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Deep learning-based anomaly detection and fault prediction method for permanent magnet fast ring network cabinet

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ABSTRACT

The ring network cabinet of the distribution network is an important part of the urban power system, and its operation state directly affects the stability and reliability of the power system. In this paper, a deep learning algorithm is used to analyze and process the partial discharge signal, and a permanent magnet fast ring main unit partial discharge detection and fault identification model based on improved DBN-LSTM is proposed. By analyzing a large amount of local discharge signal data under normal operation and fault conditions of ring main cabinet, and using these data to train a deep learning-based fault prediction model. The performance of the improved DBN-LSTM model is tested by combining the defect spectrograms of four typical ring network cabinet partial discharge models and compared with other algorithms. The proposed model has good effect on fault identification of ring network cabinet, with a combined identification accuracy of 98.41%, and the overall identification performance is better than both BP neural networks and SVM classifiers. The prediction accuracy of the fault prediction model also reaches 88.52%, and the experimental results of the method in this paper are more satisfactory.

Keywords: permanent magnet fast ring cabinet, improved DBN-LSTM, partial discharge detection, fault prediction model

1. Introduction

The occurrence of power equipment failure may lead to power supply interruption, which brings serious impact on social and economic activities such as industrial production, commercial activities, residential life, etc., and in serious cases, it may lead to safety accidents such as fires and electric shocks, which poses a threat to personal safety [1-2]. For example, anomalies such as short-circuit of power lines or failure of electrical equipment may trigger fires, bringing serious harm to people's lives and property safety. Therefore, accurate detection and prediction of power equipment faults is the key to ensure the stable operation of the power grid. Abnormal detection and fault prediction of power

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equipment is an important link in the operation of power systems, and the reliability and safety of power system operation can be effectively improved by timely detection and prediction of power equipment faults [3-4]. Traditional fault detection and prediction methods are mainly based on empirical rules and expert knowledge, and need to rely on professional and technical personnel to conduct manual analysis and judgment, detection through the form of observation, and prediction is often used to predict the probability of occurrence of faults through statistical methods and time series analysis, and these methods, although they have a certain degree of feasibility, are limited by the strong subjectivity of manual judgment, dependence on the experience of the experts and other issues, and it is difficult to ensure the accuracy rate The accuracy of these methods is difficult to be guaranteed. With the continuous deepening of the urban power grid construction and distribution project, the ring network cabinet, as one of the important components of the urban power grid, has been increasing its use in the urban power grid renovation project, and its safe and stable operation is crucial for guaranteeing the quality of urban power supply [5-6]. In order to ensure the normal operation of the ring network cabinet equipment and the timely detection of hidden dangers, regular testing and maintenance are required. In recent years, with the rapid development of deep learning technology, deep learning-based anomaly detection and fault prediction of various types of power equipment has become one of the hot spots in research.

The study firstly proposes a partial discharge detection and fault identification model for permanent magnet fast ring cabinet based on improved DBN-LSTM deep learning. The model synthesizes the advantages of DBN in extracting the global effective feature information of samples directly and autonomously and LSTM in mining the time-domain features of feature maps, and adopts Dropout technique to reduce the influence of DBN overfitting. Then we analyze the characteristics of the ring network cabinet data by improving the DBN-LSTM model, and design a FNN containing multiple hidden layers, and the model can predict the ring network cabinet faults by learning the complex nonlinear relationships. Finally, simulation experiments are designed to test the effectiveness of the deep learning-based anomaly detection and fault prediction method for permanent magnet fast ring main cabinet.

2. Overview

Whether it is anomaly detection or fault prediction for power equipment, deep learning has made a considerable contribution. In anomaly detection, literature [7] uses multi-stream convolutional neural network and deep convolutional neural network in deep learning for image detection of anomalous environments in personnel identification and fire and smoke detection in the operation of electric power IoT equipment, respectively, which improves the efficiency and accuracy of anomalous environment identification. Literature [8] utilizes the classical algorithm in deep learning-long and short-term memory network as the basis to give a long and short-term memory self-encoder network to detect abnormalities in power generation equipment, which is effective in detecting early abnormal situations. Similarly, literature [9] compares four types of commonly used algorithms in deep learning with the hair-raising convolutional neural network-long short-term memory model, and finds that the hybrid algorithm has higher accuracy in detecting generator anomalies. Literature [10] used neighborhood-preserving embedding algorithm to extract the local data features of the ring network cabinet and create a fault detection model of the ring network cabinet, which can be monitored online in real time and fault alarm. Literature [11] segmented the grid equipment in the visible light image generated by grid operation through mask region-convolutional neural network, and then combined with machine learning to distinguish between abnormal and normal equipment, and finally completed the equipment abnormality detection. Literature [12] applies deep learning to the detection of high-dimensional energy consumption anomalies in user electricity consumption, and the method can not only detect anomalies, but also predict electricity consumption in real time. Literature [13] synthesizes a variety of deep learning, assisted by an innovative blockchain network as an industry standard, and performs dual control of grid flow under the IACM (Intense Autoencoder Classifier Model) classifier model, which works together to accomplish the detection of complex grid anomalies. In terms of fault prediction, literature [14] learns and mines the tripping fault data in the power system with long and short-term memory network algorithms, joins the support vector machine to classify the mined data, and introduces the discard layer and batch normalization layer to jointly achieve the power system tripping fault prediction. Literature [15] analyzed three deep learning algorithms for power distribution fault prediction in the grid, with the highest accuracy of 92% for gated loop unit and the best performance for the rest. Ring network cabinet in long-term operation, due to a variety of objective reasons caused by the ring network cabinet in the process of installation and after the commissioning of the cable lap faults and other problems, thus bringing hidden dangers to the reliable operation of the power grid. At present, there is a lack of research on anomaly detection and fault prediction of ring network cabinets, and deep learning algorithms have not been involved in this field, based on the above contributions to equipment detection and prediction, deep learning has a better application prospect in ring network cabinet detection and prediction.

