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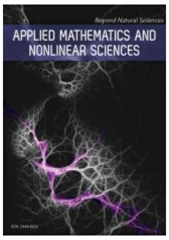

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A real-time monitoring and fault diagnosis method for underground mine electrical automation equipment combined with edge computing

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Abstract

Under the background of increasing requirements for safety, automation and intelligence in mining operations, real-time monitoring and fault diagnosis of underground electrical automation equipment have become particularly critical. In order to meet the demand for equipment status monitoring in the complex underground environment, this paper designs a set of intelligent monitoring system architecture for electrical equipment based on edge computing, which contains four main sections: real-time monitoring, data processing, data analysis, and control center. In terms of equipment fault diagnosis, this paper studies GRU neural networks in detail, combines the intelligent monitoring system designed in this paper with GRU neurons, and constructs the equipment fault diagnosis model in this paper. The equipment fault diagnosis model in this paper is tested and analyzed. The precision, recall, and accuracy of this paper's model for fault recognition are 0.899, 0.913, and 0.935, respectively, indicating that this paper's model has excellent performance in the field of electrical equipment fault recognition.

Keywords: Electrical equipment; Real-time monitoring; Fault diagnosis; GRU neurons.
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1 Introduction

In mining machinery and equipment, the electrical automation system has strong intelligence, which can be effectively controlled and managed, and through the use of modern and advanced information technology to carry out real-time monitoring and automatic processing of the power system [1-2], it can realize the requirements of safe operation of electromechanical equipment, high efficiency, and reliable use, and effectively improve the efficiency of mining machinery and equipment to ensure safe production [3-4].

Electrical automation equipment occupies a pivotal position in modern industry and daily life [5]. With the rapid development of technology, the complexity and degree of intelligence of the equipment are also increasing. However, the problem of equipment failure is always a key factor affecting its stability and safety [6-8]. How to effectively diagnose and prevent these faults has become the focus of researchers and engineers [9].

In recent years, fault diagnosis and predictive maintenance technology has been widely researched and applied, the core of which lies in the use of advanced technical means to discover potential problems in advance and carry out targeted maintenance, so as to avoid the occurrence of sudden failures [10-13]. This not only improves the reliability and service life of the equipment, but also reduces maintenance costs and downtime. In fault diagnosis technology, signal processing technology plays an important role [14-16]. By collecting and analyzing the electrical signals generated during the operation of the equipment, faults can be effectively identified and localized. Commonly used signal processing techniques include time domain analysis, frequency domain analysis and time-frequency analysis [17-19]. Among them, time-domain analysis focuses on the characteristics of the signal changes in time, which is suitable for preliminary fault diagnosis, frequency-domain analysis converts the signal from the time domain to the frequency domain through methods such as Fourier transform to identify periodic faults and harmonic components, and time-frequency analysis combines the advantages of the time domain and the frequency domain, and realizes the accurate analysis of non-smooth signals through the methods of the short-time Fourier transform and the wavelet transform[20-22]. Intelligent diagnostic techniques such as expert systems and artificial neural networks are also widely used in the fault diagnosis of electrical automation equipment. Expert systems are able to realize the diagnosis of complex faults by combining expert experience and knowledge base [23-24]. However, the construction and maintenance of expert systems require a large amount of expert knowledge and may have limitations when facing new faults. Model-based fault diagnosis methods are also important in practical applications [25-26].

Monitoring of electrical automation equipment helps to improve production safety and efficiency, how to improve the monitoring effect of electrical automation equipment, accuracy, as well as reduce the monitoring cost are worth focusing on the direction of research and optimization. Literature [27] summarizes the related research on the operation and offline condition detection and assessment of electric equipment, puts forward the insufficient problems of sensor signal acquisition, and looks forward to the prospect of electric equipment monitoring empowered by big data and IoT technology. Literature [28] envisioned an electrical automation monitoring and control scheme based on the underlying architecture of smart sensor networks, with good fault identification and effective reduction of energy consumption of building electrical equipment. Literature [29] attempts to use CAN bus communication for electrical equipment automation control and monitoring to improve control efficiency and safety.

