Advances in Computer, Signals and Systems (2025)
Clausius Scientific Press, Canada

DOI: 10.23977/acss.2025.090204
ISSN 2371-8838 Vol. 9 Num. 2

Application of Deep Learning in Mining Accident Prediction

Bin Li[1,a,*]

[1]*Yuanbaoshan Open-pit Coal Mine, Inner Mongolia Pingzhuang Coal Industry (Group) Co., Ltd., Chifeng City, 024076, Inner Mongolia, China*
[a]*17804766020@163.com*
[*]*Corresponding author*

Keywords: Mine Environment Modeling; Graph Neural Network; Accident Propagation Prediction; Spatiotemporal Graph Neural Network; Mining Safety Monitoring

Abstract: Accident prediction is crucial in the mining process, but existing methods have limitations in capturing the spatiotemporal correlation and dynamic changes of the mine environment, making it difficult to accurately predict the propagation path and impact range of accidents. To this end, this paper applies a graph neural network (GNN) model, constructs a graph structure based on the mine environment, and optimizes the accident propagation prediction algorithm to improve the accuracy and real-time performance of accident prediction. In view of the diversity of mine data, this paper constructs three main graph structures: sensor network graph (based on sensor data correlation), mine area topology graph (based on the interactive relationship between personnel, equipment and mine area units) and accident propagation path graph (based on accident trigger points and impact range). The edge weights of the sensor network graph are calculated by the Pearson correlation coefficient (PCC), the edge weights of the mining area topology graph are calculated by normalizing the number of interactions, and the edge weights of the accident propagation path graph are dynamically updated using the Gaussian decay model. In order to further improve the spatiotemporal modeling capabilities of accident prediction, this paper uses a spatiotemporal graph neural network (ST-GNN) combined with a graph convolutional network (GCN) for spatial information extraction, and a temporal convolutional network (TCN) for time series modeling. The experimental results show that the proposed GNN model has significantly improved the accident prediction accuracy, accident propagation path identification accuracy and response time. The accident prediction accuracy of ST-GNN (this study) is 92.3%, and the F1-score is 0.91, which is excellent. ST-GNN performs well in predicting accident propagation paths, can accurately capture the chain reaction of mine accidents, and provides strong support for mine safety management.

1. Introduction

Coal mining is a special operation. Unsafe behaviors of people and unsafe conditions of objects may lead to accidents, which may cause serious personal injury and property loss. Accident analysis and prediction are important guarantees for safety. The importance of the probability of occurrence of events at the top of the accident tree to system safety evaluation is unquestionable. Therefore, This paper proposes a mine accident prediction model based on spatiotemporal graph neural network (ST-GNN). By graphing the mine environmental data and modeling the spatiotemporal characteristics, it can effectively predict the occurrence of accidents and their propagation paths. Specifically, this paper first introduces the graph representation method of mine environmental data, including sensor network graph, mine area topology graph and accident propagation path graph. Then, a dynamic graph model is constructed by combining time series information to capture the propagation dynamics of accidents. Finally, ST-GNN is used for accident prediction.

This paper first introduces the background and research purpose of mine accident prediction, and proposes an innovative idea of using graph neural network (GNN) for accident prediction. Then, the paper describes in detail the graph representation method based on mine environment data, including sensor network construction, mine area topology map and accident propagation path modeling. Subsequently, combined with time series information, the paper applies the application of dynamic graph models in accident prediction and proposes a spatiotemporal graph neural network (ST-GNN) model. The following chapters present the experimental design and result analysis, focusing on comparing the performance of different models in terms of accident prediction accuracy, false alarm rate, missed alarm rate, and computational efficiency. Finally, the paper summarizes the contributions of the research and proposes directions for future research.

