Artificial Intelligence-Based Early Warning Method for Abnormal Operation and Maintenance Data of Medical and Health Equipment

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Abstract. When traditional early-warning methods for abnormal operation and maintenance data of medical care equipment are used to process nonlinear abnormal data in the operation and maintenance process of medical care equipment, the data classification accuracy is poor, resulting in insufficient reconciliation level of early-warning methods. Therefore, an artificial intelligence based early-warning method for abnormal operation and maintenance data of medical care equipment is proposed. First, the article establishes the overall framework of data anomaly early warning, including communication network layer, smart contract layer, equipment layer, and application layer. Based on artificial intelligence technology, it establishes the anomaly data detection model, uses RNN cyclic neural network as the basis, designs the anomaly data detection process, and analyzes whether medical and health care equipment is in an abnormal operating state by comparing the real value of current measurement points with the predicted value of RNN neural network model. The experimental results show that: combined with the experimental results of nonlinear data, it can be determined that the data classification accuracy of the designed early-warning method is high, the early-warning data is more comprehensive and complete, and the detection method is superior to the common detection methods.

Keywords: Artificial Intelligence · Medical and Health Care Equipment · Operation and Maintenance Data · Abnormal Warning

1 Introduction

Medical care equipment is the equipment and tools used in medical care and other work, which can facilitate medical staff to judge patients' symptoms more quickly and accurately. Use medical equipment to treat patients to the greatest extent, so that patients can get rid of the pain as soon as possible. It can be said that medical equipment is the

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most important means to help hospitals improve medical quality and efficiency [1, 2]. Medical care equipment is the integration of computing, network, detection and medical process. It can realize the safety of the physical world, monitor the patients in use reliably and in real time, and ensure the safety of patients' use. Therefore, it has a wide application prospect in the future medical process. In the process of the development of medical and health care equipment, the continuous development of wireless sensor network, biomedical sensor and cloud computing technology has given birth to the wide application of medical and health care equipment in the medical field. Medical and health care equipment mainly obtains biometric information through sensors, collects and integrates the information, and through a networked intelligent medical system composed of drug delivery medical equipment, all units in the system realize information interaction through communication network, thus realizing the interconnection of medical resources [3].

For the use and management of medical equipment, it is necessary to carry out refined management in the whole life cycle. With the continuous development of medical technology and equipment, it is necessary to carry out periodic operation and maintenance for medical and health care equipment. In the process of operation and maintenance, if the relevant data is abnormal, it means that there is a certain risk of failure inside the equipment, and it is prone to danger when people use it [4]. Therefore, early warning of the abnormal operation and maintenance data of medical and health care equipment is an important prerequisite to ensure the normal work of medical and health care equipment and improve the safety and efficiency in the medical process [5]. When the traditional early warning method of medical and health care equipment operation and maintenance data abnormality deals with the nonlinear data in the process of medical and health care equipment operation and maintenance, the accuracy of data classification is poor, which leads to the insufficient reconciliation level of the early warning method. Therefore, this paper proposes an early warning method of medical and health care equipment operation and maintenance data abnormality based on artificial intelligence.

2 Research on Abnormal Early Warning of Medical and Health Care Equipment Operation and Maintenance Data

2.1 Establish the Overall Framework of Data Anomaly Warning

Based on artificial intelligence, the abnormal data early warning of medical and health care equipment operation and maintenance is mainly aimed at the security problems of medical and health care equipment tools in recent years, and the information data security diagnosis, traceability and abnormal information early warning during equipment application are studied [6, 7]. From the overall structure of the early warning method, it can be divided into data layer, network layer, intelligent contract layer, equipment platform layer and application layer, as shown in Fig. 1.

