

Retraction

Retracted: A Mobile Intelligent Mine Platform with a Hybrid Fuzzy NN and ATT-CNN Prewarning Model

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] Y. Wu, C. Wu, J. Wang, X. Zhang, and W. Chen, "A Mobile Intelligent Mine Platform with a Hybrid Fuzzy NN and ATT-CNN Prewarning Model," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 4545936, 14 pages, 2022.

Research Article

A Mobile Intelligent Mine Platform with a Hybrid Fuzzy NN and ATT-CNN Prewarning Model

Yuliang Wu ¹, Chao Wu ², Jun Wang ³, Xiangnan Zhang ⁴, and Wei Chen ⁵

¹Blockchain Research Center of China, School of Economic Information Engineering, Southwestern University of Finance and Economics, Emergency Management Institute, Chengdu University, Chengdu, China

²Shandong University of Science and Technology, College of Intelligent Equipment, Tai'an, China

³Fintech Innovation Center, Financial Intelligence & Financial Engineering Key Laboratory of Sichuan Province, School of Economic Information Engineering, Southwestern University of Finance and Economics, Chengdu, China

⁴School of Economic Information Engineering, Southwestern University of Finance and Economics, Chengdu, China

⁵School of Mechanical Electronic & Information Engineering, China University of Mining and Technology (Beijing), Beijing 100083, China

Correspondence should be addressed to Chao Wu; sjh2100@163.com and Wei Chen; chenwdavior@163.com

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Given the existence of coal production risk, effective prewarning is important to the reliability and safety of coal mine. So, the development of a risk prewarning system has become an important safety management tool. To improve the prediction ability and the supervision level of safety production, and handle different multidimensional (temporal and spatial) information for risk prewarning, we built a new platform based on the Internet, cloud platform, mobile communication, GIS, and artificial intelligence technology, i.e., a mobile intelligent mine platform. The terminal of the platform provides real-time queries and procedures of coal mine production and risk prewarning and provides data support and technical means for daily supervision, remote networking analysis, law enforcement inspection, and emergency rescue. The prewarning model of safety risk is an essential means to realize prewarning. The complexity of production of coal mine leads to the dynamic characteristics, fuzziness, and randomness of coal mine accidents. The complex nonlinear relationship between index and risk level leads to low accuracy of the traditional back propagation (BP) neural network prewarning method. A novel model based on a compensation fuzzy neural network (NN) and an attention mechanism-convolutional neural network (ATT-CNN) are a critical part of the new design. First, to full use of the convolutional network to get a larger receptive field, one-dimensional time series is transformed into two-dimensional matrix as the input of the CNN network by mapping. The neural network is utilized to extract the advanced features of the input signal. The results are finally output through a fully connected classifier. The model fuses multisource data at the feature level, employs the temporal and spatial relationships of monitoring data, and dynamically evaluates the risk. The experiment shows that the proposed model achieves impressive performance in both quantitative and qualitative evaluations and has improved the model generalization ability. The combination of data integration, remote examinations, and approval from existing information systems enables this platform to provide dynamic reminders of approval information, various risk prewarning, and management process automation through a mobile network.

1. Introduction

As coal demand and total mining volume rise, most mines have entered the stage of deep coal mining [1]. Deep mining excavation is more difficult and has more distinctive problems and potential safety hazards than

shallow mining. The risk factors of the environment always affect the safe production of coal mines. Therefore, real-time monitoring and effective prediction in the process of coal mining have become major issues to be resolved for the healthy development of the coal industry [2, 3].

The risk estimation is normally completed through the quantitative and qualitative assessment of on-site environment, equipment and personnel operation factors by technical experts with data analysis, checklist designing and risk matrix forming, and so on. Nowadays, many literature has put forward new methods for risk assessment. Some experts and scholars use machine learning (ML) methods to predict and evaluate the risk of coal mines. However, because data processing and feature definition and selection are cumbersome, the cost of ML increases, which prevents its widespread application. In recent years, the rapid development of deep learning (DL) theory and technology has avoided the problem of relying on artificial feature engineering that afflicts traditional ML algorithms and thus has attracted extensive attention. DL can fit very complex nonlinear functions through a deep network structure and can automatically extract features.

Another harsh reality is that underground staff cannot get timely information regarding the safety of the surrounding environment, thus preventing them from predicting potential danger and evaluating their safety in real time. Every mineworker must be kept informed of any possible risk in an adequate and timely manner so that they can precisely evaluate their safety.

The powerful mobility and capability of intelligent mobile terminals ensure staff can master the overall state at the same time, issue strategies in time, and solve problems quickly. The combination of mobile terminals and cloud service technology can cover the risk prewarning service to every staff member, which is meaningful to the coal mine intelligence.

To solve the bottleneck of risk prediction and evaluation in coal mines and provide risk safety assessment information for underground personnel, this paper constructs an intelligent mobile mine platform and establishes a coal mine risk prewarning model based on a deep convolutional model.

Therefore, developing an information early warning system that can accurately evaluate the risk level of coal mine safety hazards in time and feedback the corresponding risk level countermeasures to supervisors in time is a key problem to be resolved urgently.

The rest of this paper is organized as follows. Section 2.1 gives an overview of research status at home and abroad. Section 2.2 then describes the problems. Section 2.3 introduces the points of contribution. Section 3 presents the design of an intelligent mobile mine system infrastructure. Section 4 provides a coal mine safety prewarning combination model. Section 5 illustrates the main function of the platform. Next, Section 6 summarizes key technologies and features. Conclusion is finally drawn in Section 7.

2. Theoretical Background and Motivation

2.1. Research Status at Home and Abroad. In an effort to improve mineral resource development, preserve the ecological environment, and avoid geological disasters, many scholars have proposed a series of solutions. Most of these solutions for the prewarning of typical dynamic disasters in coal mines involve high-level technologies such as ML.

Deng et al. [4] proposed a prediction model of spontaneous coal combustion in coal mine goafs based on a random forest algorithm. Qiu [5] used a deep belief network to extract the features of gas concentration time series and established a particle swarm optimization-support vector regression (PSO-SVR) model for gas concentration temporal and spatial modeling and trend prediction. To accurately predict rockburst disasters, Tian et al. and Gong et al. [6, 7] proposed a domain-aware deep neural network (DA-DNN) model based on improved adaptive moment estimation (Adam) and dropout. To construct the gas concentration distribution map, Cheng et al. [8] combined long short-term memory (LSTM) and a fully connected (FC) neural network (NN) to construct an LSTM-FC model to predict gas concentrations at different locations.

Tong and Cui [9] constructed a convolutional neural network (CNN) to classify and identify the underground environment, equipment status, and personnel behavior in video and audio to reduce the occurrence of coal mine risk disasters and accidents. Geng [10] proposed a hybrid model based on a dilated causal temporal convolutional network (DCT-CNN) and a long short-term memory recurrent neural network combined with a convolution network (CNN-LSTM) to predict the risk of local points on the roof.

