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Application of Fault Tree Analysis (FTA) Based Intelligent Platform in Fault Diagnosis of Offshore Oil Support Ship Side Push System

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Abstract: In the operation of offshore oil support ships, due to the low accuracy of fault diagnosis for the side thrust system and the inability to accurately eliminate faults, untimely diagnosis combined with incorrect fault diagnosis can easily lead to serious safety hazards and economic losses. The aim of this study is to apply an intelligent platform based on Fault Tree Analysis (FTA) to improve the accuracy and efficiency of fault diagnosis in the lateral push system. This article first uses a data collection system to monitor key parameters in real-time, and combines CNN in deep learning algorithms to predict and diagnose faults, and then constructs a fault tree model for the lateral push system to identify the main fault modes and their causes. The experimental results show that after applying the intelligent platform, the accuracy of fault diagnosis has increased to 92%, which is more than 20% higher than the single fault tree analysis method. The diagnosis time has been shortened by 30%, significantly reducing the risk of ship shutdown. The intelligent platform based on FTA can effectively enhance the fault diagnosis capability of the offshore oil support ship's side push system, providing strong technical support for the safe operation of ships.

1. Introduction

In the operation of offshore oil support ships, the lateral thrust system, as a key power device, directly affects the maneuverability and safety of the ship. However, the current fault diagnosis accuracy of the lateral push system is generally not high, often resulting in failure to detect faults in a timely manner or incorrect diagnosis. This situation not only increases the risk of vessel shutdown, but may also cause serious safety hazards and economic losses. Therefore, improving the accuracy and efficiency of fault diagnosis in the lateral thrust system has become an urgent problem to be solved in the offshore oil industry.

To address the above challenges, this article proposes an intelligent platform based on Fault Tree Analysis (FTA), aiming to significantly improve the performance of fault diagnosis through the combination of real-time monitoring and deep learning algorithms. By monitoring key parameters in real-time through a data acquisition system and applying convolutional neural networks (CNN) for fault prediction and diagnosis, the main fault modes and their causes can be effectively identified. This method not only improves the accuracy of fault diagnosis, but also shortens the diagnosis time, thereby reducing the risk of ship shutdown and providing strong technical support for the safe operation of ships.

The structure of this article is arranged as follows: the first part provides a detailed introduction to the research background and relevant literature review; the second part describes the data collection and fault diagnosis methods used; the third part presents the experimental design and result analysis; the final part is to summarize the research results and look forward to future research directions. Through systematic research arrangements, we strive to provide practical and feasible solutions for the safe operation of offshore oil support ships.

2. Related Work

In the field of machinery fault diagnosis, with the development of artificial intelligence technology in recent years, the application of various types of learning frameworks has been deepening. This article will summarize the current research progress in frameworks such as shallow machine learning, deep learning, and transfer learning, in order to better understand their practical applications in fault diagnosis. Cen J classified and summarized the current status of applications and research progress in machinery fault diagnosis[1]. Huang T proposed a new fault diagnosis method to consider the feature extraction and the time delay for the occurrence of faults[2]. Zhu J reviewed the current state of development of RNN methods in machinery fault diagnosis and presented their applications in terms of both RNN and combinatorial neural networks including RNN [3]. Furse C M reviewed the state-of-the-art of detection, localization, and diagnosis of faults in Electrical Wiring Interconnection Systems (EWIS) [4]. Feng L proposed an attribute shifting approach by proposing fault description based to solve the zero sample fault diagnosis problem [5]. Fernandes M aimed to review the recent advances in the use of machine learning methods for machinery fault diagnosis and fault prediction in manufacturing industry [6].

In addition, Ma Guangfu proposed a finite frequency domain fault diagnosis strategy based on H/L ∞ unknown input observer, which processes the system into an augmented system containing sensor faults. Then, he divided the unknown input interference of the system into two parts: decoupleable and non decoupled [7]. Bin Shiyang proposed a machine learning based fault diagnosis method for the mechanical transmission system of wind turbines to accurately diagnose faults [8]. Jiang Qiang proposed a Bayesian Le Net network model based on a combination of Bayesian linear layers and Bayesian convolutional layers. He analyzed and processed the fault data of the flywheel components in the satellite attitude control system, and then used this model to simulate the faults [9]. Xi Tao proposed multiple fault diagnosis methods based on optimization algorithms, in response to the current inability to quickly and accurately diagnose faults in mining column hydraulic systems, by establishing simulation models to analyze single fault mechanisms [10]. With the continuous innovation of machine learning and deep learning methods, the accuracy and efficiency of mechanical fault diagnosis have been significantly improved. However, further research is still needed for different application scenarios in the future to promote the further development and practical application of fault diagnosis technology.

