

Article

Research Based on Improved CNN-SVM Fault Diagnosis of V2G Charging Pile

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Abstract: With the increasing number of electric vehicles, V2G (vehicle to grid) charging piles which can realize the two-way flow of vehicle and electricity have been put into the market on a large scale, and the fault maintenance of charging piles has gradually become a problem. Aiming at the problems that convolutional neural networks (CNN) are easy to overfit and the low localization accuracy in fault diagnosis of V2G charging piles, an improved fault classification model based on convolutional neural networks (CNN-SVM) is proposed. Firstly, the hardware adaptation optimization is carried out for the CNN structure, the wavelet packet transformation is used to extract the fault current signal feature information into the CNN, and the CNN-SVM model is constructed by SVM (Support Vector Machine) instead of the SoftMax classifier in the CNN. The PSO (particle swarm algorithm) is used to optimize the parameters of the SVM model to obtain the optimal model. Finally, the superiority of the proposed method is verified by multi-working cases. The experimental results show that the fault classification accuracy of the CNN-SVM model is far higher than that of the traditional deep learning network and has practical significance for fault diagnosis of the switch module of the charging pile.

Keywords: V2G charging pile; fault diagnosis; CNN; SVM; wavelet packet decomposition; PSO



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1. Introduction

Affected by the intensification of uncertainty in the global energy market, high oil prices recently, and the government's vigorous promotion of the implementation of the "dual carbon" goal, new energy vehicles have gradually been sought by the market [1,2]; V2G (vehicle-to-grid) technology has realized the interactive relationship of "two-way charging of the vehicle network", achieving a win-win situation between the power grid and users [3]; and they have begun to operate on a large scale in the market.

The charging pile mainly works outdoors, which is susceptible to harsh environmental influences such as high temperature and humidity, and short circuit and open circuit faults occur [4]. Due to long-term working in a high-voltage environment and being used intensively, the performance of internal components gradually decreases and eventually fails [5]. The electrolyte inside the electrolytic capacitor gradually evaporates during the working process, and the capacitance decreases and fails [6]. The data point out that the short circuit and open circuit faults of the power tube and electrolytic capacitor account for about 85% of the total number of faults of the charging module. Short circuit faults generally have built-in sensing elements for monitoring and protection [7] or add fuses to convert short circuit faults into open circuit faults, but there is no perfect solution for open circuit faults. Therefore, this paper studies the open circuit fault diagnosis model of power tube and electrolytic capacitor in the charging pile, diagnoses the location of the faulty components, troubleshoots the fault in time, and improves the maintenance efficiency.

Fault characteristic diagnosis of the charging pile is essentially fault diagnosis of the power electronic circuits, and the current fault diagnosis methods can be divided into two types [8]: diagnostic methods based on analytical models or methods based on process

data. The analytical-model-based approach is by building a mathematical model. The literature [9] calculated the residual between different fault states and normal operation by establishing a four-quadrant pulse rectifier mathematical model and locating the open circuit fault of the switch tube. The authors of [10] used current vector slope and load current polarity for fault IGBT localization. Such methods rely too much on accurate models and are difficult to establish in practice.

Fault diagnosis methods based on process data have been widely used in recent years, mainly by analyzing a large amount of data accumulated during the operation process to find the relationship between the data and fault types. In [11], charging module fault characteristics were extracted by wavelet packet decomposition, PCA principal component analysis was used to reduce dimensionality, and a random forest fault diagnostic was established to realize charging module switch faults, which required manual calibration of fault characteristics, large calculations, and high model complexity. The authors of [12] used wavelet packet transformation to analyze the energy spectrum and power spectrum of charging module components to obtain fault characteristics, which avoided the problem of poor adaptability of the wavelet function to different signal decompositions, but it required repeated solution algorithms to obtain the best parameters, and the diagnosis efficiency was low. The deep learning algorithm reduced the computational complexity and improved the accuracy by independently learning the fault sample and extracting the feature information. The authors of [13] used deep neural networks to extract data signals and independently learn and diagnose them under different control strategies but did not solve the influence of noise on diagnostic accuracy. In [14], using wavelet packet transformation to extract the eight-dimensional energy spectrum of the input current of the rectifier and combining the fuzzy algorithm, the diagnostic accuracy was improved but the data processing time was longer. The study by [15] used convolutional neural network to convert fault feature signals into feature images and then realize the leap of fault diagnosis models from theoretical research to actual hardware deployment by independent analysis and diagnosis in the network.

However, there is the problem that feature information is easily lost after image input. The deep learning diagnosis method can avoid the error caused by the artificial selection of features and has good generalization ability and robustness. The traditional deep learning algorithm uses the fully connected network as the classifier, but it is difficult to achieve structural optimization; once the sample data are insufficient, it is easy to overfit, and only the local optimal solution can be obtained, which reduces the diagnostic accuracy.

The research purpose of this paper is to make better and faster diagnosis of the fault of the charging pile using technology based on deep learning. Compared with the traditional machine learning algorithm, this paper does not need to calibrate the fault characteristics manually. The neural network can make independent judgment with self-learning and analyzing the waveform difference of different faults, which greatly saves the diagnosis time and reduces the diagnosis error rate. At the same time, SVM is used to replace the SoftMax classifier in the traditional neural network to further improve the classification performance of the convolutional neural network, and the V2G charging pile fault diagnosis model based on CNN-SVM is constructed, which is the main innovation of this paper. In order to ensure the diagnostic accuracy of the model, before inputting the waveform into the convolutional neural network, wavelet packet transformation is used to analyze the signal in time and frequency domain, extract important feature information, and remove the impact of noise, which will also greatly optimize the structure of the convolutional neural network and reduce the requirements for hardware deployment. At the same time, the particle swarm optimization algorithm is used to optimize the parameters of SVM, which will help to avoid the problem that the traditional mesh parameter optimization cannot find the optimal result when the data set is too large.

2. Main Topology and Fault Analysis of Charging Pile Circuit

2.1. V2G Charging Pile

The V2G system is the abbreviation of the system after integrating two-way charging and discharging technology, two-way communication technology, safety monitoring technology, data acquisition technology, and intelligent control technology [16]. The conceptual diagram of the system is shown in Figure 1. The core of the entire system is the V2G charging pile.

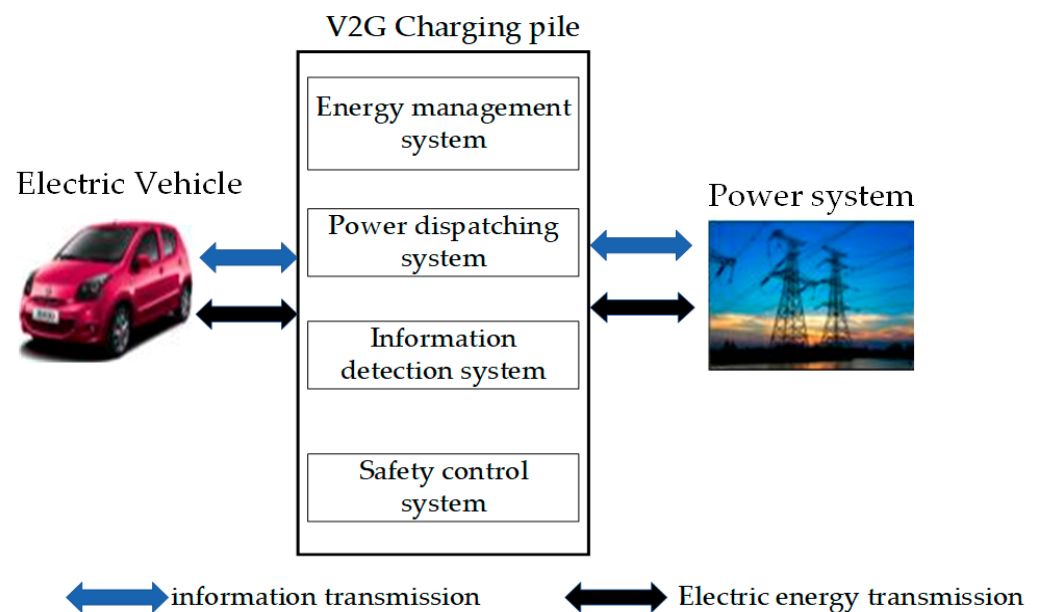


Figure 1. Concept diagram of V2G system.

