Research Progress on the Application of Artificial Intelligence to the Dynamic Response of Surrounding Rock in Deep Roadways

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Abstract

As global metal mines progressively extend to depths below one kilometer, dynamic disasters such as rockbursts, coal bursts, large deformation, and zonal disintegration induced by the deep "three highs and one disturbance" environment are becoming increasingly frequent. Traditional mechanical methods face severe challenges in terms of timeliness, accuracy, and uncertainty quantification. Artificial intelligence (AI) technology provides a new solution pathway for small-sample, high-dimensional nonlinear problems involving the dynamic response of surrounding rock. Based on the Web of Science, Scopus, and CNKI databases, relevant literature from 2000 to the present was retrieved. After systematic evaluation, deduplication, and selective screening, 125 papers were ultimately retained. Bibliometric analysis using CiteSpace and VOSviewer revealed that the application of AI in this field has evolved through three stages: "embryonic development, growth, and rapid expansion." Existing research achievements are integrated into a three-module system of "perception–prediction–control." The research progress of multi-source sensing networks, intelligent prediction models, and adaptive control strategies is reviewed in detail, with emphasis on frontier technological directions such as physics-informed neural networks (PINNs), digital twins (DTs), and federated learning (FL). Current challenges, including small samples, interpretability, data fusion, real-time performance, and standardization, are also identified. Finally, the future development directions of AI in the intelligent prevention and control of dynamic disasters in deep mines are discussed, providing a reference for related research and practice.

Full Text

Research Progress on the Application of Artificial Intelligence to the Dynamic Response of Surrounding Rock in Deep Roadways

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Abstract: As global metal mines gradually extend to depths greater than 1 000 m, dynamic disasters induced by the deep "three highs and one disturbance" environment—such as rock bursts, rockbursts/coal bumps, large deformation, and zonal fracturing—are occurring with increasing frequency. Traditional mechanical methods face severe challenges in timeliness, accuracy, and uncertainty quantification. Artificial intelligence (artificial intelligence, AI) technology provides a new solution path for small-sample, high-dimensional nonlinear problems involving the dynamic response of surrounding rock. Based on the Web of Science, Scopus, and CNKI databases, relevant literature from 2000 to the present was retrieved. After systematic evaluation, deduplication, and selective screening, 125 papers were ultimately retained. Combined with CiteSpace and VOSviewer for bibliometric analysis, it was found that the application of AI in this field exhibits a three-stage evolutionary pattern of "germination–development–explosion." Existing research results are integrated into three major modular systems – "perception–prediction–control." The research progress of multi-source sensing networks, intelligent prediction models, and adaptive control strategies is reviewed in detail, with emphasis on cutting-edge technical directions such as physics-informed neural networks (physics-informed neural network, PINN), digital twins (digital twin, DT), and federated learning (federated learning, FL). Current challenges are also identified, including small samples, interpretability, data fusion, real-time performance, and standardization. Finally, the future development directions of AI in intelligent prevention and control of dynamic disasters in deep mines are discussed, providing a reference for related research and practice.

Keywords: deep roadway; dynamic response of surrounding rock; artificial intelligence; machine learning; rockburst early warning; intelligent support

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Review of Artificial Intelligence Applications in Dynamic Response Analysis of Deep Mine Rock Masses

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Abstract: As global metal mines progressively extend below 1 000 meters, dynamic disasters induced by the "three highs and one disturbance" environment in deep zones—including rock bursts, large deformations, and zonal disintegration—are occurring with increasing frequency. Traditional mechanical methods face severe challenges in timeliness, accuracy, and uncertainty quantification. Artificial intelligence (AI)

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technology offers new solutions for addressing small-sample, high-dimensional, nonlinear rock-mass dynamic response problems. This study retrieved relevant literature from 2000 to the present from the Web of Science, Scopus, and CNKI databases. After systematic evaluation, deduplication, and quality screening, a total of 125 papers were ultimately retained. Combining CiteSpace and VOSviewer for quantitative analysis, it was found that AI applications in this field exhibit a three-stage evolutionary pattern: "infancy–development–explosion." This paper integrates existing research into a three-module system: "perception–prediction–control." It provides a detailed review of research progress on multi-source sensor networks, intelligent prediction models, and adaptive control strategies. The analysis focuses on cutting-edge technologies such as physics-informed neural networks (PINNs), digital twins (DTs), and federated learning (FL), while identifying current challenges including small sample sizes, explainability, data fusion, real-time performance, and standardization. Finally, this paper outlines future development directions for AI in the intelligent prevention and control of dynamic disasters in deep mines, providing a reference for related research and practice.

Key words: deep tunnel; rock-mass dynamic response; artificial intelligence; machine learning; rockburst early warning; intelligent support

With the increasing depletion of shallow mineral resources, more than 200 metal mines worldwide have entered mining at depths below 1 km; in China, the number of kilometer-deep mines has exceeded 60 and is extending deeper at a rate of 8-12 m per year[1–2]. Compared with shallow surrounding rock, deep rock masses are subjected to an extreme coupled environment of high geostress, high seepage pressure, high temperature, and strong mining disturbance—referred to as "three highs and one disturbance." Their dynamic responses exhibit multiple forms: they include traditional instantaneous dynamic disasters such as rockbursts and coal/rock bursts, and also commonly appear as progressive failure modes such as large deformation, structural instability, and zonal fracturing[3–4]. Such dynamic responses of deep surrounding rock combine suddenness, strong randomness, and spatiotemporal chain evolution, while also exhibiting complex characteristics such as small samples, nonlinearity, multi-field coupling, and high-dimensional uncertainty, thereby posing major challenges to engineering prevention and control[5–6].

Traditional analytical methods based on continuum mechanics are constrained by incomplete constitutive parameters, simplified boundary conditions, and difficulties in solving high-dimensional nonlinear problems, making it hard to achieve both timeliness and accuracy[7]. Numerical methods such as the finite difference method (FDM), finite element method (FEM), and discrete element method (DEM) can be used to simulate complex boundaries and fracture networks, but when dealing with multi-field coupled transient dynamic problems, they require enormous computational effort and often depend on high-performance computing clusters, making it difficult to meet the needs of real-time early warning and emergency decision-making[8–10]. In recent years, meshfree numerical methods such as peridynamics (PD) and smoothed particle hydrodynamics (SPH) have been widely applied to multi-field coupling problems in fractured rock masses because they do not require mesh generation and have stronger adaptability to large deformation and crack propagation[11–12]. For example, the PD method can effectively simulate the coupled effects of the temperature field, seepage field, and stress field in fractured rock masses[11], and the TLF-SPH (total Lagrangian formulation-SPH) method can accurately characterize crack propagation behavior during hydraulic fracturing of fractured rock masses[12]. However, when faced with the strong nonlinearity, anisotropy, and spatiotemporal evolution characteristics of deep rock masses, the above traditional methods and meshfree methods still have significant shortcomings in parameter sensitivity, computational efficiency, and field applicability.

Taking rockburst as an example[13–14], its incubation process involves complex physical processes such as energy accumulation in the surrounding rock, unstable crack propagation, transient unloading of confining pressure, and dynamic instability. Traditional discrimination criteria based on stress-strength ratio, energy density, or brittleness indices have difficulty accurately reflecting the coupled effects of complex geology and mining disturbance[15–16]. Coal/rock bursts are jointly affected by the mining-induced stress field, fault slip, and transient release of gas pressure, and their triggering mechanism remains unclear[17]. In deep soft-rock roadways, large deformation and zonal fracturing are especially prominent; existing constitutive models have difficulty describing, in a unified manner, nonlinear behaviors such as post-peak strain softening, dilatancy and expansion, and structural-plane slip[18–19]. In addition, field monitoring data exhibit characteristics such as "multi-source heterogeneity, spatiotemporal sparsity, and significant noise," which further intensify the uncertainty and error accumulation of traditional mechanical models.

Artificial intelligence (AI) technology is centered on data-driven methods. Through machine learning (ML) and deep learning (DL) algorithms, it can automatically mine latent mapping relationships in high-dimensional space and has achieved breakthrough progress in fields such as image recognition, natural language processing, and protein-structure prediction[20–22]. Over the past decade, AI technology has been introduced into deep rock mechanics and mining engineering to address four major difficulties: "unclear mechanisms, hard-to-obtain data, time-consuming computation, and delayed decision-making" [23–25]. Unlike traditional mechanics-based methods, AI technology does not rely on explicit constitutive relationships; instead, based on a data-driven modeling philosophy, it directly extracts rock-mass response charac-

features, constructing a mapping model between inputs and outputs, thereby avoiding the difficulty that complex mechanisms are hard to reveal. Its advantages are mainly reflected in the following four aspects.

