H1
   H[-1, :] = H2

   H[:, pile_start:pile_end+1] = (H1 + H2) / 2.0
```

```
    max_diff = np.max(np.abs(H - H_old))
    iteration += 1
    if max_diff < threshold:
        converged = True

print(f"Converged in {iteration} iterations, max diff = {max_diff:.6e}")

# Plot the Water Head Distribution
x = np.linspace(0.0, W, nx)
y = np.linspace(0.0, H_soil, ny)
X, Y = np.meshgrid(x, y)

plt.figure(figsize=(7, 4.8))

cf = plt.contourf(X, Y, H, levels=20)
plt.colorbar(cf, label='Head (m)')
plt.xlabel('X (m)')
plt.ylabel('Y (m)')
plt.title('Water Head Distribution in Soil Layer (FDM)')
plt.tight_layout()
plt.show()
```

REFERENCES

Yaser Abdi, Ehsan Momeni, and D. J. Armaghani. Elastic modulus estimation of weak rock samples using random forest technique. *Bulletin of Engineering Geology and the Environment*, 82(5):176, 2023.

D. W. Abueidda, Q. Lu, and S. Koric. Meshless physics-informed deep learning method for three-dimensional solid mechanics. *International Journal for Numerical Methods in Engineering*, 122 (23):7182–7201, 2021.

Diab W. Abueidda and Mohamed E. Mobasher. Variational temporal convolutional networks for i-fenn thermoelasticity. *Computer Methods in Applied Mechanics and Engineering*, 429:117122, 2024.

A. C. Adoko, Candan Gokceoglu, Liang Wu, and Qing-Jie Zuo. Knowledge-based and data-driven fuzzy modeling for rockburst prediction. *International Journal of Rock Mechanics and Mining Sciences*, 61:86–95, 2013.

Behzad Afrasiabian and Mohammad Eftekhari. Prediction of mode i fracture toughness of rock using linear multiple regression and gene expression programming. *Journal of Rock Mechanics and Geotechnical Engineering*, 14(5):1421–1432, 2022.

Fatemeh S. Alakbari, M. E. Mohyaldinn, M. A. Ayoub, I. A. Hussein, A. S. Muhsan, S. Ridha, and A. A. Salih. A gated recurrent unit model to predict poisson's ratio using deep learning. *Journal of Rock Mechanics and Geotechnical Engineering*, 16(1):123–135, 2024.

Farhan Alzubaidi, Peyman Mostaghimi, Guowei Si, Pawel Swietojanski, and Ryan T. Armstrong. Automated rock quality designation using convolutional neural networks. *Rock Mechanics and Rock Engineering*, 55(6):3719–3734, 2022.

Mohammad Aminpour, Reza Alaie, Nima Kardani, Saeed Moridpour, and Mohammad Nazem. Highly efficient reliability analysis of anisotropic heterogeneous slopes: Machine learning-aided monte carlo method. *Acta Geotechnica*, 18(6):3367–3389, 2023a.

Mohammad Aminpour, Reza Alaie, Saman Khosravi, Nima Kardani, Saeed Moridpour, and Mohammad Nazem. Slope stability machine learning predictions on spatially variable random fields with and without factor of safety calculations. *Computers and Geotechnics*, 153:105094, 2023b.

A. Argilaga, C. Zhao, H. Li, and L. Lei. Synthesising microstructures of a partially frozen salty sand using voxel-based 3d generative adversarial networks. *Computers and Geotechnics*, 170:106247, 2024.

Mojtaba Asoodeh and Parviz Bagheripour. Prediction of compressional, shear, and stoneley wave velocities from conventional well log data using a committee machine with intelligent systems. *Rock Mechanics and Rock Engineering*, 45(1):45–63, 2012.

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. In *3rd International Conference on Learning Representations (ICLR)*, 2015. doi: 10.48550/arXiv.1409.0473.

Besnik Bahtiri, Bahram Arash, Stefan Scheffler, Michael Jux, and Raimund Rolfes. A machine learning-based viscoelastic–viscoplastic model for epoxy nanocomposites with moisture content. *Computer Methods in Applied Mechanics and Engineering*, 415:116293, 2023.