3. Method

3.1 Data Collection System and Key Parameter Monitoring

The data collection system can timely obtain the operating status of the system by monitoring key parameters in real time, providing basic data for subsequent fault analysis and prediction. Taking a certain offshore oil support ship as an example, the ship is equipped with an advanced data acquisition system that can monitor multiple key parameters including pressure, temperature, vibration, and current of the lateral thrust system [11]. The changes in these parameters often reflect the health status of the equipment and provide early warning of potential faults. If there are abnormal fluctuations in the pressure and temperature of the side push system, it means that there are problems such as leaks or component wear inside the system. The data collection system adopts a high-frequency data collection method, recording key parameters every second to ensure the capture of instantaneous changes in information. By combining deep learning algorithm CNN for data analysis, the system can learn from historical data and identify potential patterns of faults. This process not only improves the accuracy of fault prediction, but also shortens the time for fault diagnosis. To demonstrate the actual effectiveness of the data collection system, Table 1 shows the key parameter monitoring data collected for offshore oil support vessels under different operating conditions.

Table 1: Key parameter monitoring data

Operating Condition	Pressure (bar)	Temperature (℃)	Vibration (mm/s)	Current (A)
Normal Operation	8.5	60	0.5	12
Minor Fault	7.0	65	1.2	14
Severe Fault	5.0	75	3.5	20
Normal Operation	8.6	61	0.4	11
Minor Fault	6.8	66	1.3	15

These data reflect the changes in key parameters of the lateral push system under three states: normal operation, minor faults, and severe faults [12]. From the above monitoring data, it can be seen that as the degree of the fault worsens, significant changes have occurred in various key parameters, especially in pressure and vibration fluctuations, which can effectively indicate the health status of the system.

3.2 Application of CNN

The fault data of the lateral push system is usually multidimensional and time-dependent. CNN can effectively extract features through convolutional layers, capture local dependency relationships and spatial features in the data, which is crucial for identifying complex fault patterns. CNN does not require manual feature selection and can automatically extract important features from raw data, thereby reducing the time and cost of feature engineering. This feature is particularly suitable for the field of fault diagnosis [13], as its data often has irregularity and complexity. After collecting the data mentioned above, a CNN model is constructed, the ReLU function as follows:

$$F(x) = \max(0, x) \tag{1}$$

The pooling layer reduces the dimensionality of data and improves the robustness of the model by maximizing pooling downsampling (as shown in formula 2).

$$Y_{i,j} = \max_{m,n} X_{i+m,i+n} \tag{2}$$

Next, the model training adopts the cross entropy loss function, and the calculation formula is:

$$L = -\frac{1}{N}\sum_{i=1}^{N}(y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)) \tag{3}$$

y_i is the true label, $\hat{y}i$ is the predicted value, and N is the sample size. Through the above steps, CNN can learn fault characteristics from key parameters monitored in real-time, improving the accuracy of fault diagnosis.

3.3 Construction of Fault Tree Model for Lateral Push System

The construction process of the fault tree model for the lateral push system begins with identifying the top event, namely the 'lateral push system fault', which is the core objective of the analysis. Next, the team will discuss and determine the main causes that may lead to the top event, usually divided into electrical and mechanical failures. In this step, expert knowledge and historical data are utilized to collect fault information related to the lateral push system, ensuring the comprehensiveness and accuracy of potential causes. Subsequently, each main cause will be further subdivided into specific sub events. For example, "power failure" can be extended to "power interruption" and "electrical component damage", while "mechanical failure" can be subdivided into "hydraulic system failure" and "transmission device failure". For each sub event, continuing to conduct in-depth analysis and identify possible root causes, such as "generator failure" and "switch failure" under "power interruption", as well as "oil pump failure" and "pipeline leakage" under "hydraulic system failure". Next, using logic gates to connect these events[14]. The AND gate indicates that all input events must occur simultaneously to cause the top event, while the OR gate indicates that only one input event needs to occur to cause the top event to occur. After completing the logical relationship, the complete fault tree structure is drawn to ensure clarity and logicality at each level. Figure 1 is a schematic diagram of the analysis of the number of faults in this article:

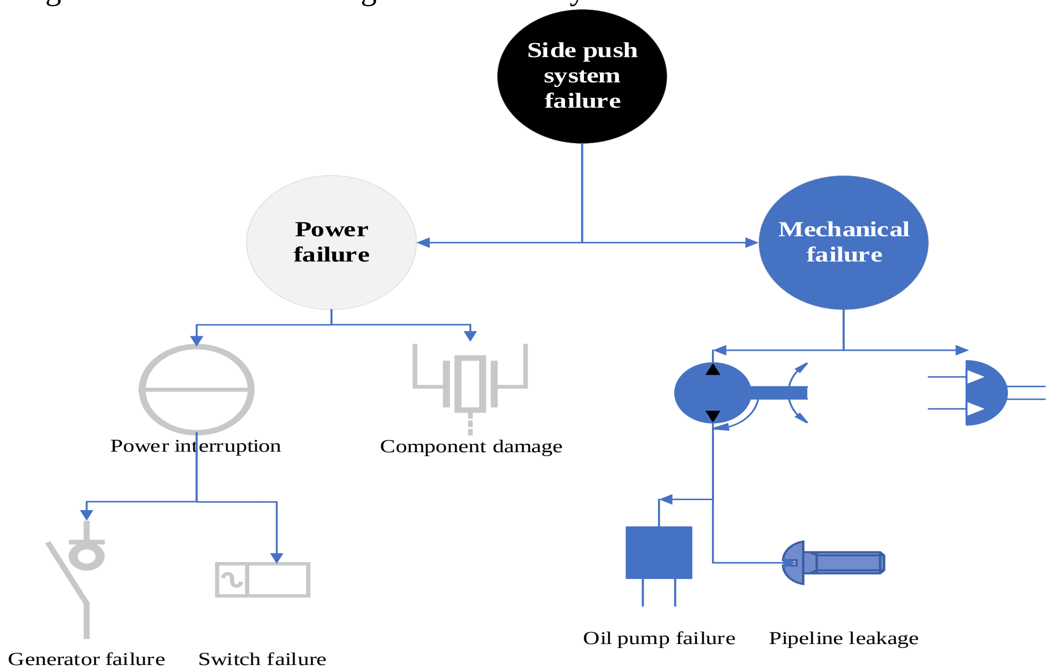

Figure 1: Schematic diagram of fault tree analysis

3.4 Implementation of Fault Mode Recognition

Collecting real-time data from sensors and monitoring devices provides a foundation for subsequent analysis. Then proceed with feature extraction, using signal processing techniques to extract key features from the raw data in order to better reflect the system's state and fault modes. The extracted features are input into the CNN model for training, and by comparing the training data with known fault patterns, the model can learn the patterns and rules of different fault features [15]. After training, the model can be applied to actual monitoring data to achieve online fault recognition. When new data is input, the model will classify it based on the learned features to determine whether there are faults and their types. In order to better demonstrate the process of fault mode recognition, Table 2 lists different fault modes and their corresponding characteristic values:

Table 2: Different fault modes and their corresponding characteristic values

Fault Mode	Feature 1 (Vibration Amplitude)	Feature 2 (Temperature Change)	Feature 3 (Current Fluctuation)
Normal Operation	0.5 mm	60 ℃	12 A
Minor Fault	1.2 mm	65 ℃	14 A
Severe Fault	3.5 mm	75 ℃	20 A
Equipment Failure	5.0 mm	80 ℃	25 A

4. Results and Discussion

4.1 Experimental Preparation

This study collected the real fault data of the push-push system, including historical fault records, equipment status parameters, maintenance records, etc. Subsequently, a fault tree model based on FTA is constructed to clarify each fault mode and its impact. In this study, the fault diagnosis method of single fault number analysis is compared with the CNN method combined in this paper, and its performance under different data amounts is compared. Diagnosis accuracy and diagnosis time are selected as performance evaluation indicators, sensors and data acquisition systems are installed to monitor equipment status parameters in real time. In the process of data collection, the integrity and accuracy of the data were ensured, noise and outliers were eliminated, several experiments were conducted to reduce unexpected errors, and the reliability of the experimental results was ensured through statistical analysis of the results.

