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Research on the construction method of intelligent operation and maintenance system for electric power pipeline equipment by fusion of digital twin and AI

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SUMMARY: *The study builds a digital twin infrastructure for electrical assembly line equipment that includes data collection, transmission and management. Facing multiple sources of data such as electrical quantity and equipment status, data characterization is used for unification. On this basis, two sets of AI diagnosis schemes are introduced. On the one hand, the ID3 decision tree algorithm is utilized to mine interpretable diagnostic rules from historical fault attribute data to achieve fast initial diagnosis. On the other hand, a deep learning model based on bi-directional Long Short-Term Memory Network (LSTM-Bi-RNN) is constructed for the temporal data with backward and forward dependency of equipment operation to realize more accurate predictive diagnosis. The decision tree model constructed based on 9 types of faults and 12-dimensional attributes generates 9 corresponding inference rules, such as heavy gas + three-phase DC resistance imbalance + high no-load loss → disconnection, light gas + chromatographic high-energy discharge + high oil temperature → joint open weld. The LSTM-Bi-RNN model achieves fast convergence in about 300 iterations, and the recognition accuracy reaches about 92%. The diagnostic F1 breaks through 95% in the test of multiple types of timing data such as voltage and current, and the running rate reaches 14.62s for 5000 current data, leading RNN, BiRNN, and comparative models such as VGG and ResNet. Dynamically mapping the physical state of equipment through digital twins and then handing it over to the fusion AI model for analysis is an effective way that can improve the automation of operation and maintenance decisions.*

KEYWORDS: *digital twin; power equipment; intelligent operation and maintenance; ID3 decision tree; power failure; LSTM-Bi-RNN*

1 Introduction

Power assembly line equipment is an automated system used for material transportation in industrial production, which can realize efficient material transportation under electric power drive to ensure industrial production [1]. However, in the process of long-time operation, the power assembly line equipment is prone to problems such as accumulation of dust, shedding of parts, aging, etc., which seriously affects the normal industrial production [2, 3]. Consequently, to guarantee the proper functioning of the equipment, enhance its stability, minimize equipment

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malfunctions and periods of inactivity, and secure the uninterrupted production of the assembly line, the day - to - day management of the equipment is of utmost importance [4, 5].

The traditional daily management of power assembly line equipment is mainly carried out manually, but it faces the problems of low efficiency, poor effectiveness, low accuracy, etc., and is affected by personal ability, equipment, etc. cannot ensure the effective management of equipment [6, 7]. Within this context, the intelligent operation and maintenance system that integrates digital twin and artificial intelligence (AI) technology emerges as a practical solution.

A digital twin serves as a digital representation of real - world entities, such as objects, operations, or systems. It establishes a link between the virtual and real worlds by maintaining a continuous flow of data and performing real - time simulations to keep both worlds in sync [8, 9]. In the intelligent operation and maintenance system of electric power assembly line equipment, it can help the staff discover equipment faults and problems in time and take corresponding maintenance measures by establishing virtual models and real-time monitoring, avoiding equipment downtime and loss and ensuring the smooth progress of production [10-13]. Furthermore, digital twins have the potential not only to enhance the dependability and operational efficacy of power assembly line equipment but also to lower maintenance expenses and risks, presenting a wide - ranging application outlook [14, 15]. In relation to this, reference [16] explored predictive maintenance relying on physical models and digital twins. It examined the condition of the equipment and computed the remaining service life by creating a virtual representation of the equipment and leveraging sensor data for simulation synchronization. The study stressed the benefits of non - invasive monitoring and ultimately validated its effectiveness via the case of industrial robots. Literature [17] explored the combination of digital twins and predictive maintenance (PM) of electric machines, analyzed that the combination of the two can improve data processing capabilities, and investigated a new definition of next-generation digital twins, emphasizing that it lays the research foundation of AI convergence for the PM field. Reference [18] delved into the utilization of digital twin technology for the predictive maintenance of power pipelines. It identified maintenance requirements by contrasting the disparities between physical apparatus and twin models. Subsequently, it evaluated the efficacy of this approach over an extended period. Moreover, it highlighted that human factor interference is the primary cause of errors that undermine the accuracy of assessments.Reference [19] explored a combined prediction approach founded on digital twins. This method integrates statistical models with machine - learning techniques to analyze equipment condition indicators and forecast the remaining service life. It also underscores the general benefits of this method, such as reduced data demands and its suitability for small and medium - sized facilities.

Conversely, artificial intelligence (AI) leverages machine learning and deep learning algorithms to examine pipeline data for purposes such as fault prediction and parameter optimization. By enabling real - time monitoring, predictive maintenance, and intelligent optimization of the pipeline, this ultimately boosts the efficiency and robustness of power pipeline equipment [20 - 22]. Regarding the relevant applications of AI in this domain, literature [23] delved into the use of AI in the predictive maintenance of power equipment. It also forecasted future trends by integrating digital twin technology with machine learning. Moreover, it underscored the significance of merging ethical practices with Industry 4.0 to enhance the efficiency and dependability of operation and maintenance. Reference [24] delved into the utilization of artificial intelligence sensors and digital twin technology in aluminum production machinery. By conducting real - time data monitoring and training machine - learning models, it aimed to forecast equipment malfunctions. Moreover, this study evaluated the efficacy of this method in enhancing reliability, minimizing maintenance expenses, and boosting productivity.Reference [25] designed a predictive maintenance system for production lines, leveraging the Internet of Things (IoT) and machine - learning techniques. This system can effectively detect potential breakdowns through real - time data analysis. The research also assessed the performance of different algorithms. It was noted that the Random Forest and XGBoost models outperformed others, and the optimal model has been implemented in practical operations. Literature [26] explored the role of AI-driven predictive maintenance in improving manufacturing energy efficiency and sustainability, emphasized its value in reducing carbon and increasing efficiency by analyzing its association with goals such as clean energy, and pointed out the need to overcome initial investment and integration barriers to promote widespread adoption. Reference [27] puts forward a building operation framework that is composed of a digital twin operation and maintenance model and machine - learning algorithms from the perspective of AI - powered operation and maintenance. It explores the modeling process and the integration mechanism with the artificial neural network (ANN). Moreover, it examines the development trajectory of the intelligent operation and maintenance system that results from this framework.

