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Safety Information Management in Mining Areas Based on Improved Convolutional Neural Networks and Automated Data Processing

Tolibjonov Shoxjaxon Otabek o'g'li
Navoi State University of Mining and Technology, Department of Automation and Control, Student

Abstract: To improve the efficiency of safety information management in mining areas and better protect the life and property of workers, this study integrates intelligent automated data processing technology into the management framework. Addressing the challenge of inaccurate boundary value judgments during security risk level classification, an improved convolutional neural network is employed to enhance the visibility of numerical features. Furthermore, the research conducts a systematic analysis through experiments, gathering existing operational data via network platforms to quantify various risk factors within mining sites. Experimental results demonstrate that the proposed intelligent safety information management system plays a crucial role in identifying safety hazards. It exhibits high accuracy in recognizing risk factors and significantly enhances the overall data processing experience for users.

Keywords: intelligent automation, mining area, safety, information management.

Introduction

Mining serves as a cornerstone of the national economy, with mineral resources acting as fundamental supplies for human production and daily living. A nation's economic strength and development potential are largely determined by the abundance, development, and utilization level of its mineral resources. Currently, informatization represents a vital pathway for elevating mining production management and an inevitable choice for accelerating modernization across the mining sector. Informationalized production drives industrialization, while industrialization concurrently fosters information production. Prior to the widespread adoption of informatization, limited technical capabilities and a lack of scientific management in mining operations resulted in low production efficiency among coal enterprises. Furthermore, major safety accidents frequently occurred in mining areas, inflicting severe consequences on national security, property, and human lives.[1]

As technology progresses, computer systems continue to evolve, driving continuous advancements in mining information management methods. For instance, developing a water inrush warning and management system enables computerized, systematic, and standardized oversight of hydrogeological data.[2] This allows for the scientific collection, aggregation, querying, and analysis of hydrogeological information, reducing the energy expended on data management and enabling a greater focus on water prevention and control methodologies, thereby boosting overall efficiency in mining areas. Additionally, by extracting critical insights from data using efficient algorithms and establishing water inrush prediction models, the system can forecast water disasters. This guides mining operations, supplies decision-makers with real-time simulation results for risk prevention, and minimizes losses caused by water inrushes. Consequently, such technologies play a critical role in mitigating the impact of mine disasters and safeguarding the personal safety of miners.[3]

How to make the collected data more accurate and reliable for mining enterprises by manually inspecting and recording data in the well. Compared three data collection methods: collecting data from various sites through management personnel inspections, relying on node devices to actively send data information to the upper level, and mixing the two methods. Based on this, the characteristics of different data collection methods were summarized, and the conclusion was drawn that the method of node devices actively sending data is more intelligent and reliable.[4] The proposed data collection method selection has reference significance. proposed a way to implement caching and transmission of data acquisition systems using the built-in DMA function of MCU. Through data processingcomparison, it was found that using DMA to quickly move data can save MCU resources and achieve high-speed data information acquisition. This research is of great significance for improving the transmission speed of data information. designed a system that uses industrial Ethernet EtherCAT to achieve real-time transmission of underground data in mining areas, in order to solve the problem of low real-time information transmission and poor resistance to external interference in underground data acquisition systems. This article analyzes the communication methods and principles of data information exchange between TwinCAT and VC++, which has reference significance in improving the reliability of data transmission and reception. designed a data acquisition substation based on DSP, which adopts a system structure combining CAN bus and Ethernet to solve problems such as data transmission loss in underground mines, coordinate the work of ventilation decision-making systems, and ensure real-time communication of underground equipment.[5]

Due to careless manual recording or equipment operation, significant data errors and delayed transmissions frequently occur. Previous studies have addressed these challenges from various angles: analyzed distance measurement error distributions within underground positioning system models, calculating maximum error impacts on worker and locomotive tracking to aid post-accident rescue operations. established a local resistance calculation formula for ventilation fans to resolve measurement inaccuracies, offering vital theoretical guidance for equipment operation.[6] proposed leveraging big data, cloud computing, and "Internet Plus" technologies to extract, analyze, and store underground safety information, thereby reducing accident rates and production costs. Additionally, compared dynamic pressure and static pressure difference methods for testing ventilation fan air volume accuracy, identifying the dynamic pressure method as superior for minimizing performance testing errors.[7]

