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Retraction

Retracted: Robot Fault Detection Based on Big Data

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

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

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

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

References

[1] F. Luo, "Robot Fault Detection Based on Big Data," *Journal of Control Science and Engineering*, vol. 2023, Article ID 8375382, 8 pages, 2023.

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Research Article

Robot Fault Detection Based on Big Data

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In order to improve the reliability of robot electrical fault detection and diagnosis, the author proposes a robot electrical fault detection and diagnosis method based on deep learning. Taking the return power and active power as constraints, the electrical fault data collection of the robot is carried out. Taking the resonant inductance and resonant capacitance of the robot electrical equipment as identification parameters, we conduct electrical fault differential feature mining. The fault features are extracted according to the time-delay distribution sequence of the electrical fault data of the robot, and the electrical fault detection and diagnosis results are output by using the deep learning function. Simulation results show that the author's method has a high accuracy probability for robot electrical fault diagnosis. The author's method is on average 14.7% higher than the neural network-based method and 24.5% higher than the expert system-based method. The accuracy rate of the author's method for robot electrical fault diagnosis is high. The author's method is 16.6% higher than the neural network-based method on average and 34.2% higher than the expert system-based method. It is proved that the robot electrical fault detection and diagnosis based on deep learning has high accuracy and short time.

1. Introduction

The rapid development of science and technology, especially the development of computer technology, has greatly promoted the complexity and intelligence of robot systems, making robots widely used in various fields such as industry, medical care, space, and deep-sea exploration. In particular, the development of industrial robots has been able to represent the latest development of today's automation technology, information technology, and system integration, and it has concentrated the latest research results from many disciplines. Industrial robots have been widely used in various automated production lines, which consist of mechanical bodies, controllers, drive systems, and sensors, etc., and are automated production equipment that can complete various tasks in three-dimensional space [1]. Industrial robots are not just a simple replacement for manual labor but an intelligent mechanical device formed by combining the strengths of humans and machines. In industrial production, they replace humans to do some repetitive and monotonous long-term operations, even in high-risk and harsh environments. However, with the increase in human demand for robots and the improvement in the complexity of robot systems, robots are prone to failure [2]. For the complex electromechanical system of an industrial robot, people need to install, program, debug, and maintain it and even operate on-site close to it. That is to say, people will participate in the working system of the robot so that safety problems may occur. At the same time, compared with other ordinary machines, the degree of freedom of the robot is much larger, its components can run in a larger space, and it has a high-power arm with local speed motion and complex autonomous actions. Once the robot fails, and if the failure is not detected and dealt with in time, its working performance will be greatly reduced, and even human life will be threatened.

The failure of the robot, resulting in various major accidents, reminds people that the safety and reliability of the robot system should be solved as soon as possible, and a set of automatic monitoring of the robot should be developed. A system that can provide early warning of faults and accurately locate them has become the top priority at present, and fault detection and diagnosis technology is coincidentally called a new approach. As shown in Figure 1, the fault detection and diagnosis technology is to collect the data in the operation of the robot, analyze and process the data, judge whether the system has faults, and the parts where the fault occurs so as to timely alarm and restore the system from the fault. In the normal state, if the fault is serious, it will be stopped [3]. In this way, the catastrophic consequences caused by improper human operation are avoided, the stability and safety of the robot are improved, and the robot can run for a long time without failure, which improves industrial production efficiency. In addition, the robot fault detection and diagnosis technology restrains the further expansion of the fault and provides safety protection for the operator. It can be seen that the research on fault detection and diagnosis of robots is of great significance.