Develop a digital replica within power equipment, mirroring the equipment's physical condition in real - time. Through continuous learning via artificial intelligence, achieve fault diagnosis and proactive alerts. This represents the central concept of this paper, which aims to construct an intelligent operation and maintenance system. The research combines sensors, Internet of Things (IoT) platforms, and data channels to establish a digital twin framework for power equipment. And the AliCloud IoT cloud platform is selected as the data hub. Meanwhile, based on data characterization, the heterogeneous monitoring data from multiple sources are regularized into a standardized dataset with clear features. Further, the ID3 decision tree algorithm is introduced to classify the equipment status and locate the cause of faults through a series of judgment rules and learning experience from historical fault data, initially realizing fault diagnosis automation. Ultimately, a timing diagnostic model founded on a bidirectional recurrent neural network is constructed. The state characteristics within the time dimension are retrieved via the configuration of the input gate and the forget gate. And based on the real-time incoming equipment operation sequence, it automatically identifies its implied fault patterns, and finally outputs the probability of different fault types via Softmax classifier, realizing the intelligent mapping from timing data to fault categories.

2 Application of digital twin and data mining in power equipment operation and maintenance

2.1 Establishment of Digital Twin Architecture for Power Equipment

2.1.1 Digital twin technology architecture

Digital twin technology encompasses four primary categories of technology: digital support technology, digital thread technology, digital twin technology itself, and human - machine interaction technology. Among these, digital thread technology and digital twin technology serve as the core technologies, while digital support technology and human - machine interaction are the fundamental technologies. This paper primarily centers on the digital support technology within the fundamental technologies to carry out relevant investigations. Digital support technology has the ability to integrate data acquisition, transmission, computation, and management to support digital twin high-quality development and utilization of the full amount of data, covering five major types of technologies: acquisition and perception, execution and control, new generation of communication, new generation of computation, and data model management. Looking ahead, it is anticipated that a comprehensive technological platform that combines five distinct types of technologies will offer fundamental foundational services for digital twins.

The ongoing innovation in data acquisition and sensing technology propels the swift progress of digital twins, allowing for more profound data gathering of physical entities. Firstly, the combined utilization of multi - sensing technology and miniaturized sensors achieves comprehensive and highly accurate data perception. Secondly, as Internet of Things technologies advance, the integration of novel communication and computing technologies refines the fundamental data acquisition and transmission protocols of digital twins. This significantly simplifies the real - time simulation, operational monitoring, and state prediction of power equipment digital twins.

2.1.2 IoT Cloud Platform Selection

The current mainstream IoT platforms mainly include Ali Cloud, Huawei Cloud, Tencent Cloud, etc.. Comparative analysis of the main parameters of the three IoT cloud platforms reveals that the performance of parameters such as the number of protocols supported by Aliyun, intermediate quality of service (QoS1) message storage time, single device upstream and downstream limits, the number of device-side and cloud-side software development kits (SDKs), the parameters of the object model, and the cloud-side downstream application programming interfaces (APIs) have a greater advantage and that, in the evaluation of the same instances, the Aliyun requires the lowest cost of fees.

2.2 Data characterization

Once the construction of the digital twin framework for power equipment is finished, the data is characterized and structured to further achieve data-driven intelligent operation and maintenance. During its operation, the power grid generates a vast amount of data with multiple time scales and spatio - temporal dimensions. In the pre - processing stage, the data sets within the same fault section are characterized as follows:

$$D_{j,t} = \left(EtD_{j,t}^{k \in K}, EvD_{j,t}^{l \in L}, EqsD_{j,t}^{m \in M}, \mathrm{Sec}\, D_{j,t}^{o \in O} \right),\ j = 1, 2, \cdots, F \tag{1}$$

In the given formula, denotes the dataset gathered from the occurrence of a type fault at time - points. This dataset encompasses various types of data, such as electrical quantity data, environmental quantity monitoring data, equipment operation status data, and security monitoring data, among others. Moreover, all the aforementioned data are presented in a standardized format:

$$D_j = \left(x_{j1}, x_{j2}, \cdots, x_{jn} \right), n = m * N * T \tag{2}$$

Here, denotes the quantity of individual monitoring indicators, signifies the rate of data gathering within the fault section, and stands for the length of time for data collection within the fault section.

2.3 Application of data mining in power equipment information management

The study primarily relies on the ID3 decision - tree algorithm to extract malfunction information from the previously processed operational data of power equipment. This extraction is aimed at providing support for the diagnosis of equipment operation and maintenance.

2.3.1 Research on Conditional Maintenance of Power Equipment

By utilizing the power equipment online monitoring system, it is possible to acquire the corresponding real - time operational data regarding the power equipment. Moreover, this system enables the analysis of the equipment's state when abnormal operation occurs. One can then make evaluations on the abnormal components, the degree of severity, and the development trajectory. Additionally, it helps in detecting the early indicators of potential failures. According to the analysis and diagnostic results in the equipment performance decline to a certain extent or failure will occur before the maintenance, thus reducing the operation and management costs, improve the reliability of power grid operation.

Fault diagnosis system is the most critical part of condition maintenance. Finding the cause of equipment failure is the first task of power system fault diagnosis. Only if we find the cause of the system failure, can we repair the equipment correctly and reasonably, and prevent the failure from recurring. The general causes of system failure include the vertical, indirect and external causes between the system level and other parts of the system fault diagnosis process is usually divided into five aspects, as follows:

(1) Mechanism of failure: The monitoring of the condition of system equipment and the diagnosis of faults rely on the failure mechanism. Various equipment malfunctions present distinct symptoms, and these different symptoms are associated with alterations in diverse state signals. By conducting research on these changes and identifying the fault characteristics corresponding to each type of fault, one can promptly and precisely perform fault diagnosis.

(2) System state monitoring: the main task is to monitor and obtain state information related to the operation of power equipment.

(3) Extraction of Fault Feature Information: Retrieve the status data of the equipment gathered through condition monitoring. Then, extract the corresponding fault feature information for subsequent analysis and validation.

(4) Failure diagnosis: analyze and study the information extracted in the third step, and again determine whether the system is running normally, and if an abnormality has occurred, find the source of the failure according to this information together with the auxiliary information.

(5) Fault planning decision-making: According to the characteristic information extracted in the fourth step, the further development trend of the fault is predicted, and the corresponding prediction decision is given.