Literature [30] conceptualized a neural network with data as the core logic in order to achieve the diagnosis of electrical automation equipment, which demonstrated reliable fault diagnosis performance in simulation experiments, as well as good noise immunity. Literature [31] designed a fault monitoring model for electrical automation equipment based on C4.5 algorithm with superior fault classification capability. Literature [32] proposes to support electrical automation equipment fault diagnosis by transmitting and fusing the fault information collected from electronic automation equipment information through the information chain technology to improve the problems such as few fault parameters and poor diagnosis accuracy in the fault diagnosis process. Literature [33] designed a new decision support system for electrical automation data analysis equipment fault diagnosis that combines detailed data from specific data processing equipment with rule-based data mining and clustering techniques, and tested the reliability based on simulation experiments. The above methods for fault diagnosis of electrical automation equipment mainly apply techniques such as neural network algorithms, information chain and data mining, which to a certain extent have improved the accuracy of fault diagnosis of electrical automation equipment, but the fault diagnosis methods proposed in the study have not been mentioned for the applicable scenarios, especially for scenarios such as underground mines, which is a frequently used scenario for electrical automation equipment, and therefore it is necessary to target the Therefore, it is necessary to conduct an in-depth study on the fault diagnosis of electrical automation equipment in underground mines.

This paper takes the real-time monitoring module as the core to design the intelligent monitoring system architecture in electrical equipment. The system consists of four segments: real-time monitoring module, data processing, data analysis, and control center, which are divided into four parts and work together in order to realize real-time detection and early warning of the equipment. Subsequently, this paper designs the raw data acquisition process, edge computing node method. At the same time, this paper discusses the structure of GRU neural networks and their classification methods. Combining the monitoring system and GRU neurons in this paper, a GRU-based fault diagnosis model is constructed. The model of this paper is applied to an electrified automatic equipment and tests are carried out to determine the hyperparameters of the model, classify the sample faults, and analyze the prediction accuracy of the model of this paper.

2 Intelligent monitoring system in electrical equipment

The architecture of the intelligent monitoring system in electrical equipment designed in this paper is shown in Fig. 1. The system is divided into 2 parts: user layer and edge layer. The architecture relies on a real-time monitoring module that integrates a variety of sensors to collect physical signals from the electrical system. The raw data collected is rapidly transmitted to the computing layer located at the edge.

