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

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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 based on 17 leading journals in rock mechanics and related engineering disciplines was conducted to capture the diffusion of AI methodologies across the field. The survey covered journals such as *International Journal of Rock Mechanics and Mining Sciences*, *Engineering Geology*, *Computers and Geotechnics*, and *Tunnelling and Underground Space Technology*, among others, representing the major publication venues for both theoretical and applied geomechanics. Using "artificial intelligence," "machine learning," "deep learning," and "data-driven modeling" as core search terms, all articles published before 2025 were systematically retrieved and filtered to ensure relevance to AI-assisted rock or geotechnical modeling. The retrieved corpus was then analyzed for publication trends, keyword co-occurrence, and methodological focus to establish the thematic landscape of AI adoption. The results highlight that AI has taken root most strongly in computational mechanics, owing to its reliance on mathematical abstraction and algorithmic optimization. Yet, compared with other branches of civil or mechanical engineering, the research volume in rock mechanics remains modest—reflecting both the difficulty of obtaining high-quality subsurface data and the still-emerging stage of methodological adaptation. Nevertheless, the keyword network analysis reveals a clear conceptual transition: the term "machine learning" now surpasses "artificial intelligence" in frequency, signaling a shift toward data-driven modeling paradigms. Among these approaches, support vector machines (SVMs) (Vapnik & Chervonenkis, 1964) first gained prominence through kernel-based nonlinear classification (Cortes & Vapnik, 1995), bridging traditional statistical learning and modern deep architectures. More recent research extends this trajectory toward physics-informed neural networks (PINNs) (Abueidda et al., 2021), which embed governing physical laws directly into loss functions, aligning data-driven inference with mechanical consistency. The growing adoption of such hybrid models underscores a collective movement within geomechanics toward interpretability, robustness, and scientific grounding—attributes once viewed as beyond the scope of purely data-driven AI.

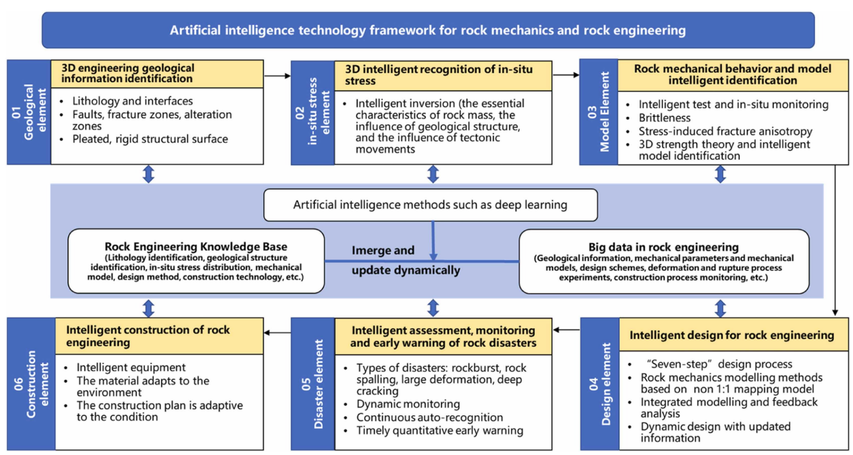

Figure 1: Systematic composition of rock mechanics and engineering in the view of the metaverse under the backdrop of artificial intelligence technology (Feng et al., 2024).

The integration of AI into rock mechanics, however, is far from a simple transplantation of algorithms(as shown in Figure 1). 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 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.

5.1 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.

5.2 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., 2023b) 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.

5.3 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.

5.4 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 subpercent 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.

5.5 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.

6 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.4), 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).

7 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

This Appendix provides supplementary materials that extend the reproducibility and analytical rigor of the review.

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., 2023b)	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 MACHINE LEARNING IN ROCKBURST

In the construction of ultra-deep tunnels in the mountainous regions of Southwest China, frequent rockburst disasters represent one of the most severe challenges to construction safety. The combination of high in-situ stress, large burial depth (up to 2 km), and hard granite strata leads to violent dynamic failures during excavation. Traditional rockburst warning approaches—typically based on single empirical indicators or static analyses—cannot adapt to the cyclic "blasting round" rhythm of tunnel excavation. As a result, these methods often exhibit poor timeliness, limited adaptability, and low predictive accuracy.

To overcome these limitations, Hu et al. (2023a) developed a machine-learning-based intelligent early-warning method that utilizes microseismic (MS) information time series, treating each blasting round as a fundamental temporal unit. The proposed framework consists of three main stages:

(i) segmentation of accurate early-warning units synchronized with the blasting cycles, (ii) pre-processing and feature extraction of MS parameters, and (iii) construction of dual long short-term memory (LSTM) models—one for MS parameter prediction and another for rockburst risk classification. This dual-model framework enables the system to issue proactive warnings of rockburst intensity several blasting cycles in advance. Figure 2 illustrates the methodological workflow and corresponding verification results.