Su et al. [11] built a safety risk assessment model for county coal mining areas with analytic network process (ANP) and probabilistic neural network. Built on Internet, cloud platform, smart mine, Internet of Things, geographic information system (GIS), and other technologies, Li [12] designed a platform for risk grading control and accident hidden danger investigation and control in coal mine. To improve the prediction accuracy of chaotic time series, Huang et al. [13] proposed a prediction model based on hybrid neural network and attention mechanism. Wang et al. [14] studied an intelligent hierarchical management and control and information early warning system for coal mine safety risks based on improved particle swarm optimization (PSO) and CNN. Yang et al. [15] proposed a new method for fault diagnosis of rolling bearings based on CNN deep learning based on attention mechanism. Wang [16] studied the classification and management strategy of coal mine safety risk and uses PSO to improve the error back propagation of CNN by utilizing the training parameters and error functions of CNN as PSO particles and fitness functions, respectively.

Liu [17] built a risk precontrol management system for mine safety that uses hazard identification and risk assessment as its basis, risk precontrol as its core, and unsafe behavior control as its focus. Li et al. [18] showed that the combination of the fuzzy analytic hierarchy process (AHP) and Bayesian network is feasible and applicable and can be used as a decision-making tool to prevent coal mine gas explosions and provide decision-makers with a technical guide for managing coal mine gas explosion risks. Li et al. calculated the weights from experts using a fuzzy AHP method based on subjective and objective expert weights [19]. Analysts and decision-makers can use the proposed batch normalization (BN) model in a coal mine as a decision support tool. Wu et al. built a mine platform with a risk

control function for coal mines [20]. Some researchers [21–23] utilized ML to study prewarning scenarios of coal mine pressure and gas and verified the effectiveness of ML. Mathatho et al. proposed a hierarchical approach consisting of principal component analysis (PCA) and an artificial neural network (ANN) model to improve the prediction accuracy of methane levels [24].

The above literature review shows that ML can mine the effective information contained in monitoring data and has made some progress in the mining field. These works provide ideas for research on risk prewarning.

Another key aspect of mining engineering for underground staff is transmitting environmental information with location and assessment data in real time. Various types of monitoring information are sent to a security model, the output of which is risk prediction. These outputs with geographic information are sent to specific areas for broadcasting to wireless nodes. Zheng et al. [25] built a client/server (C/S-) based visual danger source risk precontrol mobile phone management information system. Zhai et al. [26] described the network structure, software architecture, software design, system deployment, and system testing of Lu'an group's mobile monitoring information platform. Tan and Li [27] introduced the architecture and functional module design of a visual mobile office platform for coal mines. The mobile office employed a mobile internet and the Internet of Things (IoT). Chen [28] proposed the idea and scheme for the construction of a mobile application system platform for coal mines.

The above literature shows that research on ML is of great significance to improve risk prediction capabilities.

2.2. Problems. The above studies have achieved a certain amount of prediction progress from different perspectives, which have a great push to this problem. Although these technologies such as BP neural networks can achieve satisfactory accuracy, they still rely heavily on expert knowledge to extract features. The BP neural network algorithm with defects of local minimization and slow convergence speed makes it difficult to accurately and efficiently evaluate the safety risk of a coal mine. However, due to the complexity of the risk mechanism and the diversity of various factors, the following deficiencies still exist in practice:

- (1) Most methods determine the weight of each index. The determination of the weight by the staff is subjective; the weight is sometimes set by the experience of staff
- (2) Risk prewarning is complex and nonlinear. The risk is the result of multifactor. Some of these analytic features are definite and quantitative, while others are qualitative and fuzzy. The quantitative model of risk assessment is difficult to describe accurately by mathematical formulas and theories, which are multivariable, coupled, and highly complex
- (3) The relationship between temporal and spatial multivariable analyses has not been studied enough

- (4) The existing systems have a strong focus on the functions of the central node and neglect network terminal personnel. Although much comprehensive information is already available on the central nodes, information sharing and risk precontrol tools are seldom available to mining staff

All of these factors place higher requirements on the predictive model, communication, and terminals, and it is still necessary to explore new prediction methods. Therefore, we design a mobile intelligent mine platform and propose a new model with artificial intelligence for risk prewarning.

2.3. Points of Contribution. At present, integrated automation systems (IASs) have been built in most coal mines. Making use of IASs has enabled the monitoring and control of the important parts of underground equipment and systems [29].

An intelligent analysis of data is lacking in traditional coal mine automation and information systems. A dispatcher can only “transmit messages;” however, these messages are difficult to transmit to all mineworkers in real time.

To resolve the aforementioned issues and meet the practical requirements of underground security and the mining system, a mobile smart mine is constructed based on the comprehensive automation technology of coal mines, online data detection, computers, mobile networks, and mining-specific technologies. We propose a new prewarning model and integrate mobile security monitoring systems, geographic information systems (GIS), risk prewarning, and mobile communication into mobile smart mines and embed their functions into mobile apps. These designs are designed to play essential roles in miner safety assurance, production scheduling, and disaster relief.

The research innovation points are the following:

- (1) A novel mobile intelligent mine platform is proposed for risk prewarning with a new combination model. Mobile internet technology concerns positioning, security monitoring, and risk evaluation. With smart terminals, underground staff can get the latest risk assessment information
- (2) A novel model is proposed to construct a multivariable prewarning model. The NN prewarning model is always running and works in conjunction with the CNN model at a specific time for mutual confirmation
- (3) ATT is incorporated into CNN to improve prediction accuracy
- (4) A hazard prewarning model based on an attention mechanism-convolutional neural network (ATT-CNN) is proposed to deeply mine the behaviors or characteristics of the mining environment. It not only handles the information within all sequential data but also preserves the sequential spatiality. The model solves the problem of multisource information fusion and employs the temporal and spatial relationships of each monitoring variable

In short, by integrating IoT technology, mobile internet technology, and DL theories, we construct a comprehensive intelligent mobile mine platform that aims to provide risk prewarning that significantly improve the risk control efficiency of coal enterprises.

3. Materials and Methods in the Design of a Mobile Intelligent Mine System Infrastructure

This paper proposes an intelligent mine information system that senses every person, all equipment, and each aspect of the surroundings. The ultimate goal of this system is to allow staff members to utilize up-to-date technology and to run a coal mine with scientific and comprehensive management. Figure 1 shows the logic block diagram of the system. In this system, data related to all equipment and environmental information are sent to the intelligent mobile platform. After information fusion and risk assessment, the assessment results and relevant details are transferred to the frontline staff and supervisor through the mobile communication network as soon as possible in text, curves, and even multimedia.

A background application service center creates a seamless connection between the existing monitoring system and the intelligent mobile terminal in a coal mine. We call this center the network management platform of the system. The platform completes the instant messaging between the coal terminal and the mobile terminal simultaneously. The platform receives real-time data from the monitoring system and stores them in a database of background. The intelligent mobile terminal accesses the internet through a cellular network or IEEE 802.11 wireless networking technology (Wi-Fi). Then, the platform database is available to mobile applications. The firewall in the system is used to realize security isolation between the industrial control network and the existing information network.

The mobile system has five major functions:

- (1) System integration: all coal mine subsystem data integration, functional integration, and interconnection services
- (2) Multilevel networking: remote, real-time, and multilevel networking of coal mine subsystems and intuitive reflection of mine real-time status
- (3) Safety information management: basic mine information, safety production regulations, safety facilities and equipment, mine plans, and staff safety information [30]
- (4) Security monitoring mobile office: incident management, regulatory bulletin and notification, safety production statements, data statistics, and query functions
- (5) Wireless remote monitoring of the mine: mine managers, technicians, and crew access and control comprehensive mine information using a fourth generation (4G) mobile network

Under the special conditions of mobile application scenarios in coal mines, the mobile information platform is composed mainly of 3 modules, as shown in Figure 2.

