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Research article

Power line fault diagnosis based on convolutional neural networks

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A R T I C L E I N F O

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A B S T R A C T

With the rapid development of the national economy, power security is very important for the security of the country and people's happiness. Electricity is an important energy source for a country. Even if the power system malfunctions for a short period of time, it would cause incalculable losses to social production and people's lives. Among them, one of the most important reasons for power system faults is the occurrence of power line faults, so diagnosing faulty lines has great research significance. On the basis of analyzing the structure and working principle of the deep learning model convolutional neural network (CNN), this article used the CNN model to diagnose faults in power lines and analyzed the simulation results. It was found that different CNN structures have different fault diagnosis accuracy for power lines. The fewer the number of batches in the network structure and the more the number of training sessions, the higher its fault determination accuracy. In the power line fault diagnosis based on three deep learning algorithms, the CNN has the highest stable fault diagnosis accuracy of 100%; the recursive neural network has the second stable fault diagnosis accuracy of 93.4%; the deep belief network has the lowest stable fault diagnosis accuracy of 91.5%. In the comparison of power line fault diagnosis stability, the accuracy standard deviation of CNN is close to 0, and they are also the most stable in power circuit fault diagnosis. The stability of algorithmic recurrent neural networks is between the two, and the accuracy standard deviation of deep belief networks is 1.84% when trained 12 times. Their fault diagnosis stability is also the worst.

1. Introduction

For any country, the normal development of the national economy needs to ensure the normal operation of the power system. The main carrier of electricity is the transmission line network. However, due to the complex terrain in most areas, transmission lines often need to climb multiple high mountains, and cross high altitude areas and even remote mountainous areas with communication blockages and inconvenient transportation. Patrol terrain is the geographical terrain through which power lines pass. Power lines often need to cross various terrains, such as plains, mountains, rivers, etc. Different terrain features may have an impact on the operation and fault diagnosis of power lines. However, due to the influence of technological development and patrol terrain on traditional power lines, their diagnostic methods mainly rely on experience and theoretical derivation. Although they can also effectively explain the cause of faults, with the development of the country, the demand standards for electricity are becoming higher and higher, and the power system and equipment are becoming increasingly complex, resulting in traditional fault diagnosis methods becoming increasingly unsuitable when facing complex fault problems. The large-scale failure of the power system would not only cause huge

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economic losses to the country and have a huge impact on national defense security, but also directly lead to residents' inability to live normally and society's inability to produce normally. Therefore, conducting fault research on power lines is of great research significance.

The fault diagnosis of power lines is directly related to the national economy, social production, and national safety. Fault diagnosis and discrimination of power lines can determine the cause of the fault and solve the problem. Many researchers have analyzed and distinguished power line faults. Guo C proposed a direct current (DC) chopper topology consisting of power consumption submodules based on thyristor full bridge modules to reduce the probability of commutation faults in high-voltage DC transmission based on line inverters [1]. Li Z proposed an innovative method that combines line voltage deviation and phase voltage deviation as diagnostic variables to extract unique fault features for each fault diagnostic variable and use these features to distinguish faults [2]. Tenentes V proposed a diagnostic technology for bridges between power grids, which utilizes a new on chip feature generation unit based on power gating design in standby mode for static power analysis. The unit is sensitive to voltage levels between power rails, and its measured values are processed offline to diagnose bridges that may have adverse effects on power conservation [3]. Jin M proposed a power grid fault diagnosis algorithm based on multi-layer data fusion. By analyzing the data characteristics of the entire fault process, a diagnostic model for circuit breakers, lines, busbars, and main transformers was formed by modeling primary equipment using fault data and power grid structure diagrams. By utilizing the circuit breaker status and electrical information after a fault, the fault was accurately diagnosed and the fault area was determined. Then, a recovery path algorithm based on fault rules was used to provide the best path for quickly restoring power supply [4]. By diagnosing faults in power lines, the health of power lines can be ensured, providing a good power system for the country and people.

CNN is widely used in natural language processing, medical treatment, electric power, computer vision and other fields. It can create many models based on research objects. Among them, Pierre I F automatically detected defects in micrometer steel mesh through CNN in anomaly detection for quality control of micrometer woven mesh. Supervised classification was performed using a CNN based on the VGG19 (Visual Geometry Group network-19) architecture [5]. Ruckstuhl Y stated in his research that preserving physical characteristics in data assimilation frameworks can significantly reduce prediction errors, and training CNN can maintain quality in data assimilation. Therefore, he suggested using CNN to train based on the differences between analyses generated by standard integrated Kalman filters to correct any behavior that violates imposed constraints [6]. Das T k explored a deep learning based framework that utilizes deep CNN to diagnose tumors by utilizing clinical manifestations and MRI (Magnetic Resolution Imaging) research. A model has been developed that can be very effective and high-precision for anomaly detection in MRI data, and a deep CNN has been deployed to examine MRI brain images to track tumors [7]. Amatare S A has proposed a CNN model to predict customer churn in the telecommunications industry, and has established a CNN model to predict customer churn behavior and eliminate human attribute selection and its problems [8]. Wang Hao proposed a fault diagnosis method for multi-terminal DC transmission lines with both rapidity and accuracy, and constructed a double-branch convolutional neural network with fault classification branch and fault location branch [9]. Through the application of CNN in various fields, it can be found that they can help researchers establish reliable models, bringing certain reference value for research. In the fault diagnosis of power lines, CNNcan also be used to establish reliable models.