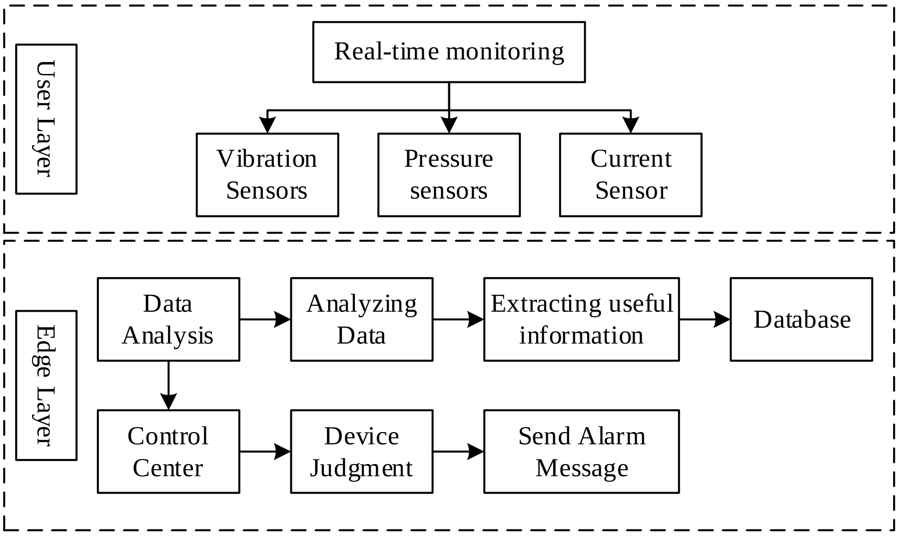

Figure 1. Intelligent monitoring system architecture

In the edge computing layer, the data processing module is responsible for processing the data collected by the sensors. The analysis and extraction module deeply analyzes the processed data, extracts key features and abnormal information from it, and stores them in the database. At the same time, the processed data is also transmitted to the control center for equipment status determination. When the system detects a potential risk or anomaly, it instantly triggers the alarm mechanism to send early warning information to the system for timely intervention and processing. The architecture designed in this paper breaks through the limitations of network delay and bandwidth bottleneck in the traditional monitoring mode. The functions of each module are examined as follows.

1) Real-time monitoring module

The real-time monitoring module collects real-time data from the electrical system by integrating sensing devices such as vibration sensors, pressure sensors, and current transformers. The sensors acquire the vibration, pressure, and other data of the electrical equipment and convert the raw data into electrical signals. The electrical signals are transmitted to the edge computing layer after analog-to-digital conversion to provide source data for analysis and decision making. After the data is sent to the edge layer, the real-time monitoring module captures raw data that is then sent to the edge computing layer for processing and analysis using the communication protocol. In the transmission process, the integrity and accuracy of the data are guaranteed, which facilitates subsequent data processing and decision making.

2) Data processing module

The data processing module of the edge computing layer is responsible for processing the original data, including data cleaning, denoising, filtering and so on. Through mathematical algorithms, signal processing, and other means, reduce data interference and improve data quality. The processed data is transmitted to the data analysis module and the control center to provide support for subsequent analysis and control decisions.

3) Data analysis module

The data analysis module extracts useful information from the data, such as the status of the equipment, performance indicators, and abnormal data, and stores the refined information in the database to provide support for decision-making. Meanwhile, the data analysis module also supports remote monitoring and traceability analysis.

4) Control Center

The control center further processes and compares the processed data and uses it to determine the status of electrical equipment. If an abnormality is detected, an alarm mechanism is triggered and the alarm information is quickly sent to the relevant personnel or system to notify them of the necessary measures to be taken so that they can be handled in a timely manner to ensure the safety and stability of the system.

3 Equipment Fault Diagnosis Modeling Framework

3.1 Raw Data Acquisition

Take the three-phase bridge controllable rectifier circuit of the electrical automation equipment as an example to collect the original data of the electrical automation equipment. First of all, the fault is categorized, according to past experience, it can be seen that in the main circuit of the three-phase bridge controllable rectifier device in electrical automation, it is rare that three and more than three thyristors fail at the same time, and the protection circuit makes the circuit short-circuit faults into short-circuit faults, so the main study of the circuit there is a short-circuit fault of one or two thyristors. Three-phase bridge controllable rectifier circuit faults in electrical automation can be divided into five types. The first type is the normal working condition, the second type is only one thyristor failure, the third type is two thyristor failure, and these two thyristors belong to the same phase power supply, the fourth situation is also two thyristor failure, but these two thyristors in the same half of the bridge, and the fifth condition is the failure of two crossed thyristors. Next, set the simulation parameters, set the trigger pulse, the pulse duty cycle is about 26%, the trigger angle can be selected 0 °, 30 °, 60 °, 90 °, 120 °, 180 °. Set the thyristor parameters, set the resistance to 0.15 Ω, the inductance to 1.1 μH, the buffer voltage to 0.11 μH, set the three-phase AC power supply, set the frequency of each phase voltage to 51 Hz, the phase angle to 120°, the sampling period to 100 μs, the sampling time is controlled at 0~51 ms. Finally, the sampling point is selected, and the voltage at the output terminal and the current at the input terminal contain rich fault information, and this fault information is very easy to be detected, so the output voltage at the load terminal and the current at the input terminal are selected as the sampling point. The output voltage and input current contain a wealth of fault information, and this fault information is very easy to detect. Therefore, the load output voltage and input current are selected as sampling points.