To enable rapid, precise, and intelligent diagnosis of system equipment malfunctions, this paper utilizes data mining techniques for fault diagnosis. The application of data mining for power equipment fault diagnosis can be segmented into the subsequent three steps. The operating principle of power equipment fault diagnosis is depicted in Figure 1.

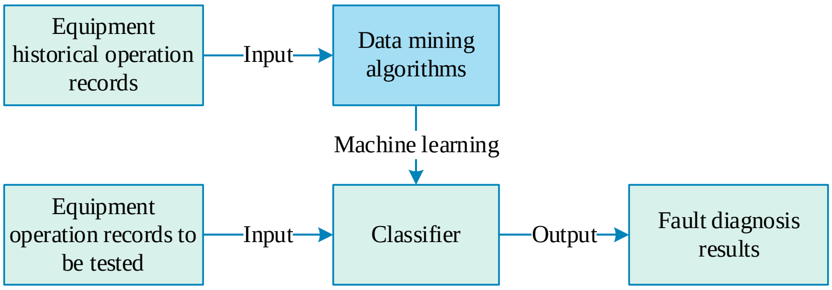


Figure 1: Principle of Fault Diagnosis for Electrical Equipment

(1) To begin with, all the operational states of electrical equipment can be classified into two groups: normal operation and malfunction.

(2) Use the data mining classification algorithm to self-learn from the historical data stored in the system, and after learning, derive a classifier that can carry out fault diagnosis on the equipment operation information, through which all the equipment operation records input at a later stage can carry out fault diagnosis and give the fault diagnosis results;

(3) Input the equipment operation records to be judged into the classifier formed in the previous step and output the diagnostic results.

2.3.2 Application of Decision Tree Classification Algorithm in Fault Diagnosis

This research paper conducts an analysis of the fault diagnosis of power equipment by utilizing the ID3 decision tree classification algorithm.

The CLS algorithm serves as the forerunner of the ID3 algorithm. Its operational procedure unfolds as follows. Initially, it identifies the most impactful factor to partition the initial dataset into several subsets. Subsequently, it assesses each subset individually and selects the predominant influential factor once more for further partitioning. This iterative partitioning persists repeatedly until every ultimate subset comprises only a single category of data.

The ID3 algorithm incorporates the notion of entropy from information theory. By computing the entropy both prior to and subsequent to segmentation, it determines the information gain. This information gain serves as a criterion for evaluating the discriminatory capacity of features.

Principle of the ID3 Algorithm: Suppose there exists a set that holds a collection of data samples. These samples can assume various values for their class - labeling attribute, which corresponds to distinct categories, denoted as [category symbols]. Let the quantity of samples within a particular category be [number symbol]. Then, the necessary information needed to classify a given sample is presented by equation (3).

$$I\left(s_1, s_2, \cdots\cdots, s_m\right) = -\sum_{i=1}^{m} p_i \log_2(p_i) \tag{3}$$

Suppose an attribute has diverse values. Divide the set according to this attribute, and it can be split into distinct subsets. Specifically, the data samples within the set for which the attribute assumes the value of a particular element are incorporated into a corresponding subset. If the selected test attribute is this specific attribute, let the quantity of samples belonging to a certain category in a given subset be denoted. Then, the entropy of the currently divided subset, based on this attribute, is computed using formula (4).

$$E(A) = \sum_{j=1}^{v} \frac{s_{1j} + s_{2j} + \cdots\cdots + s_{mj}}{s} I\left(s_{1j}, \cdots\cdots, s_{mj}\right) \tag{4}$$

In the equation presented above, represents the proportion of the total number of samples within all subsets where attribute assumes the value of, relative to the overall number of samples in the set of. A lower calculated entropy value indicates a higher level of purity in the subset definition, that is, in the most feasible direction. For a specific subset, this information is valuable:

$$I\left(s_{1j}, \cdots\cdots, s_{mj}\right) = -\sum_{i=1}^{m} p_{ij} \log_2\left(p_{ij}\right) \tag{5}$$

Respectively, the relevant information gain values can be derived from the entropy value and expected information calculated earlier. The attribute is then employed to partition each existing branch node. The calculated information gain is determined using equation (6):

$$Gain(A) = I(s_1, s_2, \cdots\cdots, s_m) - E(A) \tag{6}$$

Based on the aforementioned equation, it is evident that as the entropy value decreases, the information gain achieved through branching on a particular attribute increases. This implies that the choice of the test attribute offers more information for the classification process, meaning it is more advantageous for classifying the training data.In each step of the ID3 algorithm, the attribute with the highest information - gain value is selected. This chosen attribute serves as the test attribute for the node under analysis. Subsequently, the training set is partitioned once more. This process continues until the final decision tree is constructed.

Comprehensive Steps for Decision - Making in the ID3 Algorithm:

(1) Arbitrarily select a subset of the training set to form a sub - training set, making sure that this sub - training set includes both category and category.

(2) Invoke the decision tree creation algorithm to produce a decision tree for the present sub - training set.

(3) Utilize the decision tree constructed in step (2) to identify the remaining subsets within the training set. Subsequently, when applicable, locate instances of misjudgments.

(4) In the event that there are misclassified instances, incorporate them into (1). Subsequently, proceed to (2) and regenerate the decision - making tree. Conversely, if there are no misclassified instances, it indicates that the generated decision - making tree is reliable, and the entire computational procedure concludes at this point.

The overall process of the algorithm is depicted in Figure 2. The training set is composed of and. and are sub - groups of category, while and are sub - sets of category.