Jie Bai, G. R. Liu, Ankit Gupta, Laith Alzubaidi, X. Q. Feng, and Y. Gu. Physics-informed radial basis network (pirbn): A local approximating neural network for solving nonlinear partial differential equations. *Computer Methods in Applied Mechanics and Engineering*, 415:116290, 2023a.

Xiao-Dong Bai, Wei-Cheng Cheng, Bo Wu, Guo Li, and David E. L. Ong. Shield machine position prediction and anomaly detection during tunnelling in loess region using ensemble and deep learning algorithms. *Acta Geotechnica*, 18(11):6175–6199, 2023b.

K. Behzadafshar, M. E. Sarafraz, M. Hasanipanah, S. F. Mojtahedi, and M. M. Tahir. Proposing a new model to approximate the elasticity modulus of granite rock samples based on laboratory tests results. *Bulletin of Engineering Geology and the Environment*, 78(3):1527–1536, 2019.

Nathan Black and Amir Reza Najafi. Learning finite element convergence with the multi-fidelity graph neural network. *Computer Methods in Applied Mechanics and Engineering*, 397:115120, 2022.

Yang Bo, Xin Guo, Qiang Liu, Yong Pan, Lei Zhang, and Yong Lu. Prediction of tunnel deformation using pso variant integrated with xgboost and its tbm jamming application. *Tunnelling and Underground Space Technology*, 150:105842, 2024.

N. Ceryan, U. Okkan, P. Samui, and S. Ceryan. Modeling of tensile strength of rock materials based on support vector machines approaches. *International Journal for Numerical and Analytical Methods in Geomechanics*, 37(16):2655–2670, 2013.

Jian Chen, Ming Zhou, Hao Huang, Dan Zhang, and Zhi Peng. Automated extraction and evaluation of fracture trace maps from rock tunnel face images via deep learning. *International Journal of Rock Mechanics and Mining Sciences*, 142:104745, 2021.

Corinna Cortes and Vladimir Vapnik. Support-vector networks. *Machine Learning*, 20(3):273–297, 1995.

Fang Dong, Shuai Wang, Rui Yang, and Sen Yang. Time-series traction prediction of surrounding rock deformation in tunnel construction based on mechanical parameter inversion. *Tunnelling and Underground Space Technology*, 152:105933, 2024.

Hamed Fathipour-Azar. Hybrid data-driven polyaxial rock strength meta model. *Rock Mechanics and Rock Engineering*, 56(8):5993–6007, 2023.

Jian Feng, Qiang Teng, Bo Li, Xin He, Hao Chen, and Yan Li. An end-to-end three-dimensional reconstruction framework of porous media from a single two-dimensional image based on deep learning. *Computer Methods in Applied Mechanics and Engineering*, 368:113043, 2020.

X. Feng, C.-X. Yang, B.-G. He, Z.-B. Yao, L. Hu, W. Zhang, R. Kong, J. Zhao, Z.-B. Liu, and X. Bi. Artificial intelligence technology in rock mechanics and rock engineering. *Deep Resources Engineering*, 1(2):100008, 2024.

Xiang Feng and Ricardo Jimenez. Bayesian prediction of elastic modulus of intact rocks using their uniaxial compressive strength. *Engineering Geology*, 173:32–40, 2014.

Xiang Feng and Ricardo Jimenez. Predicting tunnel squeezing with incomplete data using bayesian networks. *Engineering Geology*, 195:214–224, 2015.

Maria D. Ferentinou and Maria G. Sakellariou. Computational intelligence tools for the prediction of slope performance. *Computers and Geotechnics*, 34(5):362–384, 2007.

Reza Gholami, Vamegh Rasouli, and Arash Alimoradi. Improved rmr rock mass classification using artificial intelligence algorithms. *Rock Mechanics and Rock Engineering*, 46(5):1199–1209, 2013.

Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In *Advances in Neural Information Processing Systems*, volume 27, 2014. doi: 10.48550/arXiv.1406.2661.

Qian Guan, Zhao Yang, Ning Guo, and Lei Chen. Deep learning-accelerated multiscale approach for granular material modeling. *International Journal for Numerical and Analytical Methods in Geomechanics*, 48(5):1372–1389, 2024.