3.2 Analysis of Edge Computing Nodes

Edge computing nodes perform core data analysis duties in electrical automation equipment monitoring and fault diagnosis systems. These nodes are located close to the data source and are responsible for performing complex data analysis tasks for real-time fault diagnosis. At edge computing nodes, the data analysis process includes feature extraction, pattern recognition, and fault determination, utilizing advanced algorithms and computational techniques to optimize performance and accuracy.

First, feature extraction is achieved through signal processing techniques, and commonly used methods include Fast Fourier Transform, which converts time-domain signals into frequency-domain signals to reveal key features of equipment performance. The formula is equation (1):

$$X(f)=\int_{-\infty}^{\infty}x(t)\cdot e^{-i2\pi ft}dt \tag{1}$$

where $X(f)$ is the output in the frequency domain and $x(t)$ is the input signal in the time domain.

Next, in order to identify the failure modes from the extracted features, the edge computing nodes utilize support vector machines. The support vector machine distinguishes different classes of data by constructing an optimal hyperplane. The process can be expressed as equation (2):

$$\begin{gathered}\min_{w,b,\zeta}\frac{1}{2}w^{T}w+C\sum_{i=1}^{m}\zeta_{i}\\ subjecttoy_{i}\left(w^{T}\phi\left(x_{i}\right)+b\right)\geq 1-\zeta_{i},\zeta_{i}\geq 0\end{gathered} \tag{2}$$

where w and b are model parameters, x_i is a nonlinear mapping, and C and ζ_i are used to control model complexity.

Finally, in order to accurately determine faults and distinguish false positives and false negatives, the confusion matrix is used to evaluate the performance of the classification model. The formula for each element in the confusion matrix is equation (3):

$$P_{ij}=\frac{\begin{gathered}Number\ of\ samples\ with\ actual\\ category\ i\ and\ predicted\ category\ j\end{gathered}}{Total\ number\ of\ samples\ in\ category\ i} \tag{3}$$

where P_{ij} denotes the probability of predicting a category j when the actual category is i.

Through these steps, the edge computing nodes are able to process and analyze large amounts of data in real time, providing fast and accurate fault diagnosis, which significantly improves the monitoring and maintenance efficiency of electrical automation equipment.

3.3 GRU neural network study

The limitation of unidirectional propagation makes the application of recurrent neural network not very wide. And in equipment fault diagnosis, the situation of the fault is different at different time periods, which requires the analysis of the state of each time node, and the antecedents and consequences of the equipment fault are analyzed in depth. With the rise of deep learning research and applications, researchers have proposed a method that applies LSTM neural networks to classification. The method automatically learns features and effectively models remotely relevant information. However, the model is more complex, with flaws in model training and long prediction times. The GRU neural network was created to solve the problem. Although GRU is not widely used today, the method inherits the advantages of the LSTM model, which can automatically learn features and efficiently model remotely relevant information. GRU has a significant speed advantage based on the fact that it has comparable segmentation performance with LSTM. In this chapter, a text classification method based on GRU neural network is proposed to classify the grid monitoring remote information according to the degree of its impact on the grid, and the classification results can be used as a reference for the grid staff to deal with different alarm information differently through the classification results, thus eliminating the waste of resources caused by manual classification.

GRU neurons contain only two gate structures: update gate and reset gate, and the structure of GRU network is shown in Fig. 2. For update gate z_t, a larger value indicates more information to be retained from the current neuron and less information to be retained from the previous neuron. For reset gate r_t, when the value of the equation is 0, it means that the data passed from the previous neuron is useless and can be discarded, i.e., only the input of the current neuron occurs as an input, so that some useless information passed from the previous neuron is considered to be discarded.