There is a significant difference between power line fault diagnosis and general digital and analog circuit fault diagnosis. The key to fault diagnosis is to extract fault features. This article establishes a power line fault diagnosis model based on CNN. CNN, as a representative of deep learning, have the ability to represent learning. Their sparse connection characteristics have a positive lateralization effect, improving the stability of the network structure and reducing the total weight parameters. This provides more possibilities for reference in China's power engineering. Sparse connection and positive lateralization effect are helpful to improve the stability of the network, making it easier to converge and more robust, that is, it can produce consistent outputs for different inputs. Convolutional neural network provides more possibilities and reference value for China electric power engineering in the power line fault diagnosis model, which means that this network structure may become an effective tool in the field of electric power engineering and can diagnose faults more reliably.

2. Fault location and diagnosis methods for power lines

2.1. Common faults in electronic circuits

During the process of using relevant power system equipment to protect transmission lines, normal electromechanical relays cannot accurately detect faults and therefore cannot reliably perform fault protection [10]. The differential protection of power transformers, as the fundamental protection, plays an important role in the reliability and safety of the power system. The main challenge of differential protection is to distinguish between internal faults and inrush currents in power transformers [11,12].

2.1.1. Faults caused by human operation

When applied in different fields of electronic circuits, effective services need to be achieved through human operations. In real life, there are also many electronic circuit failures caused by human error. In the specific use process, a lack of professional ability or unfamiliarity with electronic circuits may lead to incorrect connection of power supply, ineffective installation and connection of circuits, and inability to ensure the safety and stability of electronic circuits, let alone safe use.

2.1.2. Faults caused by components

In the actual service process, these components have a close relationship. If any internal component fails, it would paralyze the entire electronic circuit. In the actual application process, these components often stop operating due to reaching their service life, leading to electronic circuit failures, which cannot guarantee the safety and reliability of the electronic circuit.

2.1.3. Failure caused by poor contact

The most common fault in electronic circuits is poor contact of the circuit. The quality of the connection of the circuit has a very important impact on the performance of the electronic circuit. Therefore, when poor contact of the circuit is found, it is necessary to control and handle it to prevent greater hidden dangers from accumulating due to the problem. Failure to handle it in a timely manner may also lead to paralysis of the entire circuit. If the connection point is not secure, it is necessary to repair the wires to solve electronic circuit faults caused by poor contact.

2.1.4. Severely disturbed and malfunctioning

In the specific service process, electronic circuits are susceptible to various factors, including equipment factors, which seriously reduce the stability and safety of electronic circuits [13]. In power system, serious interference and fault are a common challenge for electronic circuits, which may lead to the damage of the stability and security of power system [14]. Power supply fluctuation and inrush current in power system may be caused by sudden load change, power supply instability or other external factors. This may lead to unstable power supply of electronic circuits, thus affecting the normal operation of equipment.

2.2. Accurate positioning of power line faults

Fault diagnosis in electronic circuits is an emerging research field, and fully automated diagnostic systems are being developed for circuit research. Developing testing methods for diagnosing analog circuit faults remains a complex task. Transmission lines usually need to span a long distance and have complex terrain, making it difficult to find faults. Moreover, due to the common use of dual power supply in transmission lines, it is difficult to determine the fault point. Accurately locating the fault location and quickly resolving the fault are the key to improving the power supply capacity of the power grid [15,16]. Traditional fault finding methods are not sufficient to meet the current needs. One can apply traveling wave theory and wavelet transform to fault location of power lines, and analyze and locate the fault problems of power lines to achieve precise positioning of fault information.

2.2.1. Wavelet evaluation

There is a wealth of fault information in the traveling wave signal of the power line. Effective analysis of the traveling wave signal can identify the fault point of the power line. The key to accurately analyzing the traveling wave signal is to accurately identify the initial traveling wave head characteristics and their precise arrival time [17].

Here, $\varphi(s) \in I^2(Q)$ is set, if its Fourier transform $\varphi(m)$ satisfies the condition:

$$d_{\varphi} = \int \frac{|\varphi(m)|^2}{|m|} cm < \infty \tag{1}$$

$\varphi(s)$ is the wavelet generating function. In Equation (1), by translating and scaling the basic wavelet, the function can be obtained:

$$\varphi_{x,y}(s) = \frac{1}{\sqrt{x}} \varphi\left(\frac{s-y}{x}\right) \tag{2}$$

In Equation (2), $\varphi_{x,y}(s)$ is a wavelet basis function that depends on x and y, and because the factors x and y are continuous, $\varphi_{x,y}(s)$ is called a continuous wavelet basis.

By expanding the function w(s) in any $I^2(Q)$ spaces on a wavelet basis, the continuous wavelet of the expansion w(s) is transformed, and the expression is:

$$M_w(x,y) \leq w, \varphi_{x,y} \geq |x|^{\frac{1}{2}} \int w(s) \varphi\left(\frac{s-y}{x}\right) cs \tag{3}$$

In Equation (3), w(s) represents a signal function, which is usually a time-varying signal. x and y are parameters of wavelet base, and s is time. Wavelet basis function is used to analyze the components of signals at different times and frequencies.

Continuous wavelet transform is a mathematical transformation method that can discover that the transformation value of signal wavelet is directly proportional to the signal amplitude, and it has a great modulus. Therefore, it is widely used in signal anomaly detection.