1) Strong nonlinear mapping capability: deep neural networks (DNNs) can approximate arbitrarily complex functions and effectively characterize the high-dimensional nonlinear features of the dynamic response of surrounding rock[26].
2) High pattern-recognition accuracy: convolutional neural networks (CNNs), long short-term memory networks (LSTMs), and attention mechanisms (AMs) can automatically extract disaster-precursor features from acoustic-emission waveforms, microseismic time series, and fiber-optic strain cloud maps[27–29].
3) Fast real-time decision-making: edge computing and lightweight model deployment can reduce inference latency to the millisecond level, meeting the needs of on-site real-time early warning[30].
4) Strong continual-learning and transfer capabilities: federated learning (FL) and continual learning (CL) frameworks can realize cross-mine knowledge sharing and model updating while protecting the privacy of mine data[31–32].

This study is based on the three major databases Web of Science, Scopus, and CNKI. A systematic search was conducted for literature from 2000 to the present using topics such as "deep mining + artificial intelligence," "rockburst + machine learning," and "deep tunnel + digital twin." After deduplication and quality evaluation, 125 core papers were retained. CiteSpace[33–34] and VOSviewer[35–36] were used for bibliometric and knowledge-map analysis. The results show that the application of AI in the dynamic response of deep surrounding rock has gone through three stages of development (Fig. 1).

1) Embryonic stage (2000–2010): Research focused on expert systems and BP (back propagation) neural networks. The data mainly came from laboratory rock-mechanics tests, and field applications were rare[37–39].
2) Development stage (2011–2017): Shallow models such as support vector machines (SVMs) and random forests (RFs) were combined with microseismic monitoring data to realize classification of rockburst grades and division of danger zones[40–43].

3) Explosive stage (2018 to present): Deep algorithms such as convolutional neural networks (CNNs), long short-term memory networks (LSTMs), graph neural networks (GNNs), and deep reinforcement learning (DRL) have been deeply integrated with multiphysics-field monitoring and have expanded toward engineering applications such as digital twins and edge computing[44–48].

Although AI technology has made significant progress in fields such as the dynamic response of deep surrounding rock, it still faces many challenges in engineering implementation.

Small samples and class imbalance: samples of extreme events such as rockbursts and impact ground pressure are scarce, resulting in insufficient model generalization capability.

Lack of physical interpretability: there is a gap between the "black-box" characteristics of deep neural networks and rock-mechanics mechanisms, making it difficult to obtain engineering trust.

Difficulty in fusing multi-source heterogeneous data: sensors such as microseismic, fiber-optic, vision, and geological radar systems differ markedly in sampling frequency, spatial resolution, and noise level; achieving high-precision spatiotemporal alignment remains difficult.

Trade-off between real-time performance and reliability: edge-computing resources are limited, and model compression and quantization may cause loss of accuracy. How to strike a balance between millisecond-level response and high reliability requires coordinated optimization of hardware and algorithms.

Incomplete ethics and regulations: errors in AI decision-making may lead to major safety accidents, so it is urgent to establish a "human–machine collaboration" audit mechanism and industry standards.

Fig. 1 Application of AI in the dynamic response of deep surrounding rock: number of publications vs. time.
Chart labels: Number; Year; Stage I: embryonic stage; Stage II: development stage; Stage III: explosive stage.

Therefore, this study constructs a "perception–prediction–control" closed-loop framework (Fig. 2) from the three aspects of intelligent perception, predictive modeling, and control optimization, and aligns it one by one with the challenges described above.

Fig. 2 The intelligent perception–prediction–control closed-loop framework for the dynamic response of surrounding rock in deep tunnels.
Diagram labels: perception layer; prediction layer; control layer; multimodal sensors; AE; MS; optical fiber; point cloud; geological radar; AI algorithms; CNN; LSTM; PINN; GAN; AI system; adaptive support; digital twin.

Section 1 focuses, at the "perception" level, on the high-quality ···

collection, spatiotemporal alignment, and robust fusion, addressing Challenges and ; Section 2 discusses small-sample learning and mechanism–data dual drive at the "prediction" level, constructs interpretable and transferable precursor–risk mappings, and addresses Challenges and ; Section 3, at the level of "support control," focuses on a real-time, reliable, and auditable execution closed loop, exploring digital twins + learning control + standardized processes, and addresses Challenges and .

1 Intelligent perception: multi-source sensing and data fusion

Real-time and accurate perception of the state of the surrounding rock in deep roadways is the foundation for early warning and prevention of dynamic disasters. With the development of sensing and Internet of Things technologies, surrounding-rock monitoring has evolved from traditional single-point, offline measurement toward multi-source, real-time online monitoring[49-50]. AI technology plays a key role in intelligent perception, data fusion, and state diagnosis.

1.1 Perception architecture and sensor networks

To address Challenge , "difficulty in multi-source heterogeneous fusion," and Challenge , "limited real-time performance," this section centers on a four-level perception architecture of "point–line–surface–volume," and presents an integrated pathway for sensor-network layout, spatiotemporal alignment, robust fusion, and edge deployment in deep engineering. This enables multi-parameter and all-round perception of rock masses from microscopic fracture to macroscopic deformation[51-53]. Monitoring methods at each scale are as follows.

1) Point-scale monitoring (precise identification of transient events)

Point-scale monitoring is centered on acoustic emission (AE) and microseismic (MS) sensors, with sampling frequencies ranging from 10 kHz to 1 MHz, and is used to capture transient energy-spectrum signals during crack initiation and propagation. Such signals are susceptible to electromagnetic interference and mechanical noise[54-55]. To improve recognition accuracy, Li Kangnan et al.[56] proposed a rockburst-intensity prediction model based on multiple imputation by chained equations (MICE) and a convolutional neural network (CNN), namely MICE-CNN. Without relying on manual feature extraction, it increased the recognition accuracy of rockburst precursors from 81.2% to over 91%. Luo Xiaoyan et al.[57] used a prediction model combining variational mode decomposition (VMD) and a genetic algorithm back-propagation neural network (GA-BP-NN) to denoise and classify sandstone AE signals, improving prediction accuracy by 17.5%. HUANG et al.[58] systematically studied the influence of the spatial arrangement of sensors on the source-location accuracy of microseismic and acoustic-emission events, providing a theoretical basis for optimizing point-type sensor-network layout and improving the reliability of disaster warnings.

2) Line-scale monitoring (strain tracking and prediction along a line)

Line-scale monitoring mainly relies on distributed optical-fiber sensing technologies (such as BOTDR/FBG), which can realize continuous strain monitoring along the roadway axis with a spatial resolution of 1 m and an accuracy of $\$\pm\$50$ $\mu\epsilon$. Li Yanhe et al.[59], based on weak fiber Bragg grating sensing technology, developed a quasi-distributed large-range strain-sensing optical cable with a strain range not less than 0.04, sensitivity up to 1.23 pm/$\mu\epsilon$, and an accuracy grade of 0.5. Field tests showed that the strain of the roadway surrounding rock was relatively large within 4 m, and gradually became stable beyond 7 m. Based on the convergence characteristics of strain rate, the loosened-zone ranges of the roadway sidewall and roof were determined to be 5 m and 4 m, respectively. LI et al.[60] developed a set of high-sensitivity optical-fiber microseismic monitoring systems based on 8 channels. Using an optical-fiber interferometric measurement scheme, they successfully captured the entire process of microseismic signals from microfracture to macroscopic failure in tunnel engineering, and its performance was superior to that of traditional electronic sensors.

Point-scale monitoring (AE/MS) can capture the "instantaneous energy" of microfractures, but centimeter-level positioning errors make it difficult to delineate the boundary of the loosened zone; line-scale monitoring (distributed optical fiber) can provide "strain along the path," but lacks event-level trigger signals. Therefore, how to realize "event-triggered optical-fiber sampling" will become the core difficulty in achieving a breakthrough in point–line integrated monitoring methods.