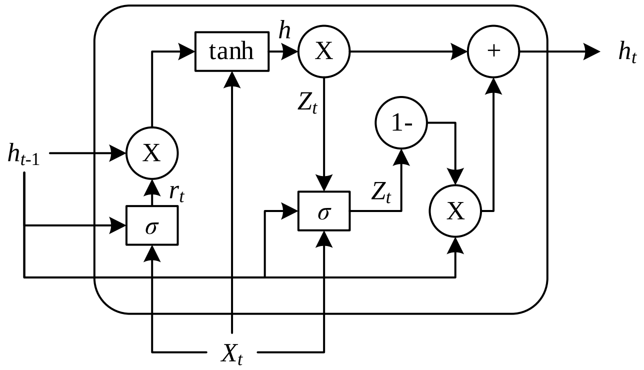

Figure 2. GRU neuron structure

Eqs. (4)-(7) are the mathematical expression formulas for the neurons of the GRU neural network.

$$z_t = \sigma\left(W_t \cdot \left|h_{t-1}, x_t\right|\right) \tag{4}$$

$$r_i = \sigma\left(W_t \cdot \left|h_{t-1}, x_t\right|\right) \tag{5}$$

$$h = \tanh\left(W \cdot \left[r_t * h_{t-1}, x_t\right]\right) \tag{6}$$

$$h_t = \left(1 - z_t\right) * h_{t-1} + z_t * h \tag{7}$$

Where Z_t is the update gate, r_t is the reset gate, h_{t-1} is the output of the previous neuron, x_t is the input of the current neuron, W_z is the weight of the update gate, W_r is the weight of the reset gate, σ is the sigmoid function, h_t is the output value of the current neuron, and h is the output value of the current neuron to be determined in the current neuron.

3.4 GRU-based fault diagnosis model construction

The inclusion of GRU neurons in the intelligent monitoring system designed in this paper makes it possible to analyze a sequence as it comes in, not only for the current time t state, but also in combination with the previous and subsequent states. By using the GRU recurrent neural network, the causes before and after the faults are correlated, not only limited to a single point, but the front is stretched out over a period of time, and thus it can be very competent in the duty of fault diagnosis. In this paper, the following equipment fault diagnosis model framework is constructed, as shown in Fig. 3.

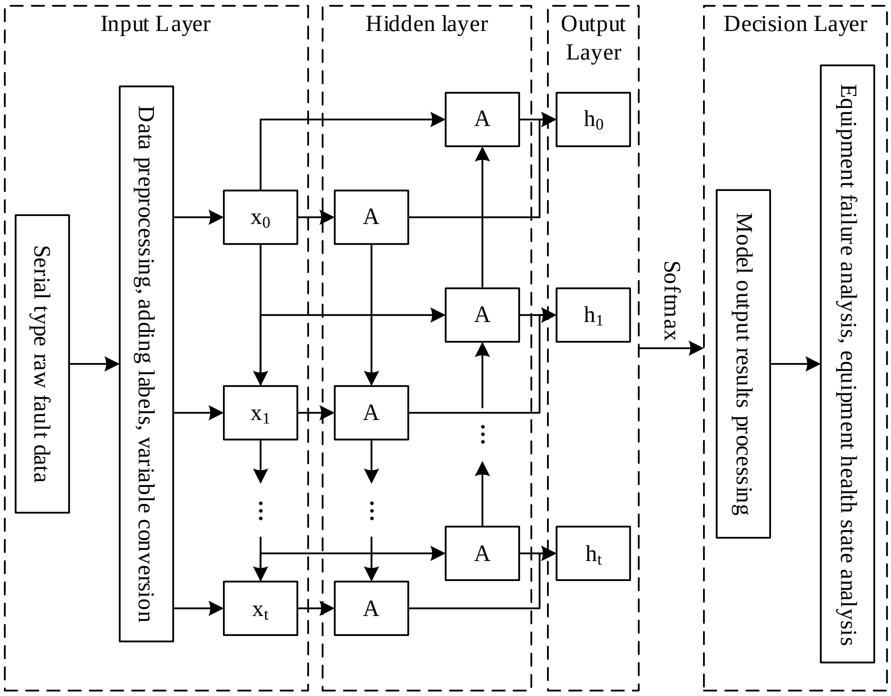

Figure 3. Fault diagnosis framework

As can be seen in the figure, the first input layer, its role is mainly responsible for processing the sequence data and performs the duties of preprocessing the data, labeling the failure modes, and transforming the variables. The second layer is the hidden layer, which contains the GRU neurons mentioned in the previous section and performs the linking back and forth, making it possible to accomplish the analysis and learning of the time series data. The third layer is the output layer, which outputs the learning output to the classifier and finally performs classification labeling and processing. The last layer is the decision-making layer, which serves to accept the final data after classification. And combined with the relevant specifications for result diagnosis and decision making.