3. Method

Permanent magnet fast ring cabinet operating mechanism is to use the suction force of the electromagnet on the ferromagnetic material to drive the movement of the components so as to realize the opening and closing of the circuit breaker, after the opening and closing of the circuit breaker is completed, the current in the coil is disconnected, and then the magnetic field generated by the permanent magnet is used to realize the maintenance of the circuit breaker opening and closing state, the structure of the permanent magnet fast ring cabinet is shown in Fig. 1. Compared with the traditional spring operating mechanism, the permanent magnet operating mechanism does not have energy storage, decoupling, locking and other devices, the structure is more simple, so that the reliability of the mechanism is greatly improved [16]. Permanent magnet operating mechanism and has the advantage of fast tripping speed, inherent tripping time can be shorter than the spring mechanism ring network cabinet tripping time of 10-20ms, is conducive to the realization of the protection of inter-level coordination.

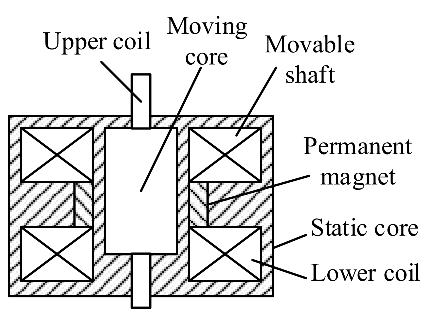


Fig. 1. Structure diagram of permanent magnet drive operating mechanism

As the ring network cabinet is generally placed in the outdoor, the environment is complex and changeable, the influence of many uncertain factors can easily lead to failure. Once the ring network cabinet fails, it will directly affect the neighboring power equipment, resulting in a large area of users with power blocked, affecting the safe and stable operation of the entire system, and may even cause a fire, resulting in major accidents.

In view of the important role of the ring network cabinet in the ring distribution network, the anomaly detection and fault prediction of the ring network cabinet is of great significance. In this paper, a deep learning algorithm is used to analyze and process the local discharge signal, and a deep learning model is constructed for fault identification and prediction.

3.1. Local Discharge and Ring Cabinet Detection

Partial discharge UHF test is a method of using UHF electromagnetic wave signals to detect the partial discharge phenomenon in the power system, which has the characteristics of high sensitivity, strong anti-interference ability, discharge localization, wide detection range and high detection efficiency [17].

In the partial discharge UHF and ultrasonic testing of the ring network cabinet of the distribution network, in order to confirm the type of equipment defects, we carried out another partial discharge retest of the gas chamber and the precise localization of the partial discharge source, as well as the qualitative analysis of the partial discharge spectrum, these measures are designed to further ensure that we understand the defects of the equipment and are able to accurately determine the type of the defects. Based on this, we have adopted specialized methods and tools to ensure the accuracy and reliability of the tests. Through these tests and analyses, we are able to more accurately determine the types of equipment faults, which provides an important basis for subsequent maintenance and treatment. Finally, we will formulate corresponding solutions based on these results to guarantee the normal operation and safety of the equipment.

UHF electromagnetic wave signals can effectively detect partial discharges and therefore have high sensitivity. Compared with traditional testing methods, UHF electromagnetic wave signals have a higher frequency and are not easily affected by other electromagnetic interference, so they have good anti-interference properties. In the field environment, the prevalence of corona discharge and other interference signals are usually in the frequency range of 300MHz or less, while the operating frequency of UHF partial discharge detection is in the range of 300~3000MHz, which avoids these interference signals and improves the accuracy and reliability of the test. According to the attenuation characteristics of electromagnetic wave signal propagation inside the equipment, the time difference of the received signal of the sensor can be used for fault localization, and this method can accurately locate the fault position and provide strong support for the maintenance and overhaul of the equipment. UHF partial discharge detection can detect different types of partial discharge phenomena, including corona discharge, spark discharge and arc discharge, etc. This wide applicability makes UHF partial discharge detection in different areas of the power system can be widely used. UHF sensors can cover a large detection range, so fewer sensors need to be installed, which improves the detection efficiency. At the same time, due to the fast propagation speed of UHF electromagnetic wave signals, the operating status of equipment can be monitored in real time, and faults can be found and dealt with in a timely manner.

Ultrasonic testing of the ring network cabinet of the distribution network is a method of using ultrasonic signals to detect the status of the internal electrical connection of the ring network cabinet, and its ultrasonic testing has the characteristics of non-destructive testing, high efficiency and convenience, accurate positioning, wide detection range, and will not cause damage to the internal circuitry of the ring network cabinet and the device, so it is a non-destructive testing method, and it also has the advantages of small size of the equipment, simple operation, etc., which can be easily carried to the site for Testing. Ultrasonic testing can determine the fault location through the received reflected wave, with high positioning accuracy and wide detection range, and can detect the connection points, welding points, plugs and other parts inside the ring network cabinet. According to the specifications of the ring network cabinet and the internal connection conditions, select the appropriate ultrasonic test equipment, including probe frequency, size, sensitivity and other parameters. According to the parts to be tested, determine the test position, including connection points, welding points, plugs, etc. When conducting the test, it is necessary to follow the operation specifications to avoid inaccurate test results caused by misoperation. According to the test results, the internal connection condition of the ring network cabinet is evaluated to determine whether there is any failure. Ultrasonic testing can be combined with other testing methods, such as insulation resistance testing, voltage withstand test, etc., to comprehensively assess the performance and safety of the ring network cabinet.