2.2.2. Anomaly detection of traveling wave signals

As is well known, when a power system malfunctions, the components of its fault signal are very complex. Through the analysis of the fault signal, it can be found that the time range of the signal is very short. The fault signal model can be described by Equation (4):

$$w(s) = \begin{cases} x \sin(ms + \beta), s < 0 \\ \sum_{j=1}^{N} X_j \sin(jms + \beta_j) + Xe^{-k}, s \geq 0 \end{cases} \tag{4}$$

In Equation (4), $\sum_{j=1}^{N} X_j \sin(jms + \beta_j)$ is the harmonic component of the fundamental and high-frequency frequencies; Xe^{-k} is the DC attenuation component; m is the angular frequency. w(s) is a fault signal model, which represents the time-varying power system fault signal, β represents the phase shift of the signal, k represents the amplitude of each harmonic component, and j represents the frequency band of the signal. When the above derivatives do not exist, that is, when a fault occurs in the power system, the fault signal is abnormal. At the abnormal points, the wavelet transform would have extreme values at these points. Then, by detecting the extreme points of wavelet transform in the electrical signal inside the power system, the fault time of the power system is determined; the sudden change points of the transient signal are identified; the maximum value of the wavelet transform is analyzed; the traveling wave signal is processed with wavelet transform and maximum value; fault information is extracted to achieve protection and fault location.

2.3. Deep learning

Deep learning is a collection of algorithms and a branch of machine learning, which is an extension of shallow learning algorithms. Shallow learning networks mainly refer to learning methods with a small number of hidden layers, mostly consisting of one layer and up to two layers. Shallow learning network usually consists of one or at most two hidden layers. In the neural network, the hidden layer is the layer between the input layer and the output layer, which is used to learn and extract the features in the input data. Typical networks include BP (back propagation) neural networks, support vector machines, etc. Compared to shallow learning, deep learning eliminates many complex processes, and its training mode is direct end-to-end training, which can directly input to classification. End-to-end training means that in the task of machine learning or deep learning, the learning process of the whole system is from the beginning of input to the final output, and there is no clear artificial design intermediate step or processing stage. End-to-end training directly starts from the original input data, and finally outputs the required results by learning the representation and mapping of data. Most deep learning networks have more layers than shallow learning networks, and do not require preprocessing of data. Deep learning networks automatically extract features and do not allow for other tasks, enabling complex recognition and classification tasks.

2.4. CNN

CNN are very common intelligent algorithms in machine learning, with strong feature extraction capabilities. The research significance of CNN lies in their excellent performance and scalability, which can lead to various network structures. The difference between CNN and traditional neural networks is that they can only input one-dimensional vector ratios, while CNN input two-dimensional matrix patterns. They are widely used in the fields of video and audio, and their composition structure is shown in Fig. 1 [18,19].

From Fig. 1, it can be seen that the convolution neural network is mainly composed of convolution layer, pooling layer and full connection layer. The convolution layer mainly obtains the optimal convolution kernel of loss function through continuous training, in order to realize the automatic extraction of data features, and then establish the corresponding relationship between input and output on the interconnected neural nodes through the activation function. The pooling layer extracts the main features of the convolutional layer, performs dimensionality reduction operations to prevent overfitting, and abstracts higher-level sequence features layer by layer.

The input model shown in Fig. 1 is:

$$A = [a_1, a_2, \cdots, a_s, \cdots, a_t]^S \tag{5}$$

In Equation (5), $A \in P^{t*c}$ represents the input parameter; c represents the number of eigenvalues; t represents the length of the input parameter; A_S is the expression of the feature vector at time s, with a dimension of c.

A convolutional layer is a series of data mapped through convolutional operations, and its expression is:

$$x_d^i = f_p\left(A \times W_d^i + y\right) \tag{6}$$

In Equation (6), W_d^i is the convolutional kernel, which represents a weight matrix ($W_d^i \in P^{n*d}$). Among them, y represents bias; n is the time window width for extracting local features of time series data; x_d^i is the i-th feature form generated by W_d^i. The range of i is [1,

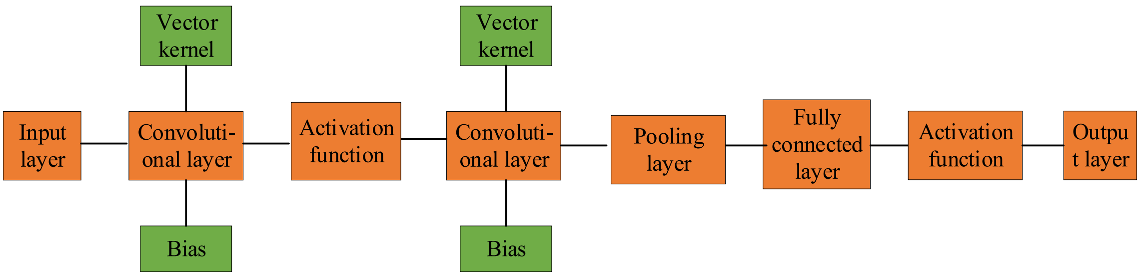

Fig. 1. Structure diagram of CNN.

m_d]; m_d is the actual number of convolutional kernels; $f_p(v)$ represents the activation function. The commonly used activation function in the field of deep learning is ReLu (Rectified Liner Unit).

