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Research on Distribution Network Fault Detection and Diagnosis Based on Deep Learning DLCN

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Abstract

This paper addresses the shortcomings of traditional methods in distribution network fault diagnosis, such as insufficient capability to capture transient fault characteristics like high-impedance grounding and intermittent arcs, difficulties in multi-source heterogeneous data fusion, and limitations in real-time performance and accuracy. It proposes a fault diagnosis method based on a Deep Learning Fusion Network (DLCN). This method combines Autoencoders (AE) and Convolutional Neural Networks (CNN), utilizing a combination of unsupervised dimensionality reduction and supervised feature extraction to achieve efficient processing and accurate identification of massive high-dimensional fault data. Simulation results show that the DLCN model achieves an accuracy rate of 99.87% in diagnosing multiple types of faults in transmission and distribution networks, significantly outperforming traditional algorithms. It demonstrates stronger feature extraction capabilities and model convergence performance, providing an effective technical path for intelligent fault diagnosis and rapid self-healing in distribution networks.

Keywords

Distribution network; Fault diagnosis; Deep learning fusion network.

1. Introduction

With the large-scale integration of renewable energy and the increasing topological complexity of distribution networks, traditional fault diagnosis methods face severe challenges[1]. On one hand, traditional mechanisms relying on steady-state electrical quantity threshold judgments have limited ability to capture transient process characteristics such as high-impedance ground faults and intermittent arc faults; weak signals are easily submerged by background noise. On the other hand, current systems often use single communication channels, which are prone to data packet loss and timing disorders in areas with strong electromagnetic interference or dense nodes, leading to impaired integrity of fault characteristic information[2]. Furthermore, the spatiotemporal alignment of massive monitoring data in distribution networks is a prominent issue. Multi-source heterogeneous data with different sampling rates and transmission delays are difficult to fuse effectively, constraining the real-time performance and accuracy of fault location. Against this backdrop, artificial intelligence technology, relying on its powerful nonlinear modeling capability, spatiotemporal feature mining potential, and adaptive learning mechanism, has become the core driving force for breaking through traditional diagnostic bottlenecks, promoting the evolution of distribution network fault handling towards intelligence, high precision, and high reliability[3].

1.1. Domestic Research Status

Research in China in the field of integrating artificial intelligence with power systems exhibits characteristics of technological diversification and application scaling. At the algorithmic level, multi-modal data fusion based on deep learning has become mainstream. For example, the "HPLC Multi-modal Communication Intelligent Positioning System" proposed by Dewei Baite Co., integrates HPLC, 5G slice networks, and low-orbit satellite communication through a dynamic optimization mechanism, combined with improved Kalman filtering to achieve spatiotemporal data alignment, significantly enhancing feature stability in high-noise environments[4]. In terms of model innovation, scholars like Nie Xianglun proposed converting three-phase current signals into RGB images, using a CNN-CBAM-LSTM hybrid model to simultaneously extract spatial local features (convolutional layers) and time series dependencies (bidirectional LSTM), and focusing on key fault information through an attention mechanism (CBAM), maintaining robust phase selection accuracy under topology change conditions[5]. In system integration, State Grid Wuhan Power Supply Company's "Virtual Dispatcher AI Platform" deeply integrates large models, constructing a closed-loop system of "full-source aggregation + bidirectional deduction + hierarchical response," reducing fault location time for non-automated switches from 47 minutes to 3 minutes, and improving power restoration efficiency by over 55%[6]; Luzhou Power Supply Company developed a low-voltage intelligent analysis tool based on the "One Map of the Grid," shortening traditional investigation work that took weeks to just a few days through cross-analysis of historical data and real-time status[7].