2. Literature Review

Ambroi proposed a fault diagnosis method for underwater robots based on the combination of model and data drive. By designing robust filters to resist disturbance, fault detection is realized based on model residuals [4]. Wang proposed a discrete-time observer-based fault diagnosis method for manipulators. The method uses the cooperation of two detection observers and a diagnostic observer. The fault detection and diagnosis of robot joint sensors can be realized, but the sensor information redundancy must be required [5]. In order to solve the fault diagnosis problem of the manipulator, H Barnes designed a novel fault diagnosis algorithm using the sliding mode observer and performed experiments on the COMAU manipulator, but this method could not realize the detection of concurrent faults [6]. Lee, in order to solve the problem that the error convergence of the classical sliding mode observer is slow, which affects the real-time performance of the fault diagnosis of the underwater robot, based on the fast convergence characteristics of the terminal sliding mode, the observer is designed to achieve rapid convergence of all estimation errors, and the equivalent error injection is adopted, the fault value is reconstructed by the method, and the fault diagnosis of the propulsion system of the underwater robot is realized [7]. Shen, divided fault diagnosis into two subprocesses of fault detection and message transmission. The detection of modular robot faults is realized by the health pulse method, and the optimal path of fault message transmission is determined based on the improved Dijkastra algorithm [8]. Wang, using the data-driven intelligent fault diagnosis method, carried out related research on the fault diagnosis of the dead reckoning subsystem of the home service robot and proposed a robot fault diagnosis method based on multi-model perception and decision fusion. It solved the problem of incomplete information perception of a single PCA model; proposed a new generalized Gaussian kernel function and a fast training method of SVM based on GPU acceleration, which improved the classification performance and increased the training speed [9].

Detection and diagnosis of robot electrical faults, it is based on the analysis of fault sample information and feature fusion of electrical equipment so as to improve the fault analysis and diagnosis ability of robot electrical equipment. So far, many experts in related fields have carried out in-depth research on the methods of robot electrical fault diagnosis and detection and achieved good research results. For example, Swpu proposed a method for detecting and diagnosing electrical faults in robots based on neural network observers, but the accuracy of this method for detecting electrical faults in robots is low [10]; Radhakrishnan created an online detection method for robot electrical faults based on expert systems, but this method takes a long time to detect robot faults, and it is difficult to achieve the ideal application effect [11]. In response to the above problems, the author proposes a deep learning-based method for detecting and diagnosing electrical faults in robots.

3. Research Methods

3.1. Robot Electrical Fault Sample Data Collection and Fault Feature Analysis

3.1.1. Sample Data Collection. In order to realize the detection and diagnosis of robot electrical faults based on deep learning, it is first necessary to analyze the resonant circuit of the robot electrical equipment and use the return power and active power as constraints to sample the abnormal data of the robot electrical equipment.

Suppose the high-frequency transformer characteristic distribution sequence $\{x(n)\}$ of robot electrical equipment is a k-order normal random sequence with zero mean, the self-adaptive learning model of robot electrical fault diagnosis is constructed. Through the series resonance impedance analysis method, the data sample sequence of robot electrical fault data is obtained as $d(s)$, through the high-frequency transformer oscillation control method, the autocorrelation function of the output robot's electrical fault is the following formula:

$$C_N(r) = x(n) + \sqrt{d(s)}\,[N(N-1) + C(r)]^2. \tag{1}$$

In the formula, N is the sparse coefficient of high-frequency transformer oscillation control; $C(r)$ is the adaptive learning model.

Under steady-state conditions, combined with the autocorrelation function of the robot's electrical faults, the resonant circuit of the robot's electrical equipment is obtained.

In the switching arc period, the vector model of the robot's electrical fault parameters is $s(t) = [s_1(t), s_2(t), \cdots, s_q(t)]^T$, and the interference vector is $n(t)$, using the resonance circuit oscillation control method, the jump sequence of the robot's electrical fault is obtained, which is the following formula :

$$f_j(u_j, s, w) = \frac{\sqrt{s(t) + n(t)}}{2} + \int_i \frac{u_j s(t) + w_i s(t)}{s_i}\mathrm{d}t. \tag{2}$$

In the formula: u_{ji} is the oscillation coefficient of the resonant tank; w_i is the jump parameter; and s_i is the switching radian period [12,13]. Assuming that the two-way resonance class transformation feature sample set of the