3.2. Deep Learning Based Anomaly Detection and Fault Recognition Models

This chapter proposes an improved DBN-LSTM-based local discharge anomaly detection and fault identification model for permanent magnet fast ring main cabinet, which combines the advantages of DBN in directly and autonomously extracting global effective feature information of the samples and LSTM in adeptly mining the time-domain features of the feature maps, so as to realize the accurate identification of local discharge faults of the ring main cabinet.

3.2.1. Deep Confidence Networks. The DBN consists of multiple Restricted Boltzmann Machines (RBMs), which not only have feature learning capabilities, but also make fault identification decisions.

The structure of RBM is shown in Fig. 2. The RBM consists of two parts, the visible layer and the hidden layer, the hidden layer is used to receive the input data and the visible layer is used to extract the features [18]. The nodes in each layer of the RBM are connected to each other by the weight matrix and the nodes within the layer are not connected. The nodes are used with 0 and 1 to denote the inactivity and activation states of the nodes, which are determined by the energy probability formula. If the RBM consists of m invisible neuron and n explicit neurons, set the visible layer bias $a=\{a_1,a_2,\cdots,a_n\}$, the hidden layer bias $b=\{b_1,b_2,\cdots,b_m\}$, and the connection weight vector $w=\{w_{11},w_{12},\cdots,w_{nn}\}$, then $\theta=\{a,b,w\}$ denotes the RBM parameters.

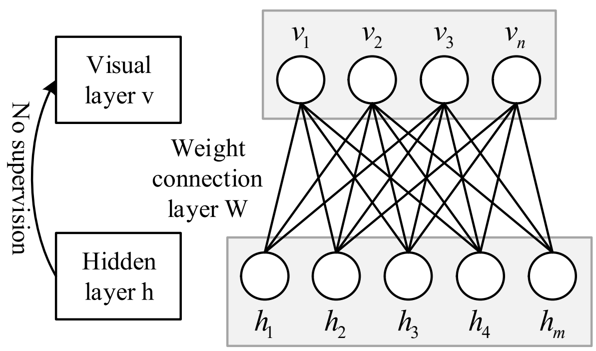


Fig. 2. RBM structure diagram

The energy function can be expressed as:

$$E(v,h\mid\theta)=-\sum_{i=1}^{n}a_iv_i-\sum_{j=1}^{m}b_jh_j-\sum_{i=1}^{n}\sum_{j=1}^{m}w_{ij}v_ih_j \tag{1}$$

Where: h_i is the j nd hidden element state in the hidden layer. v_i is the i th explicit element state in the visible layer. w_{ij} is the connection weight between i and j.

When each parameter is determined, the RBM energy distribution can also be determined, which in turn leads to the joint probability distribution between the visible layer v and the hidden layer h, as in Eq. (2):

$$\begin{cases} P_\theta(v,h)=\dfrac{1}{Z_\theta}e^{-E_\theta(v,h)} \\ Z_\theta=\sum_{(v,h)}e^{-E_\theta(v,h)} \end{cases} \tag{2}$$

where Z_θ is the energy and probability transformation factor.

Eq. (2) transforms the energy minimization problem into a probability maximization problem, so the model parameters θ can be solved by great likelihood estimation, i.e., by training the training set and constantly updating the weight matrix to maximize the probability distribution of the input data. When the distribution of the visible layer is known, the node probabilities of the hidden layer can be found and the hidden layer h is obtained as in Eq. (3):

$$P(h\,|\,v) = P(h_1\,|\,v)\times P(h_2\,|\,v)\cdots\times P(h_n\,|\,v) \tag{3}$$

When implicit layer h is known, the node probabilities of the visible layer, and hence the desired output v', can be obtained by iterating until the convergence condition is satisfied.

When visible layer v is known, $P(h\,|\,v)$, and hence v', can be obtained by iterating until v' is as close to v as possible.

3.2.2. Dropout technology to improve DBN networks. In this paper, we adopt the Dropout technique to improve the DBN network, so that the deep learning model temporarily discards some neurons with a probability of ρ when training the training set, i.e., the "dropped" neurons do not participate in the network training, and the corresponding weights are not updated, so that the network selects basically different sub-networks for This greatly increases the robustness and generalization ability of the model [19].

Dropout technique improves the DBN network for training by multiplying the input data by a random probability p, and when using the model for identification, the weight matrix parameter W is multiplied by a probability ρ, where ρ satisfies the probability of l in the Bernoulli distribution (BD) or the 0-1 distribution, and the value of p is often taken to be in the range of 0.3 to 0.5.

3.2.3. Long and short-term memory networks. LSTM is to add a gating unit structure to the original RNN structure, including forgetting gate, input gate and output gate, where the forgetting gate determines whether or not to perform the amount of data discarding.

The gating unit structure is shown in Figure 3, wherein X_t is the input data of the unit structure at time t, h_{t-1} is the output data of the unit structure at time $(t-1)$, h_r is the output data of the unit structure at time t, C_{r-1} is the state of the cell structure of the $(i-1)$ th gate at time t, C_t is the state of the unit structure of the i th gate at time t, σ is the function sigm(), tanh is the function tanh(•), the symbol $\otimes$ is the multiplication of quantity elements, and the symbol $\oplus$ is the addition of vector elements.