1.2. International Research Trends

Global research focuses on three main directions: cross-modal perception, edge intelligence, and human-machine collaborative decision-making. In sensing technology, a team from Zhejiang University proposed combining domain prior knowledge (such as preset inspection paths) with deep learning, dynamically correcting pointer meter reading offsets via drones, achieving 99.4% AP50 detection accuracy under complex electromagnetic interference, solving misjudgment problems caused by light fluctuations and motion blur[8]. In edge computing optimization, Rockwell Electric's intelligent reclosing system adopts a multi-dimensional feature fusion strategy, dynamically formulating reclosing strategies through joint analysis of transient current waveforms and grid topology, effectively distinguishing transient from permanent faults, and reducing unnecessary power outage impacts[9]. Model light-weighting has become a key research focus. For example, Dongfang Electronic's "Dual AI Operator Model" defines substation power-voltage change patterns, combines expected electricity consumption with actual value comparison to achieve rapid preliminary fault screening, significantly reducing computational load[10]. Furthermore, a patent from a Guangzhou team uses the Sparrow Search Algorithm (SSA) to optimize CNN hyperparameters, improving model generalization under the premise of no local data sharing, accurately identifying partial discharge and insulation aging hazards[11]. Notably, international research still faces challenges in adapting to extreme working conditions, such as image feature degradation caused by strong noise, which has not been fully resolved. Innovations from Chinese teams in spatiotemporal fusion modeling and communication fault-tolerant mechanisms provide important references for the industry.

In summary, the application of AI in distribution network fault diagnosis has moved from single algorithm exploration to full-stack technology integration of "communication--perception--decision--safety." Domestic progress is significant in engineering implementation and system-level innovation, while international research focuses more on underlying model optimization and cross-domain collaboration. Future efforts need to further break through core challenges like small-sample fault diagnosis and multi-agent collaborative reasoning to achieve the ultimate goal of "second-level self-healing" for domain-wide faults.

