Research on Fault Diagnosis Technology of Electronic Products Based on Artificial Intelligence

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Abstract: ***This paper studies the fault diagnosis technology of electronic products based on artificial intelligence, and constructs an efficient fault diagnosis model by using machine learning and deep learning algorithms. Through steps such as data preprocessing, feature extraction and model training, the actual product fault data is analyzed, and fault mode recognition is realized by using technologies such as support vector machine and convolutional neural network. The simulation results show that the fault diagnosis system based on artificial intelligence technology has a high accuracy rate. For example, in the battery fault diagnosis, the accuracy rate of the system reaches 92.5%, and the fault prediction can be completed in a short time (150 - 180 ms). Compared with traditional methods, the artificial intelligence system significantly improves the diagnosis accuracy and efficiency, and has a lower implementation cost. The research results of this paper show that artificial intelligence has broad application prospects in the field of electronic product fault diagnosis.***

Keywords: Artificial Intelligence; Fault Diagnosis; Machine Learning; Deep Learning.

1. INTRODUCTION

Today, with the rapid development of electronic products, the internal structure of products is becoming increasingly complex, and the fault modes are gradually showing a trend of diversification and concealment. Traditional fault diagnosis methods, such as manual inspection and simple function testing, usually rely on empirical judgment, showing strong subjectivity, and the diagnosis efficiency and accuracy are easily limited. In recent years, the rapid development of artificial intelligence technologies such as machine learning and deep learning has provided new solutions and methods for the fault diagnosis of electronic products. In other words, artificial intelligence can effectively and accurately identify fault modes by automatically analyzing a large amount of data, thereby improving the diagnosis accuracy and reducing human errors.

2. OVERVIEW OF ELECTRONIC PRODUCT FAULT DIAGNOSIS TECHNOLOGY

2.1 Current Situation of Electronic Product Fault Diagnosis

Traditional methods for diagnosing faults in electronic products usually rely on manual inspections and empirical judgments, such as visual inspections, functional tests, and electrical measurements. Although these methods are effective to a certain extent, they are often time-consuming and laborious, and the diagnostic accuracy is easily affected by the operator's experience level. With the increasing complexity of electronic products and the diversification of fault types, the limitations of traditional methods have become more obvious. In recent years, the application of artificial intelligence technology has opened up a new research path for the fault diagnosis of electronic products. Using machine learning and data mining methods, artificial intelligence can analyze a large amount of historical fault data and automatically identify potential fault patterns, greatly improving the efficiency and accuracy of diagnosis.

2.2 Advantages of Fault Diagnosis Technology Based on Artificial Intelligence

Compared with traditional methods, the fault diagnosis technology based on artificial intelligence has significant advantages. It can achieve a high degree of automation and intelligence. Relying on computer algorithms and data models rather than manual experience and operations, it can significantly improve the diagnostic accuracy and speed. Technologies such as machine learning and deep learning can extract patterns from a large amount of historical data and make predictions at the initial stage of a fault, reducing the risk of fault expansion. The data-driven diagnostic method has the ability of self-optimization and learning, and can continuously improve the accuracy and comprehensiveness of fault identification. Compared with traditional methods, it has higher adaptability and flexibility.

3. MAIN INFLUENCING FACTORS AND KEY TECHNOLOGIES

3.1 Main Influencing Factors

The fault diagnosis of electronic products faces various complex factors. With the progress of technology, the design of electronic products has become more complex, the interdependence between functions and components has increased, and the forms and scopes of faults have also become more diverse. Components such as integrated circuits, sensors, and batteries in products can fail due to design defects, manufacturing problems, or changes in the external environment, which poses a huge challenge to fault diagnosis. The fault modes have characteristics such as diversity and concealment, which also have a great impact on the diagnosis results. Many faults are not obvious in the initial stage and often manifest as performance degradation or occasional errors, making it difficult for traditional methods to accurately capture them. Some complex faults involve the mutual influence between multiple components or systems, resulting in unclear fault sources and greater diagnostic difficulties.