Figure 2(a) presents the geological cross-section of the studied tunnel section, which passes through Eocene medium-grained biotite granite (E^2R) intersected by faults (F1, F2), jointed zones, and pegmatite veins. The high strength and low permeability of the granite, coupled with localized stress concentrations near faults, create the fundamental geological conditions for rockburst occurrence. This establishes the geological boundary for subsequent monitoring and analysis.

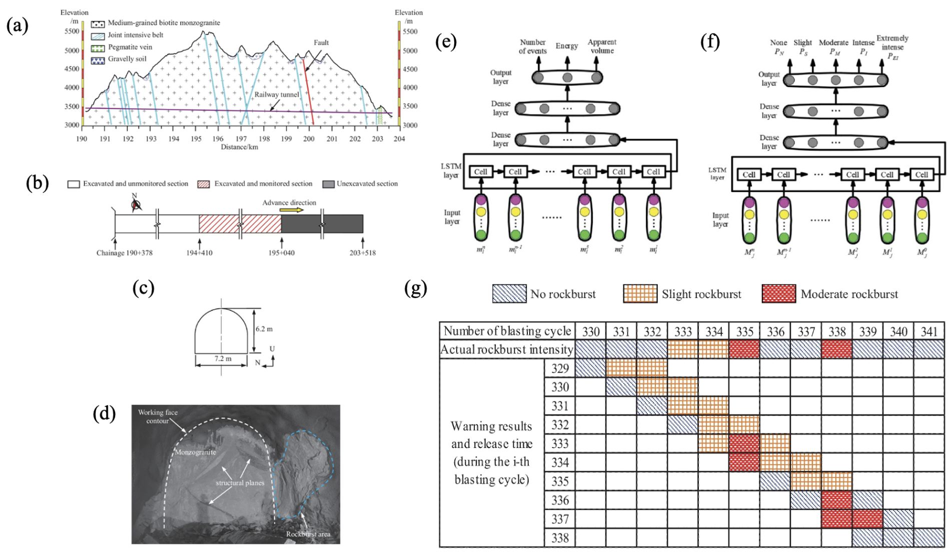

Figure 2: Case study of machine-learning-based intelligent rockburst early warning using microseismic time-series data in an ultra-deep tunnel. (a) Geological cross-section; (b) Excavation and monitoring layout; (c) Tunnel cross-section geometry; (d) Typical excavation face photograph; (e) Microseismic Information Prediction Model (MSIPM); (f) Rockburst Time Warning Model (RBTWM); (g) Comparison between predicted and actual rockburst intensities.

As shown in Figure 2(b), the plan view illustrates the spatial configuration of the microseismic monitoring system relative to the excavation progress. The monitored section (chainage 190+378 to 203+518) is instrumented with eight sensors covering a 35 m radius ahead and 25 m behind the tunnel face, ensuring that all collected MS data correspond to the most active stress disturbance zones. Figure 2(c) provides the standard "city-gate" tunnel cross-section, with a net width of 7.2 m and a height of 6.2 m (equivalent circular diameter 6.6 m). Based on this geometry, the early-warning unit extends five times the equivalent diameter laterally, encompassing all potential zones affected by rockburst events. This geometric definition forms the spatial foundation for data selection and model input consistency.

The field observation shown in Figure 2(d) depicts the excavation face with massive granite blocks, developed joints, and localized spalling pits produced by rockburst. Such visual evidence provides the ground truth for model calibration, directly linking predicted rockburst intensity with observed physical damage patterns.

The architecture of the Microseismic Information Prediction Model (MSIPM), shown in Figure 2(e), is designed to predict short-term trends of MS parameters—including event count, energy ($\times 10^3$ J), and apparent volume ($\times 10^3$ m^3). The model employs a 64-unit LSTM hidden layer with dropout (rate 0.1) to capture the temporal dependency inherent in the MS evolution process. It outputs forecasts for one to three future blasting cycles, effectively identifying precursor dynamics that indicate impending rockbursts.

The subsequent Rockburst Time Warning Model (RBTWM), illustrated in Figure 2(f), translates the MSIPM-predicted sequences into probabilistic rockburst warnings. Its input combines both measured and predicted MS data, enriched with derived cumulative and rate-based features. With 112 LSTM units in the hidden layer, the RBTWM outputs the likelihood of three categories—no rockburst, slight rockburst, and moderate rockburst—thus providing cycle-level predictive alerts. The integration of MSIPM and RBTWM constitutes a robust dual-model system that bridges forward MS prediction with real-time risk assessment.

Model validation results, as displayed in Figure 2(g), demonstrate strong agreement between predictions and field observations across 66 blasting cycles. For instance, in cycle 335, the model issued a "moderate rockburst" warning two cycles before the actual event, which was subsequently confirmed by the field-observed spalling pit. The framework achieved a one-cycle-ahead prediction accuracy of 74.6%, confirming its reliability and applicability under real construction conditions.

Overall, this case study demonstrates that temporal deep-learning methods such as LSTM can effectively integrate continuous microseismic monitoring data with the cyclic excavation process. By capturing the temporal evolution of MS activity, the dual-model framework provides a data-driven yet physically interpretable approach for real-time rockburst prediction, advancing intelligent early-warning systems in deep tunnel engineering.