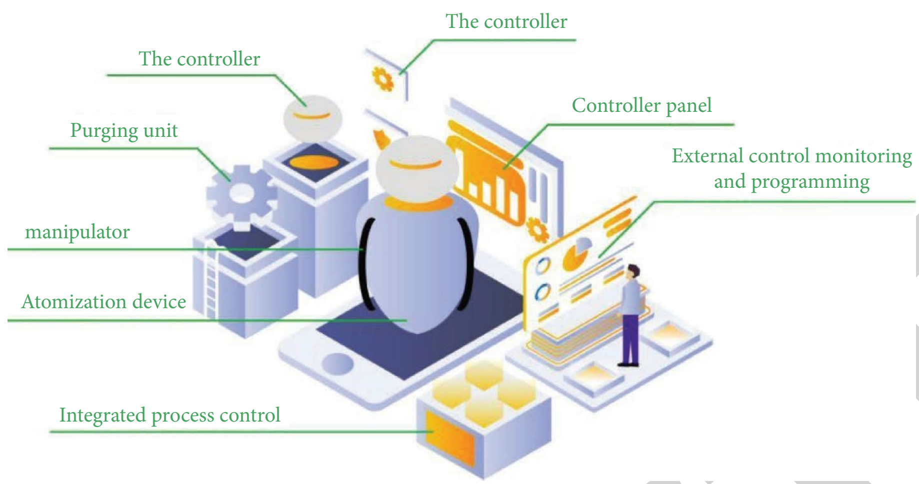

FIGURE 1: Robot fault detection.

robot electrical equipment is d^k, the load range $\Psi(\omega)$ of the faulty node of the robot electrical equipment is the following formula :

$$\Psi(\omega) = \sum_{k-1} \left[\left(\omega^k + d^k \right) + f_j \right]^2. \tag{3}$$

Taking the return power and active power as constraints, combined with the deep learning analysis method within the load range of the faulty node, the data collection output of the robot electrical fault information is obtained as the following formula:

$$V(k) = N\left[\Psi(\omega) + \omega^k\right]^2 - c_k\left[f_j\left(u_j\right) + f_j(w)\right]. \tag{4}$$

According to the above analysis, the data collection of the electrical fault samples of the robot are completed, and the fault sample information is obtained for subsequent fault feature analysis.

3.1.2. Data Normalization. Due to the different dimensions of sensor data, the range of values is quite different, and there is no comparability between the original data. Reasonable data standardization will make the algorithm achieve better results.

Advantages of data standardization:

(1) Eliminate the difference caused by the dimension.

(2) It is beneficial to the initialization of the neural network model.

(3) Helps to update the gradient value.

(4) It is beneficial to the adjustment of the learning rate value.

(5) Speed up the convergence speed, which is helpful for the model to find the optimal solution.

The author considers that the sensor data has a directional problem, the value is divided into about 0, and the positive and negative signs represent the direction, so the MinMax standardization is used to standardize the data to be between positive and negative 1.

Data normalization should pay attention to the following issues: when normalizing the training set and test set of fault data, a unified standard should be used, and the training set and test set cannot be standardized separately. Separate normalization will cause the training set and test set to use different scales, which will distort the test set data and affect the prediction effect of the model.

Step 1. Obtain a large amount of data as a training set, find the maximum and minimum values of each variable, and permanently record them as the standard maximum value and standard minimum value.

Step 2. According to the standard maximum value and the standard minimum value of each variable, data standardization is performed on the training set.

Step 3. For the test set data, data normalization is performed according to the standard maximum and standard minimum.

Step 4. When the service robot performs fault diagnosis on the cloud, each time the sensor data are uploaded to the cloud, it is standardized using the standard maximum and minimum values.

3.1.3. Failure Characteristic Analysis. According to the above resonant circuit analysis and data sampling results, the resonant inductance and resonant capacitance of the robot's electrical equipment are used as identification parameters to mine the different features of the robot's electrical faults and extract the feature quantities that can reflect the attributes of the robot's electrical faults.

The adaptive filtering method is used to analyze the electrical fault data of the robot. On this basis, the resonant inductance obtained by the proportional-repetitive control method is $\sup_t(D)$, the resonant capacitance is $\mathrm{num}_t(D)$, and the differential characteristic distribution of the electrical fault of the robot under nonlinear load conditions is the following formula:

$$T(\delta) = \sqrt{\delta + 1}\left[\sup_t(D) + \mathrm{num}_t(D)\right]^2, \tag{5}$$

where, δ is the voltage and frequency droop coefficient.

The output voltage and load differential fault features of the robot electrical equipment are fused, and the result is the following formula:

$$y(t) = u(t-\tau) + \int_i \left[u(t) + \omega_c(t)\right]\mathrm{d}t - \frac{\omega_c(t-\tau)}{u(t-\tau)}. \tag{6}$$

where, $u(t)$ is the current; ω is the resonant current polarity.

