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Diagnosis of abnormal body temperature based on deep neural network

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Abstract

INTRODUCTION: A method for diagnosing abnormal body temperature based on deep neural network is proposed.
OBJECTIVES: To improve the diagnostic accuracy, reduce the false alarm rate, and improve the diagnostic level of abnormal body temperature.
METHODS: According to the weight of the temperature sensor node itself and its neighbor nodes, the network trust relationship is established, and the node trust value is output through the combination of decision-making. Use trust value and double threshold to identify and remove malicious nodes, and optimize the network structure. The optimized temperature sensor network is used to collect human body temperature data.
RESULTS: A deep neural network is used to construct a diagnosis model of abnormal body temperature, so as to realize the diagnosis of abnormal body temperature.
CONCLUSION: The experimental results show that the method in this paper has high diagnostic accuracy, low false positive rate and high diagnostic efficiency, and can improve the diagnostic level of abnormal body temperature.

Keywords: Deep neural network; Human body temperature; Abnormal diagnosis; Temperature sensor; Malicious node.

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1. Introduction

The rapid development of sensor networks and the Internet of Things has promoted the upgrading and transformation of industry and agriculture. While reducing labor costs, the monitoring and collection of information and data has been improved in various information industries. The sensor network combines computer technology with information communication, realizes the connection of physical and digital information, expands the way of obtaining information, and improves the processing efficiency of information data. The sensor network is composed of a large number of low-power nodes, and forms a distributed network through wireless communication, which has the advantages of decentralization, flexible deployment and high fault tolerance [1]. Based on the above advantages, sensors are used in many fields, such as ecological environment monitoring and disaster warning. Among them, the temperature sensor is a basic sensor that is widely used in various fields. Due to the influence of uncontrollable factors such as weather, the data collected by the temperature sensor is prone to surrounding interference and malicious damage, and then the phenomenon of abnormal data occurs, which seriously affects the quality of the collected data [2]. At this stage, temperature sensors have been widely used in the field of human body temperature measurement, which can quickly and accurately detect human body temperature. According to the collection results of human body temperature, the physical condition of the human body can be judged, and the disease problems existing in the human body can be found in time. Therefore, it is of great significance to study a method for diagnosing abnormal human body temperature.

Aiming at the important research topic of abnormal diagnosis of human body temperature abnormality, reference [3] proposes an abnormality diagnosis method based on temperature sensor. Based on the DS18B20 temperature sensor, this paper proposes a method that takes Arduino as the center, combines temperature sensors, Bluetooth modules, energy supply devices and other electronic components with clothing, and monitors human body temperature on the mobile phone software client at the same time. The method can realize real-time monitoring of human body temperature, and detect abnormal body temperature in time. However, this method has the problem of low accuracy in diagnosing abnormal body temperature, and the practical application effect is not good. Reference [4] proposes a wireless technology-based diagnostic method for abnormal body temperature. The temperature monitoring system consists of three parts: body temperature monitoring terminal, body temperature data transmission node and body temperature monitoring management platform. The body temperature data is collected to the gateway through the wireless communication protocol of the 2.4 GHz frequency band and the 433 MHz frequency band through the body temperature data transmission node, and the gateway transmits the body temperature data to the body temperature monitoring and management platform through the USB communication protocol. The designed system complies with the relevant national standards for electronic thermometers, and is used in the inpatient department of the hospital to monitor the body temperature of patients in real time and detect abnormal conditions in time. However, this method is too complicated and has the problem of high false positive rate. Reference [5] proposes a method for diagnosing abnormal body temperature based on Android and TMP116 digital temperature sensor. The method is based on a real-time temperature monitoring system, which consists of hardware acquisition circuit, Android smart terminal and cloud server platform. The body temperature data is collected by TMP116, and then transmitted by the nRF52832 Bluetooth chip and the mobile phone, and the data display and data remote interaction are performed on the mobile phone. The system has been improved in hardware to improve the accuracy of temperature measurement, and combined with the results of temperature monitoring to realize the judgment of abnormal body temperature, but this method has a problem of low accuracy of abnormal body temperature diagnosis, and the practical application effect is not good.

In order to solve the above problems, this paper proposes an abnormal body temperature diagnosis method based on deep neural network. The deep neural network is used to build an abnormal body temperature diagnosis model to improve the accuracy of body temperature diagnosis and reduce the false alarm rate. It can quickly and effectively identify abnormal body temperature data and improve the diagnosis effect of abnormal body temperature.