Beyond data processing, safety hazard early warning systems are critical for preventing major mining accidents. analyzed mining accident statistics, linking hazards to management deficiencies and worker health, and proposed a multi-project framework that assigns numerical scores to various risk factors to assess safety coefficients. introduced a wireless safety monitoring and early warning system incorporating gas dynamics and environmental parameter tracking, utilizing wireless terminals for real-time communication to foster dynamic, collaborative safety management. Finally, advanced risk prediction by incorporating temporal impacts, safety hazard probability, severity, and controllability into a dynamic evaluation framework, enabling high-precision regional warnings tailored to specific hazard locations and handling complexities.[8]

Methodology

MINING AREA SAFETY INFORMATION MANAGEMENT SYSTEM

Risk intelligent classification Within the risk early warning layer of the intelligent management, control, and information decision analysis system for mining area safety, an intelligent safety risk classification model is proposed to construct a comprehensive risk classification framework. The primary function of this system is to analyze data processed by the safety risk data intelligent screening mechanism, thereby determining precise safety risk levels. Based on these assessed risk levels, the system decides whether to issue warnings regarding potential safety hazards and generates appropriate countermeasures.[9]

Result and discussion

Figure 1. To achieve this, the study employs a parallel fusion convolutional neural network (CNN) architecture for modeling. As illustrated in Figure 1, convolution kernels of varying scales are utilized, allowing feature extraction through dual channels. This approach increases the volume of extracted relevant features, thereby enhancing feature diversity and robustness while improving the overall classification accuracy of the network.[10]

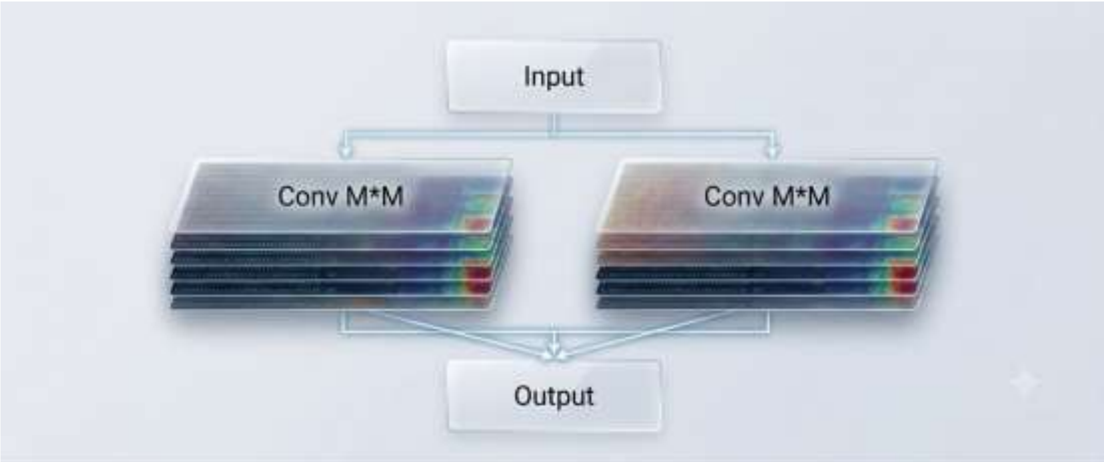

Figure 1. Convolutional neural network with parallel fusion

First, the convolution layer utilizes specially designed kernels to amplify the acquired evaluation values, after which the pooling layer applies downsampling to compress the gathered data via the average pooling method for dimensionality reduction.[11] Finally, a 3 by 3 safety risk assessment value matrix is generated. The Figure 2. values within this matrix are then compared against predefined safety grading criteria to determine the specific safety risk levels for the mining areas.[12]