In the whole early warning method, the data layer is the basis of the early warning method, in which the storage of block data, transaction data and hash address is designed. In the communication network layer, the main logic responsible for the abnormal warning of the whole operation and maintenance data has a relatively complete mechanism in

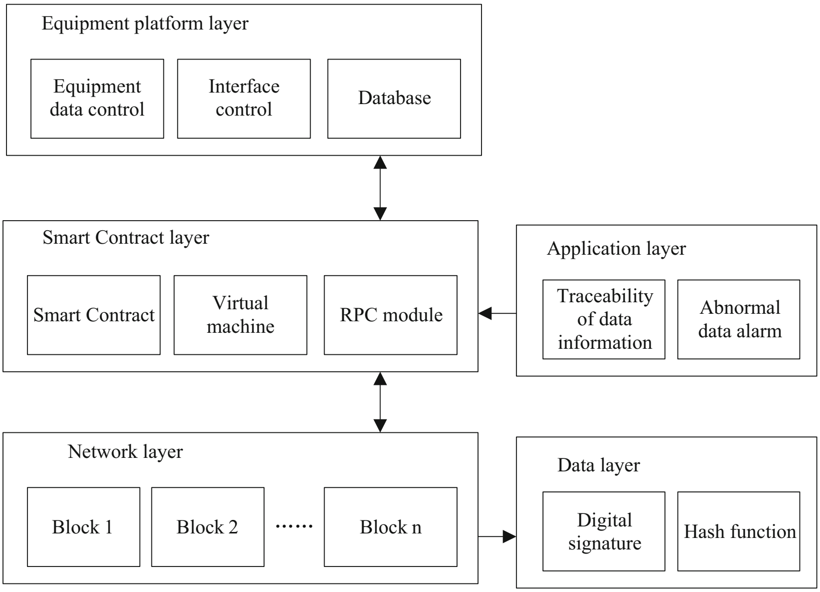


Fig. 1. Framework of early warning method

consensus and verification. In the intelligent contract layer, the interactive RPC module based on JsonStandard RPC is used to realize the request service of the remote medical care equipment program. In the remote state, the block node and consistency processing are regarded as the transaction interaction in the network layer, and the EVM module is used to run the intelligent early warning contract. In the device layer, the RPC module in the contract layer can be called to retrieve the data information of the device and related control instructions [8]. In the application layer, an interface library is designed for information exchange, so as to track the information source of medical and health care equipment and detect abnormal data in advance.

2.2 Establish Abnormal Data Detection Model Based on Artificial Intelligence Technology

Under the joint action of external factors and internal factors, the data have an impact and then form fluctuation indicators. Therefore, SPSS statistical software is used to draw the box diagram of equipment operation and maintenance data changes, from which the basically unchanged index data are found and eliminated. One of the indicators is the upper quartile, expressed as Q_u, that is, the indicator sequence is divided into four parts on average, and the calculation formula is:

$$Q_u = \frac{n+1}{4} \tag{1}$$

The value of n is determined according to the actual situation, and Q_u is further calculated. Another index is the quartile distance of IQR, and the calculation formula is:

$$IQR = 3 \times \frac{n+1}{4} - Q_u \tag{2}$$

In the box chart, the upper and lower limits are the minimum and maximum values within the non-abnormal data range, and the relevant calculation formula is:

$$\begin{cases} T_{\min} = Q_u - 1.5IQR \\ T_{\max} = Q_u + 1.5IQR \end{cases} \tag{3}$$

The biggest advantage of box chart is that it is not affected by outliers, and it can describe the discrete distribution of data in a relatively stable way [9]. By observing the box chart, we can preliminarily eliminate the non-fluctuating indicators with outliers close to 0. Normalize the remaining indexes with fluctuating data, and continue to analyze the abnormal degree of their data. The expected risky abnormal data must have the characteristics of persistence and relevance at the same time. Based on the characteristics of risky abnormal data, the continuity of indicators is first studied. Four kinds of scatter distributions can be obtained by drawing the corresponding scatter plots of each group of data in EXCEL for regression analysis.