2. Distribution Network Equipment Fault State Assessment

The operational level of the power system is directly related to national economic development and energy security. Since the second industrial revolution, humanity has entered the electrification era. The application of power systems has brought significant productivity progress and considerable socio-economic benefits to various industries. The scale of power systems has grown rapidly, voltage levels have continuously increased, and line lengths and substation capacities have grown leapfrog. However, this also brings issues of efficiency, reliability, and safety. With the development of information technology, computer technology, communication technology, and control technology, power systems have now moved into the era of large grids, digitalization, and intelligence[12]. For primary equipment, operation and maintenance have long adopted planned maintenance and post-fault maintenance methods. Planned maintenance is mainly based on equipment operating status and maintenance records, which is susceptible to incomplete information and differences in human technical experience, leading to difficulties in controlling the quality of maintenance plans and overlooking potential equipment risks. Post-fault maintenance usually occurs after equipment failure, when the equipment is already under repair or out of service. Due to tight repair times, unnecessary maintenance measures might be taken, bringing misoperations or other non-equipment issues, neglecting preventive maintenance of equipment, causing certain economic losses, aggravating equipment damage, shortening equipment lifespan, and a series of other problems, no longer meeting the requirements of safety and economic development[16]. By analyzing the characteristics of power systems, a comprehensive assessment method for power system dynamic stability based on continuous wavelet transform was proposed. Using wide-area measured data from actual grids and typical node test data, dynamic stability assessment was achieved[17]. Based on mining fault and defect texts recorded by power production enterprises, preprocessing and vectorizing text using the Markov method, a ratio-based state information fusion model was adopted to construct a life health state index for circuit breaker life state assessment[18]. By monitoring dynamic data and utilizing static data accumulated from operation and maintenance, weights were assigned based on expert experience, improving the existing state assessment method based on fuzzy comprehensive evaluation to achieve state assessment of operating grid equipment[20]. Based on the matter-element theory of Extenics, state parameters were defined from pre- and post-commissioning operation and maintenance conditions, and equipment operating status was assessed through difference evaluation[21]. Based on an existing fuzzy Petri net fault diagnosis model, Sequence of Events information from remote operations and measurement information based on wide-area measurement were collected, and their temporal characteristics were comprehensively utilized for assessment[22]. Considering multiple maintenance records of equipment, a time-varying decision model for grid equipment condition-based maintenance was established, optimizing the total grid operational risk considering relevant maintenance constraints, allowing decisions to adjust according to changes in equipment status. For secondary equipment, existing state assessment research mainly focuses on primary equipment, somewhat neglecting power secondary equipment. With the continuous development of power systems, the demand for secondary equipment state assessment is increasing. Power secondary equipment is equally crucial for the safe and stable operation of power systems. Research and application of secondary equipment state assessment need strengthening to ensure power system security and stability. In global blackout accidents, accidents related to secondary system operation account for about 70%. State assessment for secondary equipment can lay a solid foundation for scientifically mastering equipment operating status, accident prevention, and guiding operation and maintenance. State assessment for secondary equipment needs to consider more complex factors than primary equipment, such as protection devices, control devices, measurement devices, etc., requiring consideration of their function, performance, reliability, and other aspects. As the function and performance of secondary equipment are easily affected by various factors like electromagnetic interference, temperature, humidity, dust, etc., more precise and comprehensive methods are needed for state assessment. Based on State Grid Corporation's monitoring information standards, a state evaluation indicator set for smart substation secondary equipment was established. Combining communication parameters and hardware information of smart substation secondary equipment, a state evaluation system for grid secondary equipment was established using the Analytic Hierarchy Process (AHP) and fuzzy theory[23]. Based on fault maintenance records of power system relay protection devices, key information for monitoring was extracted, an evaluation model for relay protection devices was established, further quantitative evaluation was conducted on the device's historical records and online monitoring information, and finally, its operating state evaluation result was comprehensively derived. By fully mining power monitoring big data, a universal secondary equipment state evaluation model was established. Based on a two-layer structure machine learning algorithm, the upper layer uses partitioned data for k-fold validation of several base learners; the lower layer uses a fully connected cascaded neural network to fuse multiple base learners and employs an improved Levenberg-Marquardt algorithm to train this neural network to accelerate model convergence, providing guidance for the maintenance of smart substation secondary equipment[24]. A risk assessment method for secondary equipment operation status based on association rule mining and combined weighting-cloud model was proposed, using the AHP to calculate subjective weights of evaluation indicators and the anti-entropy weight method to calculate objective weights, obtaining combined weights based on a cooperative game model to improve the scientific accuracy of evaluation results[25]. For relay protection equipment, a multi-layer, multi-level demand system was established at the macro level; at the micro level, macro indicator sets were decomposed, transformed, and quantified, forming an evaluation system including testability, security, reliability, etc.[26]. The link transmission methods of various monitoring information for smart substation relay protection equipment were analyzed, the transmission methods and required monitoring information were clarified, an online monitoring scheme for smart substation relay protection equipment was designed, and practical engineering application was conducted[27]. Using operation and maintenance mobile terminals, centering around the operation and maintenance management platform, intelligent analysis of secondary equipment monitoring information and operation and maintenance processes was conducted, achieving fault early warning, defect analysis, and full-process business management and control for secondary equipment[28]. A state evaluation method for relay protection based on a matter-element model was proposed. This method establishes a matter-element model for relay protection devices, improves the existing AHP, and combines the advantages of the information entropy weight method for combined weighting, enhancing the accuracy of indicator weights[29]. State parameters were defined from pre- and post-commissioning operation and maintenance conditions of smart substation secondary equipment, proposing an operational efficiency maximization strategy; research on secondary equipment state assessment for smart substations was conducted, establishing a secondary equipment utilization rate evaluation indicator system[30]. The main monitoring content for grid secondary equipment was discussed, providing reference for sorting out data sources.

