Rockburst prediction using artificial intelligence techniques: A review

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Abstract

Rockburst is a phenomenon characterized by the sudden, catastrophic failure of rock masses that occurs in deep underground environments or regions with high tectonic stress during excavation. Rockburst disasters pose serious threats to human life and property, national energy security, and broader societal interests, making accurate prediction of rockburst events critically important. Traditional rockburst prediction methods have yet to yield sufficiently effective predictive capabilities, and research on rockburst mechanisms currently faces significant challenges.

With the rapid development of artificial intelligence (AI) techniques in recent years, an increasing number of experts and scholars have begun to introduce AI into the study of rockburst mechanisms. In previous work, some researchers have attempted to review the application of AI techniques in rockburst prediction; however, these studies either do not focus specifically on AI-based rockburst prediction or fail to provide a comprehensive overview.

Building on the advantages of extensive interdisciplinary research and an in-depth understanding of AI techniques, this paper presents a comprehensive review of rockburst prediction methods that leverage AI. First, it introduces relevant definitions of rockburst and its associated hazards. Then, it summarizes the applications of both traditional prediction methods and AI-based approaches to rockburst prediction, with particular emphasis on the respective advantages and limitations of each. Finally, it synthesizes the strengths and weaknesses of AI-based prediction methods, outlines future research trends to address existing challenges, and proposes directions for improvement to promote the advancement of this field and better meet emerging practical demands.

Full Text

Preamble

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Rockburst is a phenomenon where sudden, catastrophic failure of the rock mass occurs in underground deep regions or areas with high tectonic stress during the excavation process. Rockburst disasters endanger the safety of people's lives and property, national energy security, and social interests, making accurate rockburst prediction critically important. Traditional rockburst prediction has not yielded an effective prediction method, and the study of rockburst mechanisms faces a dilemma. With the development of artificial intelligence (AI) techniques in recent years, more experts and scholars have begun introducing AI techniques into rockburst mechanism studies. Previous research has seen several attempts to summarize AI applications in rockburst prediction, but these studies either lack specific focus on AI technique reviews or fail to provide comprehensive coverage. Drawing on extensive interdisciplinary research experience and deep understanding of AI techniques, this paper conducts a comprehensive review of rockburst prediction methods leveraging AI techniques. First, we introduce pertinent definitions of rockburst and its associated hazards. Subsequently, we summarize applications of both traditional prediction methods and AI-based approaches for rockburst prediction, emphasizing the respective advantages and disadvantages of each. Finally, we summarize the strengths and weaknesses of AI-based prediction methods, forecast future research trends to address existing challenges, and propose improvement directions to advance the field and meet emerging demands effectively.

1. Introduction

The earliest recorded foreign rockburst incident dates back to 1738, when a rockburst accident occurred in the British South Stafford Coalfield tin mine. Subsequently, rockburst accidents in coal mines worldwide have been observed periodically, drawing attention to the phenomenon and prompting in-depth research. However, no consensus exists among researchers regarding the definition of rockburst. In 1965, Cook proposed that rockburst involves the violent and uncontrolled release of energy stored in rock [?]. Later, in 2007, He et al. defined rockburst as a nonlinear kinetic phenomenon characterized by the sudden release of significant energy along the rock' s free surface during excavation processes [?]. In 2021, Farhadian defined rockburst as an immediate kinetic instability phenomenon occurring during deep or high-stress area excavation unloading conditions, resulting in immediate dynamic instability [?].

With continuous development of human society, demand for resources has risen sharply, leading to increased depth and frequency of coal mining each year and consequently resulting in more rockburst accidents. Records indicate that the number of rockburst incidents worldwide has exceeded 10,000. Specifically, from 1910 to 1989, 5,441 rockburst accidents were reported in German Ruhr coal mines, while in Fushun Shengli coal mines, such occurrences surpassed 5,000 from 1939 to the present. Chinese mines experienced a significant number of rockburst incidents, with 13,000 cases recorded from 2001 to 2007, causing over 16,000 casualties [?, ?]. Moreover, coal has consistently served as China' s primary energy source, accounting for over 70% of national energy consumption [?]. Over the period from 1949 to 2015, more than 60 billion tons of coal were extracted in China, tragically resulting in over 270,000 deaths from accidents, with approximately 40% attributed to rockburst disasters. Presently, rockburst incidents have impacted 142 mines across 20 provinces, signifying a grave and concerning situation. Fig. 1 [FIGURE:1] illustrates the global distribution of mines susceptible to rockburst [?].

This prevalence demonstrates that countries worldwide face this problem collectively. Rockburst incidents inflict significant damage on social and economic interests, threaten national energy security, and jeopardize people' s lives and property. Therefore, research on rockburst mechanisms and prediction has become urgent, possessing profound practical significance and value.