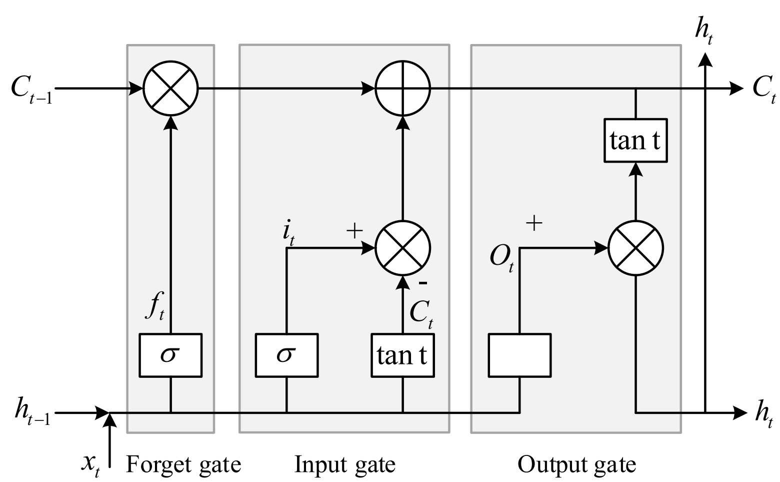


Fig. 3. Gating unit structure

3.2.4. Improved DBN-LSTM deep learning algorithm. The process of the improved DBN-LSTM deep learning algorithm can be divided into two parts, namely, the DBN feature extraction part and the LSTM fault identification part, and the specific process is shown in Fig. 4.

1) The data under different fault models are collected and normalized into a training set and a test set.

2) Cascade multiple RBM models and classifiers to construct a DBN deep learning model, and train the training data with a combination of unsupervised learning and supervised optimization search to obtain the optimal DBN model. The model is improved by combining Dropout technique to enhance the robustness and stability of the model.

3) Output the fault feature output $F=\{f_1, f_2, \cdots, f_k\}$ of the last feature layer (i.e., penultimate layer) of the DBN as input to the LSTM.

4) Process the sequence of fault features to meet the input requirements of the LSTM.

5) Data segmentation determines the input matrix and desired output of the LSTM, as well as the identification step size.

6) Determine the number of layers of the LSTM network, combine multiple LSTMs to construct a deep LSTM recognition model and train it layer by layer, and then optimize the model parameters according to the output error of each iteration until the maximum number of iterations is reached or the convergence conditions are met, and the final recognition model can be determined.

7) Use the test data to get the final recognition results.

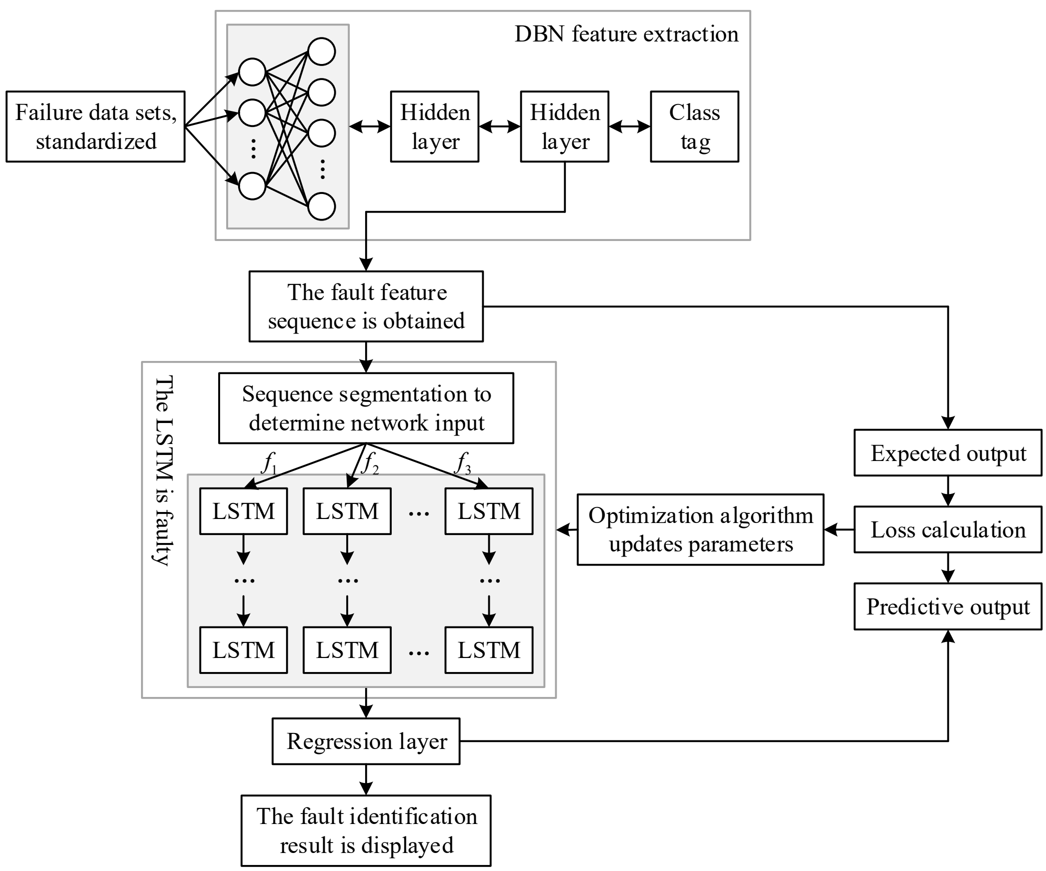


Fig. 4. Process of improving DBN-LSTM deep learning algorithm

3.3. Deep learning based fault prediction models

This section predicts failures of permanent magnet fast ring mains cabinets. By learning the historical operation data of the ring main cabinet, the model can capture the time dependencies and trends in the data to predict the future operation status [20]. When a possible failure is predicted, measures can be taken in advance for maintenance to avoid the failure.