Qian-Zheng Guan and Zhi-Xin Yang. Hybrid deep learning model for prediction of monotonic and cyclic responses of sand. *Acta Geotechnica*, 18(3):1447–1461, 2023.

Claudio Guardiani, Edoardo Soranzo, and Wei Wu. Time-dependent reliability analysis of unsaturated slopes under rapid drawdown with intelligent surrogate models. *Acta Geotechnica*, 17(4): 1071–1096, 2022.

Di Guo, Hua Chen, Lin Tang, Zheng Chen, and Pijush Samui. Assessment of rockburst risk using multivariate adaptive regression splines and deep forest model. *Acta Geotechnica*, 17(4):1183–1205, 2022.

Ehsan Haghighat, Davood Amini, and Ruben Juanes. Physics-informed neural network simulation of multiphase poroelasticity using stress-split sequential training. *Computer Methods in Applied Mechanics and Engineering*, 397:115141, 2022.

Ming He, Zhi Zhang, and Ning Li. Deep convolutional neural network-based method for strength parameter prediction of jointed rock mass using drilling logging data. *International Journal of Geomechanics*, 21(7):04021111, 2021.

Alireza Heidaripanah, Mohammad Nazemi, and Farid Soltani. Prediction of resilient modulus of lime-treated subgrade soil using different kernels of support vector machine. *International Journal of Geomechanics*, 17(2):06016020, 2017.

Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural Computation*, 9(8): 1735–1780, 1997.

Cheng-Hung Hsiao, Ai-Yun Chen, Liang Ge, and Feng-Hsiung Yeh. Performance of artificial neural network and convolutional neural network on slope failure prediction using data from the random finite element method. *Acta Geotechnica*, 17(12):5801–5811, 2022.

Cheng Hu, Samuel Martin, and Remi Dingreville. Accelerating phase-field predictions via recurrent neural networks learning the microstructure evolution in latent space. *Computer Methods in Applied Mechanics and Engineering*, 397:115128, 2022.

Xin Hu and Premal Solanki. Predicting resilient modulus of cementitiously stabilized subgrade soils using neural network, support vector machine, and gaussian process regression. *International Journal of Geomechanics*, 21(6):04021073, 2021.

Xin Hu, Jun Shentu, Nan Xie, Yue Huang, Gang Lei, Hao Hu, Peng Guo, and Xiang Gong. Predicting triaxial compressive strength of high-temperature treated rock using machine learning techniques. *Journal of Rock Mechanics and Geotechnical Engineering*, 15(8):2072–2082, 2023.

Liang Huang, Jian Li, Hong Hao, and Xibing Li. Micro-seismic event detection and location in underground mines by using convolutional neural networks (cnn) and deep learning. *Tunnelling and Underground Space Technology*, 81:265–276, 2018.

D. Jahed Armaghani, E. T. Mohamad, E. Momeni, M. S. Narayanasamy, and M. F. Mohd Amin. An adaptive neuro-fuzzy inference system for predicting unconfined compressive strength and young's modulus: A study on main range granite. *Bulletin of Engineering Geology and the Environment*, 74(4):1301–1319, 2015.

Hamed Jalalifar, Sadegh Mojedifar, Ali A. Sahebi, and Hossein Nezamabadi-pour. Application of the adaptive neuro-fuzzy inference system for prediction of a rock engineering classification system. *Computers and Geotechnics*, 38(6):783–790, 2011.

Dong Ji, Yang Chen, Chen Zhai, Chen Zhu, and Liang Xie. One-dimensional shear-wave velocity profile inversion using deep learning guided by wave physics. *Soil Dynamics and Earthquake Engineering*, 190:109186, 2025.

Zhi-Chao Jia, Yang Wang, Jun-Hua Wang, Qian-Yu Pei, and Yu-Qing Zhang. Rockburst intensity grade prediction based on data preprocessing techniques and multi-model ensemble learning algorithms. *Rock Mechanics and Rock Engineering*, 57(7):5207–5227, 2024.

Abhishek Joshi, B. Raman, C. K. Mohan, and L. R. Cenkeramaddi. A new machine learning approach for estimating shear wave velocity profile using borelog data. *Soil Dynamics and Earthquake Engineering*, 177:108424, 2024.