Prior investigations have seen scholars endeavor to summarize AI technique utilization in rockburst prediction, but these works exhibited either insufficient specialization in AI applications or lacked comprehensiveness. In the future, AI techniques will increasingly emerge as a pivotal branch, gaining greater prominence and popularity. Drawing on extensive cross-disciplinary research experience and deep understanding of AI techniques, this paper offers a comprehensive overview of AI applications in rockburst prediction. We consolidate findings from collaborative research among experts in both rockburst and AI fields to enhance comprehension for researchers interested in employing AI techniques for rockburst prediction. Section One delineates rockburst definition, elucidates associated perils, and underscores prediction significance. Section Two briefly discusses traditional rockburst prediction methods and their limitations, prompting exploration of AI techniques as an alternative solution. Section Three delves into AI technique applications in rockburst prediction, providing comprehensive analysis of strengths and weaknesses inherent in each prediction method category, accompanied by brief descriptions of relevant models. Section Four overviews strengths and weaknesses of contemporary AI technologies applied in rockburst prediction and delineates prospective applications. Lastly, the concluding section encapsulates key findings and insights derived from this paper.

2. Traditional rockburst prediction methods

Since rockburst phenomenon studies commenced in 1960, understanding has gradually increased, leading to the development of certain prediction methods. Over the years, traditional rockburst prediction methods have been extensively researched and applied, demonstrating some efficacy. These methods have significantly contributed to safeguarding mineral resources and ensuring people' s lives and property safety. Traditional rockburst prediction methods can be classified into two categories: short-term prediction and long-term prediction [**?**]. The categorization chart of traditional prediction methods appears in Fig. 2 [FIGURE:2]. Short-term prediction is primarily utilized during the engineering process to promptly identify rockburst potential, facilitating more efficient production organization and minimizing serious accident risk. Long-term prediction is mainly employed during the engineering design stage to proactively avoid regions with high rockburst probability, mitigating potential hazards in the construction phase beforehand and reducing future construction complexities.

2.1. Short-term prediction

Short-term rockburst prediction methods mainly consist of microseismic method, acoustic emission method, microgravity method, drill chip method, infrared thermal imaging method, electromagnetic radiation method, and other techniques, all falling under monitoring technology. Monitoring technology enables real-time monitoring of relevant parameters in the current environment, providing accurate depiction of rockburst mechanisms and facilitating timely risk assessment.

The microseismic method predicts rockburst based on the characteristic that rockburst is accompanied by microseismic precursor information during the gestation process [**?**]. The number of microseismic events reaches maximum value when rockburst occurs, and this method predicts by analyzing collected signals and judging location, number, released energy, and other characteristics of microseismic events. Feng et al. used microseismic monitoring technology to study deeply buried tunnels of Jinping II hydropower station, classifying rockburst into instantaneous and time-lagged types according to occurrence timing [?, ?]. The acoustic emission method predicts rockburst through frequency and energy analysis [?]. During rockburst occurrence, due to rock force instability and energy release, part of the energy propagates outward in wave form, producing acoustic emission phenomena. By analyzing collected acoustic emission parameters, rock stability can be determined to predict rockburst. Miao et al. (2009) analyzed spectral characteristics of acoustic emission from indoor simulated granite rockburst, concluding that high-frequency low amplitude characterizes the initial loading stage, low-frequency high amplitude characterizes the rockburst stage, and the amount of acoustic emission signals in the rockburst stage is much larger than in the initial loading stage. Subsequently, He et al. (2015a) completed indoor transient rockburst simulation tests of granite, analyzing acoustic emission signals in time and frequency domains to determine change rules of spectral characteristics under simulation tests. When rock is damaged, it breaks atomic equilibrium at the damage site and generates charge movement, producing electromagnetic radiation [?]. Qiu et al. concluded that sudden, discrete low-frequency electromagnetic radiation is very sensitive to rockburst, and rockburst precursors can be observed through increasing signals representing coal-rock fissures and high signals lasting for a period [?].

These methods study and predict rockburst by utilizing rock parameters and characteristics acquired through monitoring. During project execution, rockburst monitoring results play a crucial role in guiding construction programs and supporting measures. In the future, various monitoring technologies can be combined to accurately extract valuable information from vast amounts of collected data.

2.2. Long-term prediction

Long-term rockburst prediction methods mainly include rockburst propensity judgment, theoretical research method, and numerical simulation technology. Rockburst propensity judgment is generally used in investigation and design stages, where rock sampling at investigation sites and experimental analysis of specimens determine regional rockburst occurrence probability. Rockburst propensity judgment indexes mainly include brittleness coefficient, deformation brittleness index, residual elastic energy index, and effective ejection energy index [?]. The theoretical research method is based on various aspects of strength theory, energy theory, stiffness theory, energy perturbation theory, blasting reliability theory, and other relevant theories. These theories analyze rockburst mechanisms and classification, providing comprehensive theoretical foundations for prediction. Numerical simulation technology is a cost-effective tool with advantages such as high safety and low cost. Numerical methods can mitigate the necessity for extensive experimentation [?]. Consequently, it finds extensive application in rockburst assessment and prevention. Numerical simulation is mainly divided into continuous medium method, discontinuous method, and hybrid method [?]. Using various numerical methods from different dimensions can provide more information and deepen understanding of rockburst mechanisms and damage mechanisms.