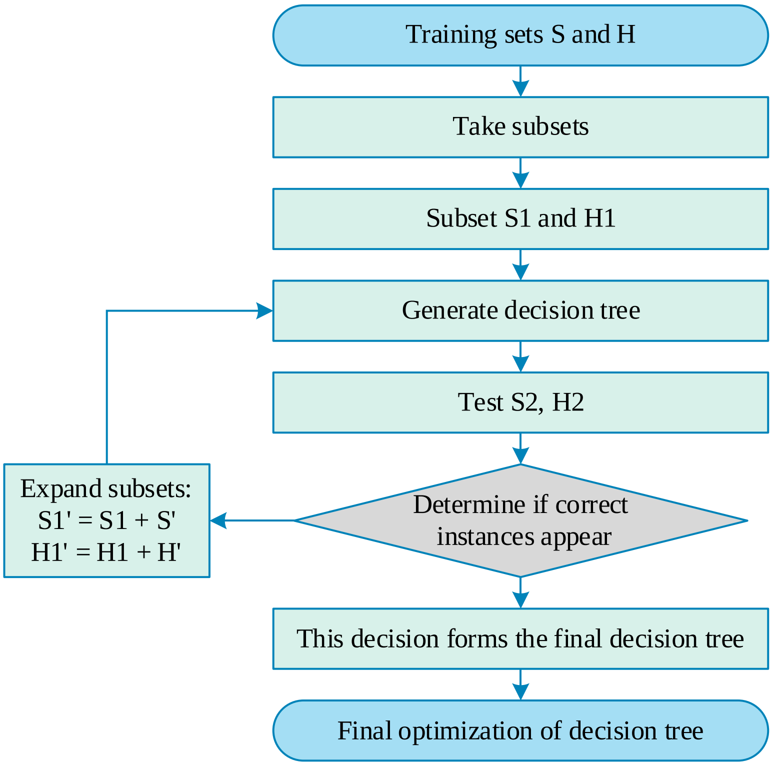


Figure 2: ID3 algorithm process

2.4 Recurrent Neural Network (RNN)-based Fault Diagnosis Models

The previous section has completed from digital twin architecture construction, unified characterization of multi-source data to data mining out the basic laws of fault information. This part puts forward a fault diagnosis model relying on the recurrent neural network (RNN). Leveraging the RNN's robust sequence - modeling capacity, the model can achieve the perception of the equipment's operational state and identify faults. Moreover, the model is capable of real - time interaction with the digital twin system. This interaction facilitates the shift of operation and maintenance (O&M) decision - making from a reactive approach to a predictive one. As a result, it enables the in - depth integration of the digital twin and artificial intelligence in the intelligent O&M of power equipment.

Recurrent neural networks (RNNs) are specialized neural networks designed for processing and forecasting time - series sequence data. In contrast, traditional neural networks utilize fully connected architectures where nodes between layers are independent. This design makes them ill - equipped to handle sequence - related issues where the current output is linked to historical outputs.RNNs possess a distinct cyclic architecture that enables them to retain historical data. The current output of an RNN is determined by both the current input and prior information, resulting in outstanding performance when processing correlated sequence data. In the field of equipment fault diagnosis, the majority of data, such as equipment operation data and monitoring point data, are classic sequence data. Equipment faults also exhibit clear sequential warning characteristics, and the operating state is strongly associated with historical abnormal features.Given the advantages of RNNs in sequence data processing, this chapter develops a fault diagnosis model founded on recurrent neural networks.

2.4.1 Recurrent Neural Networks (RNN)

In a structure of a recurrent neural network, processing units are connected through both internal feedback and feed - forward mechanisms. The network's output is determined not solely by the current input but also by the network's internal state. Due to the internal feedback connections that preserve the state of the hidden - layer nodes, the network possesses a memory function.The input to the main architecture of the recurrent neural network in RNN is composed of two elements. One part is the input from the input layer, and the other is the state data at the current time instant provided by the loop edges. This indicates that the theory of the recurrent neural network can be regarded as the outcome of infinitely replicating an identical neural network structure.

In every instance of the recurrent neural network, an input is presented. Subsequently, an output is generated based on the present state of the recurrent neural network. This current state is collaboratively determined by the state from the previous instance and the current input. Considering the structural features of the recurrent neural network, it can be inferred that it is well - equipped to deal with issues related to time series.

2.4.2 Long Short-Term Memory Network (LSTM) Structure

Recurrent neural networks have the capability to leverage historical data to support present decision - making. However, as the quantity of network layers rises, the nodes located further back in the network become less sensitive to the information from preceding nodes. In other words, they gradually lose track of the earlier information as time passes. To effectively learn long - term dependencies, Long Short - Term Memory (LSTM) networks were introduced.LSTM is a distinctive type of recurrent architecture. Unlike the single tanh recurrent setup, it is composed of three gate mechanisms: the input gate, the forgetting gate, and the output gate. The calculation of these gate structures is detailed as follows.

$$f_t = \sigma\left(w_f \cdot \left[h_{t-1}, x_t\right] + b_f\right) \tag{7}$$

$$i_t = \sigma\left(w_i \cdot \left[h_{t-1}, x_t\right] + b_i\right) \tag{8}$$

$$\tilde{C}_t = \tanh\left(w_c \cdot \left[h_{t-1}, x_t\right] + b_c\right) \tag{9}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{10}$$

$$o_t = \sigma\left(w_o \cdot \left[h_{t-1}, x_t\right] + b_o\right) \tag{11}$$

$$h_t = o_t * \tanh\left(C_t\right) \tag{12}$$

Here, represents the input of an -dimensional vector at time . stands for the forgetting gate, indicates the input gate, input node, and represents the output gate. signifies the state of the unit, and denotes the output state of the unit.,, are the weight matrices, while,, are the bias terms associated with the corresponding weights. The hyperbolic tangent function, tanh, serves as the activation function.

2.4.3 Bidirectional recurrent neural networks

The traditional recurrent neural network employs a unidirectional forward state propagation structure. Nevertheless, in the realm of equipment fault diagnosis, fault features are associated with both the prior and subsequent operational states of the equipment. Fault assessment also necessitates a comprehensive exploration of state data before and after faults, malfunctions, and maintenance activities.In light of this, this paper devises a bidirectional LSTM recurrent neural network. It integrates and amalgamates two unidirectional recurrent neural networks, allowing the model to capture both forward and backward temporal data relationships. At each time step, the input data is concurrently fed into the bidirectional network, and the ultimate output is collaboratively produced by the two networks. This enables a more precise analysis of equipment fault situations.

2.4.4 LSTM-based bidirectional recurrent neural network fault diagnosis model construction

In a bidirectional recurrent neural network, the state at the present moment is associated not only with the prior state but also with the subsequent state. During the process of equipment fault analysis and diagnosis, typically, the state alterations are examined before and after the onset of equipment malfunctions, before and after the appearance of equipment flaws, before and after equipment upkeep, and before and after equipment technological improvements. The advent of recurrent neural networks can effectively address the issue of data correlation between the pre - and post - event states, and therefore, it can be more effectively applied in the realm of equipment fault diagnosis. This paper integrates the bidirectional recurrent neural network model to formulate the subsequent equipment fault diagnosis model framework, as depicted in Figure 3.

