Automatic Detection and Early Warning of Safety Hazards in Complex Scenarios Using Graph Neural Networks

Jingyu Wang[*], Cheng Xing and Heng Zhang

College of Safety Science and Engineering, Liaoning Technical University, Huludao, China

[*]1747342548@qq.com

Abstract. Due to the increasing complexity of coal mine production environment and the rapid growth of monitoring data, the traditional methods are difficult to timely and accurately detect potential hazard and take early warning measures. Starting from existing Graph Neural Networks (GNN) model, this paper innovatively and for the first time proposes to extract fine-grained features from multi-source monitoring data and downhole geological structure information collected by sensors through the fusion of multi-layer aggregators and dynamic time convolution modules. After that, the cross-graph attention mechanism is employed to realize the effective interaction and fusion of multi-channel data. Finally, the paper employs the depth graph representation learning to merge the spatial structure characteristics of the coal mine with the time series dynamic information to develop a multi-level visual risk map, which can result in accurately identifying the potential safety hazard and warning efficiently during the coal mine operation. The experimental results demonstrate that the accuracy of potential safety hazard identification of the proposed complex GNN model can be greatly improved compared to the existing methods.

Keywords: Coal Mine Safety, Graph Neural Network, Multi-source Monitoring Data Fusion, Dynamic Time Convolution.

1   Introduction

Due to the high frequency of coal mine accidents, the safety of coal mines has always been an important issue of global concern, and it not only poses great challenges to the life safety of miners, resulting in great economic losses [1]. Due to the improvement of coal mine safety management in recent years and the introduction of various safety measures, the operating environment of coal mines still has many safety threats, including gas leakage, roof fall, equipment failure, and human error. The conventional security monitoring methods based on manual inspection, video monitoring, and sensor-based detection have various drawbacks, including delayed identification of hidden dangers, high false alarm rate, and difficulty to process large-scale and complex data

[2]. These challenges demonstrate that the supervision of coal mines must be upgraded urgently with intelligent and automated systems that can identify risks.

In these years, the application in industrial safety of artificial intelligence (AI) technology has been a hot focus, and gradually the artificial intelligence method has been introduced to coal mine safety management. As one of the deep learning models designed to handle non-Euclidean data, Graph Neural Networks (GNNs) have provided powerful modeling capabilities for complex structured data [3].

Coal mining is a type of mining characterized by numerous safety hazards, in which mine workers, equipment, ventilation systems, and geological conditions have complex interactions, which can be represented through a graph structure. Traditional machine learning methods hardly reflect the intricate dependencies among the different data entities and their relationships in the coal mine environment, whereas GNNs can significantly capture such types of dependencies and thus achieve more precise hazard detection and risk identification abilities [4].

2   Related Work

Ali et al. [5] proposed an Internet of Things-based dynamic sensor information control system (IoT-DSICS) that focuses on solving the problems of high temperature and high humidity and harmful gas emission in coal mines. The system integrates IIoT sensor networks, and control systems to monitor and control prototypes using Wi-Fi microcontroller system, activate ventilation equipment, and ground alert in case of danger. Dey et al. [6] proposed a hybrid CNN-LSTM based monitoring and prediction system to monitor and predict coal mine disasters for preventive detection based on IoT.

You et al. [7] By using artificial intelligence technology, people can make the risk of coal mine gas known and controllable, which is conducive to the prevention and control of coal mine gas accidents. Yang et al. [8] estimated that the goal of coal mine safe production management is to reduce accidents and enhance the secure production of coal mines. As a result, with a large market demand for coal, long and harsh environmental conditions in the underground coal mine, the phenomenon of safety accidents in the process of coal mining around the world sometimes occurred.

Shu et al. [9] sifting micro-seismic data and devise a classifying process for the signal, of great reference offer for early warning of coal and gas outbursts. Kong et al. analyzed the coal mine safety situation in Guizhou Province and concluded that even though the safety situation of coal mines in Guizhou Province has improved during many years, but coal mine accidents still happen from time to time. Jiskani et al. [10] Based on the integration of entropy weight and grey clustering method, Yang et al. [11] proposed to improve mine safety. In this approach, various risk factors are involved, the weight of each factor is identified by the entropy weight method.