4. Coal Mine Safety Prewarning Combination Model

4.1. Coal Mine Risk Prewarning Management. In our design, the coal mine risk precontrol management system includes hazard identification, hazard risk assessment, formulation and implementation of management standards and measures, and feedback of inspection. The task analysis method works for hazard identification, and the risk matrix method works for risk assessment. Depending on the assessment results, the system classifies the risks into different levels. Each identified hazard is ranked by a corresponding risk level, management standard measures, and supervision measures for product safety. The whole process is shown in Figure 3.

4.2. Construction of the Coal Mine Safety Prewarning Combination Model. The basic idea of the model and application is shown in Figure 4. The prewarning period T of the network model is shorter than the period L of the ATT-CNN model. This guarantees that the technical staff has sufficient time to determine the accurate weights and membership functions for the overall validity and reliability of the model. An NN dominates the prewarning process, and the ATT-CNN provides additional verification for the timely and effective prewarning of the coal mine safety status. According to the equipment data acquisition period and quantity, the prewarning period T is generally set as 5 minutes, 10 minutes, or 15 minutes by the staff.

The NN prewarning model works with the ATT-CNN during a specific time for mutual confirmation. If the two kinds of evaluation results are the same, the network model is valid and can continue to be applied. Otherwise, the weights of the output results of the two models are set so that the prewarning result value is adjusted, the original sample is expanded by adding the adjusted data, and the network training is carried out again to obtain a new network model structure. In a changing environment, the new network structure learns "new knowledge," which improves the reliability of the prewarning results in subsequent stages. The retained NN is used as a model in the follow-up cycle until it is compared with the ATT-CNN of the new stage again and adjusted.

The compensation fuzzy NN model is used for daily prewarning, and according to its calculated results, the corresponding prewarning is issued. A combination model composed of compensation, a fuzzy NN, and the ATT-CNN is applied at a certain time. The final warning result is determined according to whether the two warning results are consistent. If the two results are the same, the prewarning is issued according to the result; otherwise, the prewarning is adjusted according to their respective weights. At the same time, the training samples are extended and fed to the NN again for training to obtain a new network model for the following warning cycle.

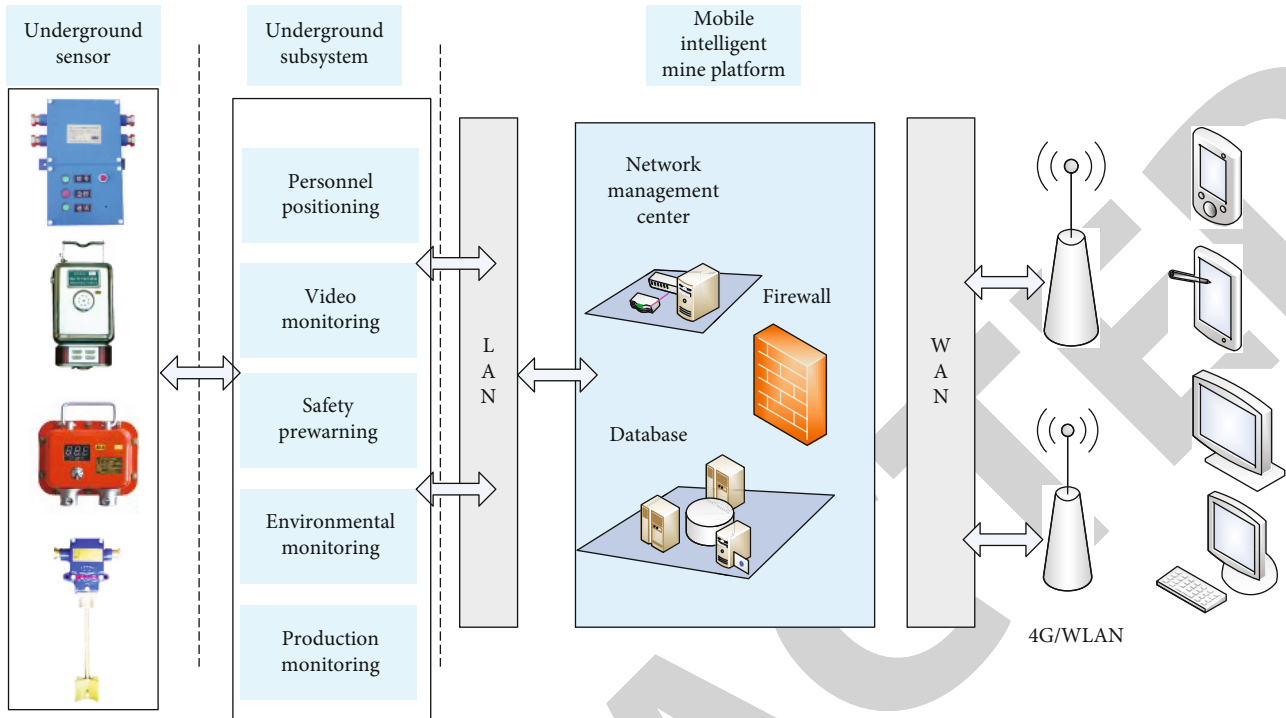


FIGURE 1: Mobile intelligent mine system infrastructure.