4 Intelligent monitoring and fault diagnosis model test

In order to accurately assess the performance of the model in this paper, fault diagnosis experiments and results are analyzed in this paper. In the experiments, the number of iterations and the optimal parameters of the model dataset are obtained. Subsequently, the fault samples of the model in this paper are classified and analyzed for performance.

4.1 Test preparation

To construct the test, the test object is selected as an electrical automation equipment, and the SIEEEVE-175 node test system is utilized to test the designed fault intelligent diagnosis technology. The electrical automation equipment fault parameters are used as the test basis for near-neighbor classification. The specific parameters of the electrical automation equipment node selected for this test are shown in Table 1.

Table 1. Node parameters of electrical automation equipment

Equipment circuit	Test node	Device configuration parameter			
		Reactive compensation/kvar	Power flow overload coefficient	Voltage limit coefficient	Voltage amplitude/V
10-11	12	0.6343	0.5745	0.608	7.3198
12-14	13	0.7262	0.6288	0.6514	7.8069
25-50	34	0.8729	0.6306	0.7284	7.3801
15-20	17	0.8748	0.9253	0.9434	7.7455
21-46	42	1.1387	1.1481	1.0001	7.1032
34-59	48	1.1699	1.1561	1.1738	7.1342
25-46	29	1.3885	1.209	1.2639	7.4435
48-58	54	1.6808	1.3002	1.6448	7.1834
15-30	25	2.3264	1.6182	1.9221	7.1785
1-10	5	2.4568	1.6386	2.1993	7.0999
45-55	52	2.7133	1.9797	2.2305	7.2747
20-25	23	2.7522	1.9974	2.8971	7.3891
25-30	27	2.933	1.9992	2.8987	7.2243
28-38	35	2.9366	2.5323	2.9199	7.2859
1-15	7	2.9845	2.9079	2.9816	7.5853

Combined with the information in Table 1, 60 faults of electrical automation equipment are set up, and simulation tests are carried out using the traditional fault intelligent diagnosis technology as well as the fault intelligent diagnosis technology designed in this paper respectively, and the traditional fault intelligent diagnosis technology is set up as the test control group. In order to ensure the accuracy of the test results, the overall test is carried out in the same environment. The number of faults diagnosed at the 12 test points is compared with the actual number of faults, and the fault intelligent diagnosis technology with a smaller number of differences has a higher fault intelligent diagnosis accuracy.

4.2 Test results

According to the design of the test, the collection of 12 nodes in the control group and the test group in the fault data is shown in Table 2. it can be seen that this paper's fault diagnosis model diagnosis of the number of faults are greater than 30, compared with the control group and the actual number of faults 60 is closer to the diagnostic accuracy of its higher.

Table 2. Comparison of the number of diagnosis faults

Group	Control group	Experimental group	Number of defect
Test point 1	5	41	60
Test point 2	32	37	60
Test point 3	11	46	60
Test point 4	2	43	60
Test point 5	45	52	60
Test point 6	18	35	60
Test point 7	23	53	60
Test point 8	26	49	60
Test point 9	37	48	60
Test point 10	31	57	60
Test point 11	3	36	60
Test point 12	19	47	60

4.3 Hyperparameterization of the model

Hyperparameters have an important impact on the performance, convergence speed, and generalization ability of the model in this paper. In practical applications, it is necessary to find the optimal combination of hyperparameters through experimental methods to improve the performance and accuracy of the model. In this study, best practices in the industry and previous engineering experience were followed to set the hyperparameters such as learning rate, convolution kernel size, and the number of iterations were selected through experiments. Figure 4 shows the variation in prediction accuracy between the training and sample sets, and Table 3 shows the hyperparameter combinations of the model.