2. Diagnosis of abnormal body temperature

2.1. Human body temperature data collection based on temperature sensor network

Before diagnosing abnormal human body temperature, the trust relationship of sensor network nodes is established first, and abnormal nodes are eliminated, and the optimized temperature sensor network is used to collect human body temperature data, so as to improve the accuracy and efficiency of human body temperature data collection. Wireless sensor network architecture usually includes sensor nodes, sink nodes and task management nodes. A large number of sensor nodes are randomly located in the monitoring area, and can organize themselves into a network. Specific protocols require mutual trust between sink nodes. Therefore, it is necessary to add authentication measures to improve the trust of base stations in order to establish the trust relationship between sensor network nodes. Global trust management means that nodes have unique trust value in the whole network, which is common in wireless sensor networks with cluster structure. Therefore, the nodes make decisions according to the locally stored trust value, eliminate abnormal nodes according to the local trust value and the recommended trust value sent by the neighbor nodes, and meet the trust relationship between nodes.

It is assumed that the temperature sensors are randomly deployed in the monitoring area, and each node has the same length of data transmission distance. The rest of the nodes in the transmission unit of any node are defined as neighbor nodes, and the overall density of the network can be expressed by the average degree of nodes. The calculation formula is:

$$u_0 = \frac{\sum_{i=1}^{s} u_i}{s} \tag{1}$$

In formula (1), u_0 represents the overall average degree of the sensor network; u_i represents the node average degree; i represents the serial number of the location of the node; s represents the number of all sensors in the monitoring area. Data anomalies randomly occur in the monitoring area. When a fault event occurs, the abnormal data should be acquired by the node and alert the surrounding area. After identifying the abnormal data, the temperature sensor uses the sensing function to diagnose the data, and outputs information to the neighbor nodes to complete the decision of abnormal diagnosis [6-7]. This paper uses the position list and trust value between adjacent nodes to determine and update the decision result of abnormal diagnosis. In this paper, the weighted directed graph is used to represent the trust value of the node, that is, the trust value of the node is reflected by the weight value. Weighted digraph is based on the digraph, which assigns weight information to the edges. It can be used to calculate the single source shortest path. Starting from a node, the greater the weight of the node, the higher the trust value, and vice versa. When the weight value is 0, it indicates a completely untrusted relationship. Any node relies on its own temperature sensor readings and neighboring node readings to make binary decisions, and the sensing data is binary. The specific rules can be expressed as follows: a value of 0 is defined as normal data, and a value of 1 is defined as abnormal data. That is, when the data of the temperature sensor is abnormal, the output result of the temperature sensor is 1. Finally, the trust result is output according to the majority vote, and the process can be expressed as:

$$\sum_{i=0}^{n} a_i > \left\lceil \frac{n}{2} \right\rceil \tag{2}$$

In formula (2), a_i represents the decision of the node; n represents the number of neighbor nodes; $\lceil \ \rceil$ represents the round-up function. Each node makes its own decision, and the decision combination of neighbor nodes is applied to the final judgment of data abnormality diagnosis.

On the basis of establishing the trust relationship of sensor network nodes, the malicious nodes are further eliminated. Each node makes decisions based on its own and neighbor node readings. In this paper, double thresholds and weighted trust values are used to identify malicious nodes and complete the final decision on fault events. The first threshold is mainly used to detect fault events, and the second threshold is used to accurately determine the detection area. After all sensor readings are received, the weight of abnormal readings is calculated, and the nodes are divided into three intervals according to double thresholds. If the faulty node is near the boundary of the temperature sensor monitoring area, the node is adjacent to many nodes, which may cause the test to fail [8]. To avoid this situation, the failed event node is acknowledged with the help of a second threshold. If it succeeds in both threshold tests, it is judged as a normal node. From the point of view of nodes, the weight of itself represents the trust value of a fault-free event, and the neighbor weight represents the trust value of a faulty event. In the process of mutual conversion between the two states, the two weights are dynamically changed and updated according to the elimination effect. In the case of no fault, the abnormal node loses the weight value, and this process can be expressed as:

$$\theta' = \begin{cases} \max\left(0, \theta - \delta\right) \\ \min\left(0, \theta + \varepsilon\right) \end{cases} \tag{3}$$