N. Kardani, A. Zhou, M. Nazem, and S. L. Shen. Improved prediction of slope stability using a hybrid stacking ensemble method based on finite element analysis and field data. *Journal of Rock Mechanics and Geotechnical Engineering*, 13(1):188–201, 2021.

A. Kayabasi, N. Yesiloglu-Gultekin, and C. Gokceoglu. Use of non-linear prediction tools to assess rock mass permeability using various discontinuity parameters. *Engineering Geology*, 185:1–9, 2015.

Young Kim, Se-Yeon Lim, Kyung-Yoon Kim, and Tae-Sung Yun. Prediction of compressional wave velocity of cement-reinforced soil from core images using a convolutional neural network regression model. *Computers and Geotechnics*, 153:105067, 2023.

M. S. Kovacevic, M. Bacic, K. Gavin, and I. Stipanovic. Assessment of long-term deformation of a tunnel in soft rock by utilizing particle swarm optimized neural network. *Tunnelling and Underground Space Technology*, 110:103838, 2021.

T. T. Le, A. D. Skentou, A. Mamou, and P. G. Asteris. Correlating the unconfined compressive strength of rock with the compressional wave velocity, effective porosity, and schmidt hammer rebound number using artificial neural networks. *Rock Mechanics and Rock Engineering*, 55(11): 6805–6840, 2022.

Yann LeCun, Bernhard Boser, John S. Denker, Donnie Henderson, Richard E. Howard, Wayne Hubbard, and Lawrence D. Jackel. Backpropagation applied to handwritten zip code recognition. *Neural Computation*, 1(4):541–551, 1989.

Young Lee, Jiho Yim, Seungwoo Hong, and Kyung-Bin Min. Application of artificial neural network for determining elastic constants of a transversely isotropic rock from a single-orientation core. *International Journal of Rock Mechanics and Mining Sciences*, 160:105277, 2022.

Jing Lei and Yan Fan. Rock ct image fracture segmentation based on convolutional neural networks. *Rock Mechanics and Rock Engineering*, 57(8):5883–5898, 2024.

Guo Li, Chao Zhu, Ming He, Yang Zuo, Feng Gong, Yong Xue, and Gui Feng. Intelligent method for parameters optimization of cable in soft rock tunnel based on longitudinal wave velocity. *Tunnelling and Underground Space Technology*, 133:104905, 2023.

Ming Li, Ming Chen, Wei Lu, Fang Zhao, Peng Yan, and Jian Liu. Rdt-fragnet: A dcn-transformer network for intelligent rock fragment recognition and particle size distribution acquisition. *Computers and Geotechnics*, 177:106809, 2025.

S. Li, H. Zhao, and Z. Ru. Relevance vector machine-based response surface for slope reliability analysis. *International Journal for Numerical and Analytical Methods in Geomechanics*, 41(11): 1332–1346, 2017.

Yong Li and Siva Kumar Vanapalli. Prediction of soil-water characteristic curves using two artificial intelligence (ai) models and ai-aided design method for sands. *Canadian Geotechnical Journal*, 59(1):129–143, 2022.

Wei Liang, Yusuf A. Sari, Guo Zhao, Stephen D. McKinnon, and Hao Wu. Probability estimates of short-term rockburst risk with ensemble classifiers. *Rock Mechanics and Rock Engineering*, 54 (4):1799–1814, 2021.

S. Lin, H. Zheng, B. Han, Y. Li, C. Han, and W. Li. Comparative performance of eight ensemble learning approaches for the development of models of slope stability prediction. *Acta Geotechnica*, 17(4):1477–1502, 2022.

J. Liu, B. Wang, Q. Ning, and D. Wang. Dynamic design system for active-passive combined support considering pre-tension force limited by geology in soft rock tunnels. *Tunnelling and Underground Space Technology*, 155:106201, 2025.

Kai Liu, Bo Liu, and Yuan Fang. An intelligent model based on statistical learning theory for engineering rock mass classification. *Bulletin of Engineering Geology and the Environment*, 78 (6):4533–4548, 2019.

Qiang Liu, Yong Xue, Guo Li, Dong Qiu, Wei Zhang, Zhong Guo, and Zheng Li. Application of km-smote for rockburst intelligent prediction. *Tunnelling and Underground Space Technology*, 138:105180, 2023.