3) Surface-scale monitoring (spatial geometric-structure identification and deformation measurement)

Surface-scale monitoring mainly uses three-dimensional laser scanning and photogrammetry to non-contact acquire high-precision point clouds and texture information of roadway surfaces. However, in complex underground environments it still faces noise, occlusion, and illumination interference[61]. Zhu Hehua et al.[62] systematically compared the effectiveness of clustering methods, region-growing methods, and neural-network methods in point-cloud identification, and pointed out that the region-growing method can realize automatic segmentation of structural planes based on a normal-vector consistency threshold; in a roadway of a certain gold mine, the identification accuracy for planar structural surfaces reached 92%. Zhang Quanping et al.[63] used mobile three-dimensional laser-scanning technology to obtain roadway point-cloud data, combined the M3C2 algorithm to process time-series point-cloud data, and characterized surrounding-rock deformation by color-value features, thereby realizing full-section deformation monitoring of a coal-mine return-air roadway. Dai Wenxiang et al.[64] proposed a VoxelNet-based deep-learning model for point-cloud denoising, followed by fitting of the roadway section using the Alphashape algorithm. In the Tashan Coal Mine, they successfully identified roof collapse and floor heave phenomena, realizing full-coverage monitoring of roadway deformation.

4) Volume-scale monitoring (deep structure and anomalous-body detection)

Volume-scale monitoring mainly relies on ground-penetrating radar, the transient electromagnetic method (TEM), and cross-hole CT (computed tomography), and is used to invert the spatial distribution of fracture zones and anomalous structures in deep rock masses. Traditional inversion methods are often limited by the non-uniqueness of solutions and low computational efficiency. To improve monitoring accuracy and reliability, a series of new technologies and algorithms have been introduced into this field. PERRI et al.[65] used cross-hole electrical-resistivity tomography to monitor and image hydraulic-fracturing fractures, focusing on the interference of borehole effects with artifacts in the inversion results, and proposed an improved three-dimensional inversion algorithm that effectively suppressed the resolution decline caused by borehole disturbance.

decreased, significantly improving the ability to reconstruct the true morphology of fracture networks. FU et al.[66] proposed a joint resistivity–fracture-density inversion framework based on a conditional generative adversarial network (cGAN). It successfully shortened the inversion time from 3 h to 5 s and kept the fracture-volume inversion error below 8%. In addition, ZHANG et al.[67] combined electrical resistivity tomography (ERT) with cross-hole seismic CT and applied it to the identification of karst zones and fracture-controlled water-conducting channels. This fusion method effectively overcomes the limitations of a single method and improves the imaging resolution of small-scale structures in underground heterogeneous media, such as water-conducting channels and fractured zones. Actual cases in karst areas show that this technique can identify structures within a depth range of 30 m, with a spatial positioning error of less than 1.5 m, demonstrating good potential for engineering application.

Laser point clouds provide "sub-centimeter-scale" deformation of the roadway surface, but they still cannot answer whether "a fracture zone within the deep 30 m has already connected through." Volume-scale geophysical inversion precisely fills this "line-of-sight blind zone," but its difficulties lie in "non-uniqueness" and "computational time consumption." Therefore, how to use AI methods to achieve dimensionality reduction and acceleration, and to complete the spatiotemporally synchronized description of two monitoring modalities—surface monitoring and volume monitoring—will be one of the key challenges to be overcome in monitoring technology for deep engineering.

The above "point–line–surface–volume" multi-scale perception architecture and its corresponding sensing-technology system are shown in Fig. 3.

Text visible in Fig. 3: 1. Point scale: 10 kHz–1 MHz; 2. Line scale: FBGI-BOTDR, distributed optical fiber, strain cloud map; 3. Surface scale: 3D laser scanning, surface scanner; 4. Volume scale: borehole logging, resistivity fracture-density inversion; multi-scale sensor network; surrounding rock of a deep roadway.

Fig. 3 Multi-scale perception framework for the dynamic response of deep roadway surrounding rock based on "point-line-surface-volume" scales

The massive heterogeneous data obtained on the basis of this system provide a solid data foundation for AI technologies in intelligent identification of surrounding-rock states and disaster early warning. AI methods not only realize the deep fusion of multi-source monitoring information, but also complete a comprehensive intelligent upgrade from signal processing to disaster prediction. Specifically, at the point scale, models such as CNN and VMD-GA-BP based on AE/MS signals significantly improve the recognition accuracy of rockburst and microfracture events; line-scale monitoring relies on hybrid models such as CNN-LSTM to realize time-series prediction of surrounding-rock deformation based on optical-fiber strain sequences; at the surface scale, deep-learning algorithms such as VoxelNet effectively complete point-cloud denoising and structural-deformation recognition; and at the volume scale, neural networks such as cGAN greatly improve the efficiency and accuracy of cross-hole CT and resistivity inversion. In addition, technologies such as drilling multiparameter-based intelligent surrounding-rock classification and convolutional-network-based quantitative evaluation of the loosening zone further expand the application scope of AI in surrounding-rock identification and control for deep engineering, realizing precise perception and intelligent early warning under multi-source information fusion.

1.2 Typical Algorithms and Performance

Fusion processing of multi-source heterogeneous data is the key to accurately judging the state of surrounding rock. In recent years, deep-learning algorithms, by virtue of their powerful feature-extraction and anomaly-diagnosis capabilities, have shown significant advantages in this field[68-69]. Studies indicate that convolutional neural networks (CNNs) can achieve an accuracy of over 90% in lithology identification[70]. However, their convolution kernels inherently lack temporal memory, making them difficult to apply directly to time-series prediction of surrounding-rock deformation. By contrast, recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), because of their excellent ability to model dynamic temporal features, have been widely used for the analysis and prediction of time-series data such as surrounding-rock deformation and stress evolution. For example, RNNs show good adaptability in processing time series of drilling parameters[71], while LSTMs, owing to their long-term memory function, perform prominently in predicting surrounding-rock movement under high-noise backgrounds, with mean squared errors significantly lower than those of traditional models[72].

In surrounding-rock monitoring for tunnel engineering in complex mountainous areas, LIU et al.[73] constructed a multi-target classification and recognition model based on microwave radar technology using the Doppler principle and combined with deep-learning algorithms, showing excellent performance. By integrating 12 deep-learning models, including VGG16, MobileNetV2, and GoogleNet, and adopting a transfer-learning strategy, the model achieved a maximum accuracy of 95.46% in identifying disaster events such as debris flows and rockfalls. In addition, ZHANG et al.[74] fused multi-source monitoring data such as geological radar scanning, support stress, and convergence deformation, and adopted a convolutional neural network–long short-term memory network (CNN-LSTM) hybrid model for temporal feature extraction and risk classification. This study achieved accurate early warning for the risk of large deformation in tunnel soft rock. Compared with traditional methods, the CNN-LSTM model increased the prediction accuracy for large deformation from 78.6% to 92.4%, the AUC (area under curve) value reached 0.947, the F_1 score increased to 0.89, and the mean squared error decreased to 0.021, significantly improving

improved the accuracy and timeliness of early warning.

Table 1 systematically summarizes representative algorithms and their performance in the application of AI technology to surrounding-rock monitoring, covering multiple application scenarios ranging from surrounding-rock classification and lithology identification to disaster early warning. As can be seen from the table, different algorithms all show good adaptability to various data sources, and the recognition accuracy of most models exceeds 90%, indicating that AI algorithms have significant advantages in improving the accuracy of surrounding-rock state identification.

Table 1. Typical applications and performance comparison of AI technology in surrounding-rock monitoring

Technology type	Data source	AI algorithm	Accuracy/precision	Application scenario	Reference
Intelligent surrounding-rock classification	Drilling parameters	SVM/BP neural network	>90%	Tunnel excavation	Ref. [68]
Lithology identification	Rock-mass images	Convolutional neural network	>90%	Tunnel excavation	Ref. [70]
Loose-zone assessment	Microwave radar signals	Deep neural network	95.46%	Debris-flow and rockfall monitoring	Ref. [73]

Technology type	Data source	AI algorithm	Accuracy/precision	Application scenario	Reference
Structural-plane identification	3D point cloud	Deep learning / hybrid machine learning	Sub-millimeter level	Working-face reconstruction	Ref. [75]
Rockburst early warning	Multi-source data	Multi-source fusion + LSTM	>88%	Mine-pressure disaster early warning	Ref. [76]

In summary, from shallow neural networks such as SVM/BP to deep neural networks such as CNN and LSTM and their combined models, AI algorithms have continued to achieve performance breakthroughs in surrounding-rock monitoring, prediction, and early warning, forming a full-stack technical system that progresses from "static identification" to "dynamic evolution modeling" and from "single-point monitoring" to "multi-source fusion." Although various algorithms emphasize different aspects of performance, all have significantly improved the accuracy and timeliness of surrounding-rock stability analysis, providing solid support for disaster prediction and control decision-making in tunneling and mining engineering.