The most critical part of the charging pile is the charging module [17]. The basic structure is shown in Figure 2:

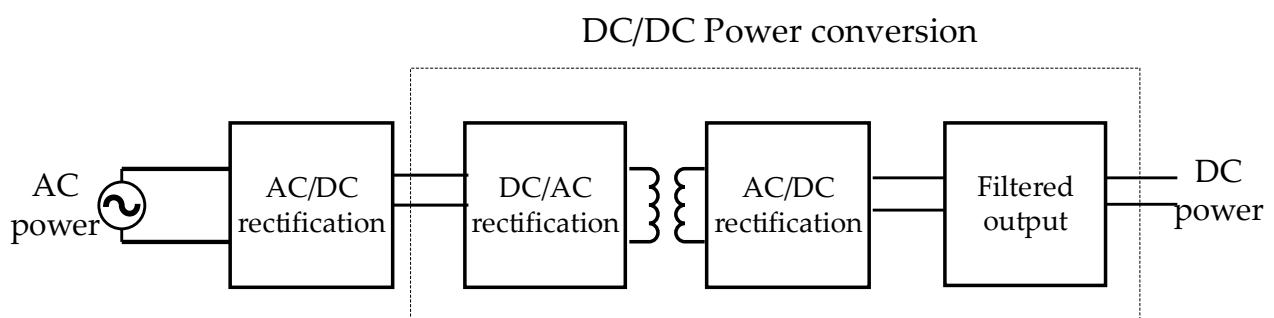


Figure 2. Structure of charging module.

2.2. Open Fault Types and Signature Signals

As shown in Figure 3, the pre-circuit uses a voltage source type three-phase full-bridge PWM converter (VSC), and the backstage DC converter module uses a Dual Active Bridge (DAB).

When the power tube has an open circuit fault, the input current contains a wealth of open circuit fault characteristics [18]. We built a simulation model according to the circuit in Figure 2 and set the circuit parameters as shown in Table 1.

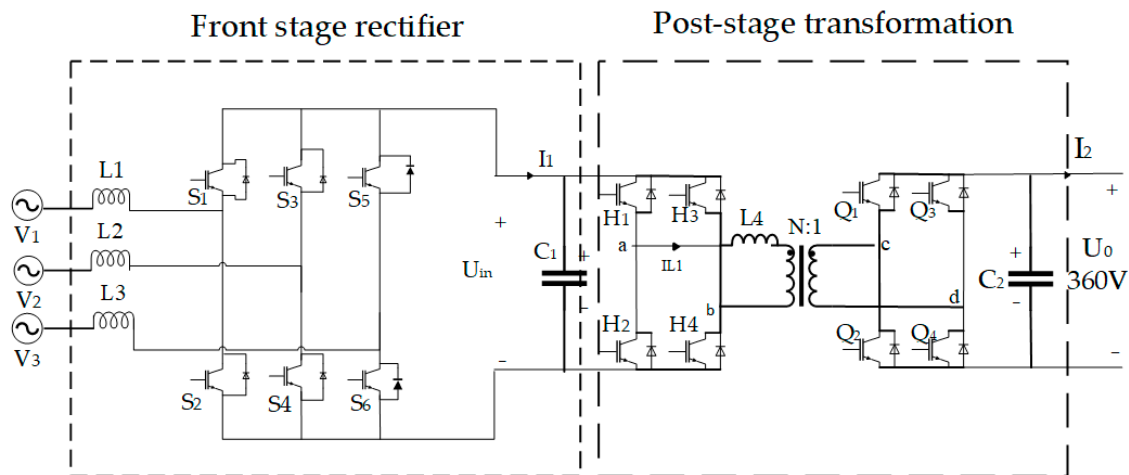


Figure 3. Topology of charging module circuit.

Table 1. Circuit parameter.

Circuit Parameters	Set Point
Input voltage	380 V $\pm$ 10%
Pre-rectified output voltage	560 V $\pm$ 10%
Front-stage inductance	1.6 mH
Pre-capacitors	3.2 mF
Backstage filter inductor	100 μ H
Post-filter capacitors	100 μ F
Post-load resistance	50 Ω
Frequency of pre-rectified switching	40 KHz
Frequency of the post-stage converter	20 KHz

This paper mainly studies the open circuit fault diagnosis of power components of electric vehicle DC charging piles; the faults are divided into 16 types, as shown in Table 2.

Table 2. Circuit parameter.

Fault Type	Fault Location	Fault Type	Fault Location
E1	S1 open	E9	H3 open
E2	S2 open	E10	H4 open
E3	S3 open	E11	Q1 open
E4	S4 open	E12	Q2 open
E5	S5 open	E13	Q3 open
E6	S6 open	E14	Q4 open
E7	H1 open	E15	C1 open
E8	H2 open	E16	C2 open

We set the sampling frequency to 4 kHz, the simulation time was 0.6 s, the pre-rectifier circuit added SVPWM modulation optimization waveform at 0.2 s, and the post-stage converter adopted single phase shift (SPS) control to collect different types of open circuit fault inductor three-phase current I_1 , I_2 , and I_3 waveforms, shown in Figure 4.