3   Methodologies

3.1   Multi-Layer Aggregator with Dynamic Temporal Convolution

On the basis of the existing GNN framework, this paper first proposes a multi-layer aggregator for multi-source perception data (including gas concentration, temperature, geological structure, etc.) in coal mines, so as to extract more comprehensive representations from neighborhood nodes in the spatial dimension. Let $H^{(l)} \in \mathbb{R}^{N \times d_l}$ be the l-layer node, indicating that $A \in \mathbb{R}^{N \times n}$ is the adjacency matrix and D is the degree matrix. A multi-layer aggregator consists of three parallel aggregation methods: Mean, Max, and Att, as shown in Equation 1:

$$H^{(l+1)} = \Phi \left(\bigoplus_{p \in \{Mean, Max, Att\}} \Gamma_p \left(H^{(l)}, A \right) \right) W_{fusion}^{(l)}, \tag{1}$$

where $\bigoplus$ is the vector splicing operation, $\Phi(\cdot)$ It can be a nonlinear function such as ReLU. The aggregators are as follows. Mean aggregator as shown in Equation 2:

$$\Gamma_{Mean} \left(H^{(l)}, A \right) = \sigma \left(D^{-1} A H^{(l)} W_{mean}^{(l)} \right). \tag{2}$$

Its function is to obtain the average information of neighborhood nodes, smoothing and highlighting the overall trend. Max aggregator as shown in Equation 3:

$$\Gamma_{Max} \left(H^{(l)}, A \right)_v = \sigma \left(\max_{u \in \mathcal{N}(v)} \left(H^{(l)}[u] \right) W_{max}^{(l)} \right). \tag{3}$$

Capture the local maximum response with neighborhood extremums to identify potentially risky "spike" features (e.g., sudden spikes in gas concentrations). Attention aggregators such as Equations 4 and 5:

$$\alpha_{uv}^{(l)} = \frac{\exp \left(LeakyReLU \left(a^{(l)T} \left[h_u^{(l)} \parallel h_v^{(l)} \right] \right) \right)}{\sum_{k \in \mathcal{N}(v)} \exp \left(LeakyReLU \left(a^{(l)T} \left[h_k^{(l)} \parallel h_v^{(l)} \right] \right) \right)}, \tag{4}$$

$$\Gamma_{Att} \left(H^{(l)}, A \right)_v = \sigma \left(\max_{u \in \mathcal{N}(v)} \alpha_{uv}^{(l)} W_{att}^{(l)} h_u^{(l)} \right). \tag{5}$$

This self-attention method dynamically measures the importance of neighborhood nodes, and is especially suitable for highlighting the most valuable information when multi-source monitoring data is cluttered. By splicing the three aggregation results and then fusing them with $W_{fusion}^{(l)}$, the spatial correlation features of the coal mine can be learned from multiple perspectives.

In the time dimension, Dynamic Temporal Convolution (DTC) is combined with historical observations. Let the node feature at time t be $H^{(l)}(t)$, and define a variable convolutional kernel $\{W_\tau^{(l)}\}_{\tau=0}^{K-1}$ of length K with the attenuation function $\rho(\tau)$ to adapt the timing characteristics of different sensors, as shown in Equation 6:

$$h_v^{(l)}(t) = \sigma\left(\sum_{\tau=0} \rho(\tau) W_\tau^{(l)} h_v^{(l)}(t-\tau) + b^{(l)}\right), \tag{6}$$

If the gas concentration changes drastically, $\rho(\tau)$ can be set to a more gradual attenuation to increase the weight of short-term information. If the temperature change is relatively stable, $\rho(\tau)$ can decay more rapidly and reduce the interference of long-term history. In this way, the spatial aggregation of the graph structure can be supplemented with temporal dynamics, forming a stronger ability to capture spatiotemporal risks.