Yan Liu, Shuo Liao, Yifan Yang, and Bin Zhang. Data-driven and physics-informed neural network for predicting tunnelling-induced ground deformation with sparse data of field measurement. *Tunnelling and Underground Space Technology*, 152:105951, 2024.

Zheng Liu, Jing Shao, Wei Xu, and Qiang Wu. Indirect estimation of unconfined compressive strength of carbonate rocks using extreme learning machine. *Acta Geotechnica*, 10(5):651–663, 2015.

Alper Mavi, Ahmet C. Bekar, Ehsan Haghighat, and Erdogan Madenci. An unsupervised latent/output physics-informed convolutional-lstm network for solving partial differential equations using peridynamic differential operator. *Computer Methods in Applied Mechanics and Engineering*, 407:115944, 2023.

W. S. McCulloch and W. Pitts. A logical calculus of the ideas immanent in nervous activity. *The Bulletin of Mathematical Biophysics*, 5(4):115–133, 1943.

Jie Meng, Hans Mattsson, and Jan Laue. Three-dimensional slope stability predictions using artificial neural networks. *International Journal for Numerical and Analytical Methods in Geomechanics*, 45(13):1988–2000, 2021.

M. A. Millán, R. Galindo, and A. Alencar. Application of artificial neural networks for predicting the bearing capacity of shallow foundations on rock masses. *Rock Mechanics and Rock Engineering*, 54(9):5071–5094, 2021.

Tiago Miranda, António G. Correia, Manuel Santos, Luís Ribeiro e Sousa, and Paulo Cortez. New models for strength and deformability parameter calculation in rock masses using data-mining techniques. *International Journal of Geomechanics*, 11(1):44–58, 2010.

V. C. Moussas and K. Diamantis. Predicting uniaxial compressive strength of serpentinites through physical, dynamic and mechanical properties using neural networks. *Journal of Rock Mechanics and Geotechnical Engineering*, 13(1):167–175, 2021.

R. A. Mozumder and A. I. Laskar. Prediction of unconfined compressive strength of geopolymer stabilized clayey soil using artificial neural network. *Computers and Geotechnics*, 69:291–300, 2015.

B. S. Narendra, P. V. Sivapullaiah, S. Suresh, and S. N. Omkar. Prediction of unconfined compressive strength of soft grounds using computational intelligence techniques: A comparative study. *Computers and Geotechnics*, 33(3):196–208, 2006.

Krishna M. Neaupane and Nawa Raj Adhikari. Prediction of tunneling-induced ground movement with the multi-layer perceptron. *Tunnelling and Underground Space Technology*, 21(2):151–159, 2006.

Dong Pan, Shuang Li, Zhen Xu, Yang Zhang, Peng Lin, and Hao Li. A deterministic-stochastic identification and modelling method of discrete fracture networks using laser scanning: Development and case study. *Engineering Geology*, 262:105310, 2019.

Dong Pan, Yu Li, Xiang Wang, and Zhen Xu. Intelligent image-based identification and 3-d reconstruction of rock fractures: Implementation and application. *Tunnelling and Underground Space Technology*, 145:105582, 2024.

Tian Pei and Tao Qiu. Machine learning with monotonic constraint for geotechnical engineering applications: An example of slope stability prediction. *Acta Geotechnica*, 19(6):3863–3882, 2024.

Xue Peng, Peng Lin, Qi Xia, Lei Yu, and Min Wang. A new method for recognizing discontinuities from 3d point clouds in tunnel construction environments. *Tunnelling and Underground Space Technology*, 152:105955, 2024.

Ali Pourtaghi and Mohammad A. Lotfollahi-Yaghin. Wavenet ability assessment in comparison to ann for predicting the maximum surface settlement caused by tunneling. *Tunnelling and Underground Space Technology*, 28(1):257–271, 2012.

Ashutosh M. S. Pradhan and Yong-Taek Kim. An artificial intelligence-based approach to predicting seismic hillslope stability under extreme rainfall events in the vicinity of wolsong nuclear power plant, south korea. *Bulletin of Engineering Geology and the Environment*, 80(5):3629–3646, 2021.