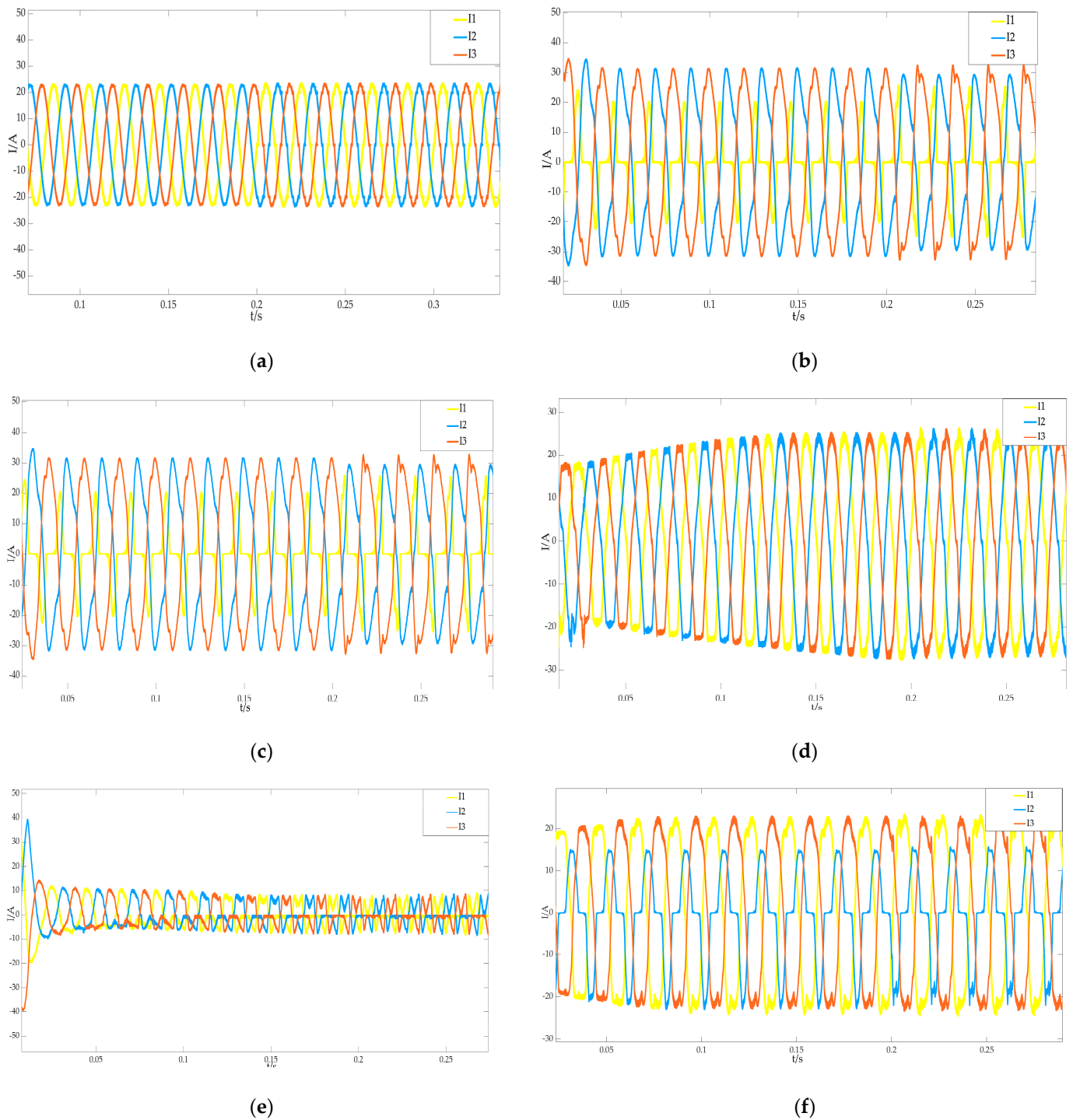


Figure 4. Three –phase inductance waveform of faults. (a) Current waveform under normal conditions. (b) Current waveform under E1 fault. (c) Current waveform under E5 fault. (d) Current waveform under E9 fault. (e) Current waveform under E12 fault. (f) Current waveform under E14 fault.

From the current waveform, the input current of each fault had different degrees of distortion, and the symmetrical power tube fault had a similar effect on the current waveform. It was found that the time-domain waveform image of the three-phase input current of the pre-inductor alone could not accurately locate the specific location of the fault. Therefore, this paper used wavelet packet transformation for time-domain analysis, extracted fault feature vectors, and then entered the model to achieve accurate classification.

2.3. Wavelet Packet Decomposition Extracts Fault Features

Wavelet packet decomposition can decompose the high-frequency and low-frequency amounts of the signal and improve noise immunity of the information [19]. Dwe drew the three-layer wavelet packet structure as shown in Figure 5.

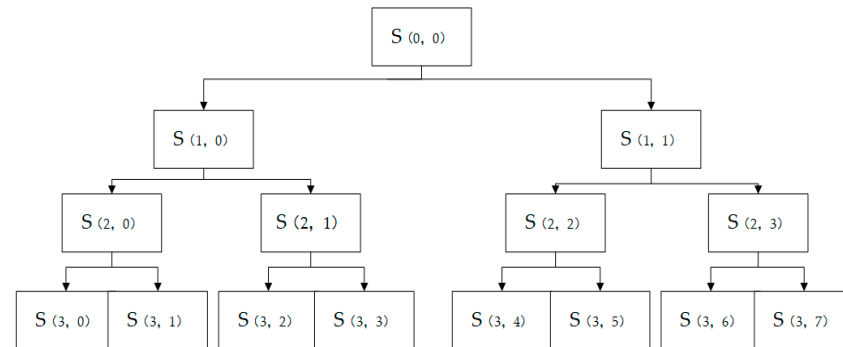


Figure 5. Structure of wavelet packet decomposition.

$S_{(0,0)}$ is the original signal, and $S(i,j)$ represents the decomposition signal corresponding to the j node of the i layer.

The specific steps to extract the fault characteristics are as follows:

- (1) Set the signal sampling frequency to 4 kHz. The analysis frequency is 2 kHz, as can be seen from Shannon sampling [20]. Perform a three-level decomposition of the sample data:

$$\begin{cases} N_k^{j+1,2n} = \sum_{k \in Z} N_p^{j,n} h_{(2p-k)} \\ N_k^{j+1,2n+1} = \sum_{k \in Z} N_p^{j,n} g_{(2p-k)} \end{cases} \quad (1)$$

P is the number of decomposition layers, $N_{p-j,n}$, N_{k-j+1} , $2n$, and so on are the decomposition coefficients, and $h_{(2p-k)}$ and $g_{(2p-k)}$ are the low-pass and high-pass filter coefficients.

- (2) Reconstruct the wavelet packet decomposition coefficient, and reconstruct the signal frequency as shown in Table 3:

Table 3. Frequency range of reconstructed signal.

Signal	Frequency/Hz	Signal	Frequency/Hz
$S_{(3,0)}$	0–250	$S_{(3,1)}$	250–500
$S_{(3,2)}$	500–750	$S_{(3,3)}$	750–1000
$S_{(3,4)}$	1000–1250	$S_{(3,5)}$	1250–1500
$S_{(3,6)}$	1500–1750	$S_{(3,7)}$	1750–2000

- (3) The signal is analyzed by wavelet packets to further eliminate the noise margin present in the high-frequency section. After wavelet decomposition, the wavelet decomposition coefficient of useful signal is larger, and the wavelet decomposition coefficient of noise is smaller. Therefore, by setting the threshold function for denoising, the decomposition coefficient greater than the threshold is retained, while the decomposition coefficient less than the threshold is eliminated by zeroing. Based on wavelet transformation, wavelet packet analysis subdivides and decomposes the unprocessed high-frequency components in wavelet transform again. Compared with wavelet denoising, wavelet packet analysis has higher frequency resolution, which can further eliminate the noise margin in high-frequency parts and improve the denoising accuracy. The image comparison of noisy signal and de-noised signal

are shown in Figure 6. The image comparison of signal spectrum diagrams are shown in Figure 7.

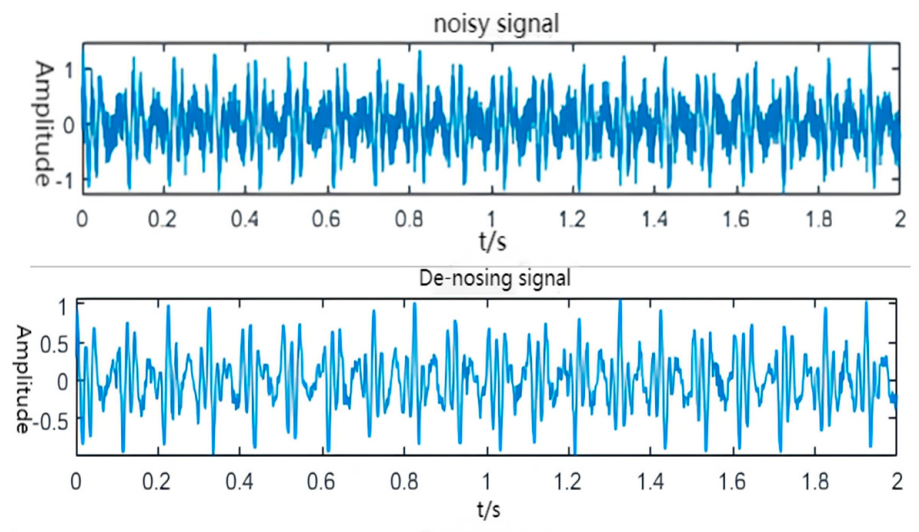


Figure 6. Waveform—comparison of noise signals.