In equipment state assessment, existing added monitoring devices bring cost and safety risks. How to make good use of existing conditions for data mining and adopt advanced algorithms for scientific and effective assessment is particularly crucial. From the literature survey above, it is evident that, limited by the lack of investigation into the current status of equipment operational data, existing state assessment research for primary and secondary equipment is still mainly based on operational mechanisms, rarely combined with equipment operational

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data. Some studies discussed sources of monitoring data and conducted state assessment research combining equipment operational data, but issues exist: numerous theoretical algorithms with poor engineering application feasibility, failure to fully utilize data resources, overly single data types difficult to fully describe equipment characteristics, weight allocation based on subjective judgment lacking consideration of objective factors, and weights obtained by evaluation methods difficult to adapt to indicator deterioration acceleration.

3. Technical Introduction

3.1. Model Construction

Utilizing artificial intelligence technology and complex mathematical models to accurately determine fault points in the system. Therefore, a fault location prediction function needs to be determined first, as shown in Equation 1:

$$\hat{y} = f(X;\theta) \tag{Eq. 1}$$

Where: $\hat{y}$ is the predicted value of the fault point location; X is the input feature vector (including parameters such as voltage, current); θ represents the model parameters.

This prediction function model aims to infer the fault location $\hat{y}$ by analyzing the system's feature vector X, thereby achieving precise fault location. CNN, as an important deep learning architecture, are essentially a typical form of deep feedforward neural networks. Their core innovation lies in introducing convolutional computation into deep neural networks, forming a unique CNN structure. The design inspiration for CNN comes from the human visual perception mechanism, enabling them to efficiently perform feature extraction and representation learning on input data with spatial or temporal local correlations. This powerful feature extraction capability makes them very suitable for learning fault patterns from grid monitoring data.

3.2. Feature Extraction and Selection

Another key link in building a high-performance fault location model is feature extraction and selection. Accurate and discriminative features are the foundation for the model to effectively locate fault points.

Feature Extraction: Focuses mainly on extracting key characteristics reflecting the system's fault state. Voltage Characteristics: When a system fault occurs, the voltage at relevant nodes usually experiences significant fluctuations (e.g., sag, distortion). The core of feature extraction is to capture the change patterns of voltage signals at each monitoring point before and after the fault occurs (such as rate of change of amplitude, specific harmonic content, waveform distortion degree, etc.). This information is the primary basis for fault location. Current Characteristics: Faults often cause abrupt changes in current signals (e.g., surge in amplitude, phase shift). By analyzing the abrupt change characteristics of current signals (such as surge amplitude, time of surge, zero-sequence current changes, etc.), key fault path information can be obtained. Frequency Characteristics: When a distribution network fault occurs, the system frequency may also show abnormal fluctuations (e.g., frequency deviation, oscillation). Detecting and extracting these frequency change features can provide important auxiliary information for fault location, especially in distinguishing fault types and judging the scope of impact.

Feature Selection: It is crucial to filter out the most discriminative, highly robust, and low-redundancy feature subset from the raw data or initially extracted large number of features. This can effectively improve model performance and reduce the risk of overfitting. Commonly used and reliable feature selection methods include: Principal Component Analysis (PCA): Uses linear transformation to project original features into a low-dimensional space, retaining the main variation information of the data, achieving feature dimensionality reduction and removing correlations. Correlation Analysis: Evaluates the statistical correlation between each feature and the fault location target variable, prioritizing features highly correlated with the target or containing high information content.

3.3. Model Training and Optimization

Under the supervised learning framework, model training involves inputting a large amount of sample data labeled with fault locations into the model, driving the continuous adjustment and update of model parameters θ, ultimately minimizing the loss function, thereby achieving optimal model performance. Common supervised learning algorithms include:

Support Vector Machine (SVM): Its core lies in constructing an optimal classification hyperplane in a high-dimensional feature space. It can effectively handle high-dimensional feature data, achieve precise classification and location of fault signals, and performs robustly especially in small sample situations.

Random Forest (RF): Combines the prediction results of multiple decision trees through an ensemble learning strategy, using voting or averaging mechanisms for the final decision. This method significantly enhances the model's generalization ability and stability, effectively reducing the risk of overfitting.