In the model established in this paper, recurrent neural network is mainly used as the basis of artificial intelligence calculation. In the neural network, the neural network layers, including the input layer, the hidden layer and the output layer, are all connected, but the neurons in the same layer are not related to each other. The time series data is dependent on the information before and after the change of time, and the prediction of time series data using neural network model will not cause information omission [10]. The reason why RN is called a recurrent neural network is that the hidden layer information of the current moment is retained to participate in the calculation of the next network, and the historical information is continuously transmitted through the interconnected hidden layers in each network. The following Fig. 2 shows the structure diagram of RNN in chronological order:

As can be seen from the figure, corresponding to the time relationship of data, the hidden layer in the middle of RNN is also sequential from left to right. The workflow of RN can be roughly divided into the following steps:

(1) x_t indicates the input at time t, which indicates a multi-dimensional vector.
(2) s_t indicates the hidden layer state at time t, which has the function of information memory, storage and transmission. The layer value is determined by the accumulated information of the hidden layer in the previous time and the input information of this layer. The value of the first hidden layer state s_0 is generally 0 after initialization. Expressed by the formula:

$$s_t = f(Ux_t + Ws_{t-1}) \tag{4}$$

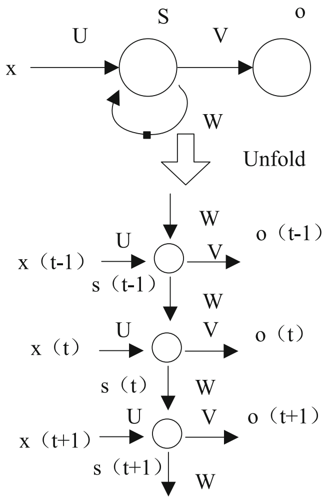


Fig. 2. RNN neural network structure diagram

In the above formula, f represents the nonlinear activation function.

(3) o_t indicates the device output at time t.

Through the above test of volatility data continuity, the index that abnormal data meet the continuity condition is obtained. These indicators are extracted, Pearson correlation coefficient is obtained by SPSS, and correlation analysis is carried out to test the linkage [11, 12]. Six groups of abnormal risk data were obtained. By using Python for programming, calculation and analysis, we can get the specific risk abnormal points of each group of data, and then we can get the abnormal degree score.

2.3 Medical and Health Care Equipment Operation and Maintenance Data Abnormal Warning

The analysis of current measuring points in medical and health care equipment is not only of great significance for the detection of the running state of the equipment, but also an essential component for the comprehensive evaluation of the medical and health care equipment and even the overall physical function of the patient. In the process of operation and maintenance of medical equipment, it will be affected by real-time environmental factors, and the operation process is quite different in different situations. The data early warning mainly includes two aspects: one is the identification of abnormal data caused by the abnormal work of sensors inside the equipment; On the other hand, in the process of communication, the identification of data tampering caused by device IoT blockchain attack. Therefore, the traditional rated threshold can’t be used in the early warning process, and the threshold needs to be updated and managed with reference to the running state of the current day. The current data model of medical care equipment is established based on the data in the normal and stable operation process. The estimated value of the current measuring point at the next moment can be obtained by acquiring the data change and development law from the historical data of equipment operation and learning. When the medical care equipment is in normal operation, the actual value of the current measuring point is very close to the predicted value, and the deviation can be guaranteed within a certain range. Therefore, by comparing the real value of current measuring point with the predicted value of RNN neural network model, it is analyzed whether the medical and health care equipment is in abnormal operation. The deviation index of equipment current measuring point is defined as the ratio of the actual value of the equipment, the difference between the predicted value and the predicted value, and the formula is as follows:

$$D_e = \left| \frac{Y_t - Y_m}{Y_m} \right| \tag{5}$$

In the above formula, Y_t represents the real value obtained by the measuring tool, and Y_m represents the predicted value output by the measuring point prediction model. When the predicted equipment is in normal operation, the deviation index is very low, and the curve is drawn as shown in the following Fig. 3:

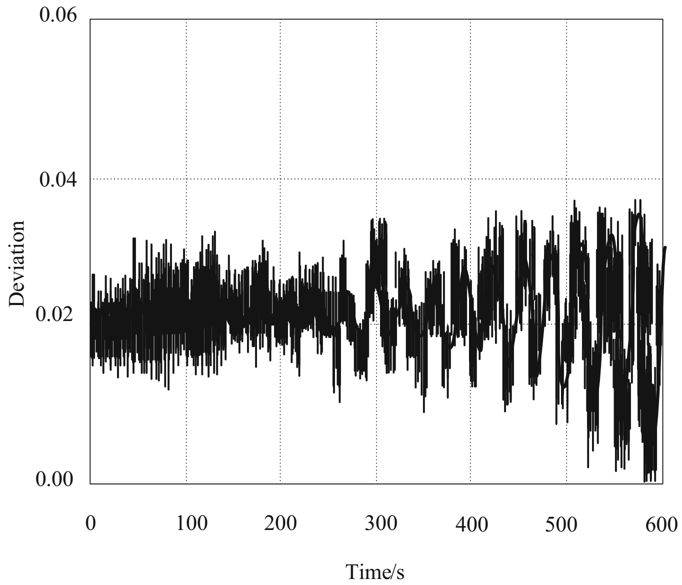


Fig. 3. Deviation curve of normal equipment

When it is within the threshold, no alarm is needed; When the predicted equipment is in abnormal operation, the real value differs greatly from the predicted value, and the deviation index will increase significantly, so it is necessary to send out an alarm. Observing the deviation curve of normal equipment, it is found that the deviation is always below 2% during operation. When external conditions or internal faults fluctuate, the burr in the deviation curve exceeds 2%, but it will soon return to below 2%. Therefore, a value of D_e of 10% is set as the first alarm threshold, and a value of D_e of 20% is set as the second alarm threshold. For the predicted equipment, calculate the deviation of the actual value of the current measuring point. If it is lower than the threshold, it is normal; if it is higher than the threshold, it is abnormal.

In order to prevent the data of each link in the process of operation and maintenance from being tampered with, while recording the data in each link, the intelligent contract is called to realize homomorphic encryption. Smart contracts can't directly operate data with the blockchain built into healthcare devices, so they need to be connected by triggers. When the operation and maintenance work is completed and data encryption is needed, the trigger will send the address of the smart contract interface with full homomorphic encryption and the data to be encrypted. When the data encryption is completed, the trigger sends the contract address and ciphertext to the blockchain network. For the abnormal data generated when the sensor is in abnormal working state, this paper uses confidence interval to identify the possible abnormal data points in the data. In the normal working state of the sensor, the sampled value fluctuates in a small range. However, when the abnormal state occurs, the sampling value will appear obvious deviation. Using this principle, firstly, K normal data are stored for each link of sensors, and according to these data and the preset confidence A, the approximate interval estimation of the total sample can be obtained $\{LCL, UCL\}$. When the data $R(t)$ at a certain time satisfies the following two expressions, it indicates that the value is abnormal data:

$$\begin{cases} LCL \leq R(t) \leq UCL \\ R(t) = R(t-1) \end{cases} \tag{6}$$

In the above formula, LCL represents the lower limit of the confidence interval, and UCL represents the upper limit of the confidence interval. Because the blockchain attack of medical and health care equipment in the Internet of Things is concealed, in order to prevent the blockchain data anomaly caused by the attack, the attack process is divided