The most useful sequence feature information within the convolutional layer is captured through pooling operations and formed into a pooling layer. Among them, the expression sub is:

$$a_r^i = \mathrm{pool}\left(a_d^i\right) \tag{7}$$

In Equation (7), pool (.) is a pooling operation, which is generally divided into maximum pooling and global maximum pooling. The most useful global information can be captured first, and the sequence length can be reduced to 1, as shown in Equation (8). It is applied when the last pooling layer appears, and the sequence length can be reduced to half of the original, as shown in Equation (9):

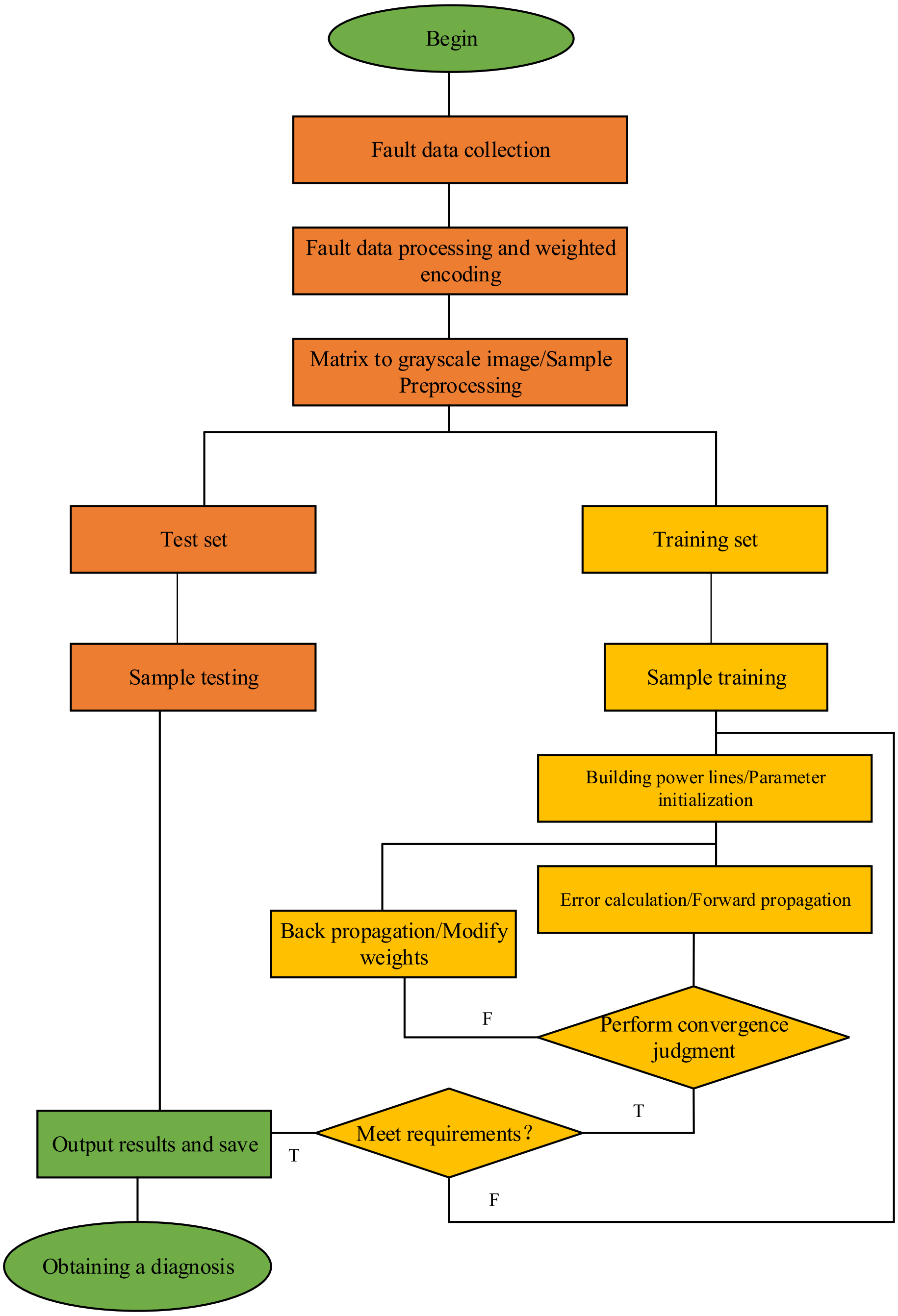

Fig. 2. Power line fault diagnosis flow chart.

$$\text{global—maxpool}(v) = \max(v[:]) \tag{8}$$

$$\text{maxpool}(V) = \max(v[2q-1], v[2q]) \tag{9}$$

In Equation (8), v[:] is to extract all parameters contained in vector v; v(q) represents the q-th parameter of the extractable vector V, and v[.] is an array slice.

In the fully connected layer, its structure is the same as traditional neural networks, with multiple hidden structures. In the fully connected layer, global temporal features are further abstracted and combined in the fully connected layer, and the final output is:

$$x_{fd} = f_p\left(x_{p-last}W_{fd} + y\right) \tag{10}$$

In Equation (10), $W_{fd} \in P^{m_{fd}}$ represents the weight matrix of the fully connected layer. Among them, y represents bias; m_{fd} represents the number of hidden units; $f_p(v)$ is the ReLU activation function.

For the binary classification problem, the number of output units is 1, and the output result through full connection is:

$$\widetilde{g} = f_\vartheta\left(x_{fd}W_{fd} + y\right) \tag{11}$$

In Equation (11), $f_\vartheta(v) = \frac{1}{1+e^{-a}}$ represents the sigmoid activation function. Among them, the classification result $\widetilde{g} \in (0, 1)$ represents the probability values of different categories.