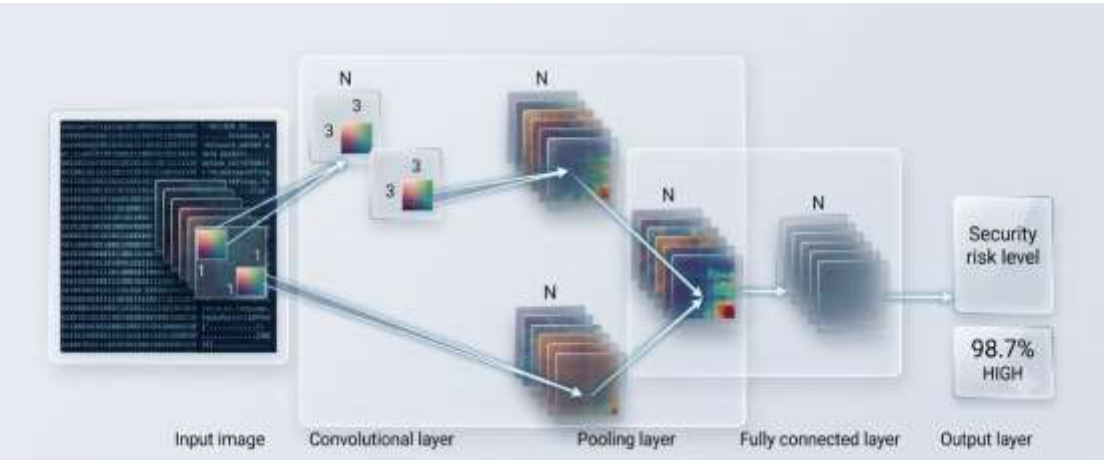

Figure 2. Construction process of security risk intelligent hierarchical model based on improved CNN

The steps of the intelligent security risk classification algorithm based on CNN are as follows: (1) The algorithm records the safety risk assessment value data for i mining areas, with each mining area incorporating four distinct assessment values. Furthermore, the algorithm analyzes the safety risk of each respective mining area and retains three decimal places for the evaluation values to construct the initial matrix data model, as illustrated in Figure 3.[13]

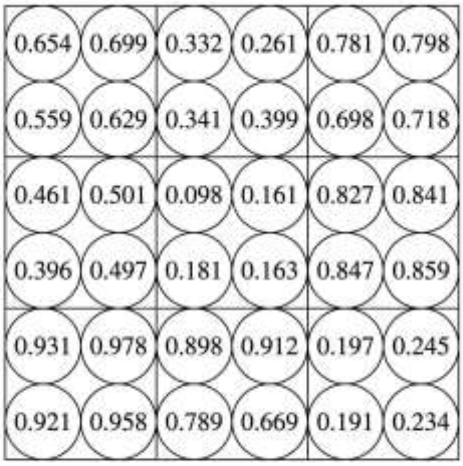

Figure 3. Evaluation value matrix model

Each point in Figure 3 represents a numbered safety risk assessment value, where the numerical data correspond to the node values in row i and column j of the matrix. Within the convolution layer, dual channels are employed to process the data. To enhance the network's feature extraction capability, a convolution operation with a 1×1 kernel is initially applied across both channels. Subsequently, one of the channels undergoes deep convolution using a 3×3 kernel for advanced feature extraction, after which the resulting output feature maps are fused together. The final convolution value of this fusion output can be expressed as shown in formula (1).

$$\begin{cases} y_{i,j}^1 = f_1\left(\sum_{i=0}^{i}\sum_{j=0}^{j} w_{i,j}^1 x_{i,j}^1 + b_m\right) \\ y_{i,j}^2 = f_1\left(\sum_{i=0}^{i}\sum_{j=0}^{j} w_{i,j}^2 x_{i,j}^1 + b_n\right) \\ y_{i,j} = f_2\left(y_{i,j}^1, y_{i,j}^2\right) \end{cases}$$

In formula (1)

$w_{i,j}^1$ and $w_{i,j}^2$ represent the weights of the i -th row and j -th column of the two channel processing matrix data, respectively. The weights constitute the convolution kernels of 1×1 and 3×3 . b_m and b_n are offsets, and f represents the activation function. $y_{i,j}^1$, $y_{i,j}^2$ and $y_{i,j}$ represent the data after the two channel convolution and channel fusion. (2) The algorithm performs an average pooling operation on the acquired $y_{i,j}$ to obtain a smaller parameter grid and reduce the calculation dimension. Formula (2) is as follows.