Although this section has systematically described the "point–line–surface–volume" sensing and monitoring system for deep engineering and its intelligent algorithms, sensing essentially only characterizes the "current state" and cannot directly answer whether a dynamic engineering disaster will occur at some future moment. Therefore, Section 2 turns to identifying disaster precursors from multi-source, high-dimensional data and mapping them to short-term risk, with emphasis on reviewing the advantages, limitations, and applicability boundaries of "mechanism–data" dual-driven prediction models.

2 Intelligent prediction: mechanism–data fusion modeling

In deep underground engineering, prediction of the dynamic response of surrounding rock is the core link in realizing disaster prevention and control. Traditional prediction methods mostly rely on mechanical models and empirical formulas, making it difficult to cope with complex and highly variable geological environments. In recent years, the introduction of AI technology has greatly promoted innovation in disaster-prediction paradigms. However, current prediction models face two major challenges: "small samples" and "lack of physical interpretability." These must be addressed through a dual pathway of "data augmentation + mechanism fusion" : for small samples, "synthetic data generation + federated learning" is adopted to expand sample size; for interpretability, "physical constraints + feature visualization" are introduced to establish the connection between AI results and rock-mechanics mechanisms [77].

2.1 Intelligent inversion of the geostress field

The geostress field is one of the key factors controlling the stability of deep surrounding rock and the occurrence of dynamic disasters such as rockburst and large deformation. Because direct measurement methods, such as stress relief, are costly, operationally complex, and can obtain only point information, data-driven intelligent inversion methods have gradually become a research hotspot [78]. By integrating multi-source geological information and monitoring data, these methods construct high-precision numerical models or machine-learning surrogate models, reflecting a trend from "pure data fitting" to "mechanism-constrained enhancement" and effectively improving model interpretability and small-sample generalization capability.

Studies show that geostress prediction models based on BP neural networks can effectively integrate multiple input parameters, including depth, core density, elastic modulus, triaxial compressive strength, measured acoustic-emission geostress values, and core fracture rate, enabling nonlinear fitting and prediction of geostress in deeply buried tunnels [79]. Such data-driven methods not only reduce dependence on simplified empirical formulas, but also demonstrate strong fusion and generalization capabilities for multi-source heterogeneous data under complex geological conditions. For example, the intelligent IA-BP algorithm (immune-algorithm back-propagation) proposed by Sun Gang et al. [80] showed relatively high accuracy in geostress-field inversion; its average relative error in a three-dimensional model was only 3.39%, significantly outperforming PSO-BP (particle swarm optimization-BP), multiple linear regression, and other methods.

At the monitoring-platform level, researchers have proposed data-acquisition systems that integrate multidimensional sensing technologies such as microseismic monitoring, distributed optical fiber, and geological radar, and have combined them with edge computing and cloud-based deep-learning platforms to realize dynamic reconstruction and visualized prediction of the geostress field [81]. This approach can efficiently process hundreds of spatiotemporal monitoring variables and adapt to the complex and variable geological environments of mining areas.

Meanwhile, algorithms such as convolutional neural networks (CNN), long short-term memory networks (LSTM), and support vector machines (SVM) have also been gradually applied to geostress inversion tasks to improve the ability to capture nonlinear stress-evolution processes. For example, the CNN-BiLSTM-Attention model (Fig. 4) proposed by Ma et al. [82] achieved, in simulations of multiple tunnel operating conditions,

achieved high-precision prediction with a root-mean-square error of only 0.016, significantly improving the identifiability of abrupt stress fluctuations.

SONG et al. [83] proposed a nonlinear intelligent inversion method for layered rock masses in deep-valley environments, successfully enabling efficient estimation of in-situ stress. This method comprehensively considers topographic evolution, geological structures, and the mechanical properties of rock masses, and uses a generative adversarial network (GAN) to optimize the lateral stress coefficient of the paleostress field, thereby accurately reconstructing the present-day in-situ stress field. On the other hand, hybrid modeling methods that combine physical mechanisms with data-driven approaches have received widespread attention. By introducing geomechanical constraints, multi-field coupling equations (such as seepage-stress-temperature coupling), or structural geological features, such methods enhance model interpretability and extrapolation capability [84]. For example, Ma Tianshou et al. [85] proposed a distributed neural-network model incorporating physical constraints for three-dimensional in-situ stress prediction. By introducing geomechanical constraints and physical laws, this model significantly improves the accuracy and reliability of in-situ stress inversion. Studies show that this method has strong adaptability and predictive capability under complex geological conditions. Compared with the traditional BP neural-network model, the physically constrained distributed neural-network model yields smaller errors in in-situ stress inversion and more accurate prediction results. To facilitate horizontal comparison, this study summarizes the principal algorithms, representative methods, key characteristics, and applicable scenarios of intelligent inversion of in-situ stress fields, as shown in Table 2.

A high-precision in-situ stress field is only the "input background field" ; what truly determines the disaster type and intensity is the three-way coupling of "stress-lithology-disturbance." Under the same stress level, granite may experience rockburst, whereas soft rock may exhibit large deformation. Therefore, Section 2.2 further introduces engineering geological parameters and mining-disturbance indicators on the basis of the stress field, and compares the similarities and differences among prediction models for four types of disasters: rockburst, coal burst, large deformation, and zonal disintegration.

Fig. 4 Schematic diagram of the CNN-BiLSTM-Attention hybrid neural-network architecture [82]

Table 2 Comparison of intelligent inversion algorithms for in-situ stress fields

Algorithm type	Representative method	Main characteristics	Applicable scenarios	References
Traditional neural network	BP neural network	Simple structure; adaptable to multiple input parameters, but prone to falling into local optima	Preliminary inversion of in-situ stress; multi-parameter linear/nonlinear fitting	Ref. [79]
Intelligent optimized neural network	IA-BP, PSO-BP	Strong global optimization capability, fast convergence, and high accuracy	Complex geological conditions; reconstruction of high-precision stress fields	Ref. [80]
Deep learning	CNN, LSTM, BiLSTM	Can capture spatial and temporal features; suitable for processing high-dimensional nonlinear data	Abrupt stress response; prediction of multi-field coupled evolution	Ref. [82]
Support vector machine	SVM	Suitable for small-sample and high-dimensional problems; good generalization capability	Stress-field inference under data-sparse conditions	Ref. [84]

Algorithm type	Representative method	Main characteristics	Applicable scenarios	References
Hybrid mechanism-data model	Structural constraints + distributed neural network	Introduces physical constraints or geological mechanisms, improving model extrapolation capability and interpretability	In-situ stress inversion in multi-field coupling and structurally controlled zones	Ref. [85]

2.2 Multi-Parameter Early Warning and Spatiotemporal Evolution Prediction of Dynamic Disasters in Deep Engineering

In deep rock-mass engineering, rockburst, coal burst, large deformation, and zonal disintegration are the four most representative types of dynamic disasters, characterized by strong suddenness, high destructive power, and complex coupling mechanisms. Traditional prediction methods mostly rely on limited monitoring parameters and empirical criteria, making it difficult to achieve accurate description of disaster evolution processes and efficient early warning. With the integrated development of artificial intelligence technologies and multi-source sensing methods, intelligent disaster prediction models have shown advantages in nonlinear feature extraction, heterogeneous data fusion, and risk-response control.

and other aspects.[86–87]

1) Intelligent prediction of rockburst

Rockburst prediction models are evolving from traditional empirical criteria toward an intelligent three-layer architecture of "indicators–fusion–decision."