The operation data of permanent magnet fast ring main cabinet is analyzed by the anomaly detection and fault identification model based on improved DBN-LSTM designed in the previous section. According to the characteristics of the ring network cabinet data, an FNN containing multiple hidden layers is designed, and each hidden layer consists of multiple neurons. By increasing the number of hidden layers and the number of neurons, the model is able to learn more complex nonlinear relationships. The mathematical expression of the model construction is shown in equation (4):

$$\hat{y} = f(W^{(l)}, b^{(l)}, x) \tag{4}$$

where $\hat{y}$ is the predicted output of the model, W^1 and b^1 denote the weights and bias of layer 1, respectively, x is the input data, and $f()$ is the activation function. Optimization algorithms are central to the model training process and are responsible for tuning the model parameters to minimize the loss function, such as Stochastic Gradient Descent (SGD), Adam, and so on. These algorithms gradually improve the predictive performance of the model by calculating the gradient of the loss function with respect to the model parameters and updating the parameters according to these gradients. By continuously adjusting the model parameters, the predicted outputs are made as close as possible to the actual labels y so as to realize the accuracy and reliability of fault prediction in permanent magnet fast ring cabinet.

4. Results and discussion

4.1. *Experimental model and partial discharge sample collection*

Based on the forms and characteristics of local discharge signals of permanent magnet fast ring network cabinet, four kinds of discharge models, namely, corona discharge, plate-to-plate discharge, pin-plate discharge and suspension discharge, are artificially constructed in the laboratory, and the local discharge signals generated by the four kinds of discharge models are collected and analyzed respectively.

In the experiments, the computer hardware conditions for processing the localized discharge signals were processor Intel(R) Core(TM) i7-4720HQ CPU@2.6GHz and 8.00 GB of RAM. The software conditions were Windows 10 64-bit operating system, matlab R2018a. Using Pytorch deep learning framework, Python language to build network models.

In this paper, a sample is formed with the discharge data collected in each IF cycle. In order to simulate different discharge severity and make the experimental samples not lose the generality in the subsequent analysis process, this experiment collects samples of each discharge type under different voltage levels, and 150 samples are collected for each discharge type, totaling 600, which contains 500 training samples, 125 for each category, and 100 test samples, 25 for each category.

4.2. *VMD-Hilbert marginal spectrum image*

Before fault identification, the local discharge signal needs to be normalized. In this paper, the Variable Mode Decomposition (VMD) algorithm is used to decompose and then the Hilbert transform is performed to obtain the marginal spectrum image.

The discharge spectrum is normalized:

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}(l_{i\max} - l_{i\min}) + l_{i\min} \tag{5}$$

where: $x_i^{'}$ is the normalized value, x_i is the original value, $x_{\max}$ and $x_{\min}$ are the maximum and minimum values of the $\{x_i\}$ sequence respectively. $l_{i\max}$ and $l_{i\min}$ are the normalized upper and lower limits, respectively.

The normalized signal $f_{(t)}^{'}$ is obtained by VMD decomposition:

$$f_{(t)}^{'} = \sum_{i=1}^{n} x_i^{'}(t) + r(t) \tag{6}$$

where: $x_i^{'}(t)$ is the i nd intrinsic modal component after VMD decomposition, n is the total number of components, and $r(t)$ is the residual component, which has a small and negligible value.

The Hilbert-Huang transform (HHT) is applied to $f_{(t)}^{'}$ to obtain $\hat{x}_i^{'}(t)$:

$$\hat{x}_{i'}(t) = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{x_i^{'}(\tau)}{t-\tau} d\tau \tag{7}$$

Constructor:

$$\begin{cases} z_i(t) = x_i^{'}(t) + j\hat{x}_i^{'}(t) = a_i(t)e^{j\varphi_i(t)} \\ a_i(t) = \sqrt{x_i^2(t) + \hat{x}_i^2(t)} \\ \varphi_i(t) = \arctan\dfrac{\hat{x}_i^{'}(t)}{x_i^{'}(t)} \end{cases} \tag{8}$$

Then the instantaneous power $w_i(t)$ is expressed as:

$$w_i(t) = \frac{d\varphi_i(t)}{dt} \tag{9}$$

Further available:

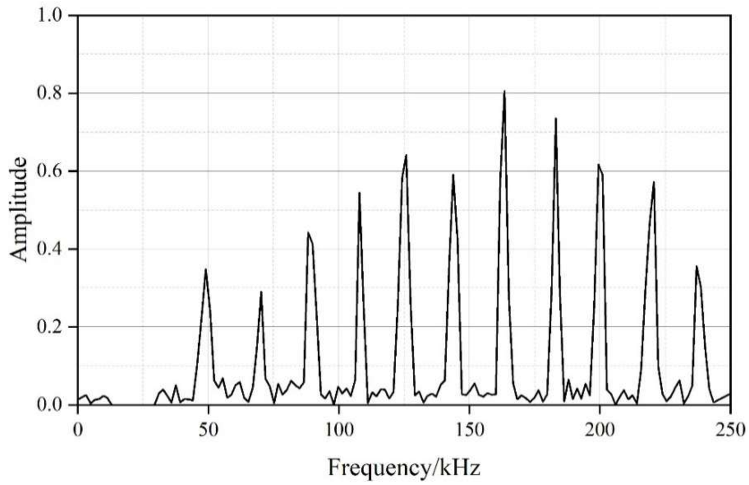
$$f_{(t)^{'}} = Re\sum_{i=1}^{n} a_i(t)e^{j[w_i(t)dt} \tag{10}$$

If the residual component is ignored, Eq. (10) can also be counted as the Hilbert spectrum $H(w,t)$, which can accurately reflect the changing law of the signal in the time and frequency domains. The marginal spectrum $h(w)$ is calculated as:

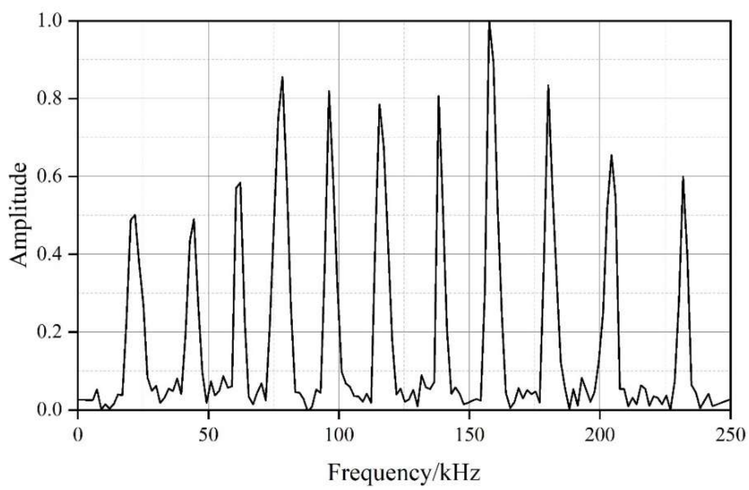
$$h(w) = \int_0^T H(w,t)dt \tag{11}$$

where: T is the time of signal acquisition. $h(w)$ represents a measure of the contribution of each frequency value to the amplitude of the whole time domain, which has a higher frequency resolution than the FFT transform.

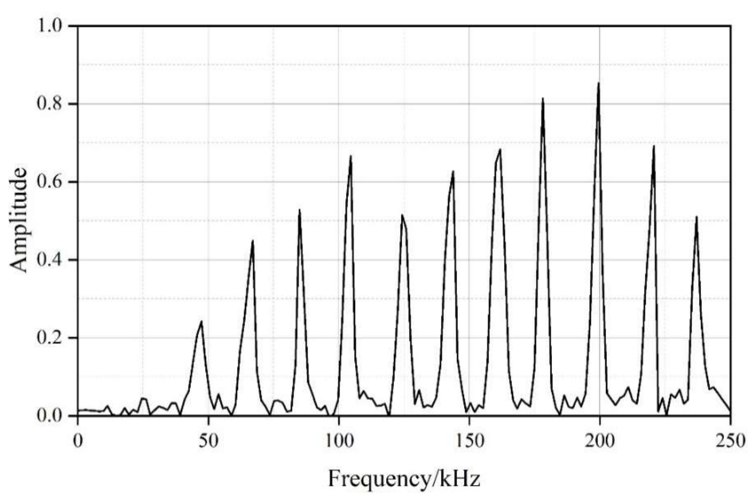
The Hilbert marginal spectra of the discharge signals obtained after decomposition transformation and normalization are shown in Fig. 5, and (a) to (d) represent the Hilbert marginal spectra of the four discharge models, namely, corona discharge, plate-to-plate discharge, pin-plate discharge, and suspended discharge, respectively. It can be seen that the marginal spectrum visualization images of the four types of local discharge signals have obvious differences, mainly in the range of the main frequency distribution, the peak size of the marginal spectrum at the same frequency is different, etc. These features provide a basis for the subsequent research on the identification of different types of discharge.