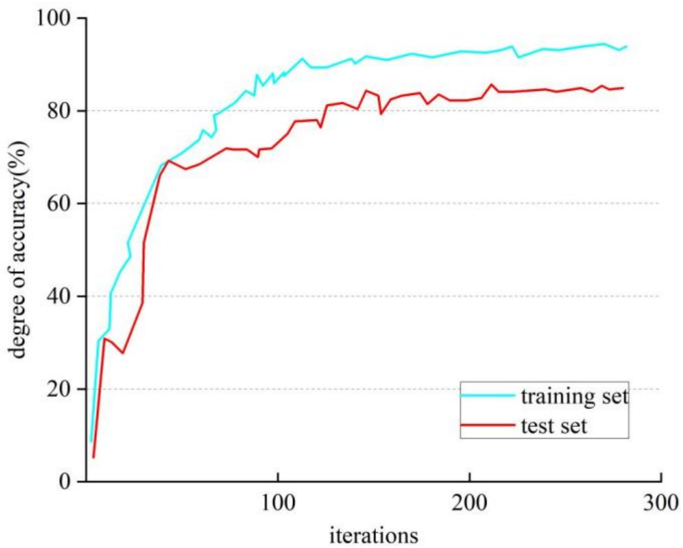

Figure 4. The effect of iteration number on model accuracy

Figure 4 shows how the prediction accuracy of the training and test sets changes as the number of model iterations increases. The results show that the accuracy of the model initially increases progressively with the increase in the number of iterations, which reflects the model's effective learning of data features. After 225 cycles of iterations, the accuracy of the model on the training set tends to stabilize and there is no obvious sign of overfitting, at which time the accuracy of the training set reaches 93.11%, showing the model's ability to fit the training data well. At the same time, the accuracy of the test set is about 85.62%, which is slightly lower than that of the training set, but still within the acceptable range, verifying the model's good generalization ability on the unknown data. As can be seen from Table 3, the optimal input data pixel of the model is 96*96, the optimal convolution kernel is 5*5, the optimal number of convolution kernels is 256, and the optimal learning rate value is 0.001.

Table 3. Model hyperparameter Settings

Name of parameter	Parameter values
Enter data pixel size	96*96
Convolution kernel size	5*5
Number of convolution kernel	256
Learning rate	0.002

4.4 Sample Fault Classification

The dataset collected for this paper contains 400 samples, and the labels corresponding to these faults are shown in Figure 5. 35 partial discharge faults, which are early signs of deterioration or damage to the transformer's internal insulation system; 75 low-energy discharge faults, which are usually associated with minor deterioration of the insulation material or localized defects; 130 high-energy discharge faults, which are often accompanied by strong energy release and may cause serious physical damage to the transformer; 90 low-heat faults, which are associated with abnormally high internal temperatures and may be caused by a variety of factors such as overloading and cooling system failure; 50 medium-heat faults; and 50 medium-heat faults. release, which may cause serious physical damage to the transformer; 90 samples of low-heat faults, which are related to the abnormal increase of internal temperature of the transformer, and may be caused by a variety of factors, such as overloading, cooling system failure, etc.; 50 samples of medium-heat faults and 20 samples of high-heat faults, medium-heat and high-heat faults are the common temperature anomalies in the operation of the transformer, and the degree of severity is increasing, which poses a threat to the long-term stable operation of the transformer. The gradual increase in severity is causing a threat to the long-term stable operation of transformers.