In formula (3), θ and θ' represent the weights before and after the update, respectively; δ and ε represent the weight reduction of the abnormal reading sensor and the increase of the normal reading, respectively. Similarly, the weight of the node itself is also updated. During this process, both faulty nodes and malicious nodes reporting abnormal data lose their weights. Correspondingly, the nodes that normally report the temperature data increase the weight, that is, the trust value of the normal data gradually increases during the update process, and stops the update when the upper limit value 1 is reached. According to formula (3), it can be seen that in the process of eliminating malicious nodes, δ and ε play an important role. If the values of the above two parameters are too large, normal nodes will be identified as malicious nodes, which will affect the abnormal diagnosis results. This paper deduces the values of the two parameters based on the probability relationship between malicious nodes and real data. The specific probability relationship can be expressed as:

$$b = \frac{1}{q\delta - \left(1 - q\right)\varepsilon} \tag{4}$$

In formula (4), b represents the event-free period required to detect malicious nodes; q represents the probability of weight reduction. When the weight becomes 0, the node is considered as malicious and removed from the temperature sensor network.

The optimized temperature sensor network is used to collect human body temperature data, so as to improve the accuracy and efficiency of human body temperature data collection. The data acquisition process is shown in Figure 1.

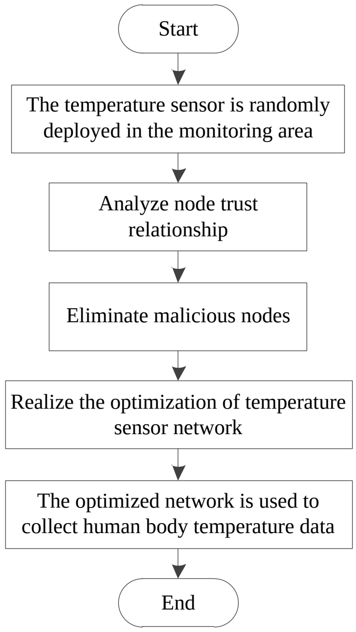

Figure 1. Human body temperature data collection process

As can be seen from Figure 1, first of all, temperature sensors need to be deployed randomly in the monitoring area, analyze the trust relationship between sensor nodes, eliminate abnormal nodes according to the locally stored trust value, optimize the network of network sensors, and provide a trusted network environment for collecting human body temperature data.

2.2. Abnormal diagnosis based on deep neural network

Deep neural networks have been widely used in many artificial intelligence applications, including computer vision, speech recognition, and robotics. Deep neural networks have shown the current best accuracy in many artificial intelligence tasks, but it also has the problem of high computational complexity. Therefore, techniques that help deep neural networks process efficiently and increase efficiency and throughput without sacrificing performance accuracy or increasing hardware costs are key to the widespread deployment of deep neural networks in AI systems. Therefore, in this paper, the deep neural network is applied to the diagnosis of abnormal body temperature, so as to improve the accuracy and efficiency of diagnosis.

The structure of the deep neural network is shown in Figure 2.

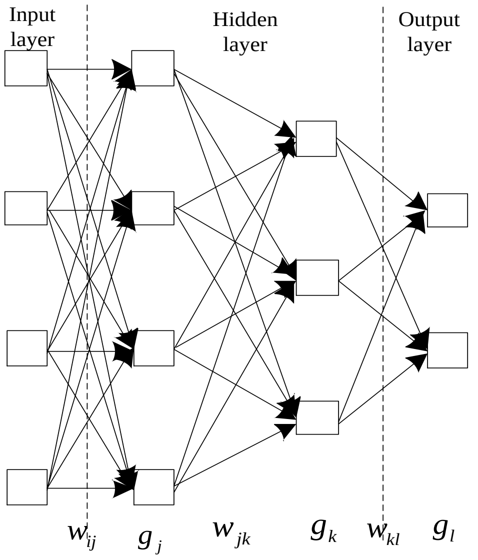

Figure 2. Deep neural networks structure

A deep neural network consists of an input layer, a hidden layer, and an output layer. Among them, g_j, g_k and g_l represent the thresholds of the input layer, hidden layer, and output layer, respectively; w_{ij}, w_{jk} and w_{kl} represent the weights between the input layer, the hidden layer, and the output layer, respectively. z_j, z_k and z_l are used to represent the input, weight and threshold calculation result of each layer node, respectively. The output obtained by using the activation function to calculate z_j, z_k and z_l can be represented by s_j, s_k and s_l.