2. Related Work

As the safety requirements of the mining industry continue to increase, researchers are committed to improving the level of mine accident prediction and safety management by using machine learning and deep learning technologies. Javaid et al. used machine learning technology to analyze the causes of past coal mine accidents. They used TF-IDF (Term Frequency-Inverse Document Frequency) technology to extract features and trained a Voting Hybrid Classifier (VHC), which combines random forests, support vector classifiers, and logistic regression, and evaluated through soft voting [1]. In order to establish an effective coal mine water inrush prediction model, Ye et al. proposed a neural network prediction method based on the improved SMOTE (Synthetic Minority Over-sampling Technique) algorithm and Deep Belief Network (DBN). The results showed that the water inrush prediction accuracy was 94%[2]. In order to predict sick leave caused by accidents, Ramos et al. used the BERT (Bidirectional Encoder Representations from Transformers) model to represent text information, combined with numerical and binary variables extracted from the report, and input it into the Multilayer Perceptron (MLP) for prediction. Through cross-validation, the median accuracy of the model was 73.5% [3]. Masood et al. developed an automated algorithm based on monitoring displacement data to detect the beginning of slope acceleration and predict instability. The model adopts a five-stage audit method. When the analysis result is positive, it means that the slope is accelerating. The start time of acceleration is used to further predict the time of slope instability, establish an early warning system, and thus improve the overall safety and performance of the mine [4]. Trirat et al. proposed the MG-TAR (Multigrid Temporal Attention Reinforcement) framework, which uses a multi-view graph neural network and a multi-attention module to achieve multi-graph association learning. The results show that MG-TAR can reduce the accident risk prediction error by 23% and improve the prediction accuracy of the most dangerous area by 27% compared with existing methods [5]. Tang pointed out that in the mining industry, AI is used for environmental monitoring, hazardous gas detection, and remote hazard assessment. The oil and gas industry uses AI to analyze safety data of wellheads, pipelines, and valves, and to provide personalized training[6]. Youhua et al. used the LightGBM model to predict the severity of occupational injuries of mining workers, and combined the SHAP (Shapley Additive Explanations) method to improve the model interpretability. The results showed that injuries to the head and neck and multiple parts of the body had a significant impact on the risk of occupational fatalities[7]. Bing et al. proposed an intelligent architecture that integrates the Internet of Things, 5G, and edge computing, and verified its effectiveness through experiments on deep learning fire prediction algorithms to improve coal mine safety and emergency response speed[8]. Hui et al. proposed a time series prediction model that combines Variational Mode Decomposition (VMD) and Deep Belief Network (DBN) to improve the accuracy of water surge prediction. Experimental results show that the VMD-DBN model has high accuracy in water surge prediction and has great practical application value[9]. To improve construction site safety, Mostofi and Toğan proposed a new bilateral construction safety network that combines the interaction of human behavior and work environment factors. The high-level information of the bilateral network is learned through a graph convolutional network to predict the severity of construction accidents. The prediction accuracy is 85.67% when tested on a dataset[10]. Babaeian et al. used the Generalized Regression Neural Network (GRNN), Gene expression programming (GEP), and GRNN (GA-GRNN) models based on genetic algorithms, and established a statistical model through multivariate regression. The results showed that the GA-GRNN model performed best in predicting the distance of flying rocks, which helped to reduce damage to buildings and mining machinery [11]. Although existing research has made some progress in mining accident prediction and safety management, it still faces bottlenecks such as data imbalance, insufficient feature extraction, and insufficient model interpretability, which limit its practical application effect.

3. Method

3.1 GNN Model Design and Optimization

The core of mining accident prediction lies in the reasonable construction of the graph structure of the mine environment so that GNN can learn and reason. Mine environment data has the characteristics of strong spatiotemporal correlation and diverse data sources (such as sensors, equipment status, personnel location, etc.). For different data types, we can construct three main graph structures: sensor network graph, mining area topology graph and accident propagation path graph.