Indicator layer: In addition to static parameters such as the rock brittleness index, stress concentration coefficient, and energy release rate, dynamic parameters such as microseismic sequences (e.g., b value, a value, and energy release rate) and acoustic-emission counts are widely adopted.[88] The multi-parameter rockburst criterion proposed by ZHANG Hengyuan et al.[89] simultaneously considers the releasable strain energy accumulated inside the rock, the critical surface energy required for failure, and the brittleness coefficient; it was also verified through secondary development on the three-dimensional distinct element code (3DEC) platform, thereby enhancing the reliability of rockburst proneness evaluation in deep underground engineering.

Fusion layer: Deep learning models have significantly improved the capability for multi-source information fusion and feature extraction. Based on true triaxial conditions, LIU et al.[90] developed a deep-learning multi-parameter early-warning model that uses neural networks to replace manual selection of feature points, reducing subjectivity; by combining cusp catastrophe theory to set thresholds for the early-warning model, they achieved integrated prediction and warning. Convolutional neural networks (CNNs) have also been used to construct data-driven rockburst prediction models, which can not only predict rockburst grades but also calculate the probability of occurrence for each grade.[91]

Decision layer: This layer is dedicated to transforming prediction information into specific prevention and control actions. Deep reinforcement learning (DRL) has been applied to construct a "rockburst-support" interactive environment; with surrounding-rock convergence rate and support-structure damage degree as reward functions, it outputs dynamic support strategies.[92] An intelligent decision support system (IDSS) can integrate geological information, real-time monitoring data, and numerical simulation results, providing engineers with selection and optimization of prevention and control schemes under multiple scenarios.[93] In addition, a virtual tunnel system constructed based on digital twin technology can map the state of physical entities in real time and simulate the rockburst evolution paths under different support schemes, thereby enabling forward-looking decision optimization.[94]

2) Multi-parameter early warning of burst ground pressure

Early warning of burst ground pressure relies heavily on integrated analysis of multi-source monitoring data and mining of time-series features. Its early-warning model architecture is developing toward a dual-driven model that "combines physical driving and data driving."

Optimization and fusion of multi-source monitoring indicators are fundamental. Based on a Bayes optimization algorithm and a long short-term memory network (LSTM), CUI Feng et al.[95] constructed a time-dependent risk-level early-warning model (Bayes-LSTM). By analyzing features such as microseismic energy level and frequency, they identified the b value, a value, $A(b)$ value, seismic quiescence, ΔF, S, and $H(t)$ as time-series early-warning indicators; the accuracy of the model test set reached 84.8%. For hard-roof conditions, WU Guandong et al.[96] used a GA-BP algorithm to screen out β_n, $P(b)$, $A(b)$, and the b value as physical early-warning indicators, and adopted a CNN-T-SNE algorithm to extract time-series early-warning indicators from microseismic and support-resistance data. By combining LSTM with the nightingale optimization algorithm (NOA), they established a time-series early-warning model, improving early-warning accuracy by 12%, with the F_1 value reaching 0.966.

A dual-driven intelligent early-warning architecture is an important development direction. CHEN Jie et al.[97] proposed a "dual-driven" (physics-driven and data-driven) intelligent early-warning architecture for burst ground pressure.

On the physics-driven side, a Bayesian probability integrated model is used to conduct dynamic-static collaborative real-time assessment using parameters such as microseismicity, roadway stress, and seismic CT. On the data-driven side, a deep-learning model, MSNet (combining CNN, RNN, and autoregressive models), is built to quantitatively predict the time, location, and energy of future microseismic events, thereby determining the impact time and hazardous areas. The prediction accuracy of risk level under this architecture reaches 0.88, and the average accuracy of location prediction reaches 0.977.

3) Prediction of the spatiotemporal evolution of large deformation

The core of predicting large deformation in soft-rock roadways of deep engineering lies in constructing models capable of capturing spatiotemporal correlations. Traditional single-point prediction models are difficult to satisfy requirements; collaborative prediction at multiple monitoring points and fusion of spatiotemporal features have become the research focus.

Multi-point collaborative prediction models significantly improve prediction accuracy and robustness by mining the spatiotemporal correlations among deformations at different monitoring points. For large deformation of surrounding rock in deep roadways, models based on spatio-temporal graph neural networks (STGNNs) can be adopted. Such models treat monitoring points at different tunnel locations as graph nodes, use graph convolutional networks (GCNs) to capture spatial dependencies, and combine temporal convolutional networks (TCNs) or long short-term memory networks (LSTMs) to learn temporal evolution laws, thereby realizing collaborative prediction of multi-point deformation.[98] For example, some studies have constructed a GRU-attention (gated recurrent unit attention) prediction model by integrating the spatiotemporal sequence of microseismic energy release with tunnel-surface displacement data; its prediction error is significantly lower than that of traditional models, and it can effectively identify hazardous zones of large deformation.[99]

Time-series prediction models are continuously being optimized in capturing the temporal dependence of surrounding-rock deformation. Long short-term memory networks (LSTMs) and gated recurrent units (GRUs) are commonly used models; they can effectively process monitoring-data time series such as tunnel convergence and roof-floor convergence.[100] For example, XIAO et al.[101] proposed an SSA-VMD-GRU decomposition–reconstruction–prediction framework: first, SSA (salp swarm algorithm) is used to adaptively optimize VMD parameters (introducing sample entropy and mean-square error as the decomposition evaluation), decomposing the surrounding-rock deformation sequence into trend and random components; then GRU is used separately for prediction and superposed reconstruction. Compared with GRU, empirical-parameter VMD-GRU, and WOA-VMD-GRU (whale

When compared with optimization algorithm–VMD-GRU and other models, the model' s R^2 increased to 0.926 5 (+7.9%), RMSE (root mean square error) decreased to 0.13 mm (−28.5%), and MAE (mean absolute error) decreased to

0.11 mm (−20.7%). This significantly improved the accuracy and robustness of large-deformation prediction for deep soft-rock roadways; moreover, it still achieved the best indicators on another set of tunnel convergence data, verifying its generalization capability.

4) Identification and prediction of zonal fracturing

The identification and prediction of zonal fracture development rely on advanced detection technologies and intelligent algorithms to accurately identify the spatial distribution patterns of fractured zones. Computer vision and image-processing techniques play an important role in crack recognition. A crack-recognition model and device based on a residual-network structure for pixel-difference edge detection can be used to identify cracks and classify their attitudes in field outcrop areas, improving the accuracy of rock-crack identification and the visibility of categories [102]. A visual detection method for fractured regions during trenchless pipeline rehabilitation constructs a fracture index by analyzing corner points within connected domains, gray-scale features, and MLBP (multi-scale local binary pattern) feature values, thereby improving detection accuracy [103]. Although these methods target different applications, their core ideas of image recognition and feature extraction can provide references for macroscopic or microscopic identification of zonal fracturing in deep surrounding rock.

Three-dimensional feature extraction and recognition technologies are key to addressing the complex three-dimensional spatial morphology of zonal fracturing. Three-dimensional convolutional neural networks (3D-CNNs) can effectively analyze three-dimensional data such as borehole imaging, laser point-cloud scanning, and acoustic CT, and identify the spatial distribution patterns of fractured zones [104]. For example, deep-learning-based methods (U-Net/lightweight attention, etc.) can segment and identify fractures in borehole/core images; by performing three-dimensional reconstruction and segmentation of the acquired internal structural images of the rock mass, they can automatically identify alternately occurring fractured zones and intact zones [105]. In addition, by combining the high-precision three-dimensional morphology of roadway surfaces obtained through laser point-cloud technology, deep-learning models such as PointNet++ can directly process point-cloud data, extract geometric features of fracture zones (such as width, density, and strike), and achieve non-contact identification of zonal fracturing [106]. Physics-informed neural networks (PINNs) incorporate physical laws such as constitutive relations and equilibrium equations of rock masses as constraints into neural-network training, enabling accurate prediction of fractured-zone thickness with only a small amount of labeled data and enhancing the model' s generalization capability [107].

In summary, this study summarizes the principal prediction models and their accuracy metrics for four typical dynamic hazards—rockburst, coal burst, large deformation, and zonal fracturing—to provide references for engineering model selection and parameter tuning, as shown in Table 3.

No matter how accurate prediction becomes, if it cannot be translated into "support actions"to prevent the occurrence of hazards, its practical effect remains zero. With the continuous advancement of AI technology, deep-roadway control is shifting from "experience-based thresholds" toward "learning control." Its core contradiction is the trade-off between "millisecond-level response" and "high reliability." Section 3 will discuss how AI technology seeks a balance point within this contradiction.