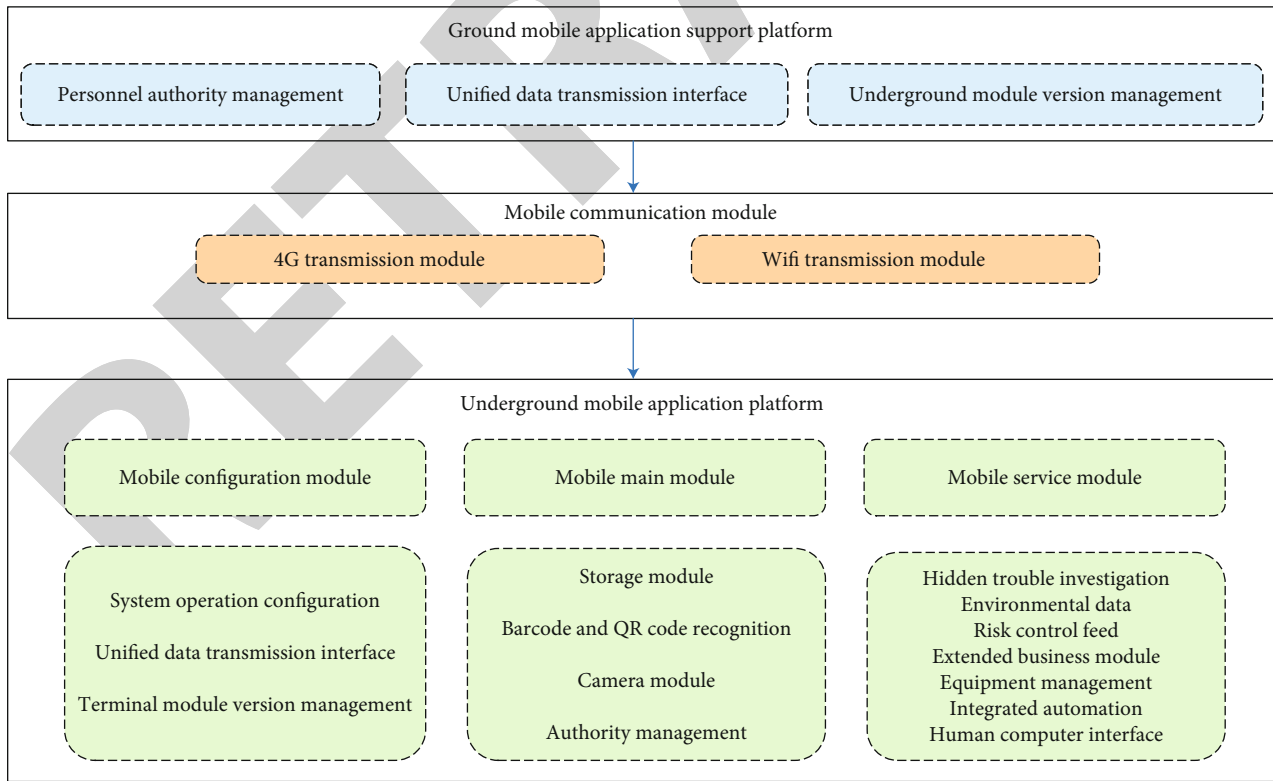


FIGURE 2: Mobile application system platform for risk prewarning. (1) Ground mobile application support platform: data support and configuration management for the regular operation of underground mobile applications are achieved through a support platform. (2) Mobile communication module: this is mainly for the underground wireless signals. (3) Underground mobile application platform: it includes a mobile configuration module, a main mobile module, and a mobile service module.

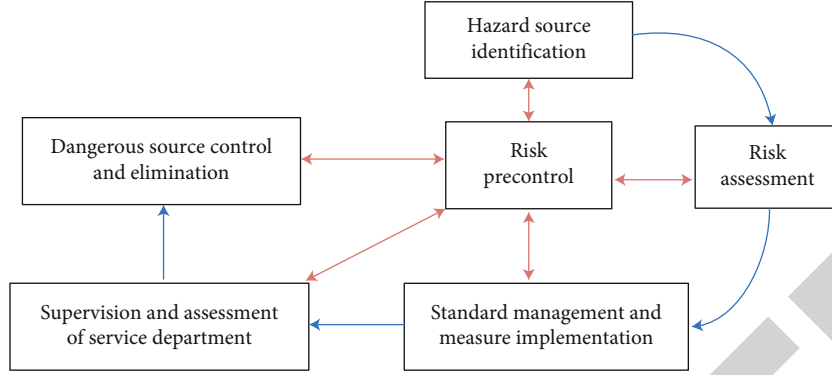


FIGURE 3: Diagram of risk prewarning management.

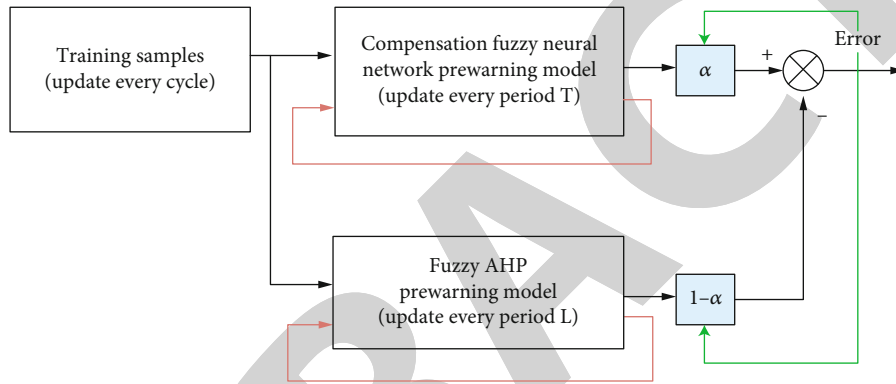


FIGURE 4: Basic idea of the model and application.

After the prewarning combination model is determined, the prewarning period of the NN model can be selected as days or weeks, and the period of the ATT-CNN model can be selected as weeks, months, or longer to ensure that sufficient time is available for accurate weights and membership functions to be determined, thereby ensuring the overall effectiveness and reliability of the method. The combination model is more valuable in the process of mutual confirmation between the two models for prewarning.

If the values of the monitoring indicators are $(x_1 x_2 \cdots x_n)$, the prewarning values y_1 and y_2 are obtained when the monitoring indicators are substituted into the network model and the ATT-CNN model. The prewarning criteria already determine the corresponding alarm level. If the prewarning values y_1 and y_2 are the same, the network model is applied and regarded as effective. If the values are different, the calculation formula of the prewarning value is adjusted. Assuming that the weight of the network model result is α , the weight of the ATT-CNN model is $1-\alpha$. The adjusted prewarning value is $y^* = \alpha y_1 + (1-\alpha)y_2$, where the value of α is $[0, 1]$. Assuming that the network model used in the above calculation was trained on a particular number of samples m , the m samples are expanded to $m+p$ samples, where $(x_{m+p1} x_{m+p2} \cdots x_{m+pn})$ denotes the n monitoring indicators, y_{m+p} is the adjusted prewarning value of y^* , and the

expanded $m+p$ samples are recorded as follows:

$$\begin{bmatrix} x_{11} & x_{11} & \cdots & x_{11} & y_1 \\ x_{21} & x_{22} & \cdots & x_{2n} & y_2 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} & y_m \\ x_{m+p1} & x_{m+p2} & \cdots & x_{m+pn} & y_{m+p} \end{bmatrix}. \quad (1)$$

A new NN structure is built after network retraining is carried out on the $m+p$ samples. The new structure is not adjusted until it is compared with the ATT-CNN model at a later stage. Through the above processing, the two combined models provide a solution for the variable weight problem. Different model parameters are adopted at various stages to adapt to the dynamic characteristics of the system. The two models confirm each other simultaneously to ensure the accuracy and effectiveness of the model and improve the reliability and credibility of the warning results.

A review of the risk evaluation of the factors impacting training samples shows that the physical meanings are different, and the numerical values fluctuate considerably. Normalization should be performed before predicting risks. To eliminate the order-of-magnitude differences and avoid

excessive training errors, the method used in this study is the normalization of the data by the maximum and minimum as follows:

$$x'_k = \frac{x_k - x_{\min}}{x_{\max} - x_{\min}}, \quad (2)$$

where x_{\min} is the minimum number in the data series, and x_{\max} is the maximum number in the series.