Through carefully designed training processes (including data preprocessing, batch training, learning rate adjustment, regularization, and other optimization strategies), the prediction error of the model (loss function value) can be significantly reduced, thereby greatly improving the accuracy, robustness, and overall reliability of fault location.

3.4. Fault Diagnosis for Transmission and Distribution Networks Based on DLCN

Faced with the massive data collected from large-scale simulation tests, traditional feature extraction methods encounter significant challenges: insufficient feature extraction capability, difficulty in fully mining effective information from high-dimensional data; simultaneously, the huge sample size also brings enormous pressure on model training efficiency and computational resources, severely restricting the learning speed and final performance of neural networks. To solve the above problems in complex fault diagnosis of transmission and distribution networks, this project proposes an innovative architecture design integrating the advantages of Deep Neural Networks (DNN) and CNN, with the core goal of achieving efficient training and high-precision recognition for transmission and distribution network fault diagnosis models. The specific technical route is as follows:

Unsupervised Dimensionality Reduction: First, use an AE for unsupervised feature learning and dimensionality reduction of high-dimensional raw samples. The autoencoder learns a low-dimensional dense representation of the data through the encoder, and then attempts to reconstruct the original data through the decoder. Its core lies in retaining the most critical information. This step aims to significantly reduce sample dimensionality, alleviate the computational burden on subsequent models, and simultaneously filter noise and redundant information.

Feature Extraction and Identification: Input the dimensionally reduced low-dimensional feature data into a CNN. Leveraging its powerful local feature extraction and spatial pattern recognition capabilities, the CNN can efficiently further extract the most discriminative deep features from these low-dimensional representations for fault diagnosis, and complete the final fault type identification and location.

This cascaded architecture design of "Autoencoder dimensionality reduction + CNN feature learning and identification" fully utilizes the advantages of unsupervised dimensionality reduction for complexity reduction and CNN efficient feature extraction, aiming to break through the processing bottleneck of massive high-dimensional data, ultimately achieving a significant improvement in the accuracy of transmission and distribution network fault diagnosis.

3.4.1. Data Preprocessing

During the transition operation period of transmission and distribution lines, the system collected time-domain sum data of voltage and current. These data completely cover the phase capacity parameters of AC and DC buses, accurately reflecting the dynamic operating state of the power system at specific moments[31]. Given the real-time requirements of fault diagnosis in engineering applications and the model's generalization ability needs, a 5 kHz high-frequency sampling strategy was adopted, obtaining 100 continuous sample points within a 20 ms time window. Although this method can be adapted to busbar monitoring at different voltage levels, differences in voltage levels lead to inconsistencies in data volume and dimensionality, which affect the reliability of simulation results. To address the impact of grid load changes on prediction accuracy, normalization processing is used to enhance network generalization performance and grid operation speed. Normalization converts data of different dimensions into dimensionless values, enhancing data comparability and consistency, thereby improving model accuracy and stability. This is crucial for building efficient and accurate transmission and distribution network fault diagnosis models. Normalization processing, as a method aimed at simplifying calculations, is a linear transformation operation performed on data. It can compress data into the interval [0, 1], making it decimal. In this process, the normalization operation plays an important role. This method can convert electrical parameters with dimensions into dimensionless electrical parameters, facilitating subsequent mathematical modeling. Normalization is a linear conversion that preserves the original data characteristics and numerical sequence. This characteristic is key during network convergence, helping the network converge more quickly to the optimal solution. In the data preprocessing stage, min-max normalization is a commonly used method. The min-max normalization conversion function is Ax=(An-Amin)/(Amax-Amin). Where: An is the nth sample containing the electrical quantity; Amax represents the maximum value of each sample; Amin represents the minimum value of each sample; Ax is the value after standardization. Secondly, based on 12,000 typical error data points, they were randomly divided into a training set and a test set. Based on this, combined with the learning characteristics of deep learning, the randomness in the experiment was effectively avoided.