Researchers have conducted numerous experiments using traditional rockburst prediction methods and in-depth investigations into rockburst mechanisms, yielding rich research results. However, rockburst occurrence is complex and sudden, affected by many complex factors including rock structure, topography, geomorphology, crustal stress, among others. The interaction between various factors has not yet been clearly studied. With deepening research, traditional rockburst prediction methods exhibit greater limitations in practice, and we have not found a very effective prediction method. Based on this, some researchers have tried applying artificial intelligence techniques to this field to predict rockburst more accurately.

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3. Rockburst prediction methods based on artificial intelligence techniques

With continuous advancement of technology in human society and rapid development of computer technology, artificial intelligence has consequently emerged. The discipline of artificial intelligence was inaugurated when McCarthy, Minsky, and other scientists first proposed the concept of "Artificial Intelligence" at the Dartmouth College meeting in the United States in 1956. Since then, AI has undergone six development stages: initiation, reflection, application, downturn, stability, and rapid growth. Fig. 3 [FIGURE:3] shows AI evolution. These stages have witnessed crucial breakthroughs in algorithms, arithmetic, and data analysis, significantly influencing research in various fields and propelling their progress.

In the rockburst domain, researchers actively explore fusion of different AI techniques with rockburst prediction, achieving encouraging results. Adequate rockburst information provides essential groundwork for comprehensive understanding of its characteristics and underlying mechanisms, as well as for achieving more accurate predictive standards [?]. Therefore, many scholars collect and analyze various rockburst data, using engineering samples and rockburst cases for validation when applying AI techniques for prediction. Fig. 4 [FIGURE:4] illustrates the overarching process of rockburst prediction employing AI techniques, encompassing seven key stages: rockburst data acquisition, data preprocessing, model selection, model training, model testing, model tuning, and eventual prediction.

AI technology applications in this area can be categorized into three main aspects: data mining methods, traditional machine learning methods, and deep learning methods. Fig. 5 [FIGURE:5] depicts classification of rockburst prediction methods based on AI techniques.

3.1. Data mining methods

Data mining integrates diverse disciplines to swiftly analyze vast datasets and extract implicit information. By employing these methods, interrelationships among factors influencing rockburst occurrences can be examined, consequently enhancing prediction accuracy.

Data mining was first proposed at the 11th International Joint Conference on Artificial Intelligence in 1989. In 2000, Ma et al. (2000) used data mining to extract twelve rules for risk assessment models to improve prediction accuracy. In 2008, Ge and Feng (2008) employed Adaptive Boosting (AdaBoost), a novel data mining technique in conjunction with artificial neural network to address constraints inherent in conventional neural network models, enhancing rockburst instance classification precision by up to 50% or more compared to singular neural networks. In 2015, He et al. (2015b) used 139 indoor rockburst test data and applied data mining methods to establish prediction models for maximum rockburst stress (σ_{RB}) and rockburst risk index (I_{RB}), improving prediction accuracy. In 2017, Ribeiro e Sousa et al. (2017) used various data mining methods in rockburst databases to establish different prediction models, each demonstrating high validation accuracy. In 2019, Shirani and Taheri (2019) studied three novel data mining algorithms—genetic algorithm-based emotional neural network (GA-ENN), C4.5 algorithm, and gene expression programming (GEP)—for rockburst prediction, conducting comparative analysis with five conventional input criteria to examine individual parameter impacts on prediction outcomes. In 2019, Zhang et al. (2019a) designed and implemented an automatic analysis system for rockburst test big data, using big data visualization technology to reveal rockburst mechanisms, laying theoretical and experimental foundations for rockburst mechanism study using big data technology. In the same year, Zhang et al. (2019b) proposed a rockburst experimental data compression storage algorithm based on big data technologies and cloud platforms, exhibiting superior performance compared to mainstream compression software like WinRAR and fundamentally addressing big data storage challenges in rockburst mechanism studies. This marked the transition of data mining methods into the big data era. In 2022, Ahmad et al. (2022) used Adaptive Boosting classifier to predict rockburst intensity levels, achieving 100% accuracy and verifying model accuracy through two real rockburst cases. In 2023, Roy et al. (2023) introduced two new database technologies to monitor cumulative rockburst damage impact, proposing a rockburst damage index and rockburst clustering index to provide better data sources and evaluation criteria for subsequent predictions.

Data mining methods successfully address challenges of extracting information from rockburst data. These methods effectively handle large datasets, enhancing prediction accuracy to a certain extent. However, data mining methods heavily rely on high-quality data samples. Due to nonlinear characteristics of rockburst phenomena, data often becomes mixed and prone to anomalies and loss, leading to biased information extraction that consequently affects prediction results.

Figure 6

Figure 1: Figure 6

3.2. Traditional machine learning methods

Addressing the nonlinear nature of rockburst phenomena, scholars increasingly apply machine learning techniques. Noteworthy examples include support vector machine (SVM), k-nearest neighbor (KNN), bayesian network (BN), logistic regression (LR), random forest (RF), and decision tree (DT), which have proven effective in rockburst prediction and classification.