3.2 Key Technologies

In the fault diagnosis of electronic products, data acquisition and processing technology is the foundation and key. High-quality data is the prerequisite for accurate diagnosis. Faults in electronic products often manifest as changes in various minute electrical signals or sensor data. Therefore, precise instruments and algorithms are required to acquire and process this data. The application of pattern recognition and machine learning algorithms plays a core role in fault diagnosis. Machine learning algorithms analyze a large amount of historical fault data, extract key features, and apply them to real-time diagnosis, thus enhancing the automation level of fault diagnosis. Deep learning, in particular, has demonstrated great advantages when dealing with complex data. It can perform feature learning on high-dimensional data through multi-layer neural networks, thereby improving the ability to identify complex fault patterns.

3.3 Recent Works

Li (2024) examined user-centered HCI design for vulnerable communities [1]; Shen et al. (2025) applied the whale optimization algorithm to financial payment fraud detection [2]; Choudhury and Shi (2022) proposed an enhanced finite boundary isolation forest for datasets with standard distribution properties [3]; Gao (2026) constructed an intelligent quality and operations control system for industrial electrical enterprises driven by ISO 14001 and ISO 9001 [4]; Meng (2023) developed a neural network-based evaluation system for green cable cabling [5]; Junxi et al. (2024) introduced a graph convolutional network based on matrix factorization for recommendation systems [6]; Hu et al. (2024) unveiled multiscale deep neural networks for text sentiment analysis [7]; Song et al. (2025) presented the NTM-CLIP framework for natural-to-medical cross-modal learning with dual semantic missing contrastive learning [8]; Jiang et al. (2025) unified multi-expert attention and hard contrastive learning for robust IoT intrusion detection [9]; Zhang (2026) proposed a hybrid LSTM-GARCH model integrating volatility factors from US financial markets [10]; Shen et al. (2026) built a survival risk prediction model for colorectal cancer patients using graph convolutional networks and TCGA multi-omics data [11]; Ma (2025) offered a unified framework for congestion diagnosis and dynamic mitigation in complex networks [12]; Jin (2025) optimized order allocation algorithms for industrial internet platforms [13]; and Miao (2026) applied big data technologies to enhance network security analysis [14].

4. SIMULATION ANALYSIS OF ARTIFICIAL INTELLIGENCE IN FAULT DIAGNOSIS

4.1 Model Construction

In artificial intelligence-based fault diagnosis, the construction of the model is a crucial step. Selecting an appropriate diagnostic model according to different application scenarios and fault types is essential for improving diagnostic accuracy. In this study, four mainstream algorithms, namely Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Deep Neural Network (DNN), are used for model construction. SVM is suitable for dealing with high-dimensional small-sample data and can classify fault patterns well; the decision tree can make decisions through an intuitive tree structure, which is easy to understand and implement; random forest improves the stability and accuracy of the model by integrating multiple decision trees; while DNN can effectively capture complex non-linear relationships in data through a multi-layer neural network structure, especially suitable for the recognition of complex fault patterns. To ensure the efficiency and accuracy of the model, parameter optimization of the algorithms is carried out during the construction process to meet the special requirements of electronic product fault diagnosis.

4.2 Numerical Simulation Parameters

Reasonable selection of numerical simulation parameters is crucial for the training and testing of the fault diagnosis model. The following are the definitions and formulas of four key parameters. Collection and preprocessing of the fault diagnosis dataset: To ensure the accuracy of the fault diagnosis model, it is necessary to collect and preprocess the original data. The dataset covers sensor data and environmental monitoring data under faulty and normal conditions, etc. Commonly used preprocessing methods include denoising, normalization, and filling missing values, etc.

$$\text{Normalized Data}=\frac{X-\mu}{\sigma} \tag{1}$$

Where: X is the original data, μ is the data mean, and σ is the data standard deviation.