3.4.2. Dataset Dimensionality Reduction Scheme

The essence of dimensionality reduction is a preprocessing method achieved through hierarchical feature abstraction, its core lies in layered sparse representation. The feature dimension after reduction is directly determined by the number of hidden layer neurons in the final autoencoder. Extensive experimental verification shows that when a double-layer autoencoder architecture is used, the CNN exhibits significantly superior classification performance on the reduced-dimension dataset, with fault diagnosis accuracy improving by about 12-15% compared to a single-layer structure. This indicates that the double-layer autoencoder can learn more discriminative feature representations, achieving optimal dimensionality reduction effects under the current technical path. Thus, the local hyperparameter values for the autoencoder are listed in Table 1. This project builds upon this, using the deep neural network as the training sample, taking fault type as the research object, and using the deep neural network method to diagnose the fault line and fault type respectively. Using 64 and 81 dimensions respectively for fault line diagnosis, the results are shown in Table 1:

Table 1 Main Hyperparameters for Dimensionality Reduction Training Process

Hyperparameter	For Fault Line Diagnosis	For Fault Type Diagnosis
Max Training Epochs	40	50
L2 Regularization Coefficient	0.0004	0.0002
Sparse Regularization Coefficient	4	4
Sparsity Parameter	0.15	0.2
1st Hidden Layer Neurons	500	600
2nd Hidden Layer Neurons	64	81
Activation Function	Sigmoid	Sigmoid

4. Simulation Verification and Analysis

This project plans to build a transmission and distribution network model based on the MATLAB/Simulink platform, use collected fault samples as training samples, and study the fault diagnosis accuracy of the transmission and distribution network based on DLCN.

4.1. Evaluation Metrics and Visualization

This project plans to use the test case set accuracy rate (%) as the main evaluation metric, employing cross-entropy loss function and the convergence degree of training accuracy during the learning process to assist the diagnosis process. Assuming there are Z test set samples, where the number of correctly diagnosed samples is Zy, and the number of incorrectly diagnosed samples is Zm, then the classification accuracy formula is:

$$\mathrm{A}_{cc} = \frac{Z_y}{Z_y+Z_m} \times 100\,\% \tag{Eq. 2}$$

For binary classification problems, the cross-entropy loss function (Loss function) can be expressed as:

$$Loss = [\alpha \ln\beta + (1-\alpha)\ln(1-\beta)] \tag{Eq. 3}$$

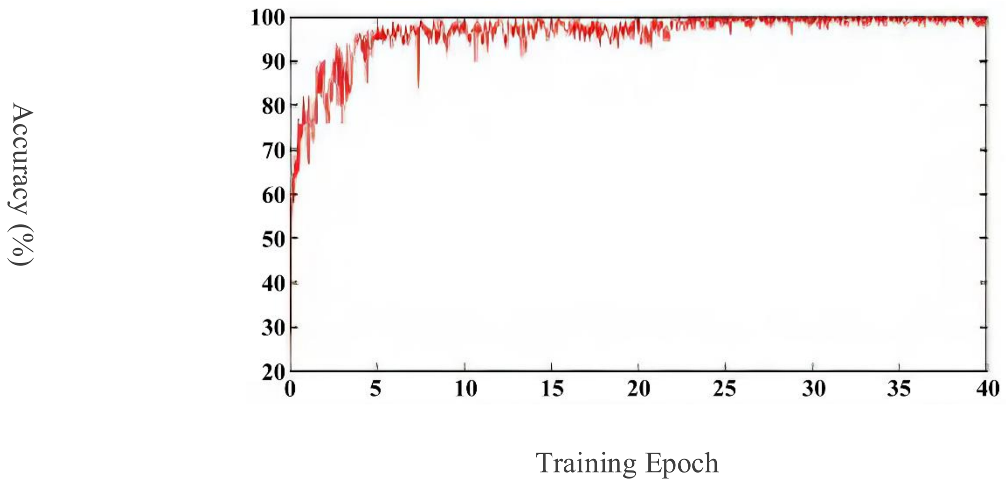
Extending the binary classification Loss function to multi-class problems yields the multi-class cross-entropy loss function:

$$Loss = \frac{1}{Z}\sum_{n=1}^{Z} * \sum_{k=1}^{N}(\alpha_{nk}\ln\beta_{nk}) \tag{Eq. 4}$$