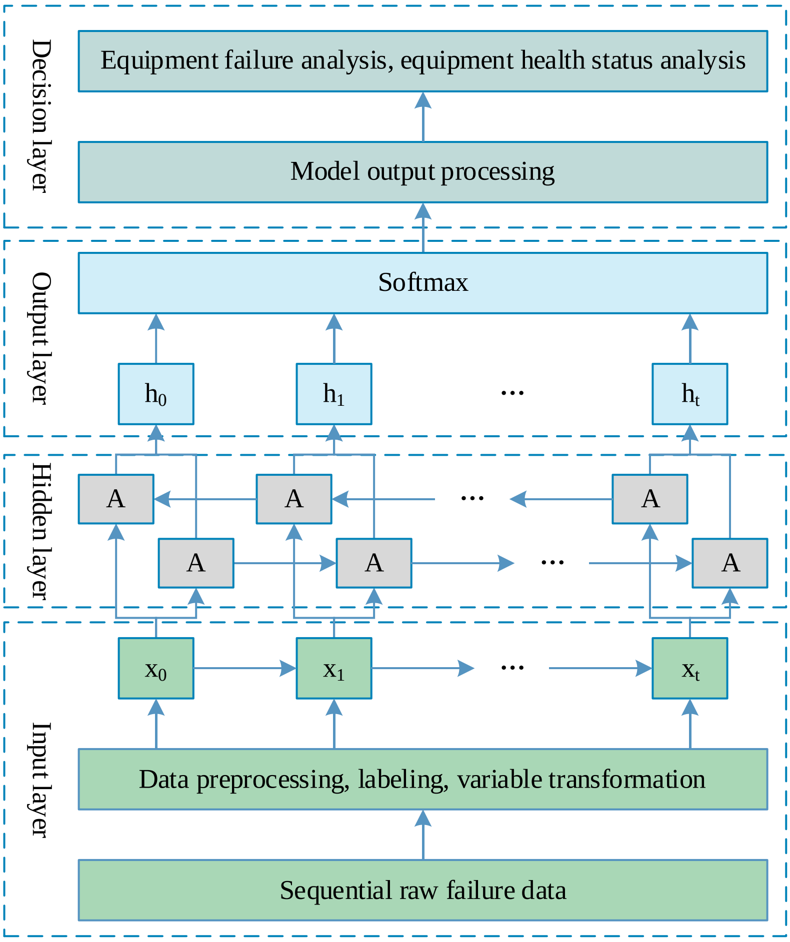


Figure 3: Fault diagnosis based on bidirectional recurrent neural networks

Typically, the fault diagnosis framework is segmented into four distinct layers: the input layer, the hidden layer, the output layer, and the decision layer.The input layer is primarily tasked with handling the incoming data. It includes a pre - processing phase for the data. This involves processing the raw sequential fault data, appending classification labels, and completing the transformation of relevant variables. Once these steps are completed, the processed data serves as the input variables for the bidirectional recurrent neural network architecture.The hidden layer represents the concealed part of the bidirectional recurrent neural network structure.The output layer integrates a Softmax classifier with the output of the bidirectional recurrent neural network to recognize the outcomes.The decision layer takes in the results of the final iteration of the predicted data. It then combines these results with the relevant data to conduct an analysis and make decisions regarding the fault diagnosis outcomes.

3 Performance Analysis of Intelligent Operation and Maintenance Methods Based on ID3 and LSTM-BiRNN

Chapter 2 elucidates the technical integration route of digital twin and artificial intelligence. In order to investigate its practical application outcome in the operation and maintenance of power equipment, this chapter examines the features and structure of equipment fault data. It employs the ID3 decision - tree algorithm to extract power equipment fault rules and primarily validates the performance of the bidirectional LSTM recurrent neural network model when dealing with multidimensional time - series fault data.

3.1 Characterization of transformer fault data based on feature analysis

Twenty-six transformer equipments of a power plant that have been in operation for many years are selected, and their historical and real-time operation status data are collected and analyzed.

The transformer fault types are divided into 9 categories: broken wire, turn-to-turn short circuit, phase-to-phase short circuit, joint welding, insulation aging, water ingress, core failure, insulation oil degradation and coil grounding. Taking core failure and coil grounding as an example, the collected data contains 142 cases of core failure and 95 cases of coil grounding. Figures 4 and 5 show the spectral distribution of the eigenvalues of the covariance matrix for core failure and coil grounding, respectively.

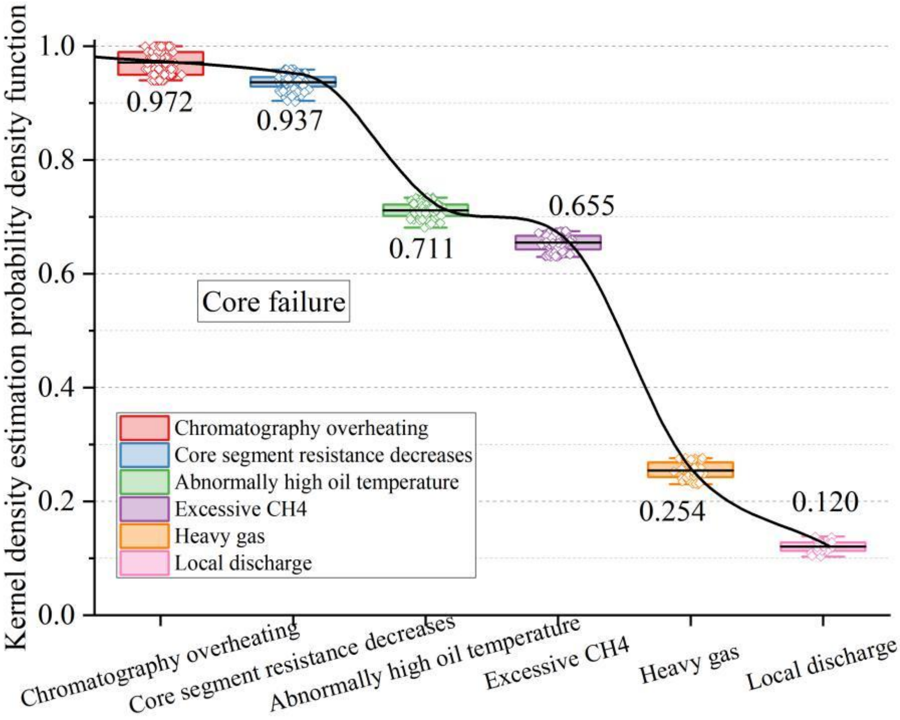


Figure 4: Spectral distribution of eigenvalues of the covariance matrix for core faults

The occurrence of core failures is often accompanied by features such as chromatographic overheating, decreased resistance of the core section, abnormally high oil temperature, and CH_4 exceedance, with kernel density estimation probability density functions of 0.972, 0.937, 0.711, and 0.655, respectively.In the 142 cases of core failures, each of the above features occurs 138, 133, 101, and 93 times, causing the data of their abnormal critical performance matrices to deviate from the normal values. The distribution of the eigenvalue spectrum of the covariance matrix shows an obvious head prominent pattern, i.e., the first four principal component features can explain most of the variance. The estimated probability density function for the kernel density of features such as heavy gas and partial discharge is small and is not the main attribute that causes the core failure.