3.2.1. Single algorithm In 2002, Feng and Zhao (2002) established three different SVM rockburst prediction models applied to tunnels, VCR quarries, and carbonized quarries, obtaining more accurate prediction results. In 2005, Zhao (2005) used 13 rockburst instances as samples to classify rockburst using SVM, predicting not only rockburst occurrence but also deriving rockburst degree. In 2018, Pu et al. (2018) trained SVM with 108 sets of rockburst data as training and test samples, applying the trained model to kimberlite rockburst prediction with results matching actual conditions. In 2019, Pu et al. (2019b) collected 246 sets of rockburst case data, processed them using t-SNE downscaling and clustering methods, then fed processed data into a support vector classifier for prediction with results matching observed rockburst events. In 2022, Jin et al. (2022) selected six indicators as input for rockburst prediction methods based on Nonlinear-SVM. After randomly selecting multiple rockburst cases for data standardization, cross-validation, hyperparameter optimization, and other operations, prediction accuracy of test samples reached high levels. The basic schematic of SVM for nonlinear data is shown in Fig. 6

. The fundamental SVM concept involves seeking the optimal separating hyperplane that correctly classifies the training dataset while maximizing geometric margin. SVM employs a kernel function to map data from lower to higher-dimensional spaces, facilitating identification of a hyperplane that effectively separates all classes. The radial basis function, also known as the Gaussian kernel function, constitutes a widely employed kernel function defined by:

$$K(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right)$$

where x_i and x_j are the input vector and centre vector, γ is a monotone function, and $\| \cdot \|$ denotes Euclidean distance between them.

In 2008, Su et al. (2008) proposed a new method based on KNN case-based reasoning that avoids establishing complex mathematical equations or models. Validation results from South African VCR mining field rockburst database and tunnel rockburst database reflect feasibility and reliability, with successful engineering application. Fig. 7 [FIGURE:7] delineates the KNN algorithm decision-making process. The KNN algorithm classifies data points by measuring distances between different feature values. If a sample in feature space has the majority of its k-nearest neighbors belonging to a certain category, the sample is classified into that category. In KNN algorithm, three frequently employed distance metrics include Manhattan, Euclidean, and Minkowski distances. The standard Euclidean distance formula is:

$$d(x_i, x_j) = \sqrt{\sum_{r=1}^{n} (x_i^r - x_j^r)^2}$$

where x_i^r denotes the r-th attribute value of sample x_i, and x_j^r denotes the r-th attribute value of sample x_j.

In 2010, Gong et al. (2010) established a bayesian discriminant model for rockburst prediction based on bayesian discriminant analysis theory, providing a new prediction approach. In 2017, Li et al. (2017) proposed a new rockburst prediction application based on bayesian network using tree-enhanced parsimonious bayesian classifiers. In 2022, Liu et al. (2022) collected 473 sets of rockburst cases to construct a naive bayes (NB) probabilistic hierarchical prediction model achieving 84.47% prediction accuracy, with model prediction accuracy in Paomashan No. 1 Tunnel rockburst section reaching 85.71%. In 2023, Mao et al. (2023) proposed a prediction model based on dynamic bayesian network (DBN), self-validated by 114 sets of rockburst data, 6-fold cross-validation, and ROC curve analysis, and validated using two cases, with rockburst early warning accuracy reaching 81.82% and 83.33% respectively.

In 2010, Heal (2010) employed a dataset comprising 254 sets of rockburst data encompassing five key indicators: stress concentration factor, excavation span, support system capacity, geological structure factor, and peak velocity of mass. He introduced the rockburst susceptibility index, employing logistic regression algorithm to calculate rockburst occurrence likelihood. In 2018, Li and Jimenez (2018) proposed a novel prediction method using logistic regression classifiers. The method utilized large amounts of data to train the model using five input parameters: tunnel depth (H), maximum tangential stress (MTS), elastic energy index (Wet), uniaxial compressive strength of rock (USC), and uniaxial tensile strength of rock (UTS). Results showed that rockburst probability increases with excavation depth. Probabilities denote relative relationships between categories. When probability of one class surpasses another, that outcome is predicted. The dependent variable in linear regression falls within range $(-\infty, +\infty)$. Thus, by establishing a mapping relationship converting these values into probabilities within range $(0, 1)$, transition from linear regression to classification problems can be effectively addressed. Fig. 8 [FIGURE:8] shows the sigmoid function in logistic regression. The logistic function is continuous, arbitrarily order-derivable with value domain $(0, 1)$. The sigmoid function is formulated as:

$$s(x) = \frac{1}{1 + e^{-x}}$$

In 2013, Dong et al. (2013) used RF model to train 36 groups of rockburst samples from domestic and international sources, testing the model with another 10 groups with results matching actual records. RF method was compared with support vector machine and artificial neural network, with misjudgment rates of 0%, 10%, and 20% respectively. Yang et al. (2017) established a RF model for rockburst grade prediction in 2017 achieving 97% prediction accuracy. In 2022, Liu and Zhou (2022) used a modified scatterplot matrix to determine the rockburst prediction index system and introduced optimized RF algorithm with prediction model accuracy reaching 92.6%. The schematic representation of random forest is depicted in Fig. 9 [FIGURE:9]. RF utilizes decision trees as fundamental building blocks, amalgamating numerous decision trees to construct the model. During prediction, each decision tree casts a vote, and the final prediction is determined by the category receiving most votes.