$$f(x) = average(y_{i,j}, 0)$$

If the pooled data is set to P , the output data of each layer is $P\{P_{1,1}, P_{1,2}, \dots, P_{3,3}\}$, and the calculation matrix as in formula (3) can be obtained:

$$f(x) = \begin{bmatrix} P_{1,1} & P_{1,2} & P_{1,3} \\ P_{2,1} & P_{2,2} & P_{2,1} \\ P_{3,1} & P_{3,1} & P_{3,1} \end{bmatrix} = \begin{bmatrix} y_{1,1} & y_{1,2} & \cdots & y_{1,6} \\ y_{2,1} & y_{2,2} & \cdots & y_{2,6} \\ \cdots & \cdots & \cdots & \cdots \\ y_{6,1} & y_{6,2} & \cdots & y_{6,6} \end{bmatrix}$$

The matrix $f(x)$ represents the combination of security risk assessment values across each layer following data processing. If the data separation obtained after a single convolution and pooling operation lacks sufficient clarity, multiple convolutional layers can be added to achieve distinct numerical boundaries. (3) The algorithm takes the output $f(x)$ from the pooling layer as the input data for the fully connected layer, processing the data through the N -layer to generate a 3×3 data matrix, which serves as the security risk assessment value matrix. (4) The algorithm categorizes the numerical ranges of safety risks across all levels, identifies the respective safety risk level for each mining area, and proposes corresponding corrective measures.[14]

Before adopting this system, mining companies depended heavily on manual data statistics and staff experience to evaluate safety risk warnings based on manually reviewed data, lacking standardized regulations to address safety hazards when they arose. To resolve these challenges, the system has been optimized in the following decision-making aspects:

(1) **In terms of data statistics:** The system retrieves information from the database to display relevant demand data visually through bar charts, pie charts, and other graphical formats. This not only provides a clear overview of the current conditions in the mining area but also forecasts upcoming safety production trends based on shifting data patterns.

(2) **In terms of security warning:** An intelligent data screening system and a risk classification system are built using particle swarm intelligence algorithms and convolutional neural networks to filter data and accurately assess risk values, thereby ensuring data accuracy and reliability.

(3) **In terms of security regulation retrieval:** Association rule mining technology is utilized to rapidly retrieve necessary safety compliance criteria, reducing manual data-entry time for staff and accelerating the overall decision-making process.

(4) In terms of evaluation criteria, four risk levels have been divided: blue, yellow, orange, and red, and corresponding response plans have been developed for each level. When safety hazards or accidents occur, staff can take effective measures faster. The application of this module makes the decision-making system more intelligent and efficient. (5) There are three roles for system administrators: regular employees, administrators, and super administrators, with different levels of operation and management of the system, making decision-making more standardized.

Model construction

In view of the main reasons for the frequent occurrence of safety accidents: inadequate inspection data records, unclear safety risk classification, untimely early warning of potential safety hazards, inaccurate accident handling measures, etc., intelligent management and control of safety risks and information decision analysis system in mining areas are designed by combining the Internet of Things and Internet technology. The overall design of mining area safety risk intelligent management and control and information decision analysis system is shown in Figure 4.