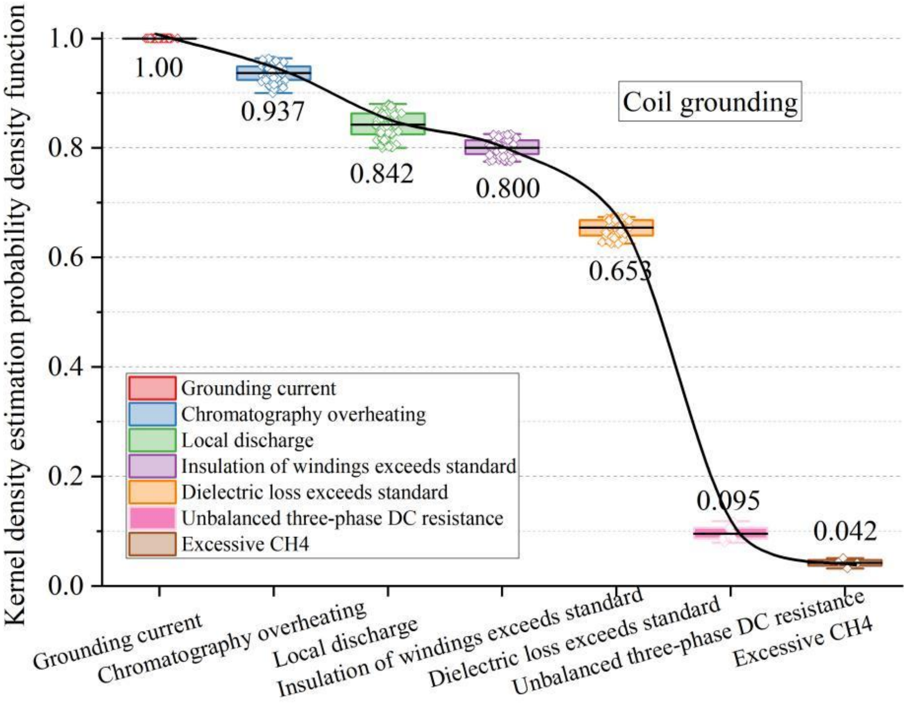


Figure 5: Spectral distribution of eigenvalues of covariance matrix for coil grounding

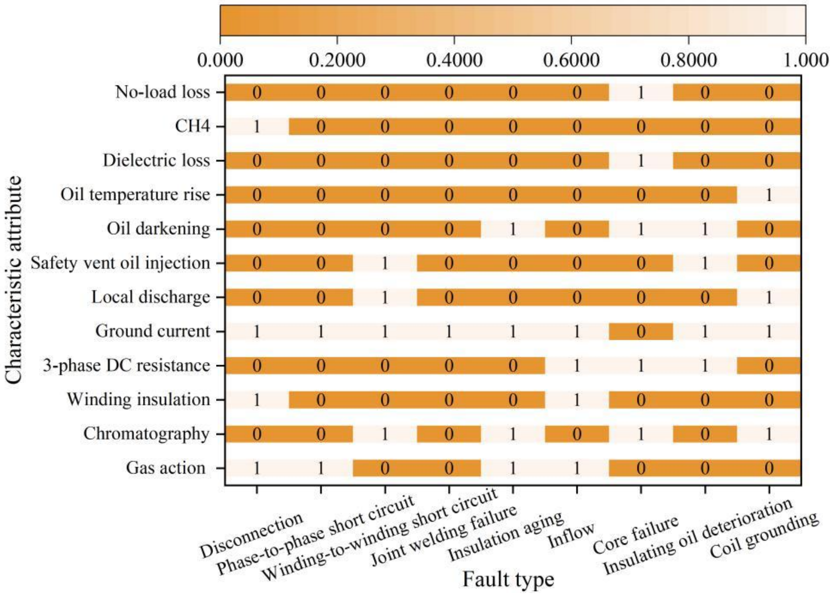
In coil grounding, ground current as a defining feature has a kernel density estimation probability density function of 1, i.e., all coil grounding case faults are necessarily accompanied by the presence of ground current. The probabilities of features such as chromatic overheating, partial discharge, winding insulation exceedance and dielectric loss exceedance lie between 0.653 and 0.937, which together constitute a cluster of fault features. The distribution of coil grounding fault features is relatively more concentrated, and the correlation between the features is weakened. At the same time, the frequency of features such as three-phase DC resistance imbalance or CH4 exceedance is very small. The decay of feature values is relatively smooth, and the fault characterization depends on multiple highly contributing feature dimensions.

3.2 Fault diagnosis discrimination based on ID3 decision tree

In this section, we will move from data analysis to algorithmic application by introducing the ID3 decision tree algorithm, which transforms the aforementioned various fault attribute features into interpretable classification rules and initially realizes fault determination.

3.2.1 Fault Correspondence Properties

Continuing to analyze the other faults, nine categories of typical transformer faults and their corresponding attributes were derived based on the data samples as shown in Figure 6. Where 1 represents abnormal performance.