Table 3 Summary of prediction models and performance metrics for surrounding-rock dynamic hazards

Tab. 3 Summary of prediction models and performance metrics for deep surrounding rock dynamic hazards

Prediction type	Recommended model	Core input parameters	Representative accuracy metrics	Applicable lead time	References
Rockburst tendency	Deep learning (CNN-BiGRU-Attention, etc.)	Microseismic data (b, a, energy, event rate, etc.), acoustic emission, electromagnetic data, lithology, and stress	Classification accuracy: see examples in the literature (commonly in the range of 0.87–0.98, varying with the dataset)	Hour-level or day-level (short-term/real-time early warning)	Literature [90–91]
Coal burst	LSTM series (Bayes-LSTM, LSTM+NOA, etc.)	Microseismic energy level, frequency, b value, a value, $A(b)$, ΔF, S, $H(t)$	Acc = 84.8% (Bayes-LSTM); $F_1 = 0.966$ (LSTM+NOA)	Hour-level	Literature [95–96]

Prediction type	Recommended model	Core input parameters	Representative accuracy metrics	Applicable lead time	References
Large deformation	Decomposition–reconstruction–prediction (SSA-VMD-GRU, etc.)	Multi-source deformation monitoring: convergence, displacement, support force, etc.	$R^2 = 0.926\ 5$, $R_{\mathrm{RMSE}} = 0.13$ mm, $R_{\mathrm{MAE}} = 0.11$ mm	Real-time early warning	Literature [98, 100–101]
Zonal fracturing	3D-CNN (CT/borehole imaging), PointNet++ (three-dimensional point cloud)	Rock-sample/borehole CT, full-section laser point cloud, acoustic CT/seismic CT	CT/rock-core images: IoU 0.55–0.70, Dice 0.70–0.80; three-dimensional point clouds: mIoU 0.50–0.70, OA 0.85–0.95	Batch processing/near real-time identification	Literature [106–107]

3 Intelligent control: adaptive support and digital-twin closed loop

The stability control of surrounding rock in deep roadways is gradually shifting from the old "experience-threshold-offline" mode toward a data-driven intelligent closed-loop paradigm of "perception-prediction-control" : one end connects multi-source perception and prediction models (such as LSTM/GRU, STGNN, PINN, etc.), while the other is implemented in adaptive support and construction-parameter optimization (such as collaborative control of hydraulic supports and adaptive adjustment of shield/TBM tunneling parameters), thereby tackling the challenge of the "trade-off between real-time performance and reliability." Achieving this closed loop depends on three core capabilities: real-time observability (online identification and visualization of the support-surrounding-rock coupled state); computability (learning-control algorithms that integrate mechanistic constraints); and executability (control strategies can be implemented safely and robustly

···transmitted underground to the actuating mechanism).

In recent years, technologies such as neural-network-enhanced PID (proportional–integral–derivative) control, sliding-mode/disturbance observation, deep reinforcement learning (DRL), digital twins (DT), and knowledge graphs (KG) have been successively applied to active regulation and risk response for deep surrounding rock, significantly improving system response speed, robustness, and interpretability[108].

3.1 Adaptive Support Systems: From "Parameter Tuning"to "Learning Control"

In deep working faces and roadways, hydraulic support–roof–surrounding rock systems constitute strongly coupled and highly nonlinear systems: support advancing, loading of columns, hydraulic-circuit fluid supply, valve-port flow, frictional hysteresis, and other links are intertwined, while underground disturbances, operating-condition switching, and time-varying uncertainty are also present. Conventional fixed-parameter PID controllers have difficulty simultaneously balancing dynamic response speed—such as settling time and overshoot—and steady-state accuracy—such as tracking error and fluctuation suppression; their performance is especially limited under strong disturbances or abrupt changes in operating conditions[109].

To address these challenges, researchers have deeply integrated neural networks, fuzzy logic, swarm-intelligence optimization, PID control, sliding-mode control, and feedforward compensation for adaptive control and predictive maintenance of support posture, support resistance, and fluid-supply systems (Fig. 5).

Text in Fig. 5: displacement sensor; pressure sensor; valve spool; intelligent controller (NN/FL/ADRC); neural-network compensation; spatiotemporal predictive feedforward; disturbance observer (ESO); hydraulic cylinder; electrohydraulic proportional valve; pump station; support system; roadway surrounding rock; perception layer; control system; actuated object.

Figure 5 Framework of an intelligent self-adaptive support system for deep tunnels
Fig. 5 The intelligent self-adaptive support system framework for deep tunnels

NN-PID (neural network-proportional integral derivative)/fuzzy adaptation: Through online learning or parameter self-tuning, the hysteresis and coupling effects of valve-controlled/cylinder-controlled systems are reduced, and overshoot, settling time, and steady-state error are improved. In multi-cylinder collaborative scenarios, high-order sliding-mode observers and neural-network disturbance-observation techniques are combined to realize state estimation and compensation under displacement-feedback-only conditions[110].

Spatiotemporal predictive feedforward/gain scheduling: Deep spatiotemporal models, such as PredRNN/PredRNN++ and CNN-LSTM, are used to model support resistance and operating-condition sequences. Short-term prediction results are taken as feedforward signals or gain-scheduling factors, effectively reducing system shocks and fluctuations during strong disturbances and rhythm-switching stages[111].

Intelligent control of the fluid-supply system: To cope with the strongly time-varying fluid demand and pressure shocks caused by actions such as "lowering columns–pulling supports–raising columns–sequential pushing," a "rapid pump-controlled replenishment and pressure stabilization" configuration is adopted. ESO-ADRC (extended state observer–active disturbance rejection control) is introduced to observe and compensate the total disturbance online, enabling the outlet flow of the pump station to rapidly match demand. Simulation results show that, compared with multi-pump linkage and PID rapid replenishment schemes, ADRC further reduces the maximum pressure fluctuation from 8.65 MPa to 6.85 MPa, shortens the action cycle from 10.14 s to 9.92 s, and reduces the number of unloading-valve opening and closing events, demonstrating the synergistic advantages of "observation–compensation–pressure stabilization" [112].

Enhancement of actuator/valve-control links: For the discrete, hysteretic, and nonlinear characteristics of high-frequency switching valves/electrohydraulic proportional valves, fuzzy adaptive PID and intelligent speed-valve designs are adopted to improve valve-port control accuracy and the overall positioning-control capability of the system[113].

Recent empirical studies indicate that, in support multi-cylinder systems and hydraulic actuation links, intelligent control strategies shorten settling time, significantly reduce overshoot, decrease steady-state error, and enhance disturbance-rejection capability. Predictive allocation strategies on the fluid-supply side significantly suppress pressure fluctuations and energy consumption. Under a coupled "prediction + control" framework, time-series prediction of support resistance reduces the number of emergency adjustments and system shocks[114-115].

In complex, time-varying, and partially observable underground environments, learning control that combines data-driven methods with mechanistic constraints has become a new trend. In support–surrounding rock or excavation–support collaborative scenarios, sample-efficient hybrid reinforcement-learning models that incorporate prior models and safety constraints are adopted. Rock-mass deformation rate, support-structure damage degree, energy consumption, and control smoothness are used as reward functions and constraint terms to output dynamic support strategies or action rhythms[116]. The corresponding weights and penalty terms can be calibrated through DT simulation and offline data, ensuring safety and auditability[117].

3.2 Digital-Twin Closed Loop: From "Visible and Measurable" to "Controllable and Optimizable"

Digital-twin (DT) systems for controlling the dynamic response of deep surrounding rock have progressed from the early stage of being "visible and measurable" toward a fully intelligent stage of being "controllable and optimizable." With "perception-modeling-prediction-control-inversion"as the core closed loop, such systems build a dynamic optimization framework for safety control in deep engineering (Fig. 6)[118].

The core links of a DT system include the following.

1) **Multi-source real-time mapping (perception)**

Convergence/subsidence, microseismic/acoustic-emission signals, support loads, excavation parameters, and geological entities—including structures and water-bearing conditions—are temporally synchronized and spatially aligned to construct a "virtual-real isomorphic" data foundation and visualization interface, supporting event replay and online quality control[119].

Diagram labels: Perception; Modeling; Prediction; Control; Feedback; Closed-loop system.