4.2 Experimental Results

(1) Diagnostic accuracy

Firstly, the diagnostic accuracy was tested by selecting a data volume of 1TB-20TB as the variable, and the accuracy under different methods was tested and recorded. Figure 2 shows the recorded results:

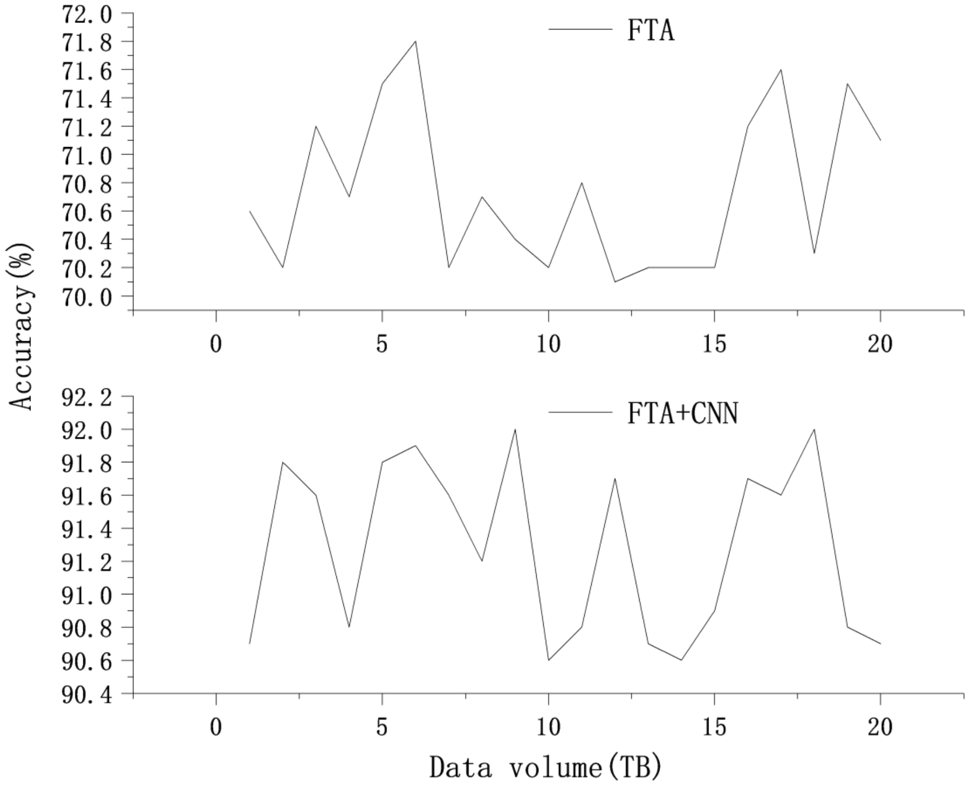

Figure 2: Diagnostic accuracy

When comparing the accuracy of the intelligent platform based on Fault Tree Analysis (FTA) and Convolutional Neural Network (CNN) combined with a single FTA fault diagnosis method in the fault diagnosis of offshore oil support ship side thrust systems, we observed that the accuracy of the FTA+CNN method was significantly higher than that of the single FTA method under different data volumes. Specific data shows that within the data volume range of 1TB to 20TB, the accuracy of FTA+CNN is between 90.6% and 92.0%, while the accuracy of a single FTA is between 70.2% and 71.8%. The fundamental reason for this difference is that the FTA method mainly relies on empirical rules and analysis of historical data, making it difficult to effectively capture complex nonlinear relationships and high-dimensional features. Therefore, it exhibits relatively stable but not flexible accuracy when processing large-scale data. The FTA+CNN method combined with CNN utilizes the powerful characteristics of deep learning to automatically extract key features from data, capture potential complex patterns, and significantly improve the accuracy of fault diagnosis.