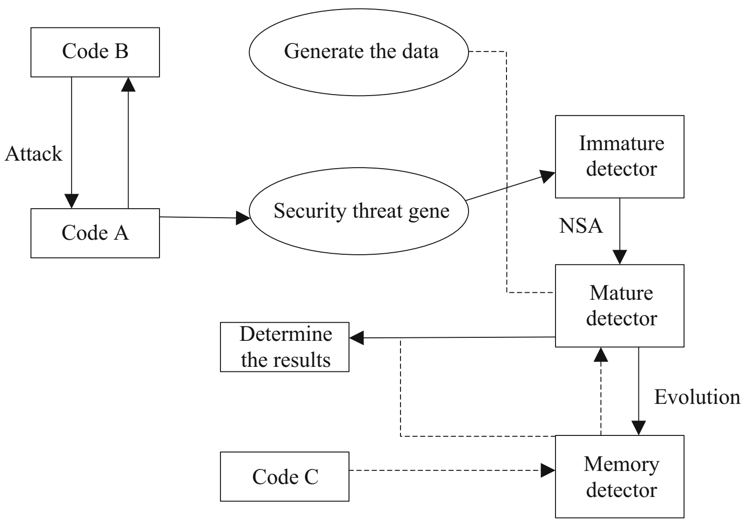


Fig. 4. Schematic diagram of abnormal data detection process

and prevented one by one. Attacks can be divided into three stages: pre-restart, restart and after restart. When the victim node B restarts, it is detected that its incoming and outgoing connections are intercepted by the attacking node A.. This indicates that the attacking node A successfully launched the attack before the node B restarted. Therefore, it is necessary to collect the data sent by node A to node B before node B restarts, so as to constitute a security threat gene. The attack detection module is divided into two parts: the first part is an immature detector, and the second part is a mature detector. The security threat gene and the data randomly generated according to its format are used as the training samples of immature detectors, and NSA algorithm is used for training until it evolves into a mature detector. After a certain number of tests, the maturity detector will evolve into a memory detector. The data detection process of a node in the device is shown in the following Fig. 4:

The node data detection process in the figure above: firstly, it is matched with the memory detector. If the matching is successful, it indicates that the node has abnormal data, and it is put into the security threat gene pool to participate in the training of the immature detector; If not, it is sent to the maturity detector for detection. When the mature detector matches successfully, it indicates that the node has abnormal data, and the security threat gene is also put in; If it doesn't match, it means that the node has no abnormal data.

3 Performance Test of Data Anomaly Early Warning Method

3.1 Preparation of Experimental Data

After the design of the abnormal early warning method of medical and health care equipment operation and maintenance data based on artificial intelligence is completed, a performance test method is designed according to the application characteristics of the early warning method. In the performance test, real medical and health care equipment operation and maintenance data are used for simulation and editing, mainly including user information, medical records, patient functions and other related information. The selected data set characteristics are shown in Table 1.

Based on the above data, aiming at the problems existing in common data anomaly early warning methods, a nonlinear data classification experiment is designed to verify the actual performance of the early warning methods. In the experiment, another data anomaly warning method is selected as a comparison, namely, the anomaly warning method based on deep learning and the anomaly warning method based on transfer learning. The proposed warning method is placed under the same experimental conditions for nonlinear data experimental analysis and early warning evaluation analysis, and the application level of each warning method is analyzed according to the experimental results.

3.2 Experimental Results of Nonlinear Data

In order to further verify the data processing ability of the anomaly early warning method, a nonlinear data experiment is designed, and two kinds of nonlinear data are constructed

Table 1. Data set characteristics

Data set	Attribute number	sample number	Category number	Data type	Whether the default
Voltage constant value	16	20000	26	numeric type	N
Current constant value	19	2561	7	numeric type	Y
running mode	8	743	2	numeric type	Y
performance period	9	632	2	mixed type	Y
User heart rate	4	492	3	numeric type	Y
The user blood pressure	166	352	2	numeric type	N
Fault indicator data	34	269	2	mixed type	Y