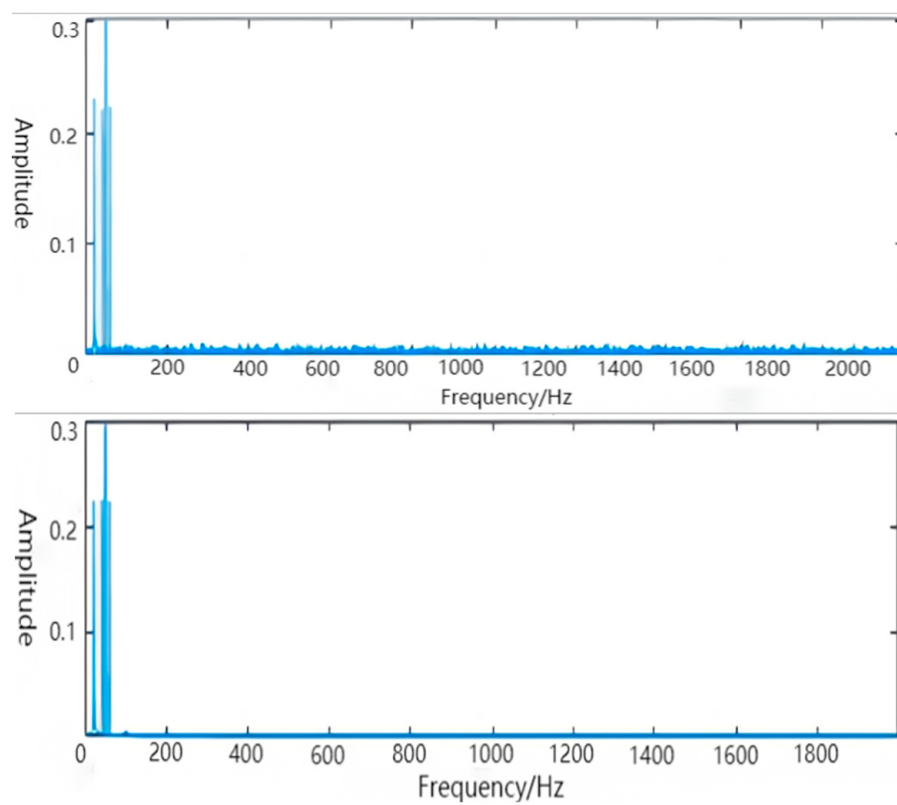


Figure 7. Signal time frequency graph.

We calculated the energy of the third layer of wavelet packet energy spectrum shown in Figure 8:

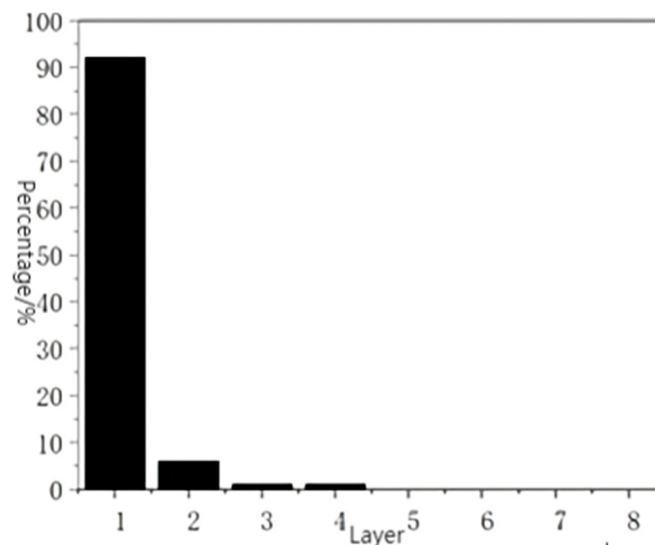


Figure 8. Structure of wavelet packet energy.

From Figure 8 we found that the signal energy corresponding to the first node of Layer 3 accounted for more than 90%, which had rich time-frequency information. Therefore, the corresponding signal of this node was selected as a feature vector to input into the neural network.

2.4. Principle of CNN

The convolutional neural network (CNN) is a multi-layer neural network [21] with strong adaptability. The weight-sharing network structure is shown in Figure 9, using local spatial correlation to connect adjacent lower neuronal nodes with similar upper neuron nodes to optimize the network structure. The image can be directly used as the input of the network to improve the diagnostic accuracy, which avoids the complex feature extraction and data reconstruction process in the traditional recognition algorithm.

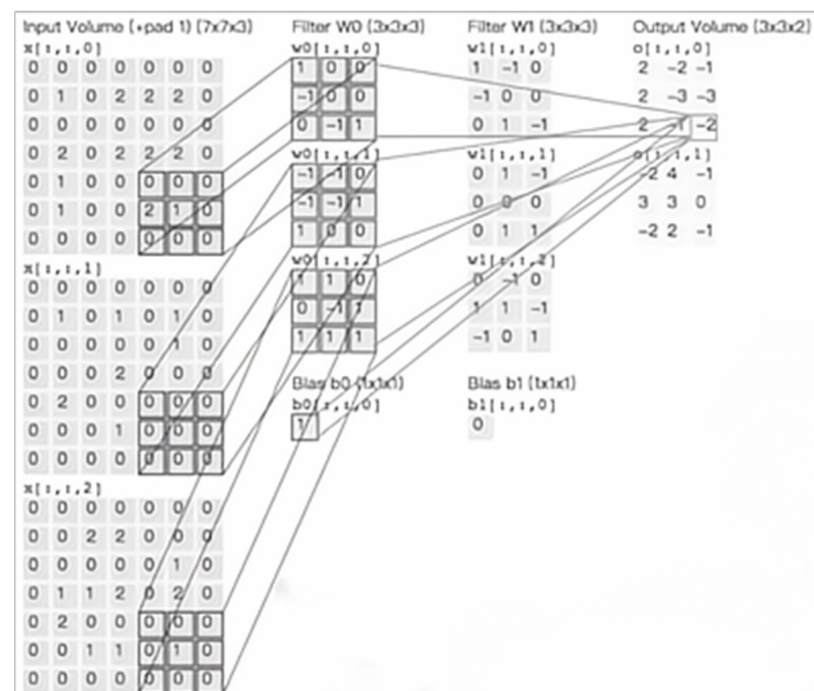


Figure 9. Structure of convolutional diagram.

Figure 9 is a schematic diagram of a three-channel convolution operation, the input image is 5 * 5 size, three channels, and then reduced to 3 * 3 size after output, the operation process includes two sets of convolution kernels, namely filters W0 and W1. The original two-dimensional image was input to the convolutional layer and the convolution kernel extracted the local features of the input image. Each convolution kernel corresponds to one feature, and by increasing the number of convolution kernels, different features were extracted from the same position of the input image, thereby forming different feature maps, which were arranged and combined as the output of the convolutional layer.

2.5. Principle of SVM

The traditional neural network learning method mainly adopts the principle of empirical risk minimization, as shown in Equation (2):

$$R_{\text{emp}}(f) = \frac{1}{N} \sum_{i=1}^N L(y_i, f(x_i)) \quad (2)$$

The $L(y_i, f(x_i))$ are the loss function, according to the law of large numbers, the sample size N approaches infinity and the empirical risk, $R_{\text{emp}}(f)$ approaches the ideal value [21]. However, in reality, the training samples are limited, and the model can only make good predictions on the training set, but the effect on the test set is poor. This is often referred to as “overfitting” [22].

Support vector machine (SVM) is a binary classification model based on the principle of structural risk minimization, which improves the overall performance of the model by controlling the ratio between empirical risk and confidence range.

$$R_{\text{srm}}(f) = R_{\text{emp}}(f) + \lambda J(f) \quad (3)$$

$J(f)$ represents the complexity of the model and λ is the coefficient, which was used to weigh empirical risk so that the desired risk on the entire sample would be controlled.