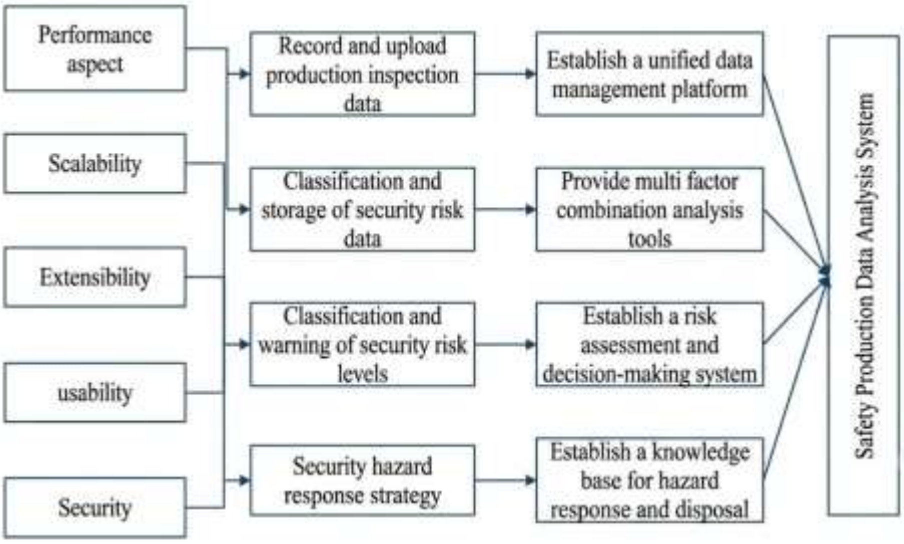

Figure 4. Overall design of intelligent management and control of safety risks and information decision analysis system in mining area

According to the design concepts and research methodologies of the intelligent management, control, and information decision analysis system for mining area safety risks, a structural model comprising five distinct layers has been constructed: the intelligent monitoring layer, data acquisition layer, data transmission layer, data processing layer, and risk warning layer. The overall system architecture is illustrated in Figure 5.

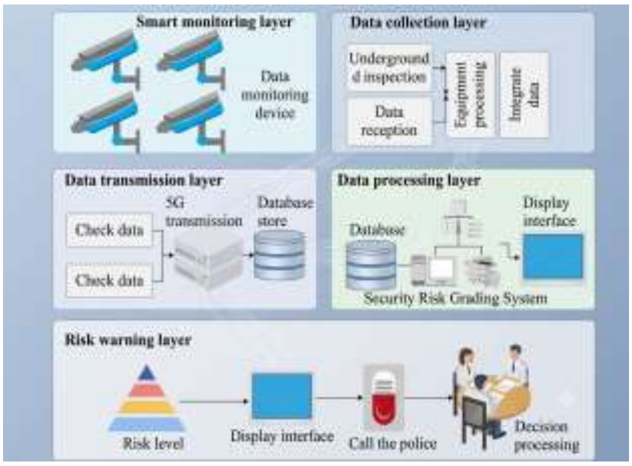

Figure 5. Architecture of intelligent management and control and information decision analysis system of mining area safety risk

The Figure 6. data processing layer structure is shown in Figure 6. The data processing layer includes the intelligent screening system of mining area safety risk data and the intelligent classification system of safety risk. The data acquisition layer uses the scheme proposed by He Qiao to calculate the risk assessment value of the working face, location, time, roadway condition and other information recorded by the staff and the data information monitored by the equipment, and imports the calculated initial value into the intelligent screening system of safety risk data, and uses the optimization characteristics of particle swarm optimization to screen out the data that does not meet the requirements. Then, the value

is processed by the intelligent safety risk classification system, and the convolutional neural network is used to amplify the features, and the safety risk value is expanded to an unambiguous range. After that, according to the safety risk classification, the current safety status of mining area production is determined.[15]

Figure 6. The structure of data processing layer

Conclusion

Addressing the safety management requirements of mining areas, this study leverages the scientific and technological information sector to harness the advantages of the Internet and Internet of Things (IoT) technologies in managing and controlling mining production safety risks. Consequently, an intelligent management, control, and information decision-making analysis system for mining safety risks has been successfully established. Furthermore, the paper provides a detailed discussion on the system's preparation, design concepts, development workflow, software implementation, and evaluation analysis.

Regarding the system's safety risk early warning mechanism, data processing yields precise safety risk assessment values that are categorized into corresponding safety levels. The safety hazard status of each mining area is then clearly displayed on the host computer interface. The location of hazards and the number of mining areas associated with each level are immediately discernible, alongside the corresponding safety risk grades and root causes, thereby delivering robust intelligent decision-making functions. Combined with experimental analysis, the findings demonstrate that the proposed intelligent safety information management system—integrated with automation technology—plays a vital role in identifying mining safety factors, exhibits high accuracy in recognizing risk levels, and effectively enhances the overall data processing experience for users.

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