With the increase of data volume, the accuracy of FTA+CNN remains above 91%, indicating that this method has good robustness and adaptability in processing large-scale data. The accuracy of a single FTA is around 70%, and it hardly improves significantly with the increase of data volume, indicating its limitations in the big data environment. The intelligent platform combined with CNN can not only process massive data, but also identify more complex and hidden fault patterns through multi-level feature learning, thereby improving the accuracy of fault recognition. In addition, during the data processing, CNN effectively reduces the dimensionality and computational complexity of the data through the design of convolutional and pooling layers, making the model more efficient in inference.

(2) Diagnosis time

Under the same data volume of 1TB-20TB, diagnostic time tests were conducted on both methods, and the test results are shown in Figure 3:

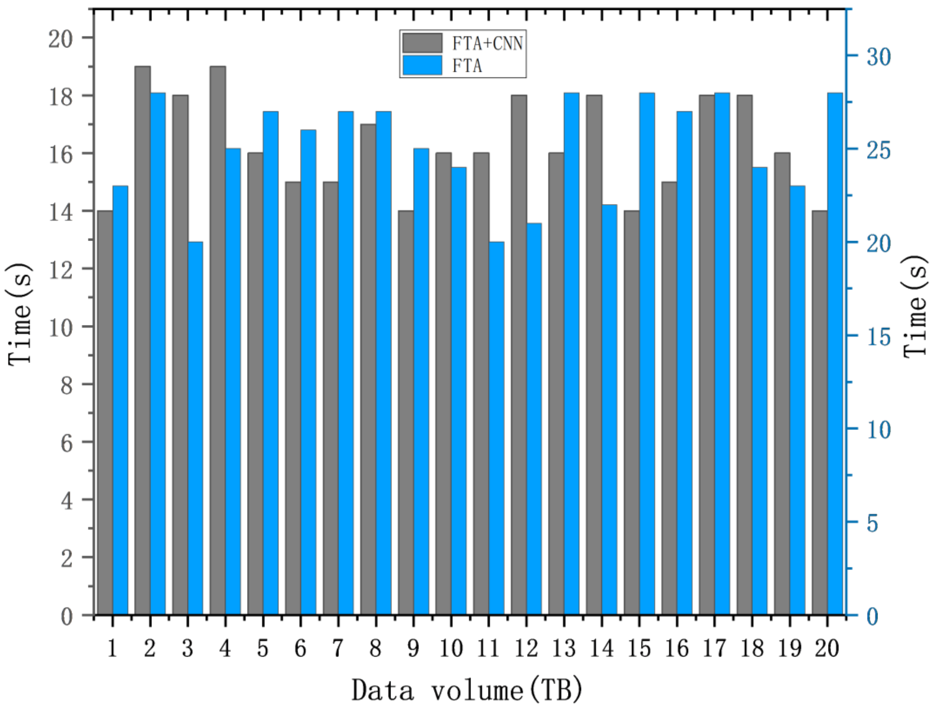

Figure 3: Diagnosis time

According to test data, the diagnostic time range of FTA+CNN is 14 seconds to 19 seconds, while the diagnostic time of a single FTA is between 20 seconds and 28 seconds. FTA+CNN showed faster response times on all test data points, indicating that the CNN model has high efficiency in processing data and can complete fault diagnosis tasks more quickly, with a time improvement of about 30%. As the amount of data increases, the diagnostic time of FTA+CNN remains relatively stable, fluctuating around 16 seconds in most cases, while the diagnostic time of a single FTA shows a gradually increasing trend, especially when processing large amounts of data, the diagnostic time is significantly prolonged, indicating its performance bottleneck under high load conditions. The FTA method mainly relies on manual analysis and historical data, and the evaluation of each potential failure mode requires a long time, especially when facing complex fault relationships, the demand for manual intervention and judgment increases. The intelligent platform combined with CNN greatly reduces the time for manual analysis through automated feature extraction and pattern recognition, and improves processing speed by utilizing parallel computing capabilities, thereby achieving faster fault diagnosis. In addition, CNN models can efficiently process large amounts of input data during the learning and inference process, reducing redundant calculation and analysis steps.