In order to update the parameters, this paper selects the loss function, whose expression is:

$$\tau = T(a, b) = \sum b_t \log(q_t) \tag{12}$$

In Equation (12), $q_t = \frac{\exp(a_t)}{\sum_{t=1}^{u} \exp(a_t)}$ (t = 1, 2, 3, …, u). In the equation, u represents the task volume of the classification task.

The expression of the loss function involves two vectors a and b, representing the output of the model and the actual label, respectively. Each element at of vector a represents the model's output for the t-th category.

3. Power line fault diagnosis model based on CNN

In order to effectively extract the fault characteristics of power lines, this paper established a diagnosis model architecture, which includes the input layer, convolution layer, pooling layer, and full connection layer. The size of convolution kernel refers to the size of filter used in convolution layer. This size is determined by the window size of convolution operation, and is usually used to extract features from input data. The goal of preprocessing is to improve the model's understanding and learning ability of input data and make it better adapt to the task and the activation function was ReLU function. The power line data would enter the output layer after pre-processing. Each convolution layer was connected to the pooling layer, and finally the diagnosis results would be output through the full connection layer. The implementation process is as follows.

3.1. *Developing and building environment*

At present, machine learning frameworks such as Pytorch, Caffe, Keras, and Theano have gradually been applied in various fields, achieving good application results. The application of the appealed machine learning framework can efficiently and quickly obtain the required classification results of CNN. This article used Pycharm and Tensorflow frameworks to build an integrated development environment.

3.2. *Fault diagnosis implementation process*

On the basis of building a development environment, this article completed the fault diagnosis of power lines through the process shown in Fig. 2. In the process shown in Fig. 2, the data can be collected, converted, and processed until the final diagnostic results are output, thus completing a complete set of neural network fault diagnosis process for power lines.

Fig. 2 shows the power line fault diagnosis process, with the main steps as follows.

(1) Fault data of power lines are collected and these data are normalized, de-duplicated and weighted by coding operations to form a matrix collection of fault states.
(2) The fault matrix set is transformed and processed to form a grayscale image.
(3) A neural network is constructed and label samples are trained.
(4) After extracting fault features through convolutional pooling, the output results of the fully connected layer are compared with the actual results to obtain error values. The gradient of loss value with respect to network parameters is calculated by back propagation. The gradient indicates the changing direction of the loss value, and then the gradient descent optimization algorithm is used to adjust the network parameters in the opposite direction of the gradient to minimize the loss value. This process is iterated, and the parameters are constantly updated, so that the network gradually learns the more accurate mapping relationship to the input data and improves the performance of the model. Convolution pool refers to the pooling layer in convolutional neural network. In convolutional neural network, the pooling layer is used to reduce the spatial dimension of

feature map while retaining important feature information to reduce the computational burden and improve the robustness of the model.

(5) It is determined whether the power line is convergent or not. If it is convergent, it goes to step (7), and vice versa, it goes to step (6). The convergence of power line is that the difference between the predicted result of power line fault diagnosis and the actual power line fault is within an acceptable range.

(6) The error value calculated in step (4) is fed back to each level of the network, and the weights of each level are corrected. Then, step (5) is carried out, and the error between the true value and the output value is calculated again until the model convergence is completed.

(7) On the basis of the determination of whether the loss function value of the power line meets the requirements, satisfying it enters step (8), and not satisfying it enters step (4) to go to the model parameters for modification and adjustment.

(8) The fault diagnosis results are output.

4. Experimental simulation and evaluation

This article used a windows10 Professional Edition 64 bit testing platform with 8 GB of memory and i5-7300HQ CPU to set up different CNN structures and set up different deep learning algorithms for fault diagnosis of power lines, in comparison with CNN. Firstly, the article analyzed the fault diagnosis accuracy of different neural network structures based on different convolutional kernels, training times, and batch processing quantities. The different CNN structures are shown in Table 1. The accuracy of fault diagnosis for different neural structures is shown in Table 2. Then, different deep learning algorithms RNN (Recurrent Neural Network), DBN (Deep Belief Network), and CNN (CNN) were compared for fault diagnosis accuracy and standard deviation of accuracy. C represents the number of convolution kernels or filters used in each convolution layer. S represents the step size of the convolution operation sliding on the input, and the step size determines the distance that the convolution kernel moves on the input.

Tables 1 and 2 were explained as follows. Taking the convolution neural network structure 6C–1S–12C–1S of No.1 as an example, C represents the convolution layer, and S represents the downsampling layer. 6C–1S–12C–1S "indicates that the neural network structure includes 6 convolution layers and 12 pooling layers. Wherein, each convolution layer is followed by a pooling layer, and the parameter of the pooling layer is 1. There were two numbers in the convolution core, namely, the convolution core of the first convolution layer and the convolution core of the second convolution layer. The training frequency, batch processing quantity, total accuracy, and phase selection accuracy were shown in the table. The results of No.1 and No.2 may be affected by the network structure and parameter setting, resulting in low diagnostic accuracy. It may be necessary to further adjust the network structure and parameters to improve the accuracy.

Training frequency refers to the frequency at which the model updates its parameters on the training data. The batch number indicates the size of the sample batch used each time the model is updated. Accuracy refers to the classification accuracy of the whole model on the test set or verification set. Downsampling layer is a common hierarchical structure in neural network, which reduces the computational burden and improves the computational efficiency of the model by reducing the dimension of feature map.