Figure 6 Closed-loop digital twin system for the dynamic response of deep tunnel surrounding rock

Fig. 6 Closed-loop digital twin system for the dynamic response of deep tunnel surrounding rock

2) Mechanism-data fusion

A physics-informed neural network (PINN) is adopted, combined with Kalman/particle filtering for state estimation and parameter assimilation. Constitutive and equilibrium equations are embedded into the learning process as soft constraints, effectively improving robustness under small-sample and domain-transfer scenarios

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3) Prediction and optimization (prediction & control)

Through solvers such as coordinated scheduling control (model predictive control, MPC) and deep reinforcement learning (DRL), the digital twin performs multi-objective optimization of "surrounding-rock deformation–support load–energy consumption–smoothness" and generates optimal control sequences. A typical approach is to use short-term prediction as a feedforward signal for gain scheduling, thereby suppressing the shocks and fluctuations caused by rhythm switching

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4) Closed-loop execution and feedback (tuition & feedback)

Control strategies are issued through a secure gateway to the execution layer, including hydraulic supports, pump stations, and valve control; execution effects are evaluated online, and deviation information is fed back to the digital twin system for parameter re-identification and model retraining, enabling the system to evolve autonomously

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In terms of closed-loop control, the digital twin system realizes the dynamic optimization and issuing of control commands through online evaluation and feedback correction of strategy effects, ultimately being implemented in actuators such as hydraulic-support regulation, shield tunneling advance-parameter optimization, and synchronous grouting. At the same time, the system serves as a safe and controllable experimental environment, supporting the verification and iteration of methods such as physics-constrained reinforcement learning (PI-DRL) and online PINN. For example, in TBM (tunnel boring machine) excavation control, by inputting geomechanical constraints of the strata, sample efficiency and strategy transferability can be improved; in shield-tunnel construction, online prediction and regulation of tail voids, lining forces, and surrounding-rock parameters have been achieved

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Against the background of "invisibility, strong coupling, and high risk" in deep rock masses, the digital-twin closed loop significantly improves geological transparency and identification accuracy, incorporates stability indicators into real-time optimization objectives, and supports the full life-cycle management of mines from "definition-design-construction-operation and maintenance"

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. Its coupling with knowledge graphs enables semantic risk expression and traceable decision-making, significantly enhancing the safety management and control level of deep engineering

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4 Challenges and Prospects

4.1 Key Challenges

Although AI technology has made significant progress in the field of dynamic response of surrounding rock in deep roadways, its implementation faces a series of domain-specific difficulties, rather than common problems of general AI technology, due to the extreme environment of deep rock masses characterized by "three highs and one disturbance"(high in-situ stress, high osmotic pressure, high temperature, and strong mining disturbance), the complex mechanical mechanisms of disaster evolution, and the particularities of engineering applications. The details are as follows.

1) The dual constraints of "spatiotemporal heterogeneity" and "difficulty of acquisition" for small samples of deep disasters

Deep dynamic disasters such as rockbursts and coal bursts have the characteristics of "low frequency and high destructiveness," and real disaster samples from the field are extremely scarce—fewer than one thousand rockburst events have been completely recorded in kilometer-deep mines worldwide. Moreover, the geological background of each sample, such as lithology and fracture-development degree, and the mining conditions, such as excavation speed and support mode, differ significantly. This leads to severe "spatiotemporal heterogeneity" among samples, and traditional data-augmentation methods, such as oversampling, are difficult to use to eliminate distribution shifts across mines and working conditions. In addition, the harsh underground environment in deep mines—high temperature, high humidity, and electromagnetic interference—causes monitoring equipment to fail easily, making it difficult to continuously capture the "full time-series characteristics" of disaster gestation processes, such as the gradual decline of the microseismic b-value and sudden precursory increases in fiber-optic strain. This further aggravates the insufficient generalization capability of small-sample learning.

2) The "disconnection" between AI models and rock-mechanics mechanisms leads to low engineering trust

The dynamic response of deep surrounding rock is essentially a mechanical process of "in-situ stress-field evolution–fracture initiation and propagation–energy accumulation and release."However, existing deep-learning models, such as CNN and LSTM, are mostly "data-driven black boxes," making it difficult to integrate them with the core mechanisms of rock mechanics, such as the Mohr–Coulomb strength criterion and rock-mass damage constitutive equations. For example, although a coal-burst prediction model based on microseismic data can output risk levels, it cannot explain the "correlation between the stress concentration coefficient and the microseismic energy rate." Although physics-informed neural networks (PINNs) introduce mechanical constraints, when dealing with multi-field coupled problems such as rockbursts and coal bursts (stress–seepage–temperature), they still have difficulty quantifying the dynamic influence of fracture propagation on the elastic modulus of rock masses. This causes model outputs to become disconnected from mechanical criteria familiar to engineers, such as the stress-strength ratio, and in engineering applications their reliability is often questioned because they are "unexplainable."

3) Fusion difficulties caused by the "domain differences" and "spatiotemporal

mismatch" of multi-source sensing data

The data generated by the "point-line-surface-volume" multi-scale sensing network for monitoring deep surrounding rock exhibit significant domain differences: point-scale AE/MS sig—

signals are transient nonstationary signals; line-scale fiber-optic strain data are continuous time-series signals; areal-scale laser point clouds are spatial-structure data; and volumetric geological radar data are dielectric-constant inversion results. These data are heterogeneous not only in "frequency-resolution-physical meaning," but also suffer from serious "spatiotemporal mismatch." For example, the spatial positioning error of AE events (centimeter scale) does not match the axial resolution of fiber-optic strain monitoring (microstrain scale), making it difficult to accurately correlate "microseismic sources" with "strain anomaly zones." Meanwhile, underground mechanical vibration (e.g., shield tunneling) and electromagnetic interference (e.g., high-voltage cables) cause significant differences in noise levels among different sensors: the signal-to-noise ratio of AE signals is often below 10 dB, whereas that of fiber-optic signals is higher than 20 dB. As a result, traditional data-fusion algorithms, such as Kalman filtering, have difficulty achieving "high-quality complementarity" among multisource data.

4) The contradiction between the "resource constraints" and "real-time reliability" of underground edge computing

The narrow space in deep roadways, power-supply limitations, and disaster-resistance requirements mean that edge-computing hardware must satisfy the characteristics of "miniaturization and resistance to harsh environments" (e.g., high-temperature resistance of 70 °C and vibration resistance of 1 000 Hz), making it impossible to deploy high-performance computing units such as GPUs. To meet the real-time requirements of rockburst early warning (millisecond-level response) and adaptive control of hydraulic supports (millisecond-level regulation), AI models must be compressed (e.g., through knowledge distillation and quantization). However, the compression process can easily lead to "loss of key features." Underground data transmission depends on mine explosion-proof networks, whose bandwidth limitations ($\leq$ 100 Mbps) make real-time uploading of multisource data difficult, further intensifying the trade-off between "real-time computation" and "high reliability."

5) The "strong constraints" of safety responsibility in deep engineering and the "blank space" in industry standards

Dynamic-disaster prevention and control in deep engineering are directly related to personnel safety. Errors in AI decision-making may trigger major accidents. However, there is currently a lack of mechanisms for defining responsibility in "AI-engineering safety." For example, if an AI misjudges rockburst risk and results in delayed support, who bears responsibility—the model developer, the engineering operation-and-maintenance party, or the equipment supplier? In addition, there are significant gaps in industry standards: there are neither "specifications for collecting monitoring data of deep surrounding rock" (such as recording fields for microseismic events and sampling-frequency standards for fiber-optic strain) nor an "AI model evaluation-index system" (for example, rockburst early warning should simultaneously satisfy a missed-alarm rate $\leq$ 5% and a false-alarm rate $\leq$ 10%). Consequently, models developed by different teams, such as LSTM models for impact ground pressure and STGNN models for large deformation, cannot be compared horizontally, and engineering model selection lacks a basis.

4.2 Future Directions

In response to the above challenges arising from domain specificity, future research should integrate the geological characteristics, mechanical mechanisms, and engineering requirements of deep engineering, and carry out targeted studies that fuse "mechanism–data–engineering." Specific directions are as follows.