In 2016, Chen et al. (2016) selected rock stress coefficient, rock brittleness coefficient, and elastic energy coefficient as evaluation indexes, establishing a rockburst intensity prediction model using decision tree with test sample prediction accuracy of 86.7%. Ghasemi et al. (2020) proposed a new C5.0 decision tree classifier application for rockburst prediction in 2020, establishing separate models for rockburst prediction and intensity prediction. In 2021, Ahmad et al. (2021) compared accuracy of J48 and random tree models for rockburst prediction using four parameters: maximum tangential stress of surrounding rock σ_θ (MPa), uniaxial compressive strength σ_c (MPa), uniaxial tensile strength σ_t (MPa), and strain energy storage index W_{et}, finding accuracies of 92.857% and 100% respectively. In 2022, Long et al. (2022) proposed a rock rupture signal recognition method using decision tree classification algorithm, selecting and analyzing 248 sets of data in Asher copper mine with recognition accuracy of 98.3%. In 2023, Owusu-Ansah et al. (2023) utilized decision tree to propose a DT prediction model for each rock type (DT-RT) and a single DT prediction model applicable to all rock types (Unique-DT), comparing them with RF, KNN, and SVM algorithms and demonstrating DT effectiveness in rockburst prediction based on depth, elastic energy index, and strength parameters. Fig. 10 [FIGURE:10] shows decision tree structure. Decision tree is a hierarchical tree structure where each leaf node signifies a specific category, while inner nodes including root node correspond to attribute divisions that segment the dataset into subsets based on varying attribute values.

In 2020, Tang and Xu (2020) introduced nine machine learning algorithms to establish nine rockburst prediction models with higher accuracy than widely used theoretical principles. In 2021, Zhang et al. (2021) conducted indoor rockburst experiments using Laizhou granite, and based on big data visualization and analysis of collected acoustic emission signals, initially obtained acoustic emission characteristic laws of Laizhou granite, laying foundations for subsequent big data technology combined with AI technology for accurate rockburst prediction. In 2022, Kidega et al. (2022) employed uniaxial compressive strength (UCS), uniaxial tensile strength (UTS), maximum tangential stress (MTS), excavation depth (D), stress ratio (SR), and brittleness coefficient (BC) as predictors in gradient boosting machine model. They systematically applied diverse combinations of input variables and implemented 3-fold cross-validation resampling to train multiple models, achieving exceptional performance with classification accuracy of 98%, Kappa coefficient of 93%, and Sensitivity of one.

Table 1 shows an ensemble of single algorithms from traditional machine learning-based rockburst prediction methods.

3.2.2. Integrated algorithms Incorporating multiple machine learning algorithms through fusion and integration can enhance rockburst prediction efficiency beyond single traditional machine learning algorithms. Consequently, researchers have explored fusing multiple algorithms to develop improved rockburst prediction models.

In 2016, Dong et al. (2016) utilized fisher classifiers, naive bayesian classifier, and logistic regression for mine seismic event and explosion discrimination, showing good discrimination ability for specific mines. In 2021, Papadopoulos and Benardos (2021) used 49 rockburst instances as a dataset, generating new data using synthetic minority oversampling technique (SMOTE) and training five algorithmic models (decision tree, naive bayes, k-nearest neighbor, random forest, logistic regression), with results showing SMOTE improved overall metrics by 5-10%. In 2021, Wojtecki et al. (2021) conducted model training for sixteen distinct machine learning algorithms including LR, DT, RF, and others using datasets from underground mining excavation sites associated with 13 diverse coal seams. After analyzing recall rate and false positives, multilayer perceptron classifier, decision tree, random forest, and gradient boosting models exhibited superior effectiveness. In 2021, Ke et al. (2021) employed evolutionary random forest to identify crucial input features, then used forward, backward, particle swarm optimization (PSO), and evolutionary algorithms to optimize naive bayes model for prediction, finding PSO the most suitable optimizer for enhancing naive bayes model accuracy. In 2021, Sun et al. (2021) combined random forest and firefly algorithm (FA) into a novel integrated classifier, showing FA effectively optimizes RF hyper-parameters and manifests better accuracy than previous models. In 2021, Wang et al. (2021) proposed three rockburst prediction methods by measuring six rockburst features, demonstrating through comparison that integrated methods offer feasible solutions. In 2022, Wojtecki et al. (2022) employed neural network, decision tree, random forest, gradient boosting, and extreme gradient boosting to forecast rockburst hazard in Upper Silesian Coal Basin, with each model demonstrating approximately 80% predictive accuracy. In 2022, Ullah et al. (2022) proposed a three-step rockburst prediction mechanism using t-distributed stochastic neighborhood embedding for dimensionality reduction, k-means clustering for classification, and XGBoost as an efficient prediction model for rockburst warning systems. In 2022, Kamran et al. (2022) proposed the ISOMAP + FCM + KNN model using isometric mapping (ISOMAP) for dimensionality reduction, fuzzy c-means algorithm (FCM) for classification, and KNN for prediction, achieving 96% accuracy on test datasets. In 2022, Liu et al. (2022) proposed a 3-group Stacking integration algorithm, solving difficulties of traditional Stacking algorithms in accepting feature information and selecting meta-models. In 2022, Tan et al. (2022) analyzed datasets using Yeo-Johnson transform and k-means SMOTE for normalization and balance, applied 15 machine learning algorithms for pre-training, and finally proposed Stacking and Voting rockburst intensity prediction methods. In 2023, Yang and Wei (2023) constructed a rockburst grade prediction model based on SSA-SVM-AdaBoost algorithm under ReliefF-Pearson feature selection, showing this feature selection method more effective and the proposed model achieving 87.5% prediction accuracy—31.25% higher than SVM alone. In 2023, Xia et al. (2023) used random forest, support vector machine, adaptive boosting tree, gradient boosting tree, and extreme gradient boosting tree to construct and compare models, showing data preprocessing and considering hole diameter indicators help improve prediction results. In 2023, Liu et al. (2023) collected 1,080 datasets covering various rock types, developing a stacking model combining tree-based model and linear regression to predict uniaxial compressive strength (UCS). Experimental findings indicated the stacking model exhibited outstanding predictive performance for UCS in metamorphic and igneous rocks, while tree-based models were more appropriate for sedimentary rocks.