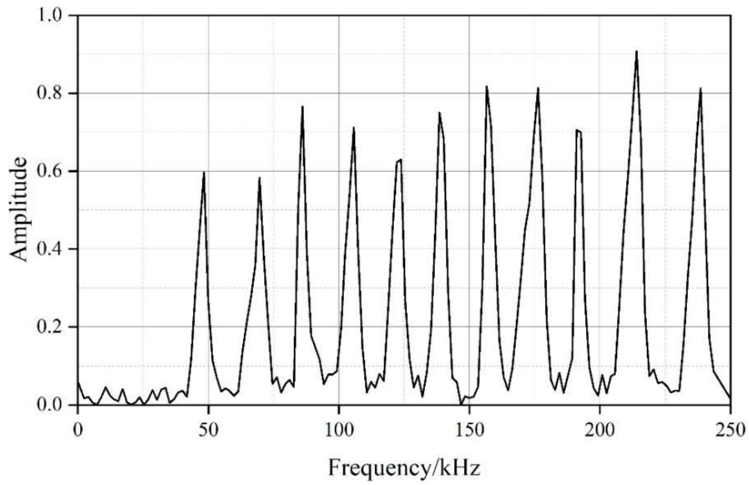
(a) Corona discharge



(b) Plate discharge



(c) Needle discharge



(d) Suspended discharge

Fig. 5. Hilbert marginal spectrum of local discharge signals

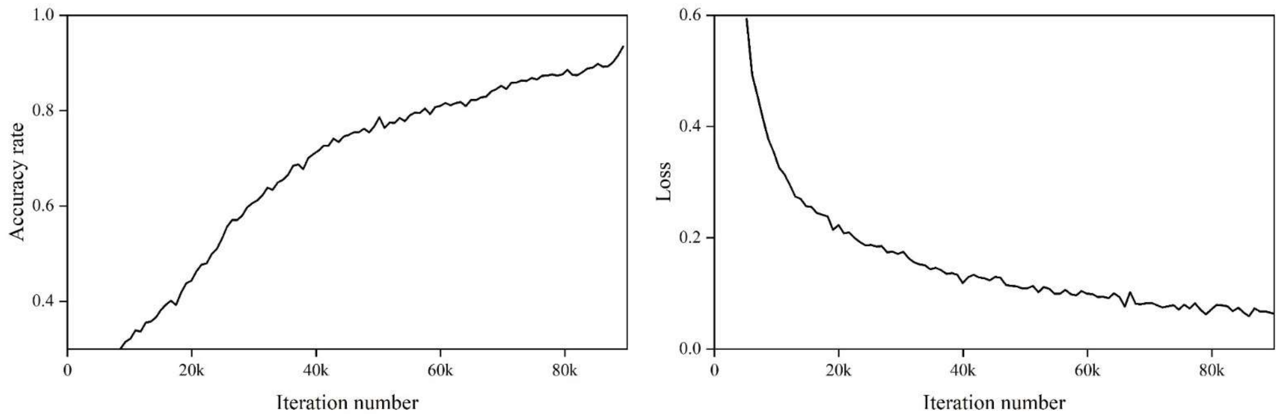
4.3. Improved DBN-LSTM model parameter setting and training

The specific parameters of the improved DBN-LSTM model are shown in Table 1. Considering the limitation of the actual image size, 3 convolutional layers are finally selected.

Table 1. Parameters of improving DBN-LSTM

Parameter name	Nuclear size	Quantity	Output size
Input layer	-	-	1260,10
Dimensional reorganization	-	-	1260,10
One-dimensional convolution layer 1	6	126	1260,126
One-dimensional convolution layer 2	6	278	1260,278
One-dimensional convolution layer 3	4	126	1260,126
Global pooling	-	-	126,1
LSTM	-	6	126,1
Full junction	-	-	126,1
Softmax	-	-	3,1

After setting all the above parameters, the training set is inputted into the model to start training, and the training process is shown in Fig. 6, with (a) and (b) representing the verification accuracy and loss curves, respectively. After 90,000 iterations, the validation accuracy at this point is 93.5%, and the loss is 0.07. Since the loss of the model does not decrease in the 10 iterations after this, the training is ended here and the model is saved to prevent the occurrence of overfitting.



(a) Accuracy rate (b) Loss curve

Fig. 6. Training process of improving DBN-LSTM

4.4. Comparison of Recognition Effect with Traditional Learning Methods

In order to illustrate the superiority of the improved DBN-LSTM model over the traditional learning methods in anomaly detection and fault identification of permanent magnet fast ring cabinet, the identification results of this paper's method are compared with those of BP neural network and SVM classifier. The number of iterations of BP neural network is set to 100, and the learning rate is 0.001. SVM classifier selects the radial basis kernel function, and the optimal kernel parameters are determined by grid search method. Since the images are stored in the form of two-dimensional matrices, it is not possible to use them directly as inputs to the BP and SVM, so the 64×64 VMD-Hilbert marginal spectral image matrix is converted into 1×4096 row vectors. In addition, the 4096-dimensional input vector is too high in dimension for traditional classifiers, and there is the problem of difficulty in running the program and not being able to derive the classification results, so in this paper, we use Principal Component Analysis (PCA) to reduce the dimensionality of the resulting vector. When the cumulative contribution rate of features reaches 80%, it is considered that the feature quantity can better reflect the essential characteristics of the data.The recognition results of BP and SVM for 4 types of discharges under different cumulative contribution rates are shown in Table 2 and Table 3. When the cumulative contribution rate of the 4 types of discharge model signals is 90%, the overall recognition rate of BP and SVM is relatively high, 65.06% and 87.11%, respectively. At this time, the eigenvalue dimension is 35, therefore, the input eigenvolume dimension of BP and SVM is selected as 35 after PCA.

Table 2. BP's recognition rate in different cumulative contribution

	80%	85%	90%	95%
Corona discharge	42.41%	47.46%	53.98%	51.24%
Plate discharge	39.90%	50.40%	64.93%	53.72%
Needle discharge	58.16%	61.17%	68.68%	64.68%
Suspended discharge	63.57%	69.63%	72.66%	71.09%
Overall recognition rate	51.01%	57.16%	65.06%	60.18%

Table 3. SVM's recognition rate in different cumulative contribution

	80%	85%	90%	95%
Corona discharge	68.31%	83.21%	86.22%	81.36%
Plate discharge	71.39%	72.56%	85.33%	81.37%

Needle discharge	86.49%	85.97%	93.65%	84.63%
Suspended discharge	88.74%	62.09%	83.22%	81.01%
Overall recognition rate	78.73%	75.96%	87.11%	82.09%

The correct recognition rates of the three methods are shown in Fig. 7. The overall correct recognition rate of the improved DBN-LSTM model is 98.41%, which has the best recognition effect among the three methods, and the recognition rate of the improved DBN-LSTM model is higher than that of the BP neural network and SVM classifiers for each type of discharge.