Chang Qi and Andy Fourie. A real-time back-analysis technique to infer rheological parameters from field monitoring. *Rock Mechanics and Rock Engineering*, 51(10):3029–3043, 2018.

Hamid Rafiai and Ahmad Jafari. Artificial neural networks as a basis for new generation of rock failure criteria. *International Journal of Rock Mechanics and Mining Sciences*, 48(7):1153–1159, 2011.

Hamid Rafiai, Ahmad Jafari, and Amir Mahmoudi. Application of ann-based failure criteria to rocks under polyaxial stress conditions. *International Journal of Rock Mechanics and Mining Sciences*, 59:42–49, 2013.

David E. Rumelhart, Geoffrey E. Hinton, and Ronald J. Williams. Learning representations by back-propagating errors. *Nature*, 323(6088):533–536, 1986.

Golnar Saadati, Shahriar Javankhoshdel, Javad M. Najm Abad, Martin Mett, Helmut Kontrus, and Bernhard Schneider-Muntau. Ai-powered geotechnics: Enhancing rock mass classification for safer engineering practices. *Rock Mechanics and Rock Engineering*, pp. 1–31, 2024.

A. D. Skentou, A. Bardhan, A. Mamou, M. E. Lemonis, G. Kumar, P. Samui, D. J. Armaghani, and P. G. Asteris. Closed-form equation for estimating unconfined compressive strength of granite from three non-destructive tests using soft computing models. *Rock Mechanics and Rock Engineering*, 56(1):487–514, 2023.

Edoardo Soranzo, Claudio Guardiani, Yi Chen, Yi Wang, and Wei Wu. Convolutional neural networks prediction of the factor of safety of random layered slopes by the strength reduction method. *Acta Geotechnica*, 18(6):3391–3402, 2023.

B. Tiryaki. Predicting intact rock strength for mechanical excavation using multivariate statistics, artificial neural networks, and regression trees. *Engineering Geology*, 99(1–2):51–60, 2008.

Alan M. Turing. Computing machinery and intelligence. *Mind*, 59:433–460, 1950.

Vladimir N. Vapnik and Alexey Y. Chervonenkis. A class of algorithms for pattern recognition learning. *Avtomat. i Telemekh.*, 25(6):937–945, 1964.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2017. doi: 10.48550/arXiv.1706.03762.

M. X. Wang, D. Huang, G. Wang, and D. Q. Li. Ss-xgboost: A machine learning framework for predicting newmark sliding displacements of slopes. *Journal of Geotechnical and Geoenvironmental Engineering*, 146(9):04020074, 2020.

Tian Wang, Daniel Trugman, and Youzuo Lin. Seismogen: Seismic waveform synthesis using gan with application to seismic data augmentation. *Journal of Geophysical Research: Solid Earth*, 126(4):e2020JB020077, 2021.

Umer Waqas and Muhammad F. Ahmed. Prediction modeling for the estimation of dynamic elastic young's modulus of thermally treated sedimentary rocks using linear–nonlinear regression analysis, regularization, and anfis. *Rock Mechanics and Rock Engineering*, 53(12):5411–5428, 2020.

Xiao-Dong Wei, Zhi-Qiang Deng, Qiang Li, Yan Huang, and Guo-Feng Zhao. A 3d grain-based reconstruction method from a 2d surface image for the distinct lattice spring model. *International Journal for Numerical and Analytical Methods in Geomechanics*, 47(11):2027–2048, 2023.

Tao Xiao, Liang-Min Zhang, Raymond W. M. Cheung, and Suzanne Lacasse. Predicting spatiotemporal man-made slope failures induced by rainfall in hong kong using machine learning techniques. *Geotechnique*, 73(9):749–765, 2022.

M. Xu, Y. Zhou, R. Pang, and B. Xu. Seismic collaborative reliability evaluation of slopes using subset simulation via support vector machine. *Soil Dynamics and Earthquake Engineering*, 165: 107673, 2023.

Jia Xue, Yu Cao, Nicolas Burlion, and Jian Shao. Influence of interface transition zone on effective elastic property of heterogeneous materials with an artificial neural network study. *International Journal for Numerical and Analytical Methods in Geomechanics*, 47(7):1134–1151, 2023.