	Disconnection	Phase-to-phase short circuit	Winding-to-winding short circuit	Joint welding failure	Insulation aging	Inflow	Core failure	Insulating oil deterioration	Coil grounding
No-load loss	0	0	0	0	0	0	1	0	0
CH4	1	0	0	0	0	0	0	0	0
Dielectric loss	0	0	0	0	0	0	1	0	0
Oil temperature rise	0	0	0	0	0	0	0	0	1
Oil darkening	0	0	0	0	1	0	1	1	0
Safety vent oil injection	0	0	1	0	0	0	0	1	0
Local discharge	0	0	1	0	0	0	0	0	1
Ground current	1	1	1	1	1	1	0	1	1
3-phase DC resistance	0	0	0	0	0	1	1	1	0
Winding insulation	1	0	0	0	0	1	0	0	0
Chromatography	0	0	1	0	1	0	1	0	1
Gas action	1	1	0	0	1	1	0	0	0

Figure 6: Fault - Attribute Mapping Matrix

Figure 6 Decision-making combs the key attribute states corresponding to 9 types of typical transformer faults, covering 12 features such as gas action, chromatographic analysis, winding insulation, three-phase DC resistance, and so on. Different fault types can be distinguished by attribute combinations. This fault-attribute mapping matrix provides rule data for subsequent decision tree modeling.

3.2.2 Univariate Decision Tree for Transformer Fault Diagnosis

Fig. 7 presents the univariate decision tree for diagnosing transformer faults, which was derived using the ID3 algorithm. This derivation is based on the aforementioned fault diagnosis and the corresponding characteristics.

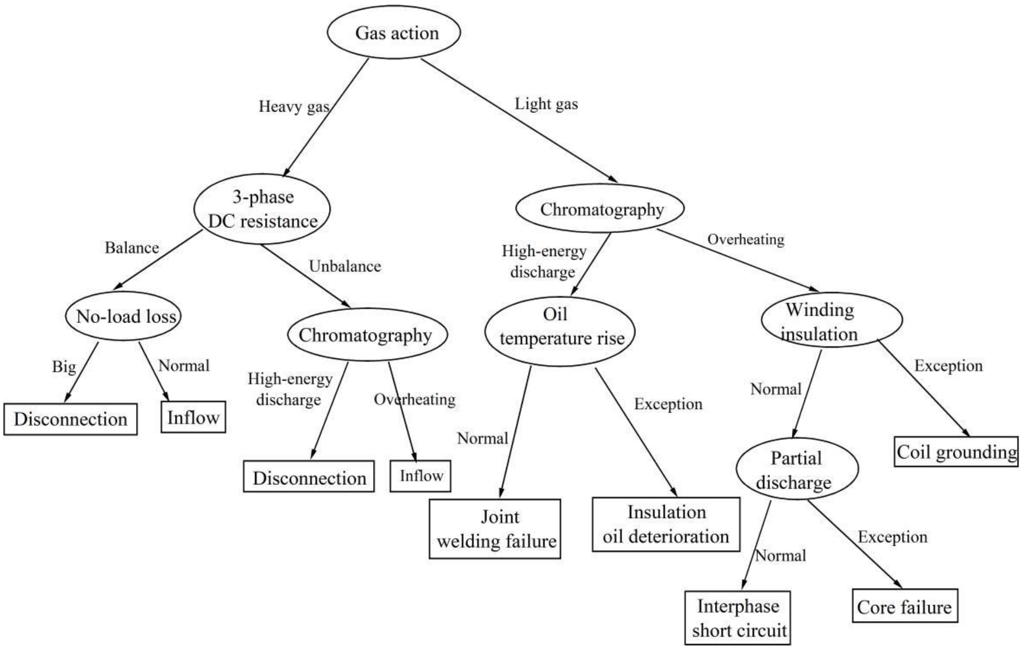


Figure 7: Transformer Fault Diagnosis Single-Variable Decision Tree

Based on the ID3 decision tree derived from the 9 fault types clear attribute path, only aggregated in the gas action, three-phase DC resistance, chromatography and other 7 aspects of the attributes, you can determine the type of fault. Such as under heavy gas, and three-phase DC resistance imbalance, if no-load damage to the large fault type that is broken, if normal is water; when the three-phase DC resistance balance, if the chromatography of high-energy discharges, the equipment failure is a turn-to-turn short-circuit, if the chromatography at this time overheating, it is the insulation aging. Similarly, the other 5 fault type attributes can be obtained. The following 9 transformer fault diagnosis rules are generated.

Rule 1: If gas action = heavy gas AND three-phase DC resistance = unbalanced AND no-load loss = large, THEN = disconnected;

Rule 2: If gas action = heavy gas AND three-phase DC resistance = unbalanced AND no-load loss = normal, THEN = disconnection.

Rule 3: If gas action = heavy gas AND three-phase DC resistance = balanced AND color spectrum = high-energy discharge, THEN = turn-to-turn short circuit;

Rule 4: If gas action = heavy gas AND three-phase DC resistance = balanced AND color spectrum = overheating, THEN = insulation aging;

Rule 5: f gas action = light gas AND chromatogram = high energy discharge AND oil temperature increase = normal, THEN = joint open weld;

Rule 6: f gas action = light gas AND chromatography = high energy discharge AND oil temperature rise = abnormal, THEN = deterioration of junction oil;

Rule 7: f gas action = light gas AND chromatogram = overheating AND winding insulation = exceeding standards, THEN = coil grounding;

Rule 8: f-gas action = light gas AND chromatogram = overheating AND winding insulation = normal AND partial discharge = yes, THEN = phase-to-phase short circuit;

Rule 9: f gas action = light gas AND color spectrum = overheating AND winding insulation = normal AND partial discharge = yes, THEN = core failure.

3.3 Fault Diagnosis Model Performance Verification Experiments

To further validate the performance of this paper's LSTM-based bidirectional recurrent neural network model in real fault diagnosis, comparative experiments are conducted with the traditional RNN and Bi-RNN, which do not introduce long and short-term memory networks, as well as four algorithms, VHH and ResNet.

The experiments are continued on the multidimensional dataset of power equipment constructed above, which not only contains fault records based on state attributes as described in Section 3.2, but also focuses on the monitoring sequence data during the operation of the equipment. Five electrical quantities, namely voltage, current, ripple, load, and harmonics, are selected as the main data types.

3.3.1 Loss function

Figure 8 presents the loss curves for 2000 iterations of the 5 models, with the data set to be recorded every 10 steps.