3.2   Cross-Graph Attention Mechanism

Since there are often multiple channels in the coal mine environment, it can be abstracted into M correlation diagrams $\{A^{(m)}\}_{m=1}^M$. In order to allow nodes to intersect the representations learned on different channels, this paper introduces the Cross-Graph Attention mechanism. Let $h_{v,(m)}^{(l)}$ represent the l-layer representation of node v in the m graph. Aligning the information of different graphs m, n yields Equations 7 and 8:

$$\beta_v^{(m,n)} = \frac{\exp\left(LeakyReLU\left(q^T\left[W_{cross}^{(l)}h_{v,(m)}^{(l)} \parallel W_{cross}^{(l)}h_{v,(n)}^{(l)}\right]\right)\right)}{\sum_{j=1}^M \exp\left(LeakyReLU\left(q^T\left[W_{cross}^{(l)}h_{v,(m)}^{(l)} \parallel W_{cross}^{(l)}h_{v,(j)}^{(l)}\right]\right)\right)}, \tag{7}$$

$$h_v^{(l+1)} = \sigma\left(\sum_{m=1}^M \left(\frac{1}{M-1}\sum_{n=1,n\neq m}^M \beta_v^{(m,n)}\right)h_{v,(m)}^{(l)}\right), \tag{8}$$

where W_{cross} and q are the learnable parameters. This attention fuses the weights of the features of the same node on different modal graphs to avoid information fragmentation and improve the comprehensive expression ability of multi-source data.

After the above aggregation, time series convolution and cross-graph attention, the higher-order feature $H^{(L)}$ of the node can be obtained. In order to implement coal mine safety early warning, this paper uses the readout function $\mathcal{R}$ to give the risk score r_v for $h_v^{(L)}$, such as Equations 9 and 10:

$$r_v = \mathcal{R}\left(h_v^{(L)}\right), \tag{9}$$

$$R_{global} = Agg(\{r_v\}_{v=1}^N), \tag{10}$$

where R_{global} represents the global risk level, $Agg(\cdot)$ It can be a maximum or average operation. As a result, a multi-level visual risk map is formed: on the one hand, the node risk r_v can be marked on the underground roadway topology or geological distribution map to help identify local high-risk points; On the other hand, the overall alarm rating is carried out by R_{global}.

4   Experiments

4.1   Experimental Setup

The experiment used the IJCRS'15 World Coal Mine Safety Monitoring Dataset, which included multi-dimensional time series data collected by gas sensors and wind speed sensors in the coal mine environment, covering the changes of gas concentration and mine ventilation in different time periods. The characteristics of the data set is high frequency sampling and multivariate recording, gas sensor is used to detect the concentration of the combustible gas in the coal mine environment, and wind speed sensor is used to assess the mine ventilation system operation status within the safe range. The data is available at https://gitcode.com/open-source-toolkit/90e34.

4.2   Experimental Analysis

We combine GNN models with four AI-based approaches, including Long Short-Term Memory Network (LSTM) an enhanced RNN model, Least Squares Support Vector Machine (LSSVM), Convolutional Neural Network (CNN), and Hybrid Model (CNN-LSTM). In Figure 1, we can observe that as the total number of learnable parameters of the model increases, the accuracy of each method shows an increasing trend, but differences in improvement amplitude and stability. At the lower parameter scales, the traditional LSTM and LSSVM are weaker, and although the parameter parameters are increased, the accuracy is improved, but the increase is limited. CNN and CNN-LSTM have achieved relatively stable performance improvement at medium parameter scales. On the contrary, our method is more accurate across the parameter space.
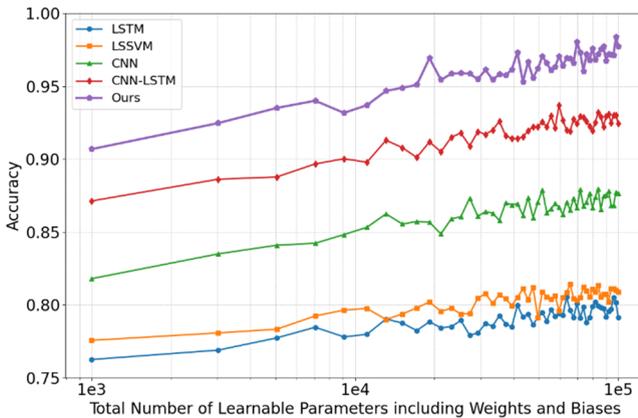

Fig. 1. Accuracy Comparison Result.