2.6. Particle Swarm Optimization Supports Parameter Selection of Vector Machines

Support vector machines have a high dependence on internal parameters, among which the two factors of nuclear parameter σ and penalty factor C directly affect the accuracy of classification [23].

Particle Swarm Optimization (PSO) iteratively finds the optimal solution by simulating the predation behavior of flocks.

Firstly, a group of random particles was initialized, and iteratively finds the optimal solution. In each iteration, the particles were updated by tracking two extremes. One was the optimal solution “ P_{best} ” of the particle itself. The expression is shown in Equation (4):

$$P_{\text{best}} = (p_{i1}, \dots, p_{iD}), i = 1, 2, \dots, N \quad (4)$$

Another extreme value is the current optimal solution of the entire population, the global extreme value “ g_{best} ”.

$$g_{\text{best}} = (g_1, g_2, \dots, g_D) \quad (5)$$

In this paper, the global search capability and local search capability of particle swarm optimization are used to reasonably optimize the parameters required in the modeling process of the support vector machine, as shown in Figure 10:

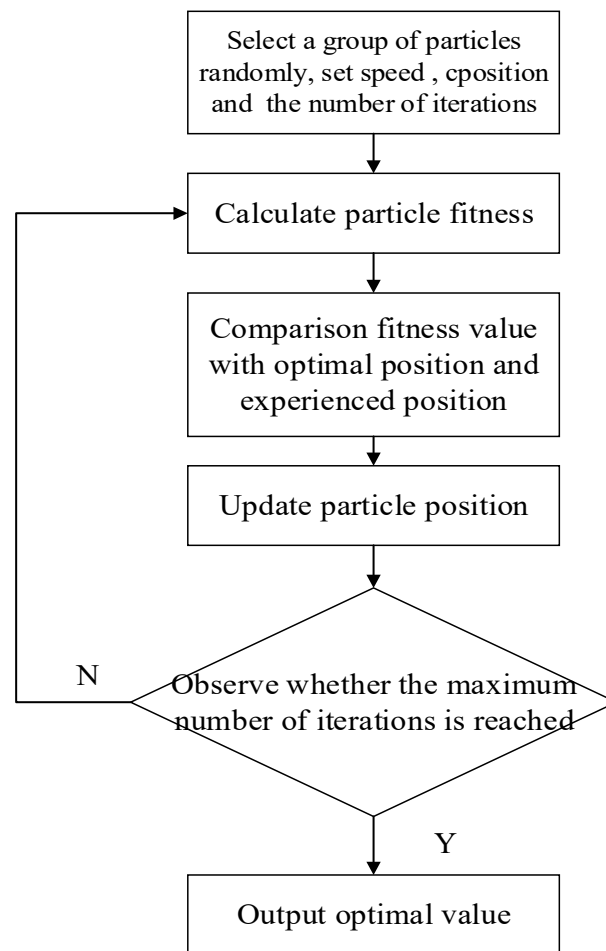


Figure 10. Flowchart of PSO.

2.7. Fault Diagnosis Based on Convolution Support Vector Machine

2.7.1. Improvement of Fault Diagnosis Model

Considering that the CNN-SVM model needed to be deployed in hardware, the structure of the traditional CNN-SVM model was improved:

- (1) The original 5×5 convolution kernel was replaced by a 3×3 size convolution kernel to further reduce the complexity of the model.
- (2) Referring to the model structure of Yolo, ResNet, and other models [24,25], we modified the number of convolution channels to 4/8/16.
- (3) The convolutional layer was increased to three layers, replacing the original double fully connected layer to further reduce the amount of parameter input.
- (4) The data retained rich feature information through wavelet packet decomposition before entering the neural network, so the filling operation in the convolution process was removed and the hardware memory occupation was reduced. The improved model structure is shown in Figure 11:

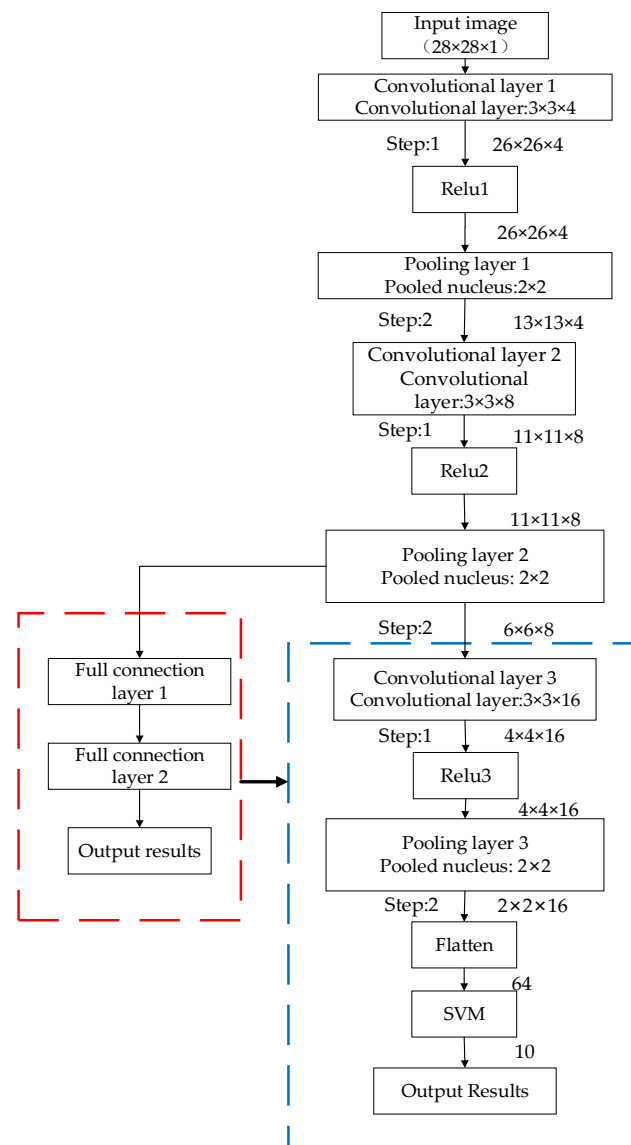


Figure 11. Structure of improved CNN–SVM model.

The statistics of the original CNN-SoftMax and the improved CNN-SVM model parameter amount (Params) and computational amount (MACC) are shown in Table 4:

Table 4. Comparison of calculation and parameter.

	CNN-SoftMax	CNN-SVM	Ratio
MACC	1,864,528	67,495	3.62%
Params	14,796,236	1,279,874	8.65%

The calculation amount and parameter amount of the improved model are 3.62% and 8.65% of the original, greatly reducing the hardware deployment requirements.