The deep neural network has the characteristics of high precision and high operation rate, and can realize the mapping of nonlinear relationships, and control the training time interval by adjusting the weights and thresholds, so as to ensure the performance of the model [9]. The training process of the deep neural network is shown in Figure 3.

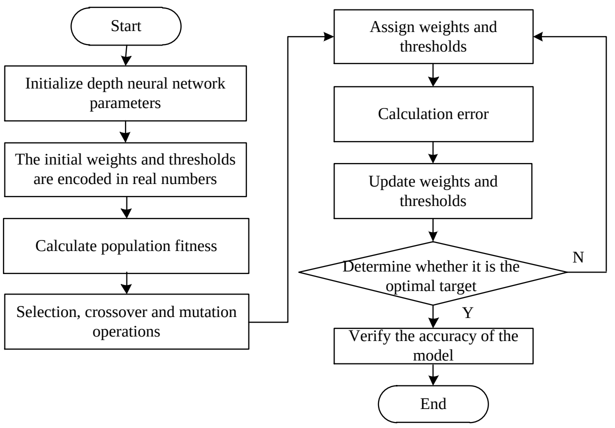

Figure 3. Training process of deep neural network

In the process of training a deep neural network, the samples are passed down layer by layer, and the error is calculated from the bottom to the top, and finally solved in a recursive way [10]. The weights and thresholds are updated using the calculated error values, and the global optimal solution is obtained after the model is continuously converged. Due to the differences in the temperature sensor samples in different regions, there are usually several orders of magnitude difference in each parameter. The more specific the function, the higher the priority. In the case of accurate matching, the transformed parameters have the same priority as the accurately matched parameters. Therefore, this paper selects premnmx function as the preprocessing function to normalize the input layer data, so as to improve the network performance and network training efficiency. The normalization calculation formula of premnmx function is as follows:

$$\begin{cases} \alpha = \dfrac{2(c - \min c)}{\max c - \min c} - 1 \\ \beta = \dfrac{2(e - \min e)}{\max e - \min e} - 1 \end{cases} \tag{5}$$

In formula (5), α and β represent the normalized values of the input and output samples, respectively; c and e represent the input and output samples, respectively; $\max$ and $\min$ represent the maximum and minimum values. In the process of using the gradient descent method to obtain the optimal value of the deep neural network, the selection of the initial value is very important [11]. In order to avoid falling into the local optimal situation, this paper adopts the GA algorithm to obtain the initial value. The individual encoding adopts real number encoding, that is, each individual is a character string, and the encoding length is set to 55. In this paper, the population size is set to 50, which is conducive to finding the best fitness value of individuals. In order to make the deep neural network model have sufficient convergence speed, this paper sets the network structure as a three-layer structure. The number of nodes in the input, implicit and output layers is 5, 7 and 1, respectively, and the output accuracy of the model is approximated by a nonlinear function. The individual length of the network is determined by the fitting function of the output and output parameters, and the optimal fitness value is obtained through selection, crossover and mutation operations [12]. The selection operation is the roulette selection method, and the spread and mutation probability are set to 0.3 and 0.08, respectively.

In this paper, a trained deep neural network model is used to diagnose abnormal body temperature. These three curves are error curves, corresponding to the error curves of training data, calibration data and test data respectively. When the training error reaches the specified accuracy, the training will be stopped. The normal data fluctuates in a small range, while the abnormal data fluctuates in a larger range, which is quite different from the normal data. Using the median and variance of the sample predicted value data set, the numerical range of the three error lines can be obtained, and the calculation formula can be expressed as:

$$\begin{cases} l_1 = k \\ l_2 = k + 3\sigma \\ l_3 = k - 3\sigma \end{cases} \tag{6}$$

In formula (6), l_1, l_2, l_3 corresponds to the values of the three error line; σ and k represent the variance and median of the predicted value of the sample, respectively. Design a normal data range according to the actual situation. If the collected data is not within this range, it is considered to be abnormal [13-14]. Use the interval difference degree to calculate the probability of leave and failure, and express the difference degree between the reading and the normal interval by the difference degree. The calculation formula is:

$$\lambda = \frac{r - l_2}{l_2 - l_3} \tag{7}$$

In formula (7), λ represents the degree of difference; r represents the reading of the temperature sensor. The larger the difference degree value, the farther the human body temperature reading is from the normal range, and the reading may be considered to be abnormal data. On this basis, further calculate the probability threshold of judging events [15]. When the probability of occurrence of an event exceeds the threshold, the reading is determined to be abnormal data, reduced diagnostic time, and the diagnosis of abnormal body temperature is realized.