Figures 4 and 5 show the failure rates for the two methods over a 30-day period, respectively:

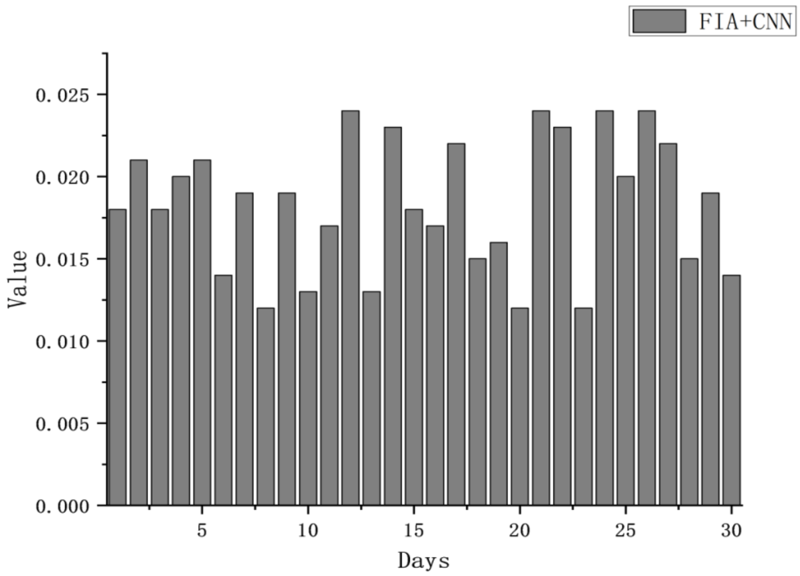

Figure 4: Failure rate of the model in this paper

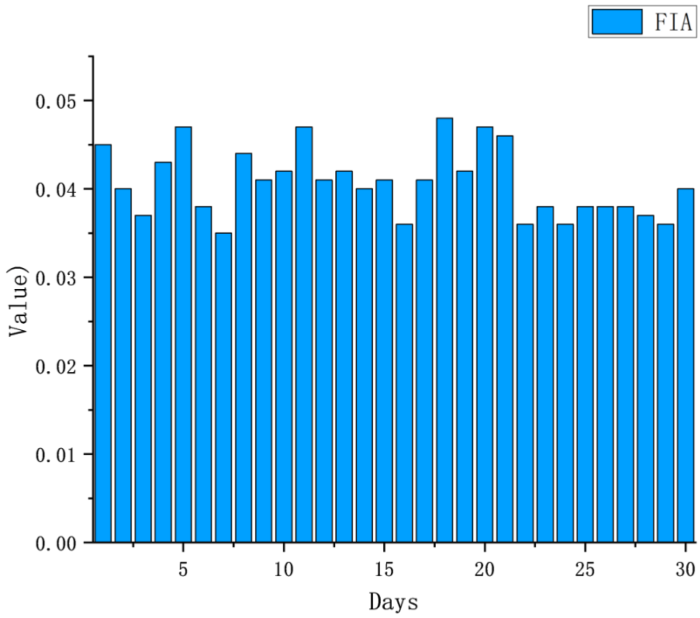

Figure 5: Single FIA model failure rate

When comparing the failure rate data of the two methods, FIA+CNN and FIA, over a period of 30 days, it can be clearly seen that the failure rate of FIA+CNN shows an overall decreasing trend from the initial 0.024 to 0.012, whereas the failure rate of FIA is relatively stable and always stays between 0.036 and 0.048. This trend suggests that FIA+CNN exhibits better stability and effectiveness in fault rate control, possibly due to its combination of feature extraction and classification capabilities of convolutional neural networks, which enhances the system's ability to predict and recognize faults. In addition, the higher failure rate of the FIA approach may be related to its lack of support from deep learning models, making it perform less well than FIA+CNN in handling complex data.

5. Conclusion

The application of an intelligent platform based on Fault Tree Analysis (FTA) in the fault diagnosis of offshore oil support ship side thrust system shows that the diagnostic method combined with deep learning technology significantly improves the accuracy and response speed of fault recognition. The experimental results show that the FTA+CNN method has a stable accuracy of over 90% when processing large amounts of data, and the diagnostic time is reduced by about 30% compared to traditional FTA methods. This indicates that intelligent platforms can effectively respond to complex fault modes, provide reliable fault diagnosis results in a timely manner, and thus provide strong technical support for the safe operation of offshore oil support ships. Intelligent platforms based on FTA+CNN are expected to be further optimized, and more advanced deep learning models such as graph neural networks (GNN) or self attention mechanisms can be explored to improve the recognition ability of complex fault patterns.

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