(1) Sensor network construction (node: sensor, edge: data correlation)

In the mine environment, a large number of sensors are deployed to monitor environmental parameters such as temperature, humidity, gas concentration, carbon monoxide content, air flow rate, vibration, etc. The sensor network can be represented as an undirected or directed graph: Nodes (V) represent sensors at different locations, and edges (E) represent the correlation between sensors. Sensors with correlation between data can also be connected. Mine sensor network diagram is as follows:

$$G_s = (V_s, E_s, X_s) \tag{1}$$

Among them: V_s is the sensor set, each sensor node v_i has a feature vector x_i, which contains the environmental parameters it monitors; E_s is the edge set between sensors, which represents the data association between sensors; X_s is the node feature matrix, which contains the measurement data of all sensors.

Edge weights can be calculated using the Pearson Correlation Coefficient (PCC):

$$w_{ij} = \frac{\sum_{t=1}^{T}(x_{i.t}-\bar{x}_i)(x_{j,t}-\bar{x}_j)}{\sqrt{\sum_{t=1}^{T}(x_{i.t}-\bar{x}_i)^2}\sqrt{\sum_{t=1}^{T}(x_{j,t}-\bar{x}_j)^2}} \tag{2}$$

Among them: $x_{i.t}$ and $x_{j,t}$ are the data collected by sensors i and j at time t, respectively. $\bar{x}_i$ and $\bar{x}_j$ are the average measurement values of sensors i and j, respectively. The value range of w_{ij} is between $[-1,1]$, and the larger the value, the higher the correlation between the two sensor data.

If w_{ij} exceeds the set threshold r, it is considered that there is an edge e_{ij} between sensors i and j. Finally, a weighted sensor network graph is formed.

(2) Construction of mining area topology (nodes: miners/equipment/mining area units, edges: interaction relationships)

The mining area topology can be modeled as a heterogeneous graph.

$$G_m = (V_m, E_m, X_m) \tag{3}$$

Among them: nodes (V) can include three types of nodes - miner V_h, equipment V_d and mining area V_z units; edges (E) represent the interactive relationship between miners and equipment (such as operation, maintenance), the positional relationship between miners and mining area units, and the association between equipment and mining area units (the location of the equipment).

Node characteristics (X):

Miners: location coordinates, working hours, operation records.

Equipment: equipment type, operating status, maintenance records.

Mining unit: area type, historical accident rate.

Defining the connection weight w_{ij} between miners and equipment:

$$w_{ij} = \frac{n_{ij}}{N_i} \tag{4}$$

Among them: n_{ij} represents the number of interactions between miner i and device j in the past period of time. N_i is the total number of all interactions of miner i in the same period of time.

If w_{ij} exceeds the threshold, it is considered that there is an interaction relationship between miner i and device j, and an edge e_{ij} is added to the graph.

The mining area topology map can be used to predict the security risks that miners may face.

(3) Accident propagation path modeling (node: accident trigger point, edge: impact range)

Mine accidents are contagious. For example, gas leakage may cause explosions, and equipment failure may cause collapse. Therefore, we can construct an accident propagation graph.

$$\mathrm{G_a} = (\mathrm{V_a}, \mathrm{E_a}, \mathrm{X_a}) \tag{5}$$

Among them: nodes (V) represent different accident trigger points; edges (E) represent possible propagation paths of accidents; node features (X) represent accident types, impact ranges, historical accident data, etc.

Assuming that the impact range of accident propagation obeys the Gaussian attenuation model, the weight of the edge can be expressed as:

$$w_{ij} = e^{-\frac{d_{ij}^2}{2\sigma^2}} \tag{6}$$

Among them: d_{ij} represents the distance between the accident source i and the affected area j. σ is the scale parameter of the impact diffusion (which can be adjusted according to the actual situation of the mine). If w_{ij} exceeds the threshold, it is considered that the accident will spread from node i to node j.

3.2 Dynamic Graph Model Combined with Time Series Information to Predict Accident Propagation Path

3.2.1 Dynamic graph representation of accident propagation

The occurrence and spread of mining accidents are usually dynamic, involving changes in time and space. For example, a gas leak may spread throughout the mine within minutes, and a mechanical failure may lead to a more serious accident through a series of chain reactions. Therefore, static graph models are difficult to capture the temporal characteristics of accident propagation, and spatio-temporal graph neural networks (ST-GNN) are needed to model the accident propagation path, predict its diffusion trend, and formulate corresponding emergency response measures.