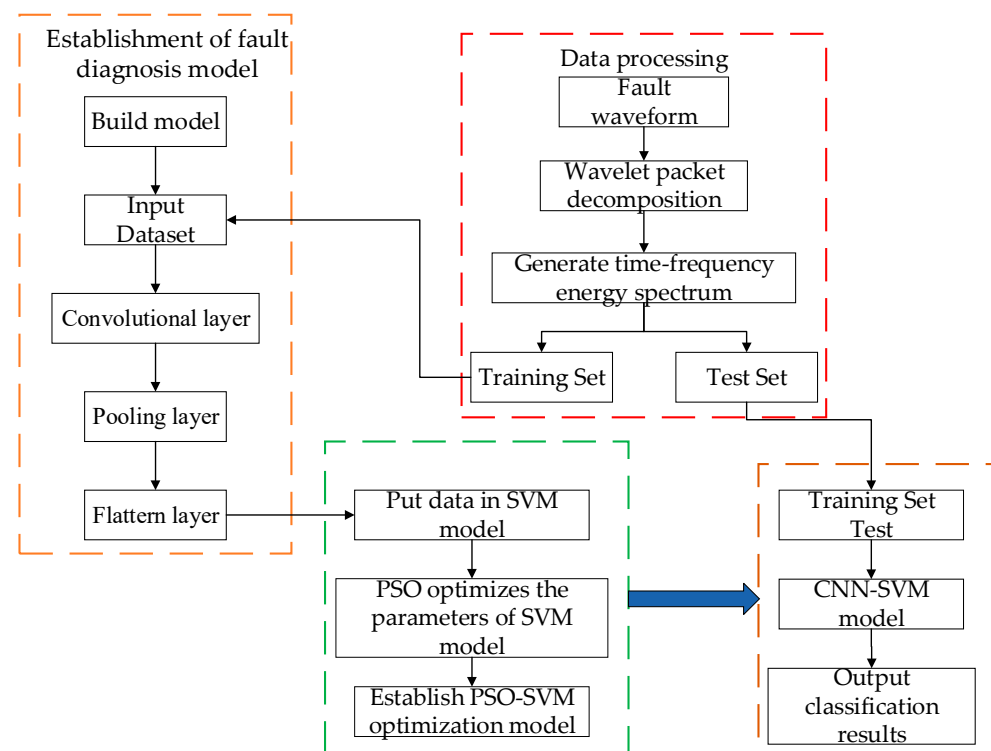
The model was built based on the TensorFlow framework. SVM adopted one-to-one learning strategy (One vs. One, OvO), CNN adopted Adam (Adaptive moment estimation) optimizer [26], and the model super parameters are shown in Table 5:

Table 5. Parameters of CNN-SVM model.

CNN	SVM
Batch Size = 100	C = 100
Learning Rate = 0.1	Gamma = Auto
Moving Average = 0.99	$\gamma = 0.09$
Rate Decay = 0.99	Kernel = RBF

2.7.2. Process of Fault Diagnosis

In this paper, SVM was used instead of the SoftMax classification layer of the CNN network, and the model training part used a large amount of fault data to train the diagnostic model. The model operation process is shown in Figure 12:

**Figure 12.** Flowchart of model diagnosis.

2.7.3. Dataset Establishment

In order to verify that the model had practical application value for the diagnosis of charging module faults of charging piles, this paper selected AMD ARTYS7 microcontroller as the main processor, UCC14240-Q1 DC/DC module and LM5021 PWM rectifier module as the front and rear stages, and ABB M2BAX IE2 low-voltage motor as the AC input power supply. The V2G charging pile circuit topology platform and main control processor are shown in Figure 13, and some of the actual output waveforms are shown in Figure 14. Different fault conditions were simulated, 6400 sets of data were obtained by recording the output current signal data, and different levels of noise were added to form the final training set.

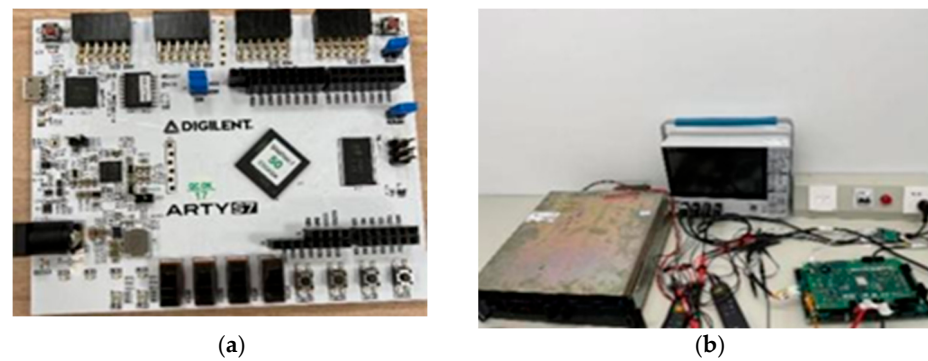


Figure 13. V2G circuit experimental platform. (a) main processor; (b) front and rear stage.

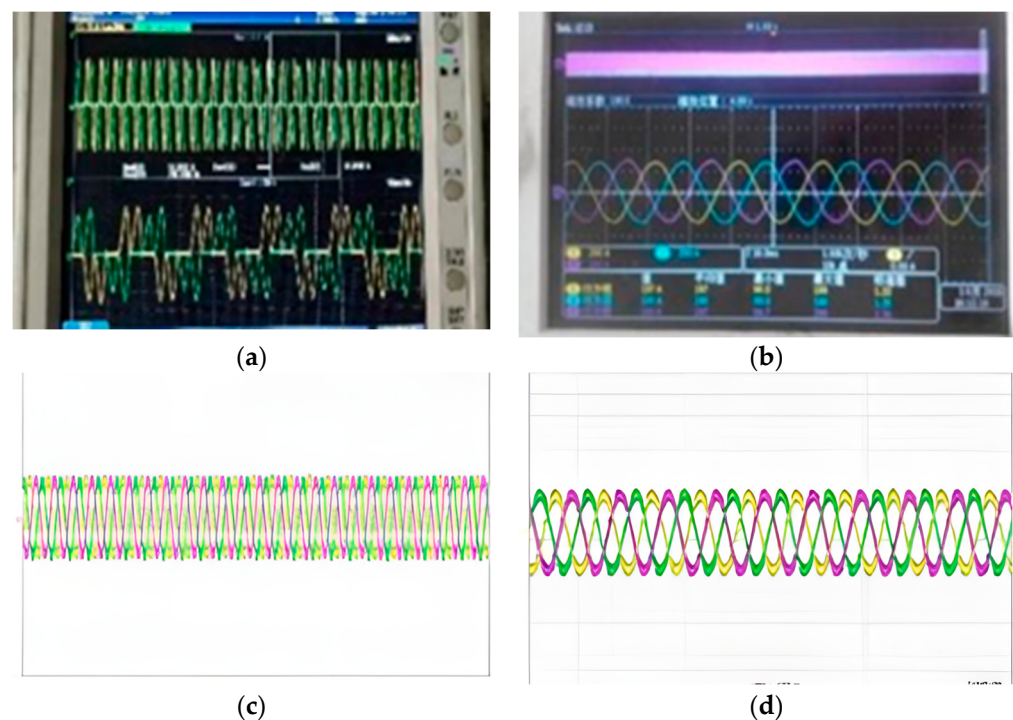


Figure 14. Diagram of three-phase current waveform. (a) Actual waveform. (b) Actual waveform. (c) Simulated waveform. (d) Simulated waveform.

The TeKtronix MDO3024 oscilloscope was selected to read the current waveform, and the display waveform is shown in Figure 14:

3. Experimental Results and Comparative Tests Discussion

3.1. Experimental Results

We set the number of training rounds to 180 rounds, the number of iterations per round was three, and the model training and testing steps are as follows:

- (1) Obtain sample data. Build a V2G charging pile circuit, set up different fault types, and collect the pre-output three-phase current waveform.
- (2) Extract fault characteristics. The upper computer decomposes the current waveform through three layers of wavelet packets, extracts the signals of each node to draw the energy spectrum, selects the signal waveform of the first node of the third layer as the fault characteristic vector, and introduces the current amplitude to further supplement the feature vector and enrich the characteristic information.
- (3) Run the fault diagnosis model. If the fault feature vector obtains the same result through the model as the expected fault, it means that the model has completed the

fault diagnosis. The accuracy of the model for faulty power devices is shown in Table 6:

Table 6. Parameters of CNN-SVM model.

Fault Type	Fault Component	Accuracy	Fault Type	Fault Component	Accuracy
E1	S1 open	99.68%	E9	H3 open	95.14%
E2	S2 open	95.62%	E10	H4 open	96.89%
E3	S3 open	95.36%	E11	Q1 open	96.92%
E4	S4 open	96.29%	E12	Q2 open	98.82%
E5	S5 open	96.71%	E13	Q3 open	98.92%
E6	S6 open	97.24%	E14	Q4 open	98.64%
E7	H1 open	96.45%	E15	C1 open	99.26%
E8	H2 open	97.69%	E16	C2 open	98.57%

We set the number of training rounds of the model as 180 and the cycle of each round was three times. We calculated the average of each round of trainings' accuracy and loss function. We displayed them comprehensively as shown in Figures 15 and 16. The model training time took 2 min 28 s, the number of iterations was 540, and the model diagnosis rate reached 98.47%.