As can be seen from the results of Figure 2, as the number of sensors increases, the early warning response time of each method increases Show more upward to varying degrees, and a significant difference in upward trend of response time and amplitude.
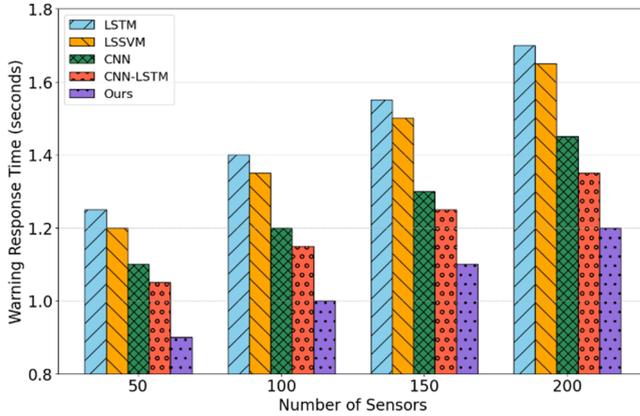
Fig. 2. Warning Response Time Comparison.

It can be seen from the comparison that with the number of sensors small, the traditional LSTM and LSSVM methods perform well, but when it reaches 200 sensors, the response time takes on a sharp increase. The response time of NN and CNN-LSTM methods decreases only slightly with more sensors, and still remain longer than ours.

On the Raspberry Pi, the inference time of the model is about 3.5 seconds/time, while the traditional CNN model takes about 6 seconds/time on the same hardware. The GNN model achieves obvious advantages in computational efficiency through simplified aggregation and convolution operations. The memory footprint of the GNN model is 50MB, while the memory footprint of the CNN model is 80MB. By reducing the number of network layers and the number of parameters, the GNN model optimizes memory usage.

The average response time of the GNN model is 5 seconds, which is faster than that of CNN (8 seconds) and LSTM (10 seconds). Although the response time of CNN-LSTM is 7 seconds, it still cannot catch up with GNN.

5   Conclusion

In conclusion, our method outperforms existing warning methods with respect to accuracy and warning time, based on the results of the experiment. Using complex GNN framework which have multi-level aggregators, dynamic temporal convolution and cross-graph attention mechanism, effectively fuses spatial, temporal and multi-modal data, extracting characteristics accurately and responding promptly in dynamic coal mine environment. Future research can further optimize the computational efficiency of the model and explore more low-power and efficient deployment options.

References

1. Mu, Wenjuan, et al. "Making food systems more resilient to food safety risks by including artificial intelligence, big data, and internet of things into food safety early warning and emerging risk identification tools." Comprehensive Reviews in Food Science and Food Safety 23.1 (2024): e13296.
2. Liang, Yu, and Qixin Liu. "Early warning and real-time control of construction safety risk of underground engineering based on building information modeling and internet of things." Neural Computing and Applications (2022): 1-10.
3. Onifade, Moshood. "Towards an emergency preparedness for self-rescue from underground coal mines." Process Safety and Environmental Protection 149 (2021): 946-957.
4. Singh, Ninni, et al. "IoT enabled HELMET to safeguard the health of mine workers." Computer Communications 193 (2022): 1-9.
5. Ali, Mohammed Hasan, et al. "Improving coal mine safety with internet of things (IoT) based Dynamic Sensor Information Control System." Physics and Chemistry of the Earth, Parts a/B/C 128 (2022): 103225.
6. Dey, Prasanjit, S. K. Chaulya, and Sanjay Kumar. "Hybrid CNN-LSTM and IoT-based coal mine hazards monitoring and prediction system." Process Safety and Environmental Protection 152 (2021): 249-263.
7. You, Mengjie, et al. "Applications of artificial intelligence for coal mine gas risk assessment." Safety science 143 (2021): 105420.
8. Yang, Li, et al. "Mining employees safety and the application of information technology in coal mining." Frontiers in public health 9 (2021): 709987.
9. Shu, Longyong, et al. "Characteristics and classification of microseismic signals in heading face of coal mine: Implication for coal and gas outburst warning." Rock Mechanics and Rock Engineering 55.11 (2022): 6905-6919.
10. Kong, Biao, et al. "Safety hazards in coal mines of Guizhou China during 2011–2020." Safety Science 145 (2022): 105493.
11. Jiskani, Izhar Mithal, et al. "An integrated entropy weight and grey clustering method–based evaluation to improve safety in mines." Mining, Metallurgy & Exploration 38.4 (2021): 1773-1787.