Accident propagation can be modeled as a dynamic graph. At different time steps t, the structure and node characteristics of the graph may change over time:

$$G_t = (V_t, E_t, X_t) \tag{7}$$

V_t represents each area, equipment or personnel in the mine that may be affected, and the state of the node will change over time; E_t represents the propagation path of the accident, such as the fire spread path and the gas diffusion path, and the weight of the edge may be updated over time; X_t represents the characteristics of each node, such as temperature, gas concentration, equipment status, etc., which evolve over time.

3.2.2 Spatio-temporal modeling method for accident propagation

(1) Spatio-temporal graph convolutional network (ST-GCN)

ST-GCN (Spatio-Temporal Graph Convolutional Network) combines sequence modeling in the temporal dimension and topological structure learning in the spatial dimension to predict how accidents spread over time.

Temporal Modeling: Temporal Convolution is used to capture the temporal evolution of the accident.

Spatial Modeling: Using GCN (Graph Convolutional Network) to capture the propagation pattern of accidents in the mine topology.

(2) ST-GCN propagation formula

The core of ST-GCN is to combine graph convolution (GCN) with time series modeling. The node feature update at each time step t is:

$$H_t = \tau(W_g G_t H_{t-1} + W_t H_{t-1} + b) \tag{8}$$

Among them: H_t is the hidden state of the node at time step t; G_t is the adjacency matrix at time step t, representing the accident propagation path; W_g and W_t are the trainable weight matrix; b is the bias term; τ is the nonlinear activation function.

4. Results and Discussion

4.1 Dataset

The experiment uses real mine environment data, the data sources include:

(1) Sensor data (temperature, humidity, gas concentration, carbon monoxide concentration, air flow rate, vibration, etc.)

(2) Miner behavior data (location, working hours, operation records)

(3) Equipment status data (type, operating status, maintenance records)
(4) Historical accident data (accident type, location, impact range, transmission path)
Data preprocessing includes:
(1) Abnormal data processing (removing sensor fault data)
(2) Time series alignment (interpolating data at different time steps)
(3) Feature normalization (normalizing sensor measurements to [0,1])

4.2 Evaluation Indicators

This paper evaluates the performance of the accident prediction model through four main indicators, including accident prediction accuracy, accident propagation path identification accuracy, prediction lead time and computational efficiency. Among them, accident prediction accuracy measures the prediction correctness; accident propagation path identification accuracy evaluates the matching degree between the predicted path and the actual path; prediction lead time indicates the lead time of the prediction result compared to the actual occurrence time; and computational efficiency focuses on the running time of the model.