On this basis, the voltage and current in one switching cycle are analyzed [14]. Assume that the output spectral sequence of the electrical fault feature of the robot is $h_i(t)$, the electrical fault distortion sequence of the robot is $z_i(t)$, and the beam oscillation sequence of voltage and current under steady-state conditions is the following formula:

$$s_i(t) = 2\pi f_0 t + \int_i \left[h_i(t) + o_i(t) + \varphi_i(t)\right]\mathrm{d}t - z_i(t). \tag{7}$$

In the formula, $\varphi_i(t)$ and $o_i(t)$ are the voltage and current that the resonant circuit of the robot electrical equipment bears, respectively [15].

Using the switching frequency resonance analysis method, after the robot electrical fault data is fused again, the ambiguity characteristic component of the beam oscillation sequence of the fault sample is obtained as the following formula:

$$E_{Tx}(l,d) = \int_i \left[u_i(t) + \varphi_i(t)\right]\mathrm{d}t - \frac{s_i(t)}{z_i(t)}. \tag{8}$$

Using the resonant current polarity invariance theory, the oscillation characteristic component output by the robot electrical equipment is obtained as the following formula:

$$X_\alpha(m) = \left[\cos(\alpha) + \sin(\alpha)\right]^2 + m_k\sqrt{\varepsilon_k + 1}. \tag{9}$$

In the formula, m_k is the statistical feature quantity of the electrical fault of the output robot; ε_k is the standard deviation. When $X_\alpha(m) = x(m)$, the voltage in the switching cycle is fused.

On this basis, the fuzziness feature matching method is used to analyze the results of the statistical feature sequence of the robot electrical equipment so as to improve the quality of the electrical fault detection and diagnosis of the robot electrical equipment.

3.2. Electrical Fault Detection and Diagnosis

3.2.1. Fault Feature Extraction. The PI regulator is used for the feedback adjustment of the robot's electrical fault information, and the feature extraction and adaptive optimization control of the robot's electrical fault are carried out in combination with the fault information fusion analysis method [16]. Based on the switching frequency resonant frequency ratio of the robot electrical equipment, the standard deviation and mean function of the fault sample sequence detection are calculated as the following:

$$M_k = \sum_{k=1}\left[x^k + \frac{E\left(x^k\right)}{2}\right] + f(x). \tag{10}$$

$$\mu_k = \sum_{k=1}\left[(x-\eta)^k - \frac{E(x-\eta)^k}{2}\right] - f(x). \tag{11}$$

In the formula, x^k is the switching frequency resonant frequency ratio; η is the variation coefficient of the fault sample sequence; $f(x)$ is the detection function of the fault sample sequence; and E is the switching frequency resonant frequency under the fault condition.

The optimal control is carried out according to the boundary conditions of the voltage borne by the resonant circuit, and the clustering output of the robot electrical fault information is obtained as the following formula:

$$E_i = s(t) + M_k\sqrt{1 + E_i(x)^k} - \frac{1}{2}\mu_k. \tag{12}$$

In the formula, M_k is the boundary condition of the voltage of the resonant tank; E_i is the electrical fault information clustering model. The Fourier analysis method is used to fuse the electrical fault information of the robot, and the output is the following formula:

$$A_j(L+1) = n_j + E_i\sqrt{A_j(L) + 1} + X_i. \tag{13}$$

In the formula, n_j is the characteristic parameter of nonlinear load variation; A_j is the fusion degree of fault information features.

Initialize the current and voltage phases and extract the electrical fault features of the robot based on the time-delay distribution sequence of the robot's electrical fault feature data, where the time-delay distribution sequence is shown in Figure 2.

According to the fusion of robot electrical fault features and the time-delay distribution sequence, a feature extraction model is constructed. It is the following formula:

$$V(a) = \sum_m \frac{V(b_1) + V(b_m)}{V(a_m)} + A_j(L+1) - \frac{1}{2}. \tag{14}$$

3.2.2. Fault Detection and Diagnosis Based on Deep Learning. On the basis of the above analysis, combined with the deep learning function to detect and diagnose the electrical fault of the robot [17], the robustness detection of the robot electrical equipment is carried out within the time window t. Combined with the active and reactive power output by the fault detection, the stable error of the output voltage is obtained as the following formula:

$$P_{ti,j} = P_{ti-1,j} + \sum_{ij\neq 0}\left(P_i + P_{ti,j} - P_{ti-1,j}\right). \tag{15}$$