The compensated fuzzy NN is a multiple-input single-output (MISO) system that consists of a single-valued fuzzy generator, a Gaussian membership function, a product inference rule, a negative-positive compensation operation, and an improved center-of-gravity antifuzzifier. Let A_i^k be the fuzzy set in the domain U , B^k be the fuzzy set in domain V , and x_i and y be linguistic variables, with $i = 1, 2, \dots, n$; $k = 1, 2, \dots, m$. The fuzzy membership function is as follows:

$$\begin{aligned} \mu_{A_i^k}(x) &= \exp \left[- \left(\frac{x_i - a_i}{\alpha_i^k} \right)^2 \right], \\ \mu_{B^k}(y) &= \exp \left[- \left(\frac{y - b}{\beta^k} \right)^2 \right], \end{aligned} \quad (3)$$

where a and α are the center and width of the input membership function, respectively, b and β are the center and width of the output membership function, respectively, x_1, x_2, \dots, x_n is defined as the input X , and $U_1 \times U_2 \times \dots \times U_n$ is defined as the domain U . For a fuzzy subset A' in domain U , an output fuzzy subset B' is generated in the output domain V according to the k -th fuzzy rule. The maximum algebraic product synthesis operation is used for the fuzzy reasoning, and then the fuzzy set B' on V is derived from the fuzzy inference rules as follows:

$$\mu_{B^k}(y) = \sup_{X \in U} \left(\mu_{A_1^k \times A_2^k \times \dots \times A_n^k} \rightarrow_{B^k(X,y)} \cdot \mu_{A'}(X) \right). \quad (4)$$

The product operation is adopted for the fuzzy implication as follows:

$$\mu_{A \rightarrow B} = \mu_A(x) \mu_B(x). \quad (5)$$

The negative operation is as follows:

$$u^k = \prod_{i=1}^n \mu_{A_i^k}(x_i). \quad (6)$$

The active operation is as follows:

$$v^k = \left[\prod_{i=1}^n \mu_{A_i^k}(x_i) \right]^{1/n}. \quad (7)$$

The compensation operation is as follows:

$$\mu_{A_1^k \times \dots \times A_n^k}(X) = \left(u^k \right)^{1-\gamma} \left(v^k \right)^\gamma = \left[\prod_{i=1}^n \mu_{A_i^k}(x_i) \right]^{1-\gamma+\gamma/n} \quad (8)$$

where γ is the compensating degree, with $\gamma \in [0, 1]$; hence, the following is obtained:

$$\mu_{B^k}(y) = \sup_{X \in U} \left\{ \mu_{B^k}(y) \mu_{A'}(X) \left[\prod_{i=1}^n \mu_{A_i^k}(x_i) \right]^{1-\gamma+\gamma/n} \right\}. \quad (9)$$

Single-value fuzzification is adopted, with $\mu_{A'}(X) = 1$, $\mu_{B^k}(b^k) = 1$; then, the following is obtained:

$$\mu_{B^k}(b^k) = \left[\prod_{i=1}^n \mu_{A_i^k}(x_i) \right]^{1-\gamma+\gamma/n} \quad (10)$$

where $f(X)$ is defined as the ant-gelatinization function as follows:

$$f(X) = \frac{\sum_{k=1}^m b^k \delta^k \left[\prod_{i=1}^n \mu_{A_i^k}(x_i) \right]^{1-\gamma+\gamma/n}}{\sum_{k=1}^m \delta^k \left[\prod_{i=1}^n \mu_{A_i^k}(x_i) \right]^{1-\gamma+\gamma/n}}. \quad (11)$$

The objective function is as follows:

$$E^p = \frac{1}{2} [f(x^p) - y^p]^2. \quad (12)$$

The b center of the output membership function is trained according to the gradient descent method, as are β , a , and α . The training formulas are as follows:

$$\begin{aligned} b^k(t+1) &= b^k(t) - \eta \frac{\partial E^p}{\partial b^k} \Big|_t, \\ \beta^k(t+1) &= \beta^k(t) - \eta \frac{\partial E^p}{\partial \beta^k} \Big|_t, \\ a^k(t+1) &= a^k(t) - \eta \frac{\partial E^p}{\partial a^k} \Big|_t, \\ \alpha^k(t+1) &= \alpha^k(t) - \eta \frac{\partial E^p}{\partial \alpha^k} \Big|_t. \end{aligned} \quad (13)$$

Let $r = c^2/c^2 + d^2$, $r \in [0, 1]$; then, the following is

obtained:

$$\begin{aligned}
 c(t+1) &= c(t) - \eta \left\{ \frac{2c(t)d^2(t)}{c^2(t) + d^2(t)} \right\} \frac{\partial E^p}{\partial r} \Big|_t, \\
 d(t+1) &= d(t) - \eta \left\{ \frac{2d(t)c^2(t)}{c^2(t) + d^2(t)} \right\} \frac{\partial E^p}{\partial r} \Big|_t, \\
 r(t+1) &= \frac{c^2(t+1)}{c^2(t+1) + d^2(t+1)},
 \end{aligned} \tag{14}$$

where η is the learning rate and $t = 0, 1, 2, \dots$.

4.3. ATT-CNN Algorithm. The simulation results of some researchers [31, 32] show that the ATT-CNN model is better in prediction accuracy and performance when tested on several chaotic time series. Inspired by that work, we propose an ATT-CNN algorithm for risk prediction.

Considering the massive amount of data involved, the computational complexity of traditional FC NNs is unfeasible. The ATT-CNN allows its input layer to input any dimension for adaptive topology. Its local connection and weight-sharing characteristics reduce the network-free parameters and speed up the calculations. We can thoroughly explore the risk status information contained in the original signal using the ATT-CNN for end-to-end automatic learning, extract features without expert experience, and obtain a better nonlinear relationship between monitoring data and risk prewarning.

The translation and scaling of the input signal are highly invariant in time and space in the ATT-CNN, which is also not sensitive to noise. These features are theoretically suitable for data processing under the complex conditions of coal mines.

Furthermore, in the ATT, the weight of each feature is calculated, and then each component is weighted and summed. The larger the weight is, the more significant the contribution of the element to the current recognition. The essence of the ATT can be expressed as a mapping of a query (Query) to a series of key-value pairs (Key-Value). The idea of the ATT is shown in Figure 5.

In the ATT, the constituent elements in the source are regarded as a series of <Key, Value> data pairs. Given an element Query in the target, the weight coefficient of Value is obtained for each Key by calculating the similarity or correlation between Query and each Key. Then, Value is weighted and summed to obtain the final attention value.

Therefore, the ATT is used to perform a weight sum of Value in Source, and Query and Key are used to calculate the corresponding weight coefficients of Value. The ATT is calculated as follows:

$$\begin{aligned}
 &\text{Attention}(\text{Query}, \text{Source}) \\
 &= \sum_{i=1}^{L_x} \text{Similarity}(\text{Query}, \text{Key}_i) * \text{Value}_i,
 \end{aligned} \tag{15}$$

where $L_x = \|\text{Source}\|$ is the length of the source; the meaning of the formula is as described above.

The process focuses on the calculation of the weight coefficient. The larger the weight is, the greater the focus on the corresponding Value; i.e., the weight represents the importance of information, and Value is the corresponding information.

Based on the CNN algorithm, the ATT-CNN is generated by adding the ATT to enhance the invariance of the CNN in time and space and to further extract features. That is, the attention layer is added between the input layer and the convolutional layer in the CNN. The ATT calculates the attention weight a_j of the input feature Z_j to weight Z_j . The weighted feature Z'_j replaces the original Z_j as the input of the next layer. After progressing through the pooling layer, the FC layer, and the output layer, the final classification model is obtained.

The algorithm structure diagram based on the ATT-CNN is shown in Figure 6. The ATT is introduced in the convolutional layer to learn a weight distribution that is used to weight the original output of the convolutional layer.