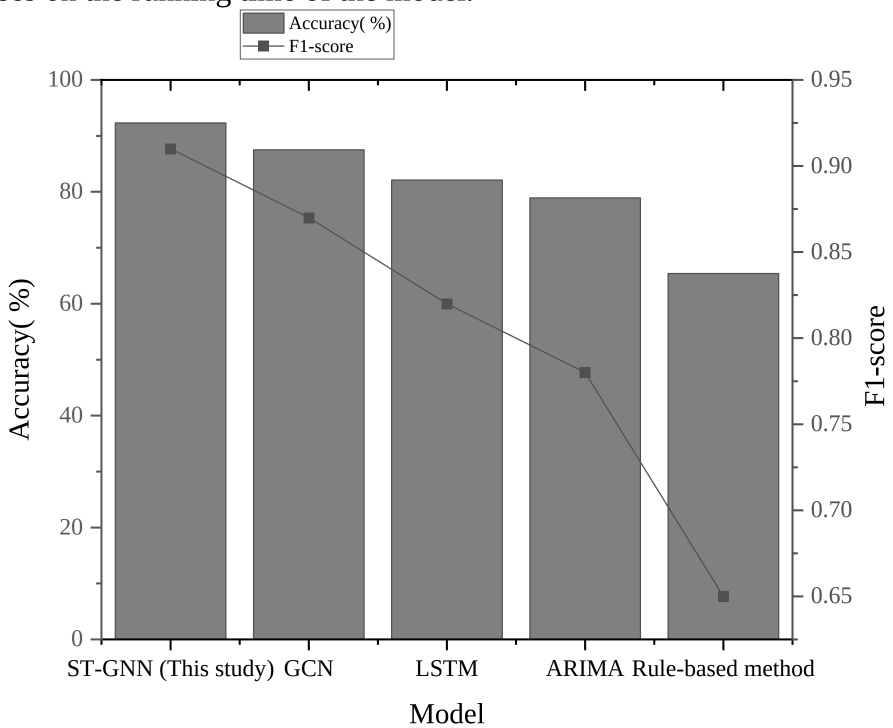

Figure 1. Comparison of accident prediction accuracy and F1-score

In the experiment, ST-GNN (this study) achieves an accident prediction accuracy of 92.3% and an F1-score of 0.91, which performs well, showing that the model can accurately predict the occurrence of mine accidents while achieving a good balance between accuracy and recall. This is mainly due to its ability to combine the spatiotemporal characteristics of the mine and comprehensively consider the spatial dependence and time evolution of accident propagation, so it has strong prediction capabilities. In contrast, the accident prediction accuracy of LSTM is 82.1% and the F1-score is 0.82. Although it can capture time series data well, it has certain limitations in spatial relationship modeling, resulting in a decrease in the prediction accuracy of complex accident propagation paths in the mine environment (as shown in Figure 1).

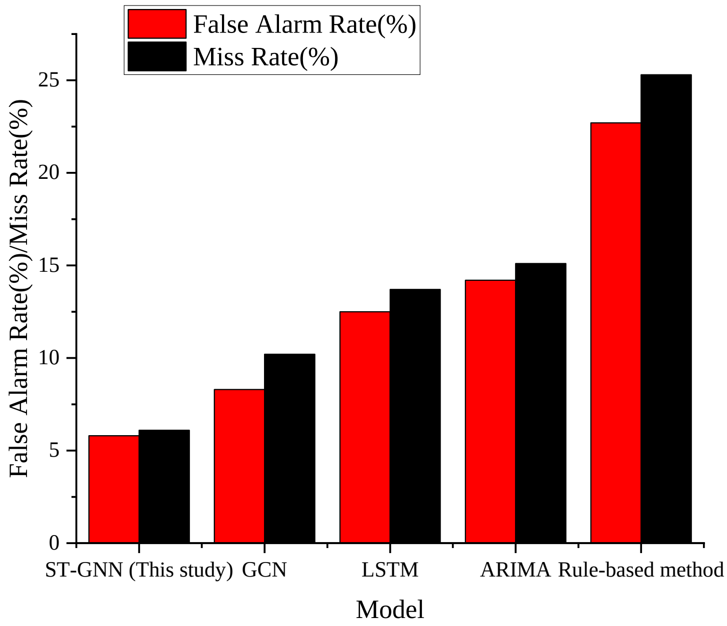

Figure 2. Comparison of model accuracy

In the evaluation of false alarm rate and false negative rate in Figure 2, ST-GNN (this study) shows the best performance, with a false alarm rate of 5.8% and a false negative rate of 6.1%. This result shows that ST-GNN can effectively distinguish between accidents and normal situations in the mine environment, with fewer false alarm warnings, and can also detect possible accident risks in a timely manner and reduce the occurrence of false negatives. This is mainly due to the fact that it fully considers the spatiotemporal dependency relationship during modeling, allowing the model to more accurately identify potential danger signals. In contrast, the false alarm rate of GCN is 8.3% and the missed alarm rate is 10.2%. Although the model performs well in modeling spatial structures, it fails to effectively integrate temporal information, resulting in inaccurate prediction of accidents in some cases, increasing the risk of missed alarms. At the same time, the false alarm rate is slightly higher than that of ST-GNN, indicating that the model is not robust enough when dealing with some noisy data. ARIMA has a false alarm rate of 14.2% and a false negative rate of 15.1%, which is a relatively average performance. As a traditional time series model, ARIMA cannot handle the spatial dependency in the mine environment, nor can it effectively capture the complex propagation path of accidents in mines. Therefore, its false alarm rate and false negative rate are high, and its scope of application is relatively limited.