Table 2 shows the ensemble of integrated algorithms for rockburst prediction methods based on traditional machine learning.

Traditional machine learning methods, compared to data mining methods, more effectively handle mixed data samples and are well-suited for addressing nonlinear rockburst occurrences, highlighting inherent advantages. Enhancing rockburst prediction model accuracy can be achieved through feature extraction from rockburst data followed by model training. Nevertheless, feature extraction in traditional machine learning primarily depends on manual efforts, tailored specifically for simple and concrete rockburst data, and is not universally applicable when rockburst characteristics are unclear.

3.3. Deep learning methods

Exponential growth in data volume and advancements in GPU technology have significantly enhanced arithmetic power, revolutionizing deep learning. This advancement facilitates automatic feature extraction, particularly beneficial when rockburst features are less discernible. Consequently, researchers have progressively incorporated deep learning methodologies into rockburst prediction. Employed techniques include artificial neural network (ANN), self-organizing map (SOM), back propagation neural network (BPNN), ant colony clustering algorithm (ACCA), genetic algorithm (GA), and other integrated deep learning models.

In 2002, Chen et al. (2002) built a neural network model for rockburst prediction, selecting 13 examples for training with results proving method effectiveness. In 2020, Zhou et al. (2020) combined artificial neural network and artificial bee colony to improve rockburst prediction accuracy and generalization ability, with RMSE and R^2 between predicted and actual values of 0.1281 and 0.9656 respectively. Then in 2021, they combined artificial neural network and firefly algorithm [**?**] to construct a relationship model between rockburst risk and influencing factors, effectively validated on 196 reliable rockburst case datasets. Fig. 11 [FIGURE:11] shows the ANN model diagram. The ANN model comprises an input layer, hidden layers, and output layer. The input layer contains numerous neurons designed to receive input data. Hidden layers establish intricate mapping relationships between input and output data. The output layer, positioned at the network end, generates model output based on learned patterns.

In 2004, Zhou and Gu (2004) proposed a fuzzy self-organized neural network model using GIS technology through interdisciplinary crossover to establish a multi-source spatial database, enriching rockburst prediction methods. In 2020, Shirani et al. (2020) used self-organized mapping and fuzzy c-mean method to study relationships between rockburst-related parameters, choosing five intensity-based empirical criteria for validation. In 2021, Yang et al. (2021) proposed a model based on self-organized feature mapping neural network, simplifying the prediction process index system and providing a new method for rockburst grade prediction. In 2024, Sun et al. (2024) introduced a rockburst precursor inversion method using self-organizing mapping neural network, validating efficacy through experimentation in three distinct rockburst trial sets. Results demonstrate that rockburst AE precursor signals comprise signals characterized by long duration, high energy, low average frequency, high energy amplitude, and low peak frequency.

In 2007, Shi et al. (2007) used BPNN to predict the 12,200-m unexcavated auxiliary cavern section of a hydropower station in Southwest China, with results showing method feasibility. In 2017, Zhang et al. (2017) intelligently identified rockburst precursor signals by BPNN, identifying 16,384 randomly selected acoustic emission signals of unknown types with correct identification rates of 99.54%, 96.53%, and 98.95% for first and second types of non-rockburst precursor feature signals and rockburst precursor feature signals respectively. In 2019, Sun (2019) improved traditional BP algorithm operation problems by optimizing the BP algorithm and establishing a MATLAB-BP prediction model containing nine main prediction indexes.

In 2010, Gao introduced the ant colony-based clustering algorithm into rockburst prediction for the first time to solve limitations in rockburst clustering problems [**?**], with this bionic optimization algorithm effectively verified in several engineering examples. Subsequently in 2012, Gao and Zhang (2012) proposed the screening ant colony clustering algorithm, providing a new rockburst prediction method by improving computational efficiency over traditional ant colony clustering algorithm.