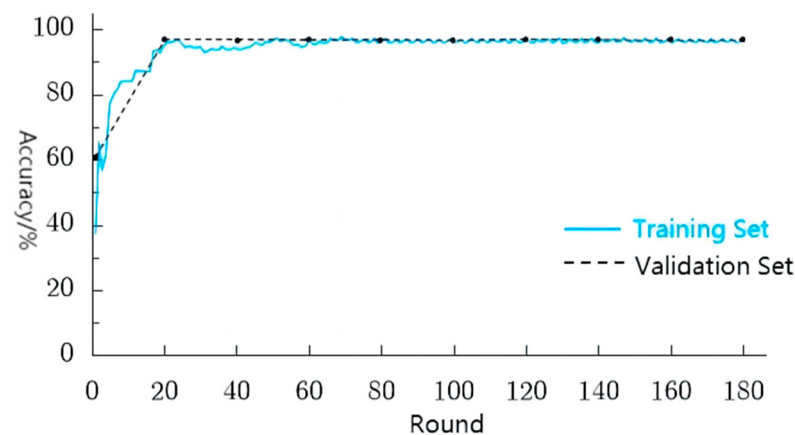


Figure 15. Curve of model diagnostic accuracy.

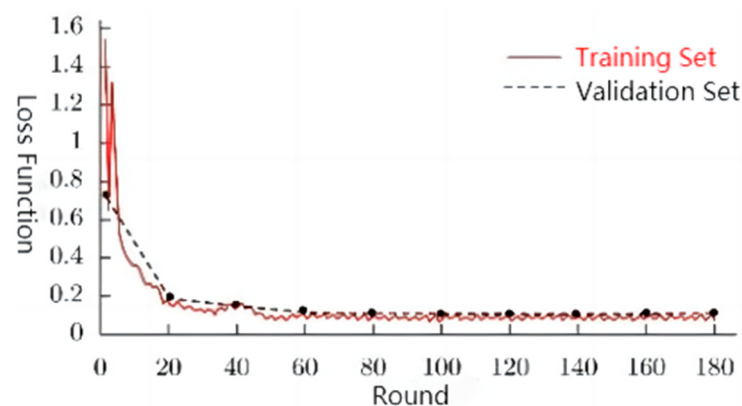


Figure 16. Curve of loss function.

3.2. Model Validation Comparison

We verified that the CNN-SVM-based V2G charging pile diagnostic model proposed in this paper has a more accurate classification effect than the CNN-SoftMax model, and the

fault simulation under different noises was carried out on the circuit topology of Figure 3; the fault type and component parameters are shown in Table 1. A total of 3620 test samples were generated, the number of training rounds was set to 100 rounds, and after training the same batch, the output was a confusion matrix as shown in Figure 17:

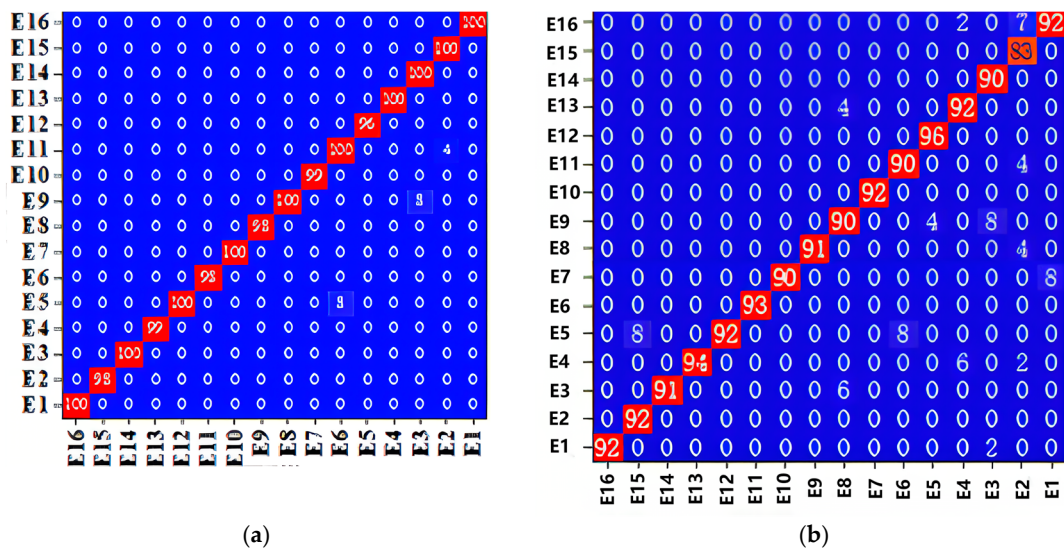


Figure 17. Confusion matrix of CNN-SVM and CNN-SoftMax. (a) CNN-SVM. (b) CNN-SoftMax.

As can be seen from Figure 17, there were more cases of misjudgment in the CNN-SoftMax model under the same conditions. The CNN-SVM model is more stable.

3.3. Comparison of Hardware Platform Occupancy

Fault diagnosis should meet the requirements of high performance and low power consumption of hardware platforms in practical applications. Table 6 shows the software and hardware experiment parameters. In this paper, a 10-fold cross-validation experiment was used to ensure that each data sample was studied as a training set. The batch size of CNN-SVM was set to 64. The number of iterations was set to 100, the learning rate of the first 40 times was 0.001, the learning rate of the next 40 times decayed 10 times, and the learning rate of the last 20 times decayed 10 times again.

This setting allowed the parameters to be updated with a larger step size at the beginning of the training and a smaller step size at the end of the training to avoid falling into the local minimum. We set the L2 regularization coefficient to 0.0001, reduced the complexity and instability of the model by limiting the weight size, and avoided overfitting the model. We chose the representative algorithms for multi-classification problems: random forest, BP neural network, and CNN-SVM model are compared for comparison, and the frequency and power consumption of the algorithm when running on GPU are shown in Table 7:

Table 7. Comparisons of GPU performance.

	CNN-SVM	Random Forest	BP
Frequency/Hz	130	1650	1390
Power/W	39.6	89.8	56
Energy/J	18.6	96.89	67

It can be seen from Table 7 that the model shows good generalization and robustness under different noise intensities and is very stable.

There will be noise in the fault recording data of the actual distribution network, so it is necessary to verify the adaptability of the proposed method under noise conditions. Stay

Gaussian white noise with a signal-to-noise ratio of 5 dB to 30 dB was added to the test set point position, and the fault type was set as per Section 3.1.

We set different noise intensities, put test data into the model, and obtained the accuracy of different algorithms, as shown in Table 8:

Table 8. Comparison of model diagnostic.

Model	Diagnostic Rate/%					Average
	0 dB	5 dB	10 dB	20 dB	30 dB	
CNN-SVM	97.5	94.57	94.08	92.86	91.21	94.044
Random forest	94.3	95.28	91.26	89.76	86.28	91.376
BP	92.1	90.04	86.45	82.46	82.35	86.68
CNN	90.6	90.15	89.42	88.62	86.88	89.134

According to Tables 7 and 8, the accuracy of random forest is similar to CNN-SVM, but the running time is longer, and the running time of the BP neural network is shorter, but the comprehensive diagnosis accuracy is greatly reduced.