So far, the design of human body temperature abnormality diagnosis based on deep neural network is completed.

3. Experimental study

3.1. Experimental scene settings

The design method of this paper is developed based on python2.7 platform, and the simulation experiment is carried out on MATLAB platform. The temperature sensor network is randomly distributed in a 50×50 area, and there is no mutual influence between nodes. It is assumed that each temperature sensor node has the same failure rate, which is 25%, that is, each node has a 25% probability of failure. Temperature sensors generate readings from characteristics of the actual application environment, and faulty nodes are randomly selected according to a normal distribution. The specific parameters of the experiment are shown in Table 1.

Table 1. Experimental parameter table

Serial number	Parameter	Numerical value
1	Temperature sensor network area	50×50
2	Good sensor reading range	18-20℃
3	Fault sensor reading range	24-26℃
4	Communication radius	3
5	Probability range of node failure	5-45%

To eliminate the randomness of the experiment, this study was repeated 100 times in each simulation scenario to make the results more statistically significant. In order to verify the application effect of human body temperature abnormality diagnosis based on deep neural network in this paper, the method in this paper is compared with the reference [3] method, reference [4] method, and reference [5] method. In this experiment, the three indicators of diagnostic accuracy, false positive rate and diagnostic efficiency are used to measure the performance of the above abnormal data diagnosis method. The calculation formula of the indicator can be expressed as:

$$p_1 = \frac{N_1}{N_2} \tag{8}$$

In formula (8), p_1 represents the correct rate of diagnosis; N_1 represents the number of abnormal data successfully diagnosed; N_2 represents the total number of abnormal data.

$$p_2 = \frac{M_1}{M_2} \tag{9}$$

In formula (9), p_2 is the false alarm rate; M_1 is the number of good data diagnosed with defects; M_2 is the total number of good readings. The performance of each abnormal body temperature diagnosis method in different experimental scenarios was compared to verify the feasibility of the design method in this paper.

The diagnosis time of abnormal human body temperature is one of the important indicators to measure the efficiency of diagnosis. The shorter the diagnosis time of abnormal human body temperature, the higher the efficiency and the better the practical application effect.

3.2. Experimental results and analysis

The diagnostic accuracy and false positive rate of each diagnostic method under the two sample sizes were tested, and the comparison results are shown in Figure 4 and Figure 5.

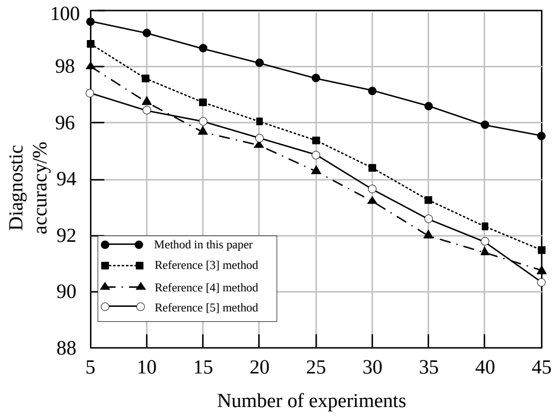

Figure 4. Comparison of the diagnostic accuracy of each diagnostic method

According to the experimental comparison results in Figure 4, it can be seen that with the increase of the number of experiments, the diagnostic accuracy of each abnormal body temperature diagnosis method shows a downward trend. When the number of experiments is 25, the diagnostic accuracy of the method in this paper is 97.74%, which is 2.58%, 4.68%, 3.52% higher than that of the reference [3] method, the reference [4] method, and the reference [5] method, respectively. In general, the diagnosis accuracy of the anomaly diagnosis method based on deep neural network is significantly higher than other comparison methods. Therefore, the diagnostic method designed in this paper has high diagnostic accuracy and can effectively diagnose abnormal body temperature. This is because this paper uses the deep neural network to build the abnormal temperature diagnosis model. On the basis of establishing the trust relationship between sensor network nodes, it further eliminates malicious nodes and can effectively improve the accuracy of abnormal temperature diagnosis.