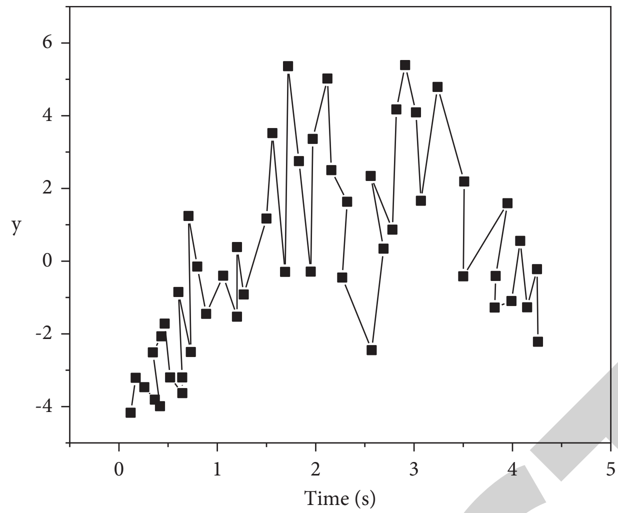

Figure 2: Time-delay distribution sequence of robot electrical fault data.

In the formula, P_i is the voltage and frequency droop coefficients under the electrical fault condition of the ith robot; $P_{ti,j}$ is the equivalent gain of the inverter.

Under the adjustment of the power-frequency difference, according to the stable error analysis method, the robot fault detection function is obtained as the following formula:

$$N_i(t) = \sum_{j=1}\left[\frac{x_j(t) + l_j(t)}{2} - \left(x_j(t) + l_j(t)\right)^2\right]. \tag{16}$$

In the formula, $x_j(t)$ is the deep learning iterative function under the state of the robot electrical fault; $l_j(t)$ is the control parameter of the robot voltage droop.

On the basis of obtaining the robot fault detection function, denoting $\Delta M\imath mn$ as the nth sample of the mth fault, the deep learning function for the robot electrical fault diagnosis is obtained as the following formula:

$$Q = \int_i \left[x_j(t) - l_j(t)\right]\mathrm{d}t + y_{i,j}\left(\frac{B_i}{A_i}\right) + N_i(t). \tag{17}$$

To sum up, through the data collection, fault feature analysis, and extraction of the robot electrical fault samples, the fault detection model and the deep learning function of the robot electrical fault diagnosis can be obtained so as to realize the detection and diagnosis of the robot electrical fault and improve the detection and diagnosis of the robot electrical fault.

4. Analysis of Results

In order to verify the application performance of the proposed deep learning-based robot electrical fault detection and diagnosis method in the realization of robot electrical fault detection, simulation experiments were carried out.

The output harmonic impedance is set to 50 Ω, the switching frequency is 120 kHz, the number of samples collected for electrical faults of the robot is 5000, and the training sample set for fault feature sampling is 1500, the test sample set is 3500, and the return power of the electrical equipment is 250 W. According to the above parameter settings, the robot electrical fault detection and diagnosis are carried out [18–20].

The test method, the neural network-based method, and the fault detection accuracy based on the expert system method are shown in Table 1, the comparison results are shown in Table 1.

From the analysis of Table 1, it can be seen that the author's method has a higher accuracy probability for robot electrical fault diagnosis, which is 14.7% higher on average than the neural network-based method, and it is on average 24.5 higher than expert system-based methods [21]. On the basis of the above experiments, the accuracy of robot electrical fault diagnosis is compared, and the results are shown in Table 2.

From the analysis of Table 2, it can be seen that the accuracy rate of the author's method for robot electrical fault diagnosis is high. The author's method is 16.6% higher than the neural network-based method on average, and 34.2% higher than the expert system-based method.

In order to further compare the comprehensive performance of the three methods, the robot electrical fault detection time and diagnosis time are compared, and the results are shown in Figures 3 and 4.

Analysis of Figures 3 and 4 shows that the author's method is lower than the method based on neural network and the method based on expert system, whether it is the detection time of robot electrical fault or the diagnosis time, it shows that this method can realize the rapid detection and diagnosis of robot electrical faults [22–27].

Table 1: Comparison of fault detection accuracy.