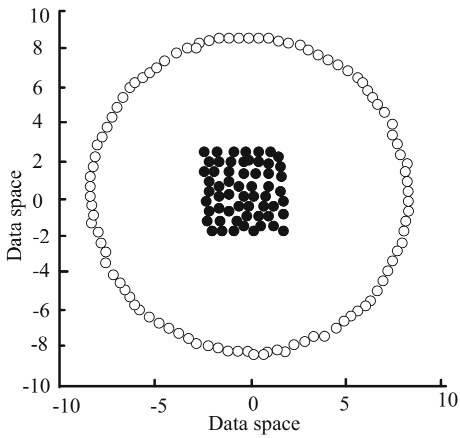
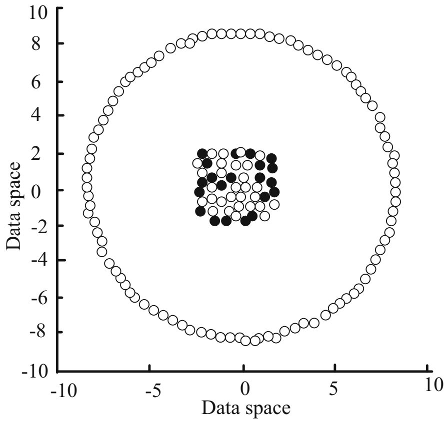


Fig. 5. Schematic diagram of nonlinear data distribution

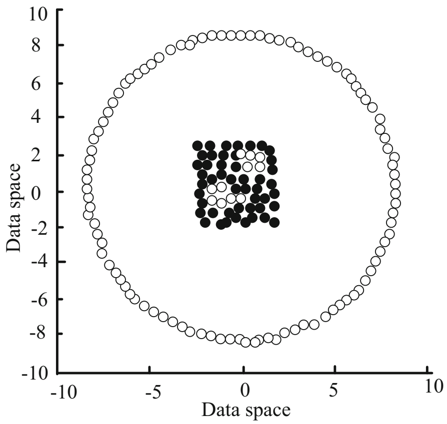
in the same space, one is distributed in a ring with the origin as the center, and the other is distributed in a square shape. The specific distribution is shown in Fig. 5.

The Gaussian kernel parameter is set to 0.4, and the initialization center point is (0, 0). Three different abnormal data warning methods are used to process nonlinear data, and the third-party software is used to output the experimental results. The details are shown in Fig. 6.

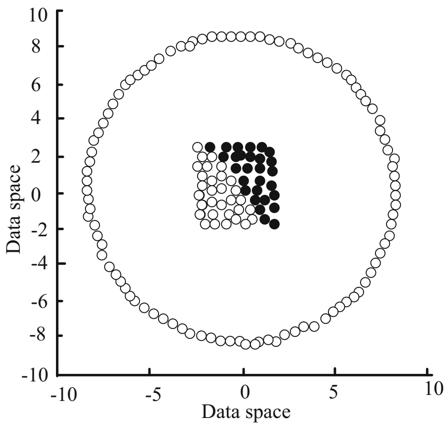
According to the experimental results shown in the figure, when the data anomaly detection method deals with nonlinear data, the data classification results of the experimental results of the early warning method based on deep learning are not ideal. The data distributed in the ring are fused in the square, and there is no clear dividing line



(a) Experimental results of early warning method based on deep learning



(b)Experimental results of early warning method based on transfer learning



(c)The experimental results obtained by the early warning method in this paper

Fig. 6. Experimental results of different data anomaly detection methods

between the two data. The early warning method based on transfer learning has the same problem. In the experimental results, the data distributed in the ring is distributed in the square, which is aggregated and not completely separated. In contrast, the experimental results of the proposed early warning method show that the nonlinear data classification is more obvious and disjoint, and the nonlinear data classification effect is better. To sum up, the proposed data anomaly early warning method has higher data classification accuracy, and can efficiently process various types of data.