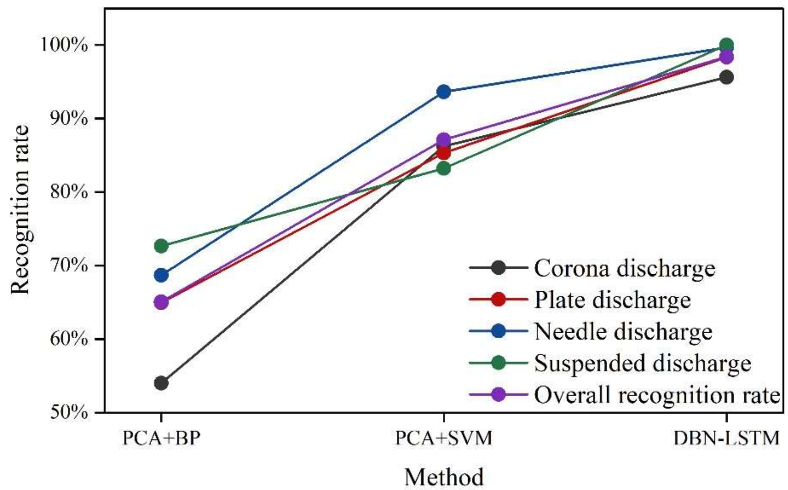


Fig. 7. The correct identification rate of the three methods

4.5. Analysis of model prediction effects

The data used in the model prediction simulation experiments are from the operation data of permanent magnet fast ring main cabinet in the capital city of province D. In this paper, a total of 150 running data from a district between April 2022 and March 2023 are extracted as training samples, and running data from May 2023 to March 2024 are used as test samples. The running data are identified by the improved DBN-LSTM anomaly detection and fault identification model, and then the predictive model is used to capture the dependencies and trends in the data for fault prediction.

The prediction model training curve is shown in Figure 8. It was found that better results were achieved when the depth was 2. The information pooling of the model was not sufficient when the depth was 1 and the loss was higher. So the value of k was selected as 2 based on the actual test results.

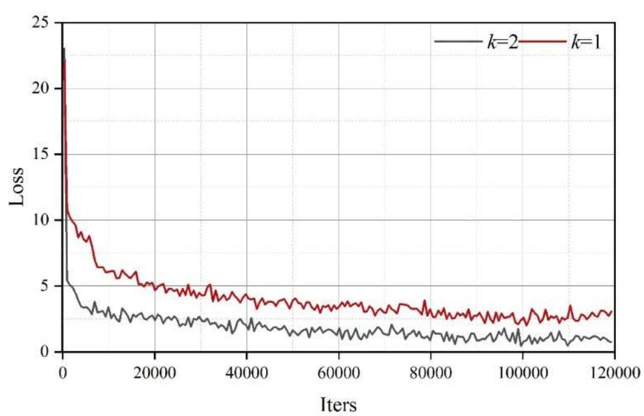


Fig. 8. Prediction model training curve

Comparative analysis was performed using the prediction methods in this paper with RBF-SVM and ADABoost methods. The data were used from June 2023 to March 2024 as mentioned above, and the accuracy of the model prediction was counted separately according to the month, and the statistical results are shown in Figure 9. In different months, the prediction accuracy of the model in this paper stays above 80%, and the final average accuracy reaches 88.52%, which is 12.41% and 12.9% higher than that of RBF-SVM and ADABoost methods, respectively. The deep learning-based anomaly detection and fault prediction method for permanent magnet fast ring cabinet designed in this paper has achieved better results.

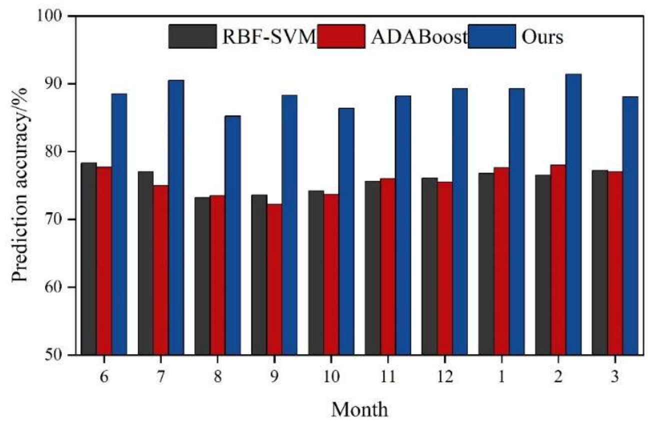


Fig. 9. Prediction accuracy statistics

5. Conclusion

The deep learning-based fault prediction model mainly uses the powerful feature extraction and recognition capability of the improved DBN-LSTM deep learning algorithm to analyze the operation data of the permanent magnet fast ring cabinet to predict potential faults. The experiment combines four discharge models, namely corona discharge, plate-to-plate discharge, pin-plate discharge and suspended discharge, for fault identification verification. The improved DBN-LSTM deep learning algorithm achieves an accuracy of 98.41% for the identification of partial discharge faults in permanent magnet fast ring main cabinet, and the method can ensure the anomaly detection effect of the ring main cabinet. The average prediction accuracy of the deep learning-based fault prediction model is 12.41% and 12.9% higher than that of the RBF-SVM and ADABoost methods, respectively. It shows that the method in this paper has some engineering reference value.

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