In 2012, Zhang et al. (2012) used GA to optimize radial basis function (RBF) neural network parameters and established GA-RBF model for rockburst intensity prediction. In 2017, Li et al. (2017) introduced GA to optimize multi-metrics based extreme learning machines (ELM) model to obtain GA-ELM model for rockburst prediction with maximum relative error not exceeding 5%. In 2021, Xie et al. (2021) proposed XGB model optimized based on GA, with prediction accuracy ranging from 80.95 to 88.89, higher than original XGB, SVM, DT, and Bayesian models.

In 2013, Adoko et al. (2013) explored five distinct models utilizing fuzzy inference systems and adaptive neuro-fuzzy inference systems, with experimental findings conclusively demonstrating significant utility of fuzzy inference systems in predicting rockburst intensity.

In 2013, Jia et al. (2013) used PSO algorithm to optimize general regression neural network (GRNN) parameters, solving topology determination difficulties with simple coding. The model predicted Cangling Tunnel and Dongguashan Copper Mine with maximum extreme difference of prediction results not exceeding 0.02. In 2013, Yan et al. (2013) established particle swarm optimization partial least squares logistic curve model, solving variable multicollinearity and function parameter optimization problems.

In 2019, Wu et al. (2019) addressed variable uncorrelation of probabilistic neural network (PNN) by using principal component analysis (PCA) for data preprocessing, establishing PCA-PNN model to predict rockburst intensity. Compared with RF and SVM models, PCA-PNN showed better prediction results and faster convergence speed. In 2022, Zhang constructed a rockburst parameter monitoring platform, established probabilistic neural network, and optimized Faster R-CNN model, with results showing prediction error rate in training and test sets more than 0.3% lower than original probabilistic neural network model [?]. In 2023, Jin et al. (2023) proposed improved projection pursuit (IPP) and probabilistic neural network (PNN) models for rockburst classification. After applying IPP-PNN model to rockburst prediction of Zhuling Tunnel section 11-19, prediction accuracy improved from 66.67% to 100%, providing reference for Sichuan-Tibet Railway construction.

In 2020, Tian and Meng (2020a) improved Adam algorithm and applied it to deep neural network (DNN) rockburst prediction model for Jinping II hydropower station and Dongguashan copper mine, achieving over 95% prediction accuracy and providing scientific basis for similar projects. In the same year, Tian et al. (2020b) established DA-DNN model achieving 98.3% prediction accuracy when setting training iterations to 60 and learning samples to 231 groups. They established a database containing 301 rockburst engineering examples, comparing prediction accuracies of DA-DNN, IGSO-SVM, and RF-AHP-cloud models at 98.3%, 90.0%, and 85.0% respectively [?].

In 2020, Wilkins et al. (2020) harnessed extensive microseismic information datasets to train CNN, proving efficacious in identifying microseismic events in mining contexts, particularly significant for rockburst intensity prediction. Fig. 12 [FIGURE:12] shows a typical CNN schematic diagram. The CNN model comprises an input layer, convolutional layer, max pooling layer, multi-layer convolution and pooling, fully connected layer, and finally softmax output layer.

In 2021, Yin et al. (2021a) proposed a real-time rockburst intensity prediction model integrating CNN-Adam-BO algorithm, achieving 91.67% accuracy on test set with Kappa of 0.8392. Moreover, for minor and moderate rockburst cases, warnings could be issued 1.75 hours and 1 hour in advance respectively using CNN-Adam-BO model.

In 2021, Gong et al. (2021) introduced a DNN prediction model employing dropout technique and enhanced Adam algorithm, curating a dataset of 305 rockburst engineering cases as sample data with model accuracy exceeding 95%.

In 2021, Zhang et al. (2021) employed dynamic moving-window method with CNN to construct diverse prediction models including univariate, multivariate, and multivariate multi-step models, with predictive efficacy surpassing LSTM-based models across various metrics.

In 2021, Liu et al. (2021) proposed a CNN-LSTM model to predict rockburst state quantities, combining future hazard class calculated by PSO-GRNN model with future states of rockburst characteristic variables to achieve dynamic prediction.

In 2021, Yin et al. (2021b) built four integrated models—KNN-RNN, SVM-RNN, DNN-RNN, and KNN-SVM-NN-RNN—using ensemble learning superposition techniques. Results showed integrated models outperform single models in cases of data imbalance, solving single algorithm limitations in recognizing minority classes and representing a promising prediction method.

In 2022, Zhang et al. (2022) constructed a new D-P-Transformer rockburst prediction model by improving Transformer embedding structure, adopting sparse self-attention instead of self-attention, and employing distilling operations combined with multiple layer replicas. Validation on seven large-scale rockburst acoustic emission datasets experimentally proved model accuracy better than Transformer model.

In 2022, Li et al. (2022b) used Feedforward Neural Network (FNN) to construct rockburst prediction model, introducing Bayesian optimization to regulate FNN hyper-parameters and combining synthetic minority oversampling technique with Tomek Links to process the dataset, effectively improving accuracy.

In 2022, Li et al. (2022a) constructed and optimized Deep Forest (DF) algorithm for rockburst prediction, solving overfitting and hyperparameter adjustment problems of integrated models.