3.3 Experimental Results and Analysis of Anomaly Detection and Evaluation

In the abnormal early warning and evaluation, it is mainly based on the experimental results of the above nonlinear data and the early warning performance of the early warning method itself. In the experiment, the recall rate and precision rate are used as index variables, and the F value is calculated according to these two sets of values, which indicates the harmonic average level of anomaly detection methods. The relevant calculation formula is as follows:

$$Pre = \frac{w^{+}}{w^{+} + c^{+}} \tag{7}$$

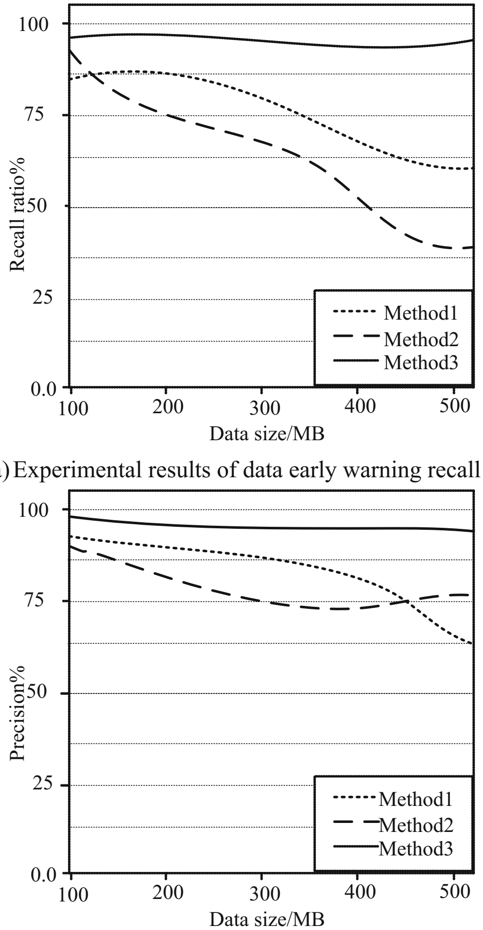
$$Rec = \frac{w^{+}}{w^{+} + c^{-}} \tag{8}$$

$$F = \frac{2Pre \cdot Rec}{Pre + Rec} \tag{9}$$

In the formula, *Pre* indicates the precision rate, w^{+} indicates the correct warning example, *Rec* indicates the recall rate, c^{+} indicates the positive warning error example, and c^{-} indicates the negative warning error example. Three different data anomaly warning methods are used to process the experimental data, and after the warning is completed, the experimental results of each method are output. As shown in Fig. 7.

In Fig. 7, Method 1 and Method 2 are two common early warning methods, and Method 3 represents the data anomaly early warning method proposed in this paper. In the three groups of experimental results, the proposed detection method is calculated to determine that the F value is 0.536, the F value of method 1 is 0.253, the F value of method 2 is 0.328, and the F value of method 3 is 0.421. Combined with the changes of recall and precision in the above figure, it can be seen that the recall and precision are higher than those of common detection methods, and the F value is also higher, which indicates that the medical care equipment operation and maintenance data anomaly warning based on artificial intelligence proposed in this paper. Combined with the experimental results of nonlinear data, it can be determined that the data classification accuracy of this early warning method is high, and the early warning data is more comprehensive and complete. This detection method is superior to common detection methods.

To sum up, the artificial intelligence based early warning method for abnormal operation and maintenance data of medical and health care equipment studied has higher data classification accuracy, more comprehensive and complete data that can be alerted, and can efficiently process various types of data.



(a) Experimental results of data early warning recall rate

(b) Experimental results of data early warning precision rate

Fig. 7. Experimental results of different data anomaly detection methods

4 Concluding Remarks

In this paper, artificial intelligence technology is applied to the abnormal warning of medical equipment operation and maintenance data. Through the combination of RNN neural network and early warning, the data transmission and detection between equipment nodes are realized. At the same time, the detection model of abnormal data is constructed by using the principle of artificial intelligence learning, so as to realize the early warning of abnormal data. After testing, the scheme proposed in this paper can better realize the detection and early warning of nonlinear data.

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