From Tables 1 and 2 and it can be seen that under a certain sample size, the network structure, convolutional kernel size, training times, and batch processing quantity of CNN would all affect the accuracy of fault diagnosis and fault phase selection in power circuits. From the comparison between No.1 and No.2, No.4, No.7 and No.11, it can be seen that the size of the convolutional kernel affected its accuracy in fault diagnosis. When the size of the convolutional kernel and the network structure were constant, it can be observed that the smaller the number of batches, the more weight adjustments weremade during the training process, and the higher the accuracy. By comparing numbers 8, 9, and 10, it can be found that when the number of batches was constant, the more training times there were, the higher the accuracy. When the training times reached a certain value, the accuracy also remained at a constant value. After multiple experiments, it can be found that number 9 had the highest accuracy, reaching 100%, when the network structure was 6C–1S–12C–2S and the convolutional kernels were 2*2 and 4*4. The simulation results of training times and accuracy under this

Table 1
Different network structure indicators of CNN.

Number	Network structure	Convolutional kernel	Training frequency	Batch processing volume
1	6C–1S–12C–1S	42	4	50
2	6C–1S–12C–1S	33	4	50
3	6C–2S–12C–1S	32	4	50
4	6C–1S–12C–2S	42	4	50
5	6C–1S–12C–2S	33	4	100
6	6C–1S–12C–2S	24	4	200
7	6C–1S–12C–2S	24	4	50
8	6C–1S–12C–2S	24	8	100
9	6C–1S–12C–2S	24	12	100
10	6C–1S–12C–2S	24	4	100
11	6C–1S–12C–2S	22	4	50
12	6C–1S–12C–3S	23	4	50
13	1C–1S–1C–1S	11	4	50
14	1C–1S–1C–1S	11	12	100
15	1C–1S–1C–1S	11	100	100

Table 2
Fault diagnosis and simulation results of CNN structure.

Number	Network structure	5. Total accuracy	Phase selection accuracy	Training time
1	6C–1S–12C–1S	9.2%	9.4%	116
2	6C–1S–12C–1S	10%	11%	106
3	6C–2S–12C–1S	88%	88.6%	70
4	6C–1S–12C–2S	98.2%	98.4%	92
5	6C–1S–12C–2S	99.4%	99.5%	119
6	6C–1S–12C–2S	98.4%	98.5%	50
7	6C–1S–12C–2S	60%	61.2%	124
8	6C–1S–12C–2S	99.2%	99.3%	220
9	6C–1S–12C–2S	100%	100%	425
10	6C–1S–12C–2S	98.6%	99.2%	81
11	6C–1S–12C–2S	96.4%	96.6%	130
12	6C–1S–12C–3S	72%	76%	125
13	1C–1S–1C–1S	78.6%	78.9%	10
14	1C–1S–1C–1S	96.6%	96.9%	32
15	1C–1S–1C–1S	96.7%	97.5%	599

structure are shown in Fig. 3.

Fig. 3 shows the relationship between the training frequency and fault accuracy of the network structure 6C–1S–12C–2S. The x-axis represents the training frequency, and the y-axis represents the fault judgment accuracy. It can be observed that as the training frequency increased, the fault judgment accuracy increased. When the training frequency reached the 4th time, the fault judgment accuracy and fault phase selection accuracy were both close to 98%. When the training frequency reached the 7th time, the accuracy of fault diagnosis and fault phase selection was close to 100%. When the training frequency reaches more than 7 times, the accuracy of fault diagnosis and phase selection is always at the peak. When the training frequency exceeds 7 times, the accuracy of fault diagnosis and phase selection remains at a high level, and there is no obvious improvement trend, that is, it reaches a stable high level. This means that further increasing the training frequency will not significantly improve the accuracy.

Under the analysis of power line fault diagnosis using different CNN structures, this paper identified 6C–1S–12C–2S CNN structures with convolutional kernels of 2*2 and 4*4 with an accuracy of 100%. Next, different deep learning algorithms RNN, DBN, and CNN would be compared to analyze the fault diagnosis accuracy and accuracy standard deviation of different deep learning algorithms with different training times.

Fig. 4 shows the relationship between the training frequency and the fault accuracy of different deep learning algorithms (RNN, DBN and CNN). The x-axis represents the training frequency, and the y-axis represents the fault diagnosis accuracy. The accuracy of the three deep learning algorithms would improve with the increase of training frequency. It can be observed that the accuracy of power circuit fault diagnosis based on CNN was the highest. When the training frequency reached 7 times, the accuracy of power circuit fault diagnosis would stabilize at 100%, and the training time was relatively long. Using CNN to diagnose the power circuit fault, after the training frequency reaches 7 times, its accuracy will reach 100% and remain stable, but it takes a relatively long training time. This means that further increasing the training times will not significantly improve the accuracy, because the model has learned enough information for accurate fault diagnosis. The accuracy of power circuit fault diagnosis based on DBN was the lowest, and would eventually stabilize at 91.5%. The accuracy of power circuit fault diagnosis based on RNN was in the middle of DBN and CNN, and it would stabilize at 93.4%. After evaluating the accuracy of power circuit faults, this article continued to analyze the stability of three deep learning algorithms in power circuit fault diagnosis based on the stability of fault diagnosis. By analyzing the standard deviation