In 2023, Di et al. (2023) introduced an integrated warning methodology employing three signals—rockburst microseismic, acoustic emission, and electromagnetic radiation (MS-AE-EMR). The approach utilized LSTM-RNN to discern precursor signals, followed by CNN for predicting MS-AE-EMR signals, achieving 100% identification rate for rockburst risk and issuing warnings one to three days in advance.

In 2023, Li et al. (2023) devised a hybrid rockburst prediction model integrating BPNN and beetle antenna search algorithm. A total of 173 rockburst datasets were assembled, and after meticulous preprocessing involving outlier detection and SMOTE, predictive analysis achieved 94.3% accuracy.

Deep learning methods exhibit superior predictive capabilities compared to traditional machine learning. Their learning mechanisms are faster, facilitating easier data training and analysis. They enable automatic feature extraction without explicit input-output relationship knowledge, minimizing human intervention. Moreover, incorporation of numerous parameters and datasets allows more effective resolution of interactions among factors influencing rockburst occurrence, thereby elucidating authentic rockburst mechanisms and significantly enhancing prediction accuracy.

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4. Summary and outlook

After years of extensive research, understanding of rockburst breeding processes and occurrence mechanisms has significantly deepened. From traditional rockburst prediction methods to AI-based techniques, prediction accuracy has been considerably enhanced. Although AI-based rockburst prediction methods exhibit certain performance advantages, room for further improvement remains. Table 3 summarizes advantages and disadvantages of AI technique applications in rockburst prediction.

Existing studies in rockburst prediction have been conducted on limited data, leading to insufficient rockburst data and lack of training samples. Consequently, small data amounts hamper model ability to achieve high accuracy. Moreover, current computational power is inadequate to support large model training, representing a significant limitation for engineering applications. AI technique applications in rockburst prediction also exhibit drawbacks such as poor model generalization and extended training times, posing considerable challenges. Despite extensive efforts, a completely effective rockburst prediction method remains elusive. In light of these challenges, potential research directions to advance the field are outlined in Table 4 .

(a) Establishment of a large-scale, standardized rockburst database. The database would be a large-scale repository of worldwide rockburst data with unified standards, enabling researchers to access more representative information. Enhancing quantity and quality of input data is crucial for accurate rockburst prediction. By conveying comprehensive rockburst characteristics to training models, challenges of poor model generalization can be addressed, ensuring model applicability across various projects and enhancing safety measures. Thus, establishing a large-scale, standardized rockburst database becomes imperative in the big data era.

(b) Application of novel large model algorithms such as pre-training and continual learning. Researchers can initially pre-train rockburst prediction models on large datasets from the aforementioned database to enhance generalizability. Subsequent fine-tuning enables specific rockburst prediction tasks using smaller datasets. Before deployment in engineering applications, models require creation and training that might vary across projects. Pre-trained models boast larger scales and wider applicability, effectively reducing training time and enhancing suitability for engineering applications.

(c) Incorporation of continual learning methods. Continuous information flow enables rockburst prediction models to expand knowledge bases, mitigating forgetting issues encountered in deep learning models. This enhances learning efficiency and facilitates knowledge transfer to associated tasks. Consequently, rockburst prediction models obviate the need for training from scratch, addressing computational and storage resource wastage considerably. This not only enhances model applicability in engineering scenarios but also reduces prediction process time.

(d) Large arithmetic power and distributed training. Growing data volume necessitates augmented computational power to address prolonged model training duration. The future heralds an era of substantial AI computing power, and with AI industry expansion, computing power demand escalates. Supercomputers worldwide—such as the U.S. Oak Ridge National Laboratory' s Frontier, Japan' s Kobe Riken Center for Computational Science, and China' s Shenwei-TaihuLight—stand at the forefront of global supercomputer rankings. The rockburst prediction field should similarly leverage substantial computational power and multi-GPU setups for distributed training, thereby enhancing model training speed and precision.

In summary, future developments in rockburst prediction should focus on increasing data volume, enhancing model training methodologies, and augmenting computational power to improve prediction accuracy and efficiency.

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5. Conclusion

This paper begins by defining rockburst and outlining its hazards, followed by a review of traditional prediction methods. It then progresses to explore evolution of rockburst prediction methods, emphasizing those based on artificial intelligence techniques. The discussion includes examination of data mining, traditional machine learning, and deep learning methods currently applied in rockburst prediction. Finally, the paper summarizes integration of AI techniques in rockburst research and offers perspectives on future developments in this area.

Figure 13

Figure 2: Figure 13

CRediT authorship contribution statement

Yu Zhang: Writing –review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. Kongyi Fang: Writing –review & editing, Writing –original draft, Methodology, Investigation, Formal analysis, Conceptualization. Manchao He: Writing –review & editing, Supervision, Methodology, Investigation, Conceptualization. Dongqiao Liu: Writing –review & editing, Supervision, Methodology, Investigation, Conceptualization. Junchao Wang: Writing –review & editing, Visualization, Methodology, Investigation. Zhengjia Guo: Conceptualization, Investigation, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Figures

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