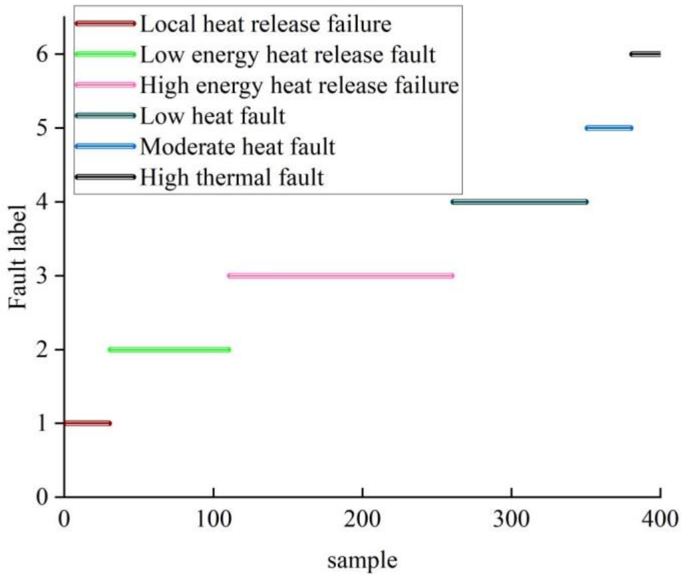

Figure 5. Fault corresponding label

4.5 Analysis of model prediction accuracy

Figure 6 shows the values of the three evaluation metrics of this paper's model. Combined with Fig. 6, it can be seen that the precision, recall, and accuracy of the GRU-based fault diagnosis model proposed in this paper to recognize transformer faults have the values of 0.899, 0.913, and 0.935, respectively, which indicates that the model in this paper has excellent performance in the field of transformer fault recognition, which can not only efficiently and accurately recognize the working state of transformers, but also make precise classification among the complex and changeable types of faults. It can also accurately classify complex and changing fault types, which can provide strong technical support for the stable operation of the power system.

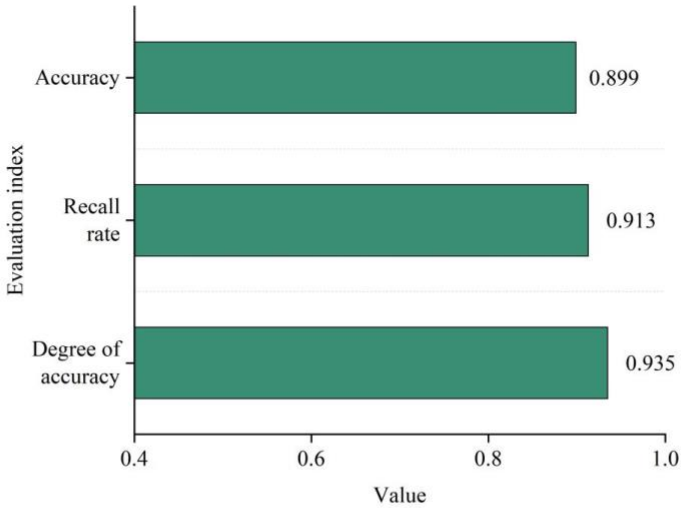

Figure 6. Textual Model prediction accuracy

5 Conclusion

For the real-time monitoring needs of electrical equipment in mining operations, this paper proposes an intelligent monitoring system architecture based on real-time monitoring, supplemented by data processing and analysis. It is capable of comprehensively detecting abnormalities and potential risks, instantly triggering the alarm system to ensure the safety and stability of the equipment system. Subsequently, this paper combines GRU neurons with the intelligent monitoring system discussed in this paper to derive the model presented in this paper. In the hyper-parameter determination, the accuracy of this paper's model reached 93.11% in the training set and 85.62% in the test set, indicating that this paper's model has good fitting ability for the training data. In the model prediction accuracy analysis, the accuracy and precision of this paper's model are 0.899 and 0.935 respectively, which indicates that this paper's model can accurately identify the working state of electrical equipment and accurately classify the fault state.

This paper successfully explores an intelligent monitoring and fault diagnosis system for electrical automation based on the edge computing method, aiming to break the limitations of the traditional detection system in terms of data processing speed and fault diagnosis efficiency. The experimental results verify the excellent performance of this paper's model in real-time equipment detection and fault warning, which has high practical value.

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