In the experiments of lead time and inference time, ST-GNN (this study) performs well in both indicators. Its lead time is 15.2 minutes, which means that the model can predict the occurrence of accidents a long time in advance, providing more preparation time for the prevention and emergency response of mine accidents. In addition, although the computational efficiency of ST-GNN is 35.4 milliseconds, which is slightly higher than other models, considering its advantages of high-precision prediction and long lead time, this computational efficiency is still within an acceptable range, and it still has higher real-time performance than traditional methods. The prediction lead time of GCN is 10.5 minutes, which is slightly shorter than ST-GNN, but it can still provide effective warning for accident prediction within a certain period of time, as shown in Figure 3. In general, ST-GNN performs best in terms of advance prediction and can provide long-term warning for mine accidents. Although its computational efficiency is slightly lower than other models, it can still complete high-precision predictions within a reasonable time and has high practical value.

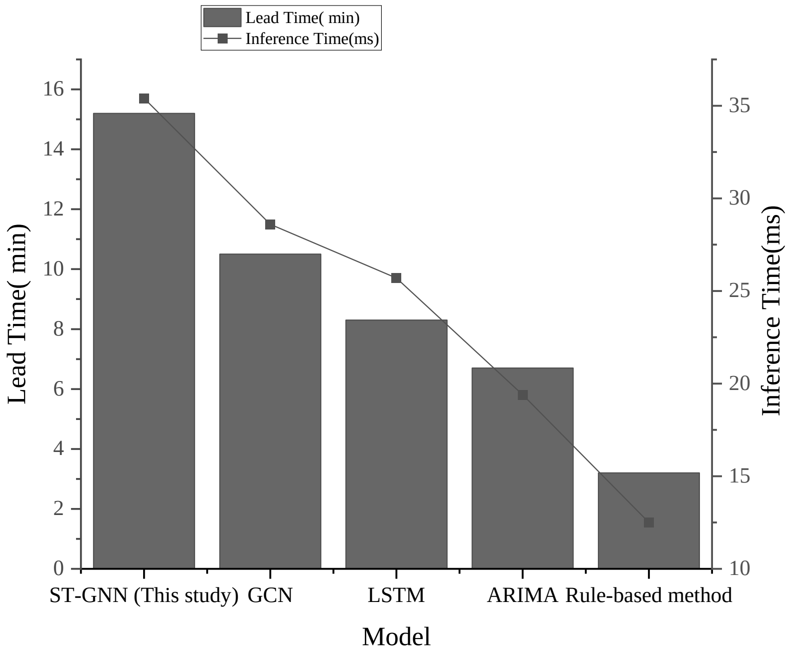

Figure 3. Model's lead time and computational efficiency

Visualization results: Plotting the accident propagation path, comparing the prediction results with the actual results

Table 1. Comparison of accident propagation paths

Model	Actual Propagation Path	Predicted Propagation Path
ST-GNN (This study)	Gas leak → Fire → Equipment failure → Collapse	Gas leak → Fire → Equipment failure → Collapse
GCN	Gas leak → Fire → Equipment failure → Collapse	Gas leak → Fire → Equipment failure
LSTM	Gas leak → Fire → Equipment failure → Collapse	Gas leak → Fire → Equipment failure
ARIMA	Gas leak → Fire → Equipment failure → Collapse	Gas leak → Fire
Rule-based method	Gas leak → Fire → Equipment failure → Collapse	Gas leak → Equipment failure

From the data in Table 1, it can be seen that in the comparison between the actual propagation path and the predicted propagation path, the predicted propagation path of ST-GNN (this study) is completely consistent with the actual propagation path, both of which are gas leakage → fire → equipment failure → collapse. It indicates that the model performs well in predicting the accident propagation path and can accurately capture the chain reaction of mine accidents. ST-GNN uses the deep learning advantages of spatiotemporal information to successfully predict the evolution of accidents from one stage to another, providing strong support for mine safety management.