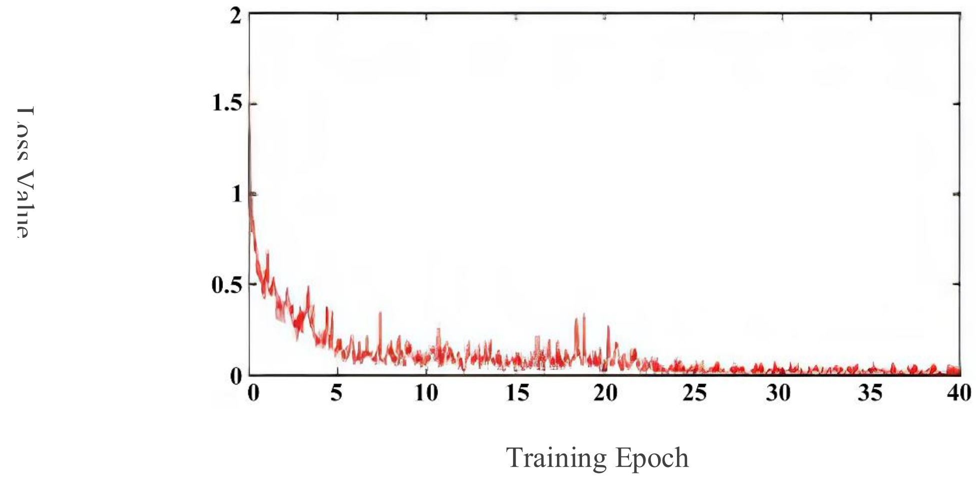
Where: β represents the predicted category value for the corresponding sample, α represents the actual label data, N represents the number of output categories for the multi-class task. The Loss function indicates that when the prediction result is close to the actual data, the output β tends towards 1, meaning the loss function value is low. Conversely, when β tends towards 0, it receives a larger "penalty." Its changing trend can directly reflect the changes of various parameters in the network [4]. Methods such as cross-entropy loss reduction function, recognition accuracy, and confusion matrix are planned to be used to visually evaluate the fault diagnosis.

4.2. Result Analysis

First, analysis based on fault diagnosis for multiple lines. Various types of fault states were divided into several categories, and the AI network was trained on them. The relationship between its accuracy and learning time was obtained, as shown in Figure 1:



(a) Accuracy Curve



(b) Loss Value Curve

Figure 1 Relationship between Accuracy/Loss and Learning Time

As shown in Figure 1(a), the fault identification accuracy continuously improves with the training process, showing typical learning curve characteristics:

Rapid Improvement Stage (0-5 epochs): Identification rate increases exponentially.

Convergence Transition Stage (5-25 epochs): Growth rate significantly slows, the curve gradually flattens.

Saturation Stable Stage (>25 epochs): Accuracy asymptotically approaches the 100% theoretical limit.

The loss function curve in Figure 1(b) shows a complementary evolutionary pattern:

Rapid Decline Stage (0-5 epochs): Loss value drops steeply with a decay rate >85%.

Smooth Convergence Stage (5-25 epochs): Decline gradient reduces to 15%-20% of the initial value.

Global Optimal State (>25 epochs): Loss function value stabilizes approaching zero, indicating network parameters have completed global optimization, and the model has reached the optimal convergence state.

5. Conclusion

This paper focuses on the many problems existing in the current field of fault diagnosis and proposes a method specifically applied to transmission and distribution network fault diagnosis, based on a DLCN. Test results show that when diagnosing different fault lines in transmission and distribution networks based on the DLCN network, its accuracy can reach 99.87%. Compared with traditional algorithms, the DLCN method has unique advantages.

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