1) Sample-generation technology driven jointly by "mechanical simulation–real data"

To address the scarcity of disaster samples, a sample-augmentation framework of "numerical simulation + transfer learning" can be constructed. On the one hand, mechanical simulation software such as FLAC3D and 3DEC can be used to simulate the evolution processes of rockburst and impact ground pressure under different in-situ stress and rock-mass conditions, generating synthetic samples with "mechanical consistency" (such as microseismic time series and strain-field distributions). On the other hand, through federated learning (FL), "distributed training" across mines can be achieved while protecting the privacy of mine data. "Geological similarity weights" (such as distance metrics based on lithology and burial depth) can also be introduced to reduce the influence of spatiotemporal heterogeneity among samples.

2) An "explainable AI (explainable artificial intelligence, XAI)" framework coupled with rock-mechanics mechanisms

To break through the limitations of the "black box," an interpretable framework of "mechanism constraints + feature visualization" should be constructed: at the model-design stage, constitutive equations of rock damage and inversion formulas for the in-situ stress field can be embedded into a PINN as hard constraints, so that model outputs, such as stress distributions, satisfy conservation laws of mechanics; at the model-inference stage, attention-mechanism visualization (e.g., heat maps in CNNs corresponding to zones of concentrated microseismic energy) and SHAP value analysis can be used to quantify the contribution of each input parameter to disaster prediction, such as the influence weight of the b-value, thereby establishing a mapping relationship between "AI results" and "mechanical judgments."

3) Fusion algorithms for "spatiotemporal alignment–noise suppression" oriented toward multiscale sensing

To address the heterogeneity of multisource data, fusion technologies dedicated to deep engineering need to be developed. For spatial alignment, a "sensor coordinate unification framework" can be established based on the three-dimensional laser point cloud of the roadway. Through rigid transformation, the spatial positions of AE sensors and the layout paths of optical fibers can be precisely matched with the point-cloud model, so that monitoring results from different sensors correspond to the same geological unit, such as a specific fracture zone.

For time synchronization, "high-precision time stamps (error ≤ 1 μs)" can be used to achieve temporal alignment between transient AE signals and continuous fiber-optic strain. For noise suppression, adaptive wavelet-threshold filtering can be designed for specific underground disturbances, such as excavation vibration, so that while retaining microseismic precursor features, the signal-to-noise ratio of AE signals is raised to above 15 dB.

4) Coordinated optimization of "lightweight hardware-robust models" adapted to underground environments

To balance real-time performance and reliability, breakthroughs are needed at both the "hardware-algorithm" ends. On the hardware side, mining edge-computing modules should be developed (volume ≤ 100 cm^3, power consumption ≤ 10 W), integrating low-power AI chips to support real-time inference by lightweight models. On the algorithm side, "structured pruning + quantization-aware training" should be adopted, so that while compressing the model (reducing the volume to 1/10 of the original), high reliability is maintained through "key-feature distillation," such as retaining core precursor features including the microseismic b-value and abrupt strain increases.

5) Establish an industry-standard system of "human–machine collaboration-responsibility definition"

Promoting the safe application of AI in deep engineering requires improving standards and ethical frameworks: formulate the *Technical Specification for AI Monitoring and Early Warning of Deep Surrounding Rock*, clarifying data-acquisition requirements (e.g., microseismic events should record energy, location, and frequency), model-evaluation indicators (e.g., limits for missed-alarm and false-alarm rates in rockburst early warning), and human–machine collaboration procedures (e.g., after an AI warning, engineers must conduct a secondary confirmation in combination with geological-radar data); establish an "AI safety responsibility traceability mechanism," using blockchain to record the sources of model-training data and the parameters of the inference process, and clarifying the boundaries of responsibility for developers (model-accuracy responsibility) and the project side (data-quality responsibility); construct a "standard dataset for mine AI," including microseismic, optical-fiber, and point-cloud data as well as disaster cases under different geological conditions, thereby providing benchmarks for model comparison and validation.

To clearly present the correspondence between the domain-specific challenges above and targeted solutions, Table 4 systematically organizes the core content, providing a framework for the subsequent outlook section.

Table 4 Key challenges and future research directions for AI applications in deep tunnels

Tab. 4 Key challenges and future research directions for AI applications in deep tunnels

Key challenges (domain specificity)	Future research directions (targeted technologies)	Potential technical pathways
"Spatiotemporal heterogeneity" and "difficulty of acquisition" for small samples of deep disasters	Mechanics-simulation and real-data dual-driven sample generation	FLAC3D/3DEC and other numerical simulations to generate synthetic samples; federated transfer learning; SMOTE oversampling optimization
"Disconnection" between AI models and rock-mechanics mechanisms	Explainable AI (XAI) coupled with mechanical mechanisms	Embed rock-mass constitutive equations in PINNs; visualize attention mechanisms; use SHAP to quantify the contribution of mechanical parameters
"Domain differences" and "spatiotemporal mismatch" in multi-source sensing data	Spatiotemporal alignment–noise suppression fusion for multiscale sensing	Unified laser point-cloud coordinates; high-precision timestamp synchronization; adaptive wavelet-threshold filtering
The contradiction between "resource constraints" and "real-time performance–reliability" in underground edge computing	Collaborative optimization of lightweight hardware and robust models	Mining edge-computing modules; structured pruning + feature distillation; TensorFlow Lite optimization

Key challenges (domain specificity)	Future research directions (targeted technologies)	Potential technical pathways
"Strong constraints" on safety responsibility in deep engineering and the "gap" in industry standards	Industry norms for human-machine collaboration and responsibility definition	*Technical Specification for AI Monitoring and Early Warning of Deep Surrounding Rock*; blockchain-based responsibility traceability; standard AI dataset for deep engineering

5 Conclusions

This study systematically reviews the research progress of artificial intelligence in the dynamic response of surrounding rock in deep tunnels, constructs an intelligent closed-loop framework of "perception–prediction–control," and comprehensively organizes the key technologies and application practices of AI in multi-source monitoring, disaster prediction, and support control (Fig. 7). The main conclusions are as follows.

Figure 7 diagram text

- **AI support**
  - **Intelligent perception**
    - AE
    - MS
    - Optical-fiber sensing
    - Laser scanning
    - Geological radar
  - **Intelligent prediction**
    - Core
    - CNN-LSTM
    - PINN
    - GAN
    - 3D-CNN
  - **Intelligent control**
    - Application system
    - Adaptive support
    - Digital twin (DT)
    - Deep reinforcement learning (DRL)
  - **Future directions**
    - XAI
    - Data generation
    - Fusion technology

    * Model compression
    * Standards and ethics
- **Common foundation:** multi-source data fusion, small-sample learning, edge computing

Figure 7 AI technology research on the dynamic response of deep tunnel surrounding rock: key challenges and future directions

Fig. 7 AI technology research on dynamic response of deep tunnel surrounding rock: key challenges and future directions

1) An integrated "perception–prediction–control" framework is proposed: the application pathways of AI in the dynamic response of deep surrounding rock are systematically integrated, realizing closed-loop intelligent regulation and control from data perception and state prediction to decision-making control, and breaking through the limitations of traditional experience-driven modes.

2) A multiscale intelligent perception system is constructed: a "point–line–surface–volume" multi-source sensing architecture is innovatively proposed, integrating multimodal data such as AE/MS, optical fiber, laser point clouds, and geophysical imaging, thereby significantly improving the accuracy of surrounding-rock state identification and the capability of spatial coverage.

3) Disaster prediction is promoted from experience toward data–mechanism fusion: intelligent prediction models for typical disasters such as rockburst, impact ground pressure, large deformation, and zonal fracturing are systematically reviewed. The advantages of algorithms such as PINN, CNN-LSTM, and STGNN in multi-parameter fusion and time-series modeling are highlighted, improving the generalization capability and physical interpretability of prediction models.

4) Support control advances from "parameter calibration" to "learning control" : by introducing NN-PID, deep reinforcement learning, and digital-twin closed-loop control strategies, the adaptability and robustness of support systems are significantly improved, supporting intelligent construction and active risk prevention and control in deep tunnels.

5) Core challenges and key breakthrough directions are clarified: current AI applications in deep engineering still face challenges such as small-sample generalization, multi-source data fusion, and the balance between real-time performance and reliability. In the future, key efforts should focus on synthetic data generation (GANs), explainable AI (XAI), edge-computing model compression, and other technologies, while simultaneously establishing "human–machine collaboration" audit mechanisms and industry standards.

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Note: Figure translations are in progress. See original paper for figures.