Number of trials	Fault detection accuracy rate/(%)		
	Method	Based on neural network	Expert system-based approach
10	93.4	87.3	76.2
20	97.3	89.1	79.2
30	98.1	90.1	81.1
40	99.3	91.3	81.4
50	94.5	82.5	73.5
60	98.6	83.1	78.7
70	97.2	80.1	81.2
80	99.6	82.5	80.7
90	95.8	80.3	74.7
100	96.1	81.1	72.9

Table 2: Comparison of fault diagnosis accuracy.

Number of trials	Fault detection accuracy rate/(%)		
	Method	Based on neural network	Expert system-based approach
10	96.5	86.3	75.6
20	96.9	82.4	70.3
30	99.2	85.6	72.4
40	98.7	82.7	75.1
50	96.7	80.1	73.5
60	98.5	82.5	74.9
70	98.4	86.2	72.1
80	96.8	83.4	72.8
90	97.7	84.6	70.2
100	98.8	85.4	72.5

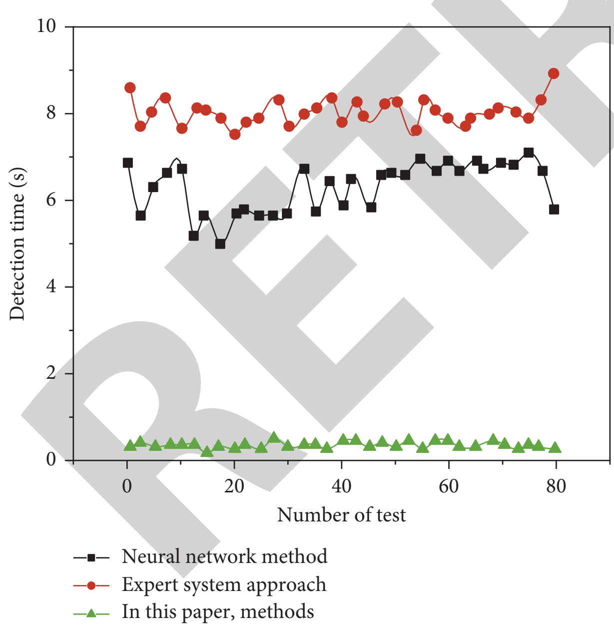

Figure 3: Comparison of detection time and diagnosis time of different methods.

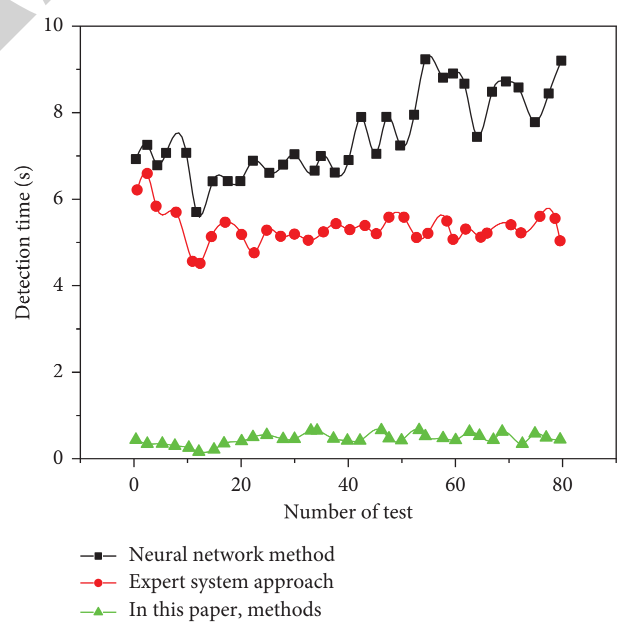

Figure 4: Comparison of the diagnosis time of different methods.

5. Conclusion

In order to improve the reliability of robot electrical fault detection and diagnosis results, the author proposes a robot electrical fault detection and diagnosis method based on deep learning. Then, built an adaptive learning model for robot electrical fault diagnosis and used the Fourier analysis method to fuse robot electrical fault information, extracting robot electrical fault features. Thereby, the fault detection model and the deep learning function of the robot electrical fault diagnosis are obtained so as to realize the detection and diagnosis of the robot electrical fault. The analysis shows that the author's method has high accuracy, short time, and good reliability for robot electrical fault detection and diagnosis, which can be further promoted and used in practice.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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