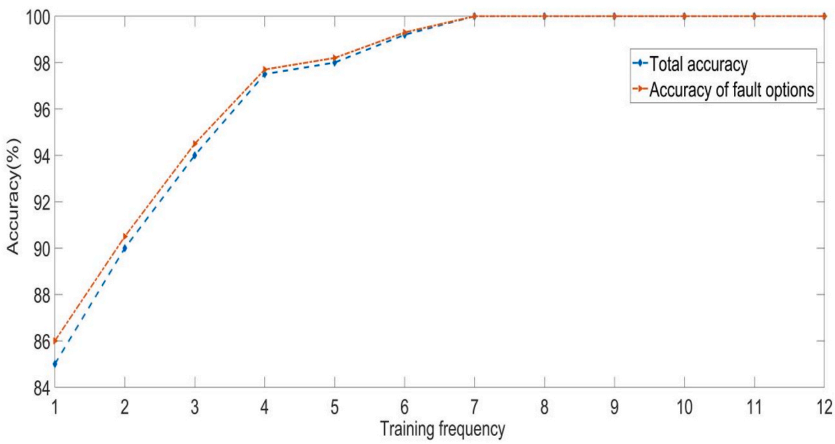

Fig. 3. Relationship between the number of training times and the accuracy of fault diagnosis for a certain neural network structure.

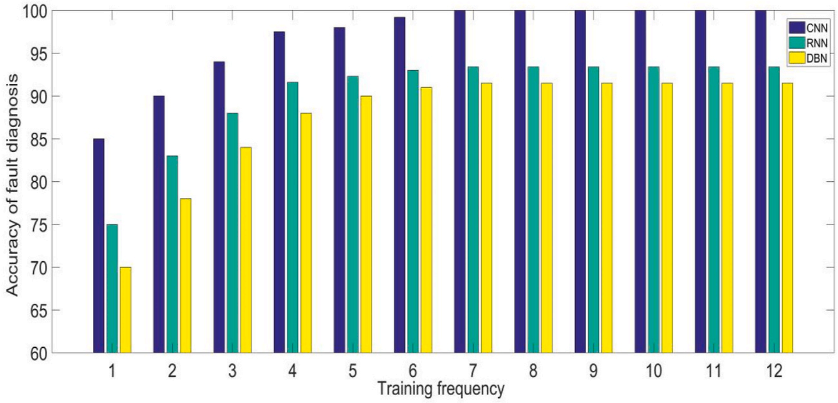

Fig. 4. Relationship between training frequency and fault accuracy of different deep learning algorithms.

of fault diagnosis accuracy, the stability of the three deep learning algorithms in power line fault diagnosis was expressed. In order to analyze the performance of convolution neural network in power circuit fault diagnosis more comprehensively, compared with RNN and DBN, convolutional neural network has better performance.

Fig. 5 shows the relationship between the training frequency and the standard deviation of accuracy for different deep learning algorithms, where the x-axis represents the training frequency and the y-axis represents the standard deviation of accuracy. From Fig. 5, it can be seen that the accuracy standard deviation of the three deep learning algorithms decreased with the increase of training times. Among them, CNN had the lowest accuracy standard deviation, and when the training times reached the fourth time, its accuracy standard deviation was less than 1%. As the number of training increased, the accuracy standard deviation of CNN approached 0, so CNN was the most stable in fault diagnosis of power circuits. The accuracy standard deviation of RNN was relatively higher than CNN, and its accuracy standard deviation was between CNN and DBN. Its stability was also based on the relationship between the two, while DBN had the highest accuracy standard deviation. When the training frequency reached 12, its accuracy standard deviation was 1.84%, which was higher than the CNN accuracy standard deviation of 1 training frequency. Its stability was the worst among the three deep learning algorithms. Therefore, it can be concluded that the CNN based power line fault diagnosis had the best stability. However, in the simulation iteration process, compared to the other two algorithms, its iteration frequency was higher and the training time was longer.

5. Conclusions

A power line is a distribution conductor circuit that connects a power distribution station with various electrical users and equipment, and is distributed and transmitted by the power supply end. The fault diagnosis of power lines is related to the safety of the nation. In the process of diagnosing power lines, one need to understand common faults in electronic lines and the positioning methods of common power line faults. Different electronic line faults have different fault diagnosis methods and strategies. This article used wavelet analysis and traveling wave signal anomaly detection to locate faults in power lines. Based on the deep learning model CNN, a fault diagnosis model for power lines was established and a fault diagnosis process framework for power lines was established. Different CNN structures were also set up on the windows10 Professional Edition 64 testing platform. It was found that the network structure, convolutional kernel size, training frequency, and batch processing quantity of CNN can all affect the fault diagnosis of power circuits. In the process of comparing CNN with other deep learning algorithms, CNN have the highest accuracy and stability in fault diagnosis of electronic circuits. In the comparison of three deep learning algorithms for power line fault diagnosis, convolutional neural network shows the highest stable fault diagnosis accuracy, reaching 100%. Recursive neural network and deep belief network are 93.4% and 91.5% respectively. This article used CNN to diagnose power line faults, which can effectively improve the accuracy and stability of fault diagnosis.

Data availability statement

All data generated or analyzed during this study are included in this published article.