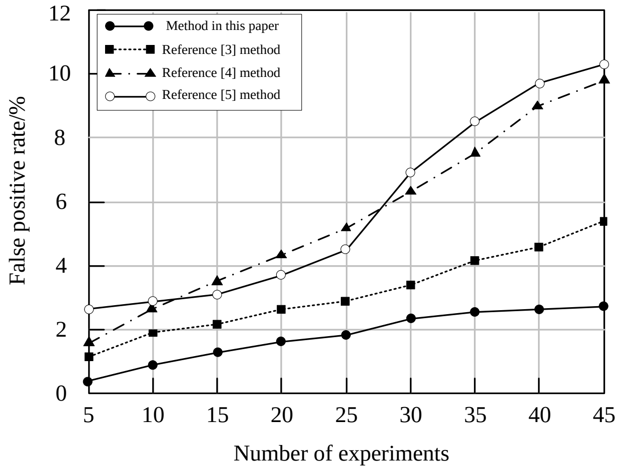

Figure 4. Comparison of false alarm rates of each diagnostic method

According to the experimental comparison results in Figure 5, with the increase of the number of experiments, the false alarm rate of each abnormal body temperature diagnosis method shows an upward trend. The false positive rate of this method is 2.25%, which is lower than that of the reference [3] method, the reference [4] method, and the reference [5] method. On the whole, the false alarm rate of the anomaly diagnosis methods designed based on deep neural network in this paper remains at a low level, which is significantly lower than the four comparison methods.

Finally, the time for diagnosing abnormal body temperature of different methods is compared to verify the diagnostic efficiency of different methods. The results are shown in Table 2.

Table 1. Diagnosis time of abnormal body temperature

Number of experiments	Diagnosis time/s			
	Reference [3] method	Reference [4] method	Reference [5] method	Method in this paper
5	1.56	1.36	0.98	0.75
10	1.47	1.47	0.96	0.68
15	1.58	1.88	1.32	0.69
20	1.42	1.53	1.12	0.74
25	1.33	1.64	1.25	0.86
30	1.52	1.21	1.33	0.47
40	1.64	1.96	1.21	0.56
45	1.85	1.22	1.19	0.67
Average value	1.55	1.53	1.17	0.68

Analysis of the data in Table 2 shows that the average time for diagnosing abnormal body temperature by the reference [3] method is 1.55s, and the average time of diagnosis of abnormal body temperature by the reference [4] method is 1.53s. The average time for diagnosing abnormal body temperature by the reference [5] method is 1.17s. Compared with these methods, the average time for diagnosing abnormal body temperature in this method is 0.68s, which shows that this method has shorter diagnosis time and higher efficiency. This is because the design method in this paper can calculate the probability threshold of judging events according to the difference degree. When the probability of event occurrence exceeds the threshold, the readings are determined as abnormal data, which shortens the diagnosis time and realizes the rapid diagnosis of abnormal body temperature.

Based on the above experimental results, the proposed method can ensure the diagnostic accuracy of 97.74% and the false alarm rate of 2.25%. The average time for diagnosing abnormal body temperature is 0.68s, which has good abnormal diagnostic efficiency and good performance.

4. Conclusion

With the development of Internet of things technology, using temperature sensors to collect human body temperature data has become a research hotspot. In order to diagnose abnormal body temperature quickly and accurately, a method of abnormal body temperature diagnosis based on deep neural network is proposed. The simulation results show that the diagnostic accuracy of this method is 97.74%, the false alarm rate is 2.25%, and the average diagnostic time of abnormal body temperature is 0.68s, which can effectively improve the efficiency of abnormal diagnosis. The method in this paper can realize the rapid screening and automatic identification and alarm of abnormal body temperature, so as to greatly reduce the labor cost of preliminary screening of abnormal body temperature, improve the efficiency of temperature screening, and bring greater convenience to human healthy life.

However, due to time constraints, this paper only considers the abnormal events and node failures in the optimization process of temperature sensor networks, ignoring the measurement errors in the practical application of the research methods, which has shortcomings. In the future, it is necessary to analyze the causes of abnormal temperature sensor network, and classify the causes of abnormal temperature sensor network, so as to further improve the diagnostic effect of abnormal temperature. After improving the method designed in this paper, we can try to apply this method to the scene that needs real-time body temperature measurement, provide technical support for different scenes, and meet the needs of accurate and fast body temperature measurement.

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