5. Conclusion

This study proposes a mine accident prediction method based on spatiotemporal graph neural network (ST-GNN), aiming to improve the accuracy, advance time and computational efficiency of mine accident prediction. By graphing the mine environmental data and modeling the spatiotemporal features, this paper can effectively capture the complex spatiotemporal dependencies of mine accidents and provide more accurate and comprehensive support for accident prediction. The experimental results show that compared with the traditional prediction model, ST-GNN performs well in multiple evaluation indicators. However, this paper also points out that although ST-GNN has shown high performance in mine accident prediction, there is still room for improvement. First, future research can further optimize the model structure to improve computational efficiency, especially when processing large-scale data. In addition, for different types of mine accidents, it may be necessary to apply more domain-specific knowledge into the model to further improve the adaptability and generalization ability of the model. The mine accident prediction model based on ST-GNN provides an innovative solution for mining safety management. It can provide timely warning and decision support for mine managers, help reduce the occurrence of mine accidents and protect the lives of miners. In the future, with the enrichment of mine environmental data and the continuous advancement of model optimization, accident prediction technology based on graph neural networks is expected to play a greater role in the field of mining safety.

References

[1] Javaid A, Siddique M A, Reshi A A, et al. Coal mining accident causes classification using voting-based hybrid classifier (VHC)[J]. Journal of Ambient Intelligence and Humanized Computing, 2023, 14(10): 13211-13221.

[2] Ye Z, Shoufeng T, Ke S, et al. An evaluation of the mine water inrush based on the deep learning of ISMOTE[J. Natural Hazards, 2023, 117(2): 1475-1491.

[3] Ramos P M S, Macedo J B, Maior C B S, et al. Combining BERT with numerical variables to classify injury leave based on accident description[J]. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 2024, 238(5): 945-956.

[4] Masood M M, Verma T, Seervi V. Development of an algorithm for the prediction of slope failure in surface mines[J]. Journal of the Institution of Engineers (India): Series D, 2024, 105(2): 875-885.

[5] Trirat P, Yoon S, Lee J G. MG-TAR: Multi-view graph convolutional networks for traffic accident risk prediction[J]. IEEE Transactions on Intelligent Transportation Systems, 2023, 24(4): 3779-3794.

[6]Tang K H D. Artificial intelligence in occupational health and safety risk Management of Construction, mining, and oil and gas sectors: advances and prospects[J]. J. Eng. Res. Rep, 2024, 26(6): 241-253.

[7] Youhua M O, Zhang P, Yishuo G U, et al. Exploration of predicting occupational injury severity based on LightGBM model and model interpretability method[J]. Journal of Environmental and Occupational Medicine, 2025, 42(2): 157-164.

[8] Bing Z, Wang X, Dong Z, et al. A novel edge computing architecture for intelligent coal mining system[J]. Wireless Networks, 2023, 29(4): 1545-1554.

[9] Hui L I U, Guiqin L I U, Dianyan N, et al. Mine water inrush prediction method based on VMD-DBN model[J]. Coal Geology & Exploration, 2023, 51(6): 13-21.

[10] Mostofi F, Toğan V. Predicting construction accident outcomes using graph convolutional and dual-edge safety networks[J]. Arabian Journal for Science and Engineering, 2024, 49(10): 13315-13332.

[11] Babaeian M, Sereshki F, Ataei M, et al. Application of soft computing, statistical and multi-criteria decision-making methods to develop a predictive equation for prediction of flyrock distance in open-pit mining[J]. Mining, 2023, 3(2): 304-333.