By performing feature aggregation on the feature maps generated by the convolutional layer, each feature map is turned into a feature vector that can be considered a global receptive field. The weight vector a_j learned by the ATT is matched and multiplied by the feature map of the convolutional layer. Finally, the new feature Z'_j learned under the ATT network is obtained. The BN layer reduces the impact of changes in the middle layer data distribution. The activation layer enhances the nonlinearity of the model. The rectified linear unit (ReLU) accelerates the convergence of the CNN as an activation function. When the parameters are adjusted by the backpropagation learning method, the ReLU makes the weights of the shallow layer easier to train. Max pooling has the advantage of obtaining features that are unrelated to location information. The FC layer is usually used with softmax regression to classify the convolutional layer features and the pooling layer.

These operations together constitute a feature extraction layer. By stacking multiple feature extraction layers, feature extraction is realized layer by layer, and classification is realized in the last layer of the FC layer and softmax layer.

The crossentropy function is often used in combination with softmax in ML. We take the crossentropy function as the objective function. After using the error backpropagation algorithm to calculate the derivative of the objective function relative to the NN parameters, the optimization process employs the Adam algorithm.

5. Platform System Main Function

5.1. Production Scheduling and Information Management System. The production scheduling and information management system includes the system management module, the production scheduling information module, the query and report module, and other functional modules.

System management module is as follows: this module enables management of the department, account and role,

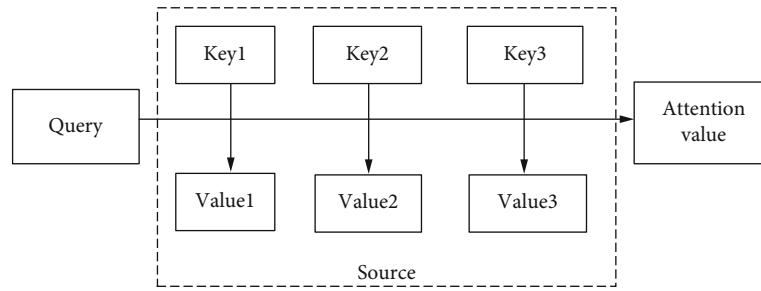


FIGURE 5: Idea of the attention mechanism.

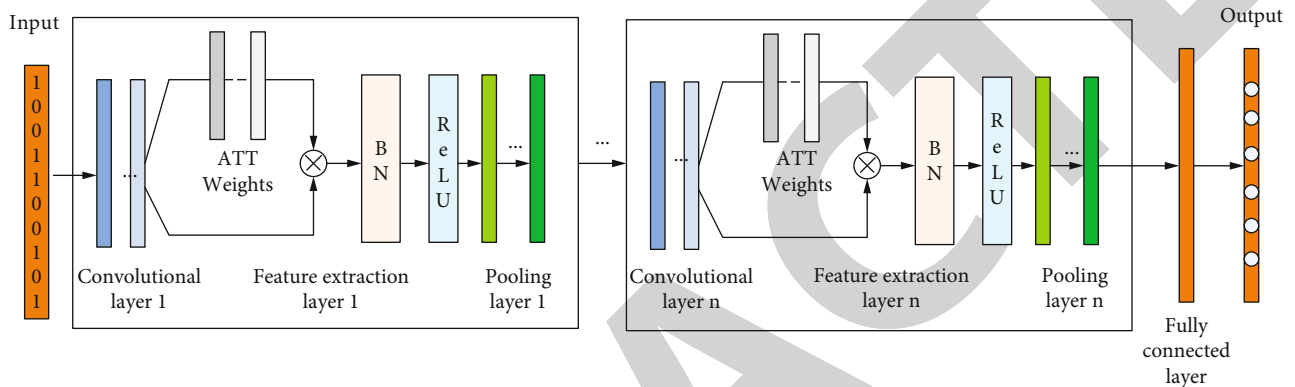


FIGURE 6: Algorithm structure based on the ATT-CNN.

password maintenance, landing inquiry, and management of the common tools and menu.

- (1) Production scheduling and information module: this module provides the completion of much information management, such as the monthly manufacturing program, daily drifting footage, daily drilling footage, daily water inflow, daily production information, gas monitoring, a list of leaders on duty, the weekly production schedule report, the address book, the driving moraine frontline, drill hole location information, and all information maintenance
- (2) Report view: this view provides daily, weekly, and monthly production reports, monthly manufacturing program data, tunneling data, drilling data, water inflow data, and the report from the leader on duty
- (3) Report upload: mine flood data, work accident data, and monthly reports are uploaded

5.2. Data Acquisition System. The functions of real-time data collection, storage, statistics, and analysis are available for every subsystem, including risk monitoring, underground substations, domestic water supply, online monitoring of fans, gas drainage, the water supply of the air shaft, personnel positioning, and safety information management [33].

5.3. Mine Mobile Information Platform. The mobile information platform supports multiple functions, e.g., real-time parameter monitoring, alarm recording, and trend curve

query functions. It can be used in 12 systems, including mine risk monitoring, personnel positioning, safety information management, production reports, address books, belt transportation, ventilation monitoring, wind well water supply, domestic water supply, gas drainage, and central substations.

6. Key Technologies and Features

6.1. Open Crossplatform Web Services. As a software component, web services are also a popular new technology that serves other applications by open standards for web protocols and data formats (such as HyperText Transfer Protocol (HTTP), Extensible Markup Language (XML), and Simple Object Access Protocol (SOAP)). It can be used as a service element to construct a distributed architecture system with advantages such as decentralized architecture dynamic integration, burden balance, and cell upgrades [34].

Open crossplatform web services can readily integrate different applications developed from different programming languages and run on different operating systems by adopting open standards.

In our design, by depending on web services and integrating the mobile 4G network and PC network, we can schedule work management in optional modes, which can significantly reduce an application's geographical and temporal constraints.

6.2. Visual Analysis Method. The system adopts advanced graphical analysis tools and strategies [35]. With the use of animation, the system changes the traditional original lengthy, complicated summary, and statistical data into

intuitive, clear pictures with animation. Under the visual data conditions, we can apprehend the statistical data by only a glance owing to the sharp contrast.

6.3. Advanced Concept of Ajax Technology. The system has been implemented using asynchronous JavaScript and XML (Ajax). Ajax was chosen because it offers a more definitive and better experience. Ajax is not a single technology but a group of technologies. HyperText Markup Language (HTML) and Cascading Style Sheets (CSS) can be used in combination to mark up and style information.

Ajax is a web development technique that uses many web technologies on the client side to create asynchronous web applications. With Ajax, web applications can communicate with a server asynchronously (in the background) without interfering with the display and behavior of the existing page. By decoupling the data interchange layer from the presentation layer, Ajax allows extension web applications to change content dynamically without reloading the entire page. The following technologies are incorporated into Ajax:

- (1) HTML (or Extensible HyperText Markup Language (XHTML)) and CSS for presentation
- (2) The document object model (DOM) for the dynamic display of and interaction with data
- (3) JavaScript object notation (JSON) or XML for data interchange and Extensible Stylesheet Language Transformations (XSLT) for data manipulation
- (4) The XML Http Request object for asynchronous communication
- (5) JavaScript to bring these technologies together

XML is no longer required for data interchange; therefore, XSLT is no longer required to manipulate data. JSON is often used as an alternative format for data interchange, along with other formats such as preformatted HTML or plain text.