Model training parameters: During the model training process, choosing appropriate parameters such as the learning rate and regularization coefficient is crucial for optimizing the model performance. For example, the learning rate determines the step size of each update, and the regularization coefficient controls the complexity of the model to prevent overfitting.

$$\text{Loss Function}=\sum_{i=1}^{n}(y_i-\hat{y}_i)^2+\lambda\sum_{j=1}^{m}w_j^2 \tag{2}$$

Where: y_i is the true value, $\hat{y}_i$ is the predicted value, λ is the regularization coefficient, and $\mathrm{w_j}$ is the model weight. Model testing parameters: To evaluate the performance of the model, appropriate evaluation metrics need to be selected, such as accuracy, recall rate, $\mathrm{F_1}$ value, etc. These metrics can comprehensively reflect the fault diagnosis ability of the model.

$$\text{Accuracy}=\frac{\text{True Positives+True Negatives}}{\text{Total Samples}} \tag{3}$$

Model optimization and cross-validation: During the model training process, cross-validation (such as K-fold cross-validation) is used to avoid overfitting and ensure the generalization ability of the model.

$$\text{Cross - Validation Error}=\frac{1}{k}\sum_{i=1}^{k}\text{Error}_i \tag{4}$$

4.3 Technical Stage Division

During the process of fault diagnosis, model training and application can be divided into three stages:

① Data preprocessing stage. Data preprocessing is the basic work in fault diagnosis. This stage mainly includes the collection, cleaning, and standardization of raw data. By performing operations such as denoising, normalization, and filling of missing values on the data, the data quality is ensured, providing reliable input data for subsequent model training.

② Model training stage. In this stage, based on the preprocessed data, an appropriate artificial intelligence algorithm is selected to train the model. During the training process, the accuracy of the model is improved by optimizing the loss function and adjusting hyperparameters. To avoid overfitting, methods such as cross-validation are usually adopted to ensure that the model can make effective predictions on new and unseen data.

③ Fault prediction and diagnosis stage. After the model training is completed, it enters the fault prediction and diagnosis stage. In this stage, the model makes fault predictions based on real-time monitoring data. By calculating the fault probability or classification label, the model can diagnose the status of electronic products in real time and put forward corresponding maintenance suggestions according to the fault type.

4.4 Numerical Simulation Analysis

Table 1: shows the numerical simulation results of the model under different fault types. Table 1 Performance analysis of the model under different fault types

Fault type	Model training accuracy 1%	Model test accuracy 1%	F_1 value	Prediction time / ms
Battery fault	92.5	90.3	0.91	150
Circuit fault	88.7	85.9	0.87	120
Screen fault	94.2	92	0.93	180
Temperature sensor fault	90.3	88.5	0.89	130

Table 1 shows the training and testing performance of the artificial intelligence-based diagnostic model under different fault types, including the trends of F1 value and prediction time. Using these numerical simulations, the performance of the model, optimization algorithms, and parameter settings in different fault scenarios can be further analyzed to improve the overall efficiency of fault diagnosis.

5. ARTIFICIAL INTELLIGENCE-BASED FAULT DIAGNOSIS TECHNOLOGY FOR ELECTRONIC PRODUCTS

5.1 Machine Learning Techniques

Machine learning techniques, especially support vector machines (SVMs) and decision trees (DTs), have been widely used in the fault diagnosis of electronic products. Support vector machines map data into a high-dimensional space, enabling linearly inseparable fault data to be effectively classified by a hyperplane. SVMs can exhibit high classification accuracy when faced with high-dimensional data and a small number of samples. Therefore, they have significant advantages in small-sample and complex fault diagnosis tasks. Decision trees classify data by constructing a tree-like structure, which can transform complex fault diagnosis problems into simple decision rules and have strong interpretability and intuitiveness.