A.3 Case Study of Physics-Informed Neural Network in Tunnel Engineering

With the rapid expansion of metro and tunnel infrastructure in global megacities, accurately predicting tunnel-induced ground deformation (TIGD) has become essential for ensuring the safety of surrounding structures and surface facilities. Although shield and TBM excavation methods provide advantages such as reduced environmental disturbance and high construction efficiency, complex geotechnical conditions and strict deformation control requirements still pose major engineering challenges. Conventional prediction approaches—including analytical solutions based on idealized assumptions, computationally expensive finite element simulations, costly physical model tests, and spatially limited field monitoring—are often constrained by practicality, computational cost, or data availability, making it difficult to achieve high accuracy under real-world conditions.

To address these challenges, recent advances have introduced *physics-informed neural networks* (PINNs), which embed governing physical laws directly into data-driven learning frameworks. By coupling data learning with physical constraints, PINNs achieve greater interpretability and robustness, especially when dealing with sparse monitoring data. A representative implementation is the Data–Physics-driven Neural Network (DPNN), developed for high-fidelity prediction and inverse identification of soil parameters in complex tunneling environments. Figure 3 presents a case study illustrating the DPNN's architecture, validation process, and predictive capability (Liu et al., 2024).

As shown in Figure 3(a), the DPNN architecture integrates four categories of input—construction parameters, spatial coordinates, soil properties, and tunnel geometry—into a unified neural framework. Multiple nonlinear hidden layers capture the complex interactions between these factors to produce deformation predictions. The model is trained through a composite loss function that combines three terms: a data loss minimizing deviations from measured or simulated data, a physics loss enforcing analytical and constitutive relationships, and a coordinate loss maintaining empirical boundary conditions. This hybrid optimization not only improves prediction accuracy but also allows inverse estimation of key geotechnical parameters such as shear modulus and volume loss.

Figure 3(b) shows the numerical model and data acquisition process used for validation. A detailed PLAXIS 3D finite element model of Shanghai soft soil was constructed to provide reference data. From 176 potential monitoring points, a sparse subset of 26 was selected to emulate realistic field conditions with limited data availability. The deformation results from these points were used to train and validate the DPNN, enabling systematic evaluation of its interpolation and generalization capabilities under sparse data scenarios.

In Figure 3(c), the DPNN's predictive accuracy is compared with conventional machine-learning models such as BPNN, RF, and SVM. The DPNN's predicted deformation contours and error distributions exhibit excellent agreement with FEM reference results, achieving a coefficient of determination of $R^2 = 0.9145$ and a normalized error of $L_2 = 0.2430$. The inclusion of physical constraints within the learning process significantly enhances prediction stability, suppresses non-physical oscillations, and ensures consistent deformation patterns across heterogeneous soil zones.

Finally, Figure 3(d) demonstrates the DPNN's parameter inversion and deformation characterization capabilities. The inferred soil parameters rapidly converge to their true reference values with minimal residual errors, while the reconstructed longitudinal settlement profile accurately reproduces the characteristic "hump-shaped" deformation pattern induced by shield advancement—a complex feature often missed by traditional analytical models. These results collectively highlight the DPNN's dual strengths in physically consistent prediction and reliable parameter identification, establishing it as a powerful and data-efficient computational framework for tunnel deformation analysis.

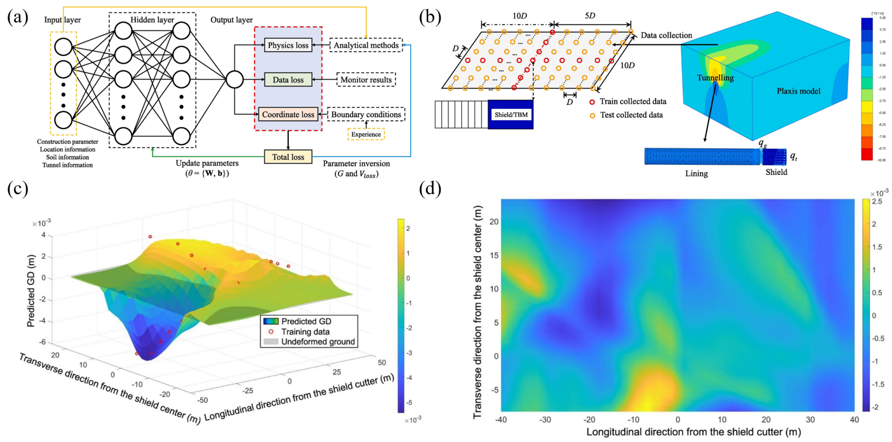

Figure 3: Case study of the Data–Physics-driven Neural Network (DPNN) for predicting tunnel-induced ground deformation (TIGD). (a) DPNN architecture; (b) Numerical model and data acquisition; (c) Prediction accuracy and model comparison; (d) Parameter inversion and deformation characteristics.

A.4 Usage of 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()
```

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