Yong Xue, Chao Bai, Dong Qiu, Fang Kong, and Zheng Li. Predicting rockburst with database using particle swarm optimization and extreme learning machine. *Tunnelling and Underground Space Technology*, 98:103287, 2020.

Saffet Yagiz, E. A. Sezer, and Candan Gokceoglu. Artificial neural networks and nonlinear regression techniques to assess the influence of slake durability cycles on the prediction of uniaxial compressive strength and modulus of elasticity for carbonate rocks. *International Journal for Numerical and Analytical Methods in Geomechanics*, 36(14):1636–1650, 2012.

N. Yesiloglu-Gultekin, C. Gokceoglu, and E. A. Sezer. Prediction of uniaxial compressive strength of granitic rocks by various nonlinear tools and comparison of their performances. *International Journal of Rock Mechanics and Mining Sciences*, 62:113–122, 2013.

Peng Yin and Guo-Feng Zhao. Stochastic reconstruction of gosford sandstone from surface image. *International Journal of Rock Mechanics and Mining Sciences*, 70:82–89, 2014.

Mohammad Zare Naghadehi, Ricardo Jimenez, Reza KhaloKakaie, and S. M. E. Jalali. A new open-pit mine slope instability index defined using the improved rock engineering systems approach. *International Journal of Rock Mechanics and Mining Sciences*, 61:1–14, 2013.

Marcos A. Zeni, Rodrigo D. L. Peroni, and Fabricio A. D. Santos. Semiautomatic determination of the geological strength index using sfm and ann techniques. *International Journal of Geomechanics*, 21(12):04021245, 2021.

Hao Zhang, Jun Zeng, Jie Ma, Yue Fang, Chen Ma, Zhi Yao, and Zhi Chen. Time series prediction of microseismic multi-parameter related to rockburst based on deep learning. *Rock Mechanics and Rock Engineering*, 54(12):6299–6321, 2021.

J. Zhang, Z. Wang, J. Hu, S. Xiao, and W. Shang. Bayesian machine learning-based method for prediction of slope failure time. *Journal of Rock Mechanics and Geotechnical Engineering*, 14 (4):1188–1199, 2022.

Jie Zhang, Yan Wang, Yue Sun, and Guo Li. Strength of ensemble learning in multiclass classification of rockburst intensity. *International Journal for Numerical and Analytical Methods in Geomechanics*, 44(13):1833–1853, 2020.

Ning Zhang, Ao Zhou, Yong-Fan Jin, Zhi-Yong Yin, and Shui-Long Shen. An enhanced deep learning method for accurate and robust modelling of soil stress–strain response. *Acta Geotechnica*, 18(8):4405–4427, 2023a.

Q. Zhang, J. Song, and X. Nie. Application of neural network models to rock mechanics and rock engineering. *International Journal of Rock Mechanics and Mining Sciences*, 28(6):535–540, 1991.

W. S. Zhang, Y. Yuan, M. Long, R. H. Yao, L. Jia, and M. Liu. Prediction of surface settlement around subway foundation pits based on spatiotemporal characteristics and deep learning models. *Computers and Geotechnics*, 168:106149, 2024.

Zhao Zhang, Qiang Pan, Zhi Yang, and Xiang Yang. Physics-informed deep learning method for predicting tunnelling-induced ground deformations. *Acta Geotechnica*, 18(9):4957–4972, 2023b.

Gao-Feng Zhao, Yu-Hang Wu, and Xin-Dong Wei. A high-fidelity digital rock representation based on digital grinding combined with deep learning for four-dimensional lattice spring model. *International Journal of Rock Mechanics and Mining Sciences*, 186:106004, 2025.

Jie Zhou, Song Zhu, Yan Qiu, D. J. Armaghani, An Zhou, and Wei Yong. Predicting tunnel squeezing using support vector machine optimized by whale optimization algorithm. *Acta Geotechnica*, 17(4):1343–1366, 2022.

B. M. Świtała, C. Guardiani, E. Soranzo, and W. Wu. Machine learning-aided reliability analysis of rainfall-induced landslide of root-reinforced slopes. *Canadian Geotechnical Journal*, 60(12): 1877–1894, 2023.