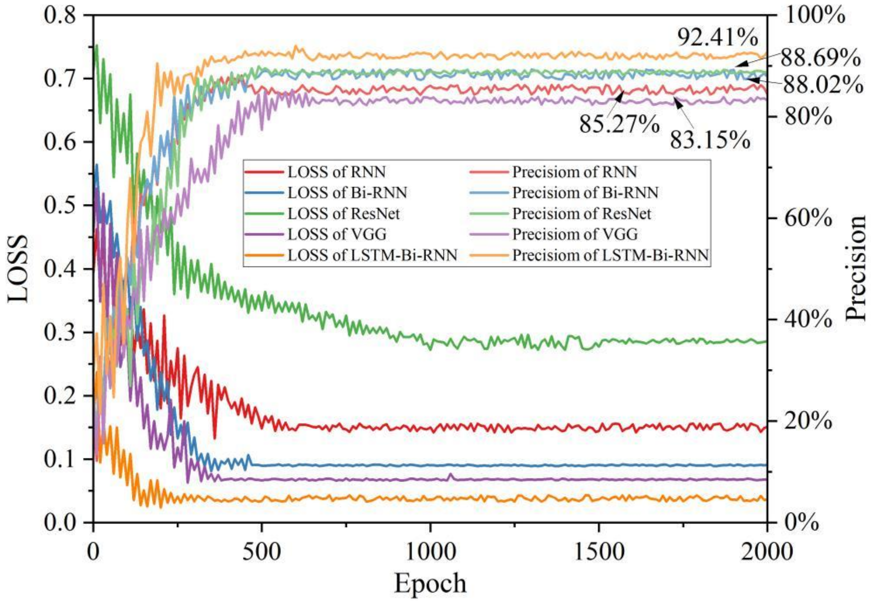


Figure 8: The loss curves of 5 models after 2000 iterations

Under 2000 iterations, the LSTM-Bi-RNN model in this paper converges quickly and smoothly, and the model accuracy has stabilized at around 92% in about 300 iterations, which is the fastest convergence stabilization and the highest accuracy among all the compared models. Focusing on the red curve of the baseline RNN, the loss stabilizes only after 600 iterations, and the final accuracy stabilizes at about 85.27%, and under the bidirectional recurrent neural network, the loss is reduced and the convergence speed is accelerated, and the accuracy finally reaches 88.69%.The convergence effect of the VGG model is good, but it only achieves an accuracy of about 83.15% in the end, and the convergence effect of ResNet is not good. The VGG model converges well, but only achieves an accuracy of about 83.15%, and the ResNet convergence is not good, and the model stabilizes only after about 1000 iterations and still has a loss value of about 0.3, with a final accuracy of 88.02%.

3.3.2 Validation of Model Fault Diagnosis for Different Data Types

Continuing with the testing of the above models, 5000 different data samples were selected for each type of voltage, current, ripple, load, harmonics, etc. for validation. The results of the test samples for each model are shown in Figure 9. Where the vertical axis and the size of the data bubbles all indicate the F1 composite value, and the color mapping is the mapping of the model running time, i.e., it indicates the number of processed data units processed in 1s by the model.

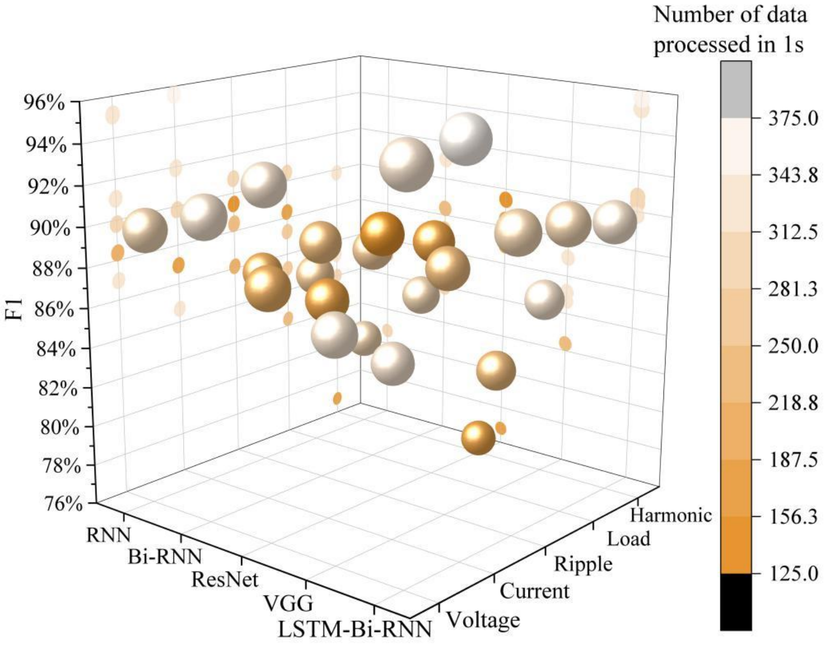


Figure 9: Fault diagnosis results of models for different data types

Focusing on the X-Y plane projection, it can be found that the LSTM-Bi-RNN model has the largest data points and the lightest color mapping, indicating that it has the best F1 value for the combined recall and accuracy, and processes the most data in 1s. Specifically, on voltage and current data, its F1 values are 95.11% and 95.61%, respectively, which are 4.46% and 4.01% higher compared to the Bi-RNN without the introduction of long-time memory network. Even for the more challenging harmonic data, its F1 reaches 89.92%, which is 5.56% higher than the 85.17% of the second-place VGG. Its operation efficiency also leads at the same time, for voltage or current data, the LSTM-Bi-RNN model can process 342 and 375 data samples in 1s, which is significantly higher than that of RNN and Bi-RNN, respectively.The introduction of Long Short-Time Memory (LSTM) units and bi-directional structure improves the model's parallel computation capability, which enables it to maintain an efficient throughput rate on the vast majority of data types.

4 Conclusion

In this research, commencing with the establishment of the digital twin's database, an effective diagnostic combination is formed by the rule - based decision tree and the learning - based neural network.

(1) ID3 decision tree forms a set of easy-to-deploy fast screening rules by virtue of clearly distinguishing 9 types of transformer faults such as broken wires, turn-to-turn short circuits, and water ingress by means of only 7 key attributes such as gas action, color spectrum, and winding insulation.

(2) The diagnostic F1 values of the LSTM-Bi-RNN model on current and voltage data are 95.11% and 95.61%, respectively, and the accuracy rate reaches 90.76% and 89.92% even for the ripple and harmonic data containing complex interference. This is a triple advantage in terms of accuracy, stability and operation speed.

The neural network model based on temporal correlation supplements the in - depth mining rules for fault prediction and recognition, elevating the operation and maintenance of electrical power equipment to a more intelligent stage.

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