Asynchronous HTML and HTTP (AJAX) involves using the XML Http Request to retrieve (X) HTML fragments, which are then inserted directly into the web page.

6.4. Examples of Hazard Prediction. We trained our models on one machine with a RX 5500 XT 8GB graphics processing unit (GPU). This model uses Keras 2.3, a DL framework based on Python 3.7.3 (with TensorFlow 2.1.0 as the back end), to quickly build a deep hybrid NN. The ATT-CNN parameters are shown in Table 1.

The strip and padding of the convolution layer are set to 1, the learning rate is $1e-3$, and the batch size is 256. The size of the convolution kernel is 3×3 , and the maximum number of network iterations is 1000. The dropout layer is not employed in the experiments since the data came from sensors.

Coal and gas outbursts (CGOs) are the result of the common effects of ground stress, coal seam gas, and the physical and mechanical properties of coal structures. The main fac-

tors affecting gas outbursts are uncertain. The prediction of CGO risk can be regarded as the prediction of an ambiguous event determined by multiple factors. In the following, this risk prediction process is explained.

Combining the analysis of the risk factors for CGOs and the ranking of the importance of outburst influence by the triangular fuzzy comprehensive evaluation method, the input variables of the NN prediction model are the following:

- (1) Initial gas release velocity
- (2) Index of coal destruction
- (3) Gas pressure
- (4) Index of the geological structure
- (5) Index of the coal firmness coefficient
- (6) Permeability coefficient
- (7) Gas content
- (8) Attenuation coefficient of the drilling gas emission volume
- (9) Depth of mining

The output vector is the characteristic of the CGO. The coal seams or areas are divided into 4 categories according to the degree of danger by combining relevant theories and knowledge of CGOs, detailed rules for the prevention and control of CGOs, and an evaluation index system for the risk of CGOs. The output vector contains the four types of coal seam outburst hazards, represented by four nodes, where 1000 means serious danger, 0100 means greater danger, 0010 means average risk, and 0001 means small risk.

The number of input layers n in the NN is 9 according to the triangular fuzzy method, the output layer l is 4 by the classification of the prominent danger, and the number of nodes of the hidden layer neurons is set to 17 from the empirical formula. Therefore, (9, 17, 4) denotes the structure of the fuzzy NN. The sample data are shown in Table 1.

The data are obtained from the database copy of monitoring system of Xuyong Coal Mine in Sichuan Province, where the gas content increases with the coal depth. The relation between gas content and coal seam depth is not a simple linear relation such that the gradient of content is large in shallow areas and small in deep areas. The relative gas emission is $20.1 \text{ m}^3/\text{t}$. The variation gradient of the gas content is generally between 3 and $8 \text{ m}^3/\text{t-daf}/100\text{m}$. The permeability coefficients of coal seams are different in spatial distribution due to the other occurrence conditions. There are abnormal features in local areas such that the permeability coefficient shows apparent characteristics of the partition and subband.

For colliery gas, the gas concentration is related to not only its own historical data but also the influence of other factors on the coal seam, such as the influence of the underground water volume, the tunneling speed in the process of underground coal mining, and the grade of the mine

TABLE 1: The detailed settings of the ATT-CNN parameters.

No.	Item	Kernel size	Amount	Output size	Activation function
1	Input layer				
2	CNN layer 1	3×3	48	$8 \times 8 \times 48$	ReLU
3	Pooling layer 1	3×3	1	$6 \times 6 \times 48$	
4	ATT layer 1				
5	CNN layer 2	3×3	128	$6 \times 6 \times 128$	ReLU
6	Pooling layer 2	3×3	1	$4 \times 4 \times 128$	
7	ATT layer 2				
8	CNN layer 3	3×3	384	$4 \times 4 \times 384$	ReLU
9	CNN layer 4	3×3	256	$4 \times 4 \times 256$	ReLU
10	Pooling layer 4	3×3	64	$2 \times 2 \times 256$	
11	FC	1×1024	1	4×1	ReLU
12	Output layer			4×1	Softmax

TABLE 2: Data of the coal seam gas outburst risk sample.

No.	b1	b2	b3	b4	b5	b6	b7	b8	b9	b10	b11
a1	c19	18.24	0.5	0.65	0.5	0.33	0.73	9.814	0.657	139	0100
a2	c19	18.24	0.5	1.75	0.8	0.33	0.73	13.909	0.657	135	0100
a3	c19	10.17	0.5	1.2	0.8	0.54	0.54	9.591	1.09	182	0010
a4	c19	10.17	0.5	0.85	0.5	0.54	0.54	9.943	1.09	160	0010
a5	c19	20.34	0.6	1.2	0.9	0.24	0.24	13.305	1.535	341	1000
a6	c19	20.34	0.6	1.55	0.5	0.24	0.24	14.982	1.535	212	1000
a7	c19	20.34	0.6	0.84	0.9	0.24	0.24	11.278	1.535	232	1000
a8	c19	20.34	0.6	1.2	0.9	0.19	0.19	13.303	1.535	342	1000
a9	c19	24.01	0.5	0.48	0.9	0.21	0.21	8.299	0.193	200	1000
a10	c24	12.54	0.5	0.85	0.5	0.55	0.55	10.121	0.193	290	0100
a11	c24	12.54	0.5	0.7	0.9	0.55	0.55	9.059	0.588	292	0001
a12	c24	10.17	0.5	1.6	0.5	0.34	0.34	16.326	0.588	316	0001
a13	c24	10.17	0.5	1.65	0.9	0.34	0.34	16.54	0.588	288	0001

TABLE 3: Results of the CGO risk prediction based on the neural network model network mode.

No.	v1	v2	v3	v4	Output	Predicted level of danger
a1	0.0038	0.9764	0.0012	-0.0026	0100	Medium
a2	0.0034	1.0084	0.0107	-0.0231	0100	Medium
a3	-0.018	-0.026	0.9935	0.0985	0010	General
a4	0.0186	0.0429	0.9788	-0.075	0010	General
a5	1.0213	-0.085	0.0386	-0.0703	1000	Serious
a6	0.9901	-0.006	-0.005	0.017	1000	Serious
a7	1.0058	0.0254	0.011	-0.0002	1000	Serious
a8	0.9841	0.0646	-0.0438	0.0498	1000	Serious
a9	-0.003	1.0042	-0.0083	0.0258	0100	Medium
a10	-0.013	0.9877	0.0115	0.0238	0100	Medium
a11	0.0075	0.0035	0.0103	0.9341	0001	Smaller
a12	0.0029	0.0011	0.004	1.0321	0001	Smaller
a13	-4E-04	0.0036	-0.0033	0.9884	0001	Smaller