CRediT authorship contribution statement

Liang Ning: Writing – original draft. **Dongfeng Pei:** Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to

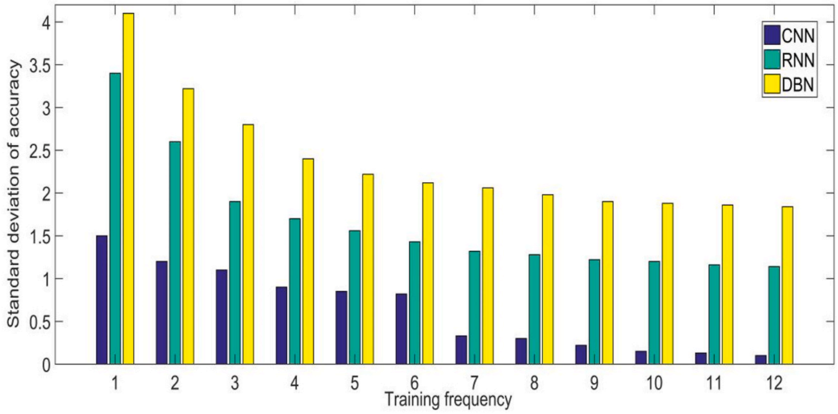

Fig. 5. Relationship between training frequency and standard deviation of accuracy for different deep learning algorithms.

influence the work reported in this paper.

References

[1] C. Guo, B. Liu, C. Zhao, A DC chopper topology to mitigate commutation failure of line commutated converter based high voltage direct current transmission, Journal of Modern Power Systems and Clean Energy 8 (2) (2020) 345–355.

[2] Z. Li, P. Wheeler, A. Watson, A. Costabeber, B. Wang, Y. Ren, Z. Bai, et al., A fast diagnosis method for both IGBT faults and current sensor faults in grid-tied three-phase inverters with two current sensors, IEEE Trans. Power Electron. 35 (5) (2020) 5267–5278.

[3] V. Tenentes, I.E.E.E. Member, Senior D Rossi, Leakage current analysis for diagnosis of bridge defects in power-gating designs, IEEE Trans. Comput. Aided Des. Integrated Circ. Syst. 37 (99) (2018) 883–895.

[4] M. Jin, H. Li, J. Xie, Z. Yang, M. Li, Rule based intelligent fault diagnosis and recovery power delivery algorithm, Dianli Xitong Baohu yu Kongzhi/Power System Protection and Control 47 (4) (2019) 176–181.

[5] I.F. Pierre, Anomaly detection in textured images with a convolutional neural network for quality control of micrometric woven meshes, Fluid mechanics and material processing 18 (6) (2022) 1639–1648.

[6] Y. Ruckstuhl, T. Janji, S. Rasp, Training a convolutional neural network to conserve mass in data assimilation, Nonlinear Process Geophys. 28 (1) (2021) 111–119.

[7] T.K. Das, P.K. Roy, M. Uddin, Early tumor diagnosis in brain MR images via deep convolutional neural network model, Cmc -Tech Science Press- 68 (2) (2021) 2413–2429.

[8] S.A. Amatare, A.K. Ojo, Predicting customer churn in telecommunication industry using convolutional neural network model, IOSR J. Comput. Eng. 22 (3) (2021) 54–59.

[9] Hao Wang, Dongsheng Yang, Bowen Zhou, Xiaoting Gao, Yongheng Pang, Fault diagnosis of multi-terminal DC transmission lines based on parallel convolutional neural networks, Power System Automation 44 (12) (2020) 84–92.

[10] Sitton Candanedo, Reactive power optimization of power system based on distributed cooperative particle swarm optimization algorithm, Distributed Processing System 1 (2) (2020) 46–53, https://doi.org/10.38007/DPS.2020.010206.

[11] Manohar Kintali, Srinivasa Rao Sura, Nageshwara Rao Pulivarthi, Aravind Kumar Kondaj, Euclidean metric based fault diagnosis IJITEE, Int. J. Innovative Technol. Explor. Eng. 9 (2S3) (2021) 226–231.

[12] M. Afrasiabi, S. Afrasiabi, B. Parang, M. Mohammadi, Power transformers internal fault diagnosis based on deep convolutional neural network, J. Intell. Fuzzy Syst. 37 (1) (2019) 1–16.

[13] Boneparth Alexis, Distributed generation on phase-to-phase short circuit protection in distribution network, Distributed Processing System 1 (1) (2020) 9–16, https://doi.org/10.38007/DPS.2020.010102.

[14] Umma Sadia, Three phase power flow calculation of weak loop distribution network with multiple distributed generators, Distributed Processing System 3 (1) (2022) 36–45, https://doi.org/10.38007/DPS.2022.030105.

[15] D. Binu, B.S. Kariyappa, RideNN: a new rider optimization algorithm-based neural network for fault diagnosis in analog circuits. Instrumentation and measurement, IEEE Transactions on 68 (1) (2019) 2–26.

[16] C. Zhang, X. Yuan, M. Shi, J. Yang, H. Miao, Fault location method based on SVM and similarity model matching, Math. Probl Eng. 2020 (1) (2020) 1–9.

[17] V.F. Syvokobylenko, V.A. Lysenko, Application of wavelet transdorm for phase-to-ground fault protection in medium voltage electrical nerworks, Technical Electrodynamics Electrodynamics 2021 (4) (2021) 55–62.

[18] J. Jeong, K. Lee, J. Park, D.D.O. Henriquez, K. Yoon, M. Kang, et al., High accuracy real-time multi-gas identification by a batch-uniform gas sensor array and deep learning algorithm, ACS Sens. 7 (2) (2022) 430–440.

[19] V. Smit, J.H. Thusen, D. Cohen, L.M. Hondelink, M. Huyuk, P.E. Postmus, et al., Development and validation of a supervised deep learning algorithm for automated whole-slide programmed death-ligand 1 tumour proportion score assessment in non-small cell lung cancer, Histopathology 80 (4) (2022) 635–647.