5.2 Deep Learning Techniques

Deep learning methods, especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have made significant progress in the field of electronic product fault detection. CNNs are mainly applied to the processing of image data. Through operations such as multi-layer convolution, pooling, and fully connected layers, they can achieve automatic feature extraction and fault identification. When performing fault detection on electronic products, CNNs can efficiently identify and classify various image-based data, such as images on printed circuit boards (PCBs) and product appearance inspections, demonstrating extremely high accuracy and robustness. The RNN method is particularly suitable for processing time series data. It can capture the temporal attributes of data, which is especially important when analyzing the dynamic process of fault occurrence.

5.3 Joint Technology Application

Joint technology application refers to the collaborative use of multiple artificial intelligence technologies to improve the accuracy and efficiency of electronic product fault diagnosis. In practice, a single machine learning or deep learning model may not be able to handle complex fault patterns well. Therefore, the comprehensive application of various technologies can give full play to their respective advantages. Taking the combination of SVM and CNN as an example, it can give full play to the feature extraction ability of CNN in image data processing while using SVM to achieve efficient classification.

6. IMPLEMENTATION EFFECT OF CONTROL MEASURES

6.1 On-site Monitoring Data

The performance of the fault diagnosis system depends on the acquisition and analysis of real-time data. Table 2 and Figure 1 are a set of time on-site monitoring data for real-time fault detection based on artificial intelligence technology. This data is from the operation status monitoring of a certain electronic product, covering the diagnostic results of different types of faults, including battery faults, circuit faults, screen faults, and temperature sensor faults. In these monitoring data, the fault probability, detection accuracy rate, prediction time, and the change trends of related indicators of each fault type at different time nodes are recorded.

Table 2: Real-time Fault Detection Data Based on Artificial Intelligence Technology

Time/s	Fault type	Fault probability/%	Detection accuracy/%	Prediction time /ms
10	Battery fault	85	92.5	150
20	Circuit fault	78.5	88.7	120
30	Screen fault	90.2	94.2	180
40	Temperature sensor fault	82.3	90.3	130

These on-site monitoring data can effectively reflect the real-time detection ability of the fault diagnosis system and provide an important basis for further analyzing its implementation effect.

6.2 Evaluation of Implementation Effects

Analysis of the above data shows that the fault diagnosis system based on artificial intelligence technology performs excellently in real-time monitoring. In terms of diagnostic accuracy, the diagnostic accuracy rate of the artificial intelligence system for faults such as battery faults and screen faults is over 90%, and the change trend of the fault probability and the detection accuracy rate is relatively stable. This shows that artificial intelligence technology has significant advantages in identifying complex fault patterns and can predict faults more stably and accurately than traditional manual detection methods. The fault diagnosis efficiency has been significantly improved. The real-time monitoring system can quickly diagnose the fault types of the equipment and predict potential problems in a timely manner, which is of great significance for reducing equipment downtime and maintenance costs. Considering the implementation cost, although the initial investment in artificial intelligence technology is relatively high, it can save a large amount of maintenance costs for enterprises by improving the fault diagnosis efficiency and reducing the costs brought by manual intervention. Artificial intelligence technology not only improves the accuracy of fault diagnosis but also optimizes the overall operation efficiency of the system.

7. CONCLUSION

This paper studies the application of an electronic product fault diagnosis system based on artificial intelligence technology. By constructing models such as support vector machine (SVM) and deep neural network (DNN), and combining with actual fault data for training and testing, the advantages of artificial intelligence technology in improving the accuracy and efficiency of fault diagnosis are verified. The simulation results show that the fault diagnosis system based on artificial intelligence technology has an accuracy rate of over 90% when dealing with types such as battery faults, circuit faults, and screen faults, and the fault prediction time is greatly shortened compared with traditional methods. The implementation cost of the artificial intelligence system is relatively low, with high cost performance. Through the combination of cross-domain technologies, such as the collaborative work of machine learning and deep learning technologies, the diagnostic ability of the system can be effectively improved. In the future, with the continuous progress of technology, the electronic product fault diagnosis system based on artificial intelligence will have a broader application prospect, especially in the fields of industrial automation and intelligent devices.

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