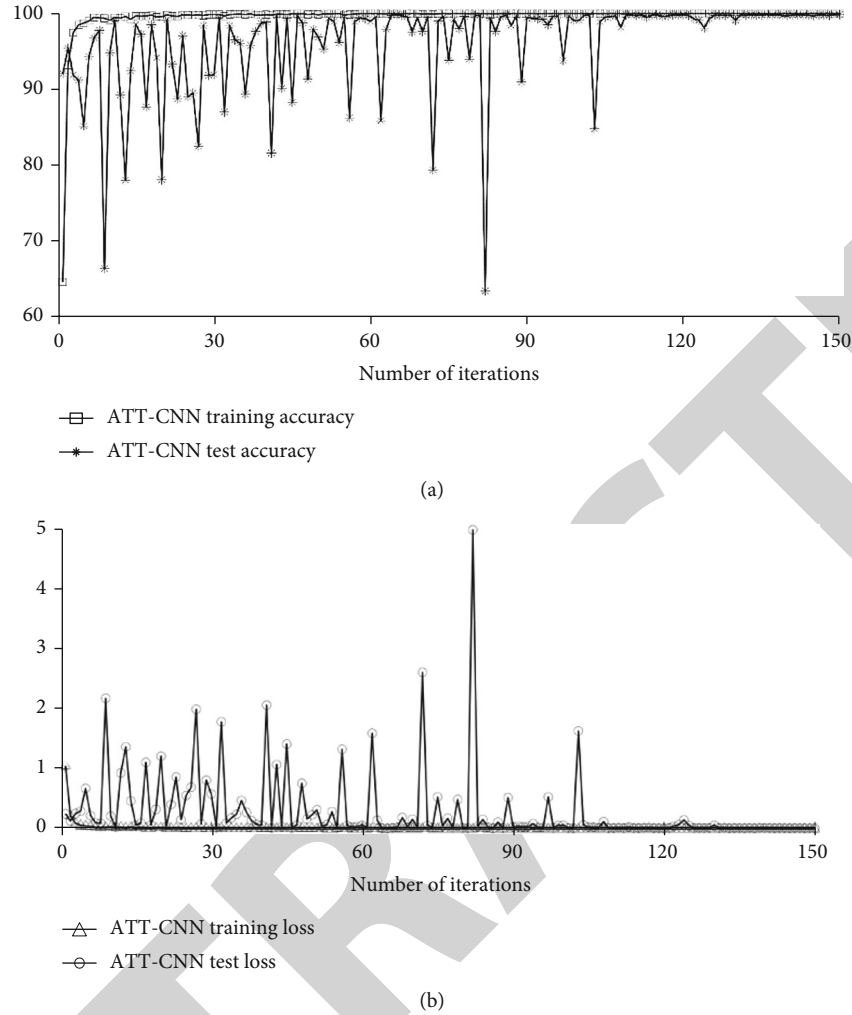


FIGURE 7: (a) Model accuracy diagram of the epoch process of the ATT-CNN model. (b) Loss value curve diagram of the epoch process of the ATT-CNN model.

surrounding rock itself. The input of the gas concentration prediction model is 10.

The gas data used in this paper comprise a total of 17280 groups of gas concentration samples collected every 5 minutes for 60 consecutive days. For training, the data are divided into a training set and a test set at a ratio of 7:3, in which the samples in the first 42 days are used as the training set and the remaining 18 days are used as the verification set. In this paper, there is no manual feature handle except for the standardization and one hot coding of the data.

In Table 2, b1 is the coal seam location; b2 denotes the initial speed of the gas release (mmHg); b3 represents the coal destruction type, and b4 stands for the gas pressure (MPa); b5 denotes the geological structure type; b6 represents the coal firmness coefficient; b7 stands for the coal seam permeability coefficient ($\text{m}/\text{MPa}^2 \text{d}$); b8 denotes the gas content (m^3/t); b9 represents the drilling gas attenuation coefficient (d^{-1}), b10 stands for the depth of mining (m), and b11 denotes the output expectations.

The number of neurons in the network's hidden layer is 17, and the number of neurons in the output layer is 4. The first layer transfer function is a logarithmic sigmoid func-

tion, and the second layer transfer function is a linear function of purelin.

The predicted CGO risk results based on the NN model after training are shown in Table 3.

The predicted values of the model are in good agreement with the output data. The ATT-CNN simulation result is shown in Figure 7. By continuously updating the loss curve, the parameters learned by the model gradually increase, and the fitting ability is steadily improved. After 120 iterations, the test accuracy is stable. After 150 iterations, the model terminates training.

When the accuracy of the model is relatively high, the corresponding error loss value is relatively low. When the test accuracy rate oscillates, the test loss value curve also oscillates. Therefore, the accuracy and loss are consistent in reflecting the changes in the model's parameters and the state of data fitting in the iterative process. The performance of signal classification can be verified by combining these two indicators.

As a vital part of the model, the ATT is the key to obtaining the feature sequence, affecting the classification accuracy. Additionally, combining the opinions of on-site experts and

comprehensive factors, we believe that the ATT-CNN model is suitable for describing the objective phenomenon, where 0.7 is set as the weight of the ATT-CNN and 0.3 is set as the weight of the NN.

The objective state of the system at a certain moment is theoretically unique. The prediction of the fuzzy NN is not always consistent with the ATT-CNN in three aspects: prewarning results, environmental factors, and equipment factors. The cause lies in the insufficient quantity of training data of the model. If inconsistent results between the ATT-CNN and the NN occur, the final risk levels are regulated by the weight. Periodically compare performance of the ATT-CNN model to results of the fuzzy NN and switch to your predictions when they become more accurate.

In order to train prediction methods that aim to work well for a different kind of risk, it is sufficient to provide training data from others sensor for model.

7. Conclusions

Risk prewarning is critical in the coal mine safety management. In this paper, a mobile intelligent mine platform with a combination model is proposed to achieve the risk prewarning and information transmission to personnel. Any staff member with a mobile terminal working in the platform can obtain data for management and risk prewarning at any time.

The proposed risk prewarning model is formed by a compensation fuzzy NN with a novel ATT-CNN hybrid prewarning model focuses on the hidden features and evaluates these features under learned weights and aggregates not only the information within all sequential data but also the sequential spatiality.

CNN processes high-dimensional data without pressure and can automatically extract features. The sliding window of CNN has no sequential relationship, and there is no mutual influence between different convolution kernels. Therefore, it has a very high degree of parallel freedom which is a very good advantage.

ATT can be regarded as an automatic weighting. It learns a weight distribution and then employs on the feature. That is ATT can assign higher weights to the features with greater impacts on prewarning to improve the prediction accuracy. ATT has a great advantage that it can visualize the attention matrix to show what parts the neural network pays more attention.

The ATT-CNN takes full advantage of the powerful nonlinear learning ability and avoids the traditional reliance on experts for knowledge extraction. The model is free from artificial determination of the index weights, which are difficult to allocate reasonably, and is a completely data-driven approach.

The experimental results show that our proposed hybrid prewarning model is very effective for risk prewarning in terms of both quantitative and qualitative evaluations.

The hybrid model in this paper can effectively solve the problem of large capacity, multidimensional, and unbalanced time series classification and can become more detailed by increasing the number of output nodes.

Although the hybrid model achieves effective performance on test data, the model has a large number of parameters and calculations, which is not suitable for running on mobile terminals and embedded devices. The design of a lighter and faster risk prewarning model suitable for the wireless terminals of personnel will be our future research topic.

Data Availability

The raw data required to reproduce these findings cannot be shared at this time as the data also forms part of an ongoing study.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

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