4. Conclusions

In this paper, a fault diagnosis research model of charging piles based on CNN-SVM is proposed, and the circuit topology model of the V2G charging pile is constructed and analyzed by example. The following conclusions were obtained:

- (1) The deep learning model adopted in this paper avoids the problems with traditional machine learning, such as how it is easy to lose some features when manually extracting fault signals and the signal difference characterization is weak under complex fault conditions, which cannot be accurately identified. This model improves the classification accuracy
- (2) Wavelet packet decomposition was introduced to extract the time-frequency feature map of the signal to prevent the image from being directly input into the neural network to generate a large amount of data redundancy, and at the same time, the SSO was used to optimize the SVM model to find the optimal parameters and penalty factors and to further optimize the model.
- (3) The structure of the traditional convolutional neural network was modified to reduce the complexity of the model. Through the hardware platform test, the improved model still maintained high classification accuracy and calculation speed under different noise intensities, and the operating power consumption was also greatly reduced, which is of practical significance.

The proposed CNN-SVM fault diagnosis model has unique advantages and higher accuracy in fault diagnosis of the front and rear stages of the charging pile. However, it still has certain limitations and drawbacks in its practical application which should be well addressed in future studies.

Firstly, in future research, we will further focus on how the fault diagnosis model based on deep learning can better adapt to new energy electric equipment, such as electric vehicles and charging piles, and improve some of the problems in previous studies. These improvements include how the model can maintain high diagnostic accuracy when the front and rear modules of the charging pile adopt different topological structures (three-phase Vienna structure, PWM rectifier) and using different types of power electronic components (electric vehicle charging station, low-voltage frequency converter). Additionally, the robustness of the proposed method was affected owing to the limited dataset used for the model. Accordingly, in future work, the experimental tests will be conducted on the accuracy of fault diagnosis of the model on different front and rear circuits in the laboratory. Different from the traditional simulation circuit, we will build more actual circuit platforms and carry out experimental tests under various parameter conditions to expand the test set

and experimental set of the model. Actually, the selection of the optimization algorithm for this task is not unique. In the future, other intelligent algorithms, such as information fusion and deep residual shrinkage network [25], FASSA-SVM [23] will be further applied to the fault diagnosis model to improve the diagnostic accuracy and speed.

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Abbreviations

Terms	Full Name and Explanation
CNN	Convolutional Neural Networks
SVM	Support Vector Machines
PSO	Particle Swarm Optimization
V2G	Vehicle to Grid
SPS	Single Phase-Shift Control
DAB	Dual Active Bridge Converters
OvO	One-to-One Learning Strategy
Adam	Adaptive Moment Estimation Optimizer
VSC	Three-Phase Full-Bridge PWM Converter
Symbol	Meaning
$h_{(2p-k)}$	low-pass filter coefficient
$g_{(2p-k)}$	high-pass filter coefficient
$L(y_i), f(x_i)$	loss function
$R_{emp}(f)$	ideal value
$J(f)$	complexity of the model
λ	coefficient
P_{best}	optimal solution of the particle itself
g_{best}	the global extreme value of the entire population
$R_{srm}(f)$	the overall performance of the model

References

1. Feng, H.; Xiong, Z. Opportunities and development strategy of new energy vehicle industry under the background of “dual carbon”. *J. Decis. Inf.* **2022**, 68–76. [\[CrossRef\]](#)
2. Cheng, X.; Yang, K.; Pan, Z.; Tan, J. Development status and countermeasures of China’s new energy vehicle industry. *Coop. Econ. Technol.* **2021**, 20–22. [\[CrossRef\]](#)
3. Gao, Y. How to effectively control the charging and discharging of electric vehicle charging piles under V2G technology. *Sci. Technol. Inf.* **2018**, 16. [\[CrossRef\]](#)
4. Cao, K. *Research on Grid Connection Technology of V2G Charging Pile and Smart Microgrid*; Guangxi University of Science and Technology: Guangxi, China, 2019.
5. Jiang, Y.; Jia, Y.; Liu, H. EV charging fault analysis and precise maintenance. *Electr. Eng. Electr.* **2021**, 68–70. [\[CrossRef\]](#)
6. Li, M. Fault diagnosis and detection of electric vehicle charging pile. *Automot. Pract. Technol.* **2019**, 162–163. [\[CrossRef\]](#)
7. Zhou, R.; Feng, G. Design of operating status and fault diagnosis system of automobile charging pile. *Electron. Compon. Inf. Technol.* **2020**, 4, 124–125.
8. Liu, Z.; Jin, T.; Liu, Y.; Gong, Z.; Liao, H.; Lan, M. Open Circuit Fault Diagnosis Method of DC Charging Pile for Electric Vehicle Based on Tensor Reconstruction Fusion Diagnosis. Available online: <http://h-p.kns.cnki.net.shiep.vpn358.com/kcms/detail/11.2107.tm.20220518.1524.002.html> (accessed on 25 December 2022).

9. Wang, Q.; Dai, W.; Wang, X.; Su, S. Operation and maintenance of DC electric vehicle charging pile. *Rural Electr.* **2021**, *29*, 35–36.
10. Yang, F.; Xu, S.; Zhou, J.; Chen, L. Research on open-circuit fault diagnosis of power devices of DC charging piles for electric vehicles based on wavelet packet analysis. *Electr. Energy Manag. Technol.* **2018**, *23*, 79–85.
11. Wang, Q.; Yin, Z.; Tao, E. Research on fault diagnosis of V2G charging pile based on random forest algorithm. *Electr. Meas. Instrum.* **2021**, pp. 1–9. Available online: <http://h-p.kns.cnki.net.shiep.vpn358.com/kcms/detail/23.1202.TH.20210726.0904.002.html> (accessed on 25 December 2022).
12. Jin, Y.; Liang, L.; Liu, T.; Xin, S. Fault detection of AC charging pile based on fault dictionary method. *Electron. Technol. Appl.* **2018**, *44*, 56–59+67. [[CrossRef](#)]
13. Zhao, X.; Chen, L.; Liu, T. A fault diagnosis method for DC charging pile based on deep neural network. *Electr. Meas. Instrum.* **2021**, *58*, 148–152. [[CrossRef](#)]
14. Wu, W.; Deng, L.; Tao, Y.; Wang, X. Research on Evolutionary Game of Value Co-Creation Behavior of Shared Private Charging Piles of Electric Vehicles. *Discreet. Dyn. Nat. Soc.* **2022**, *2022*, 9884962. [[CrossRef](#)]
15. Corning. *Research on Fault Characteristics Extraction of Charging Module of DC Charging Pile*; Beijing Jiao Tong University: Beijing, China, 2019.
16. Lv, X. *Research on Bidirectional DC-DC Converter Based on V2G Technology*; Zhejiang University: Hangzhou, China, 2013.
17. Ji, X.; Chen, J.; Zhang, Y.; Liu, Q.; Gong, Z.; Xu, B. Research on fault classification of distribution network based on CNN-SVM. *Smart Power* **2022**, *50*, 94–100. [[CrossRef](#)]
18. Harikrishnan, S.; Kanagarajan, K.; Elsayed, E.M. Existence and stability results for differential equations with complex order involving Hilfer fractional derivative. *TWMS J. Pure Appl. Math.* **2019**, *10*, 94–101.
19. Wang, J.; Chen, X.; Ji, L. Research on Fault Diagnosis of DC Charging Pile Power Device Based on Wavelet Packet and Elman Neural Network. *IOP Conf. Ser. Mater. Sci. Eng.* **2019**, *486*, 012086. [[CrossRef](#)]
20. Yu, Y.; Liang, S.; Samali, B.; Nguyen, T.N.; Zhai, C.; Li, J.; Xie, X. Torsional capacity evaluation of RC beams using an improved bird swarm algorithm optimised 2D convolutional neural network. *Eng. Struct.* **2022**, *273*, 115066. [[CrossRef](#)]
21. Vivek, D.; Kanagarajan, K.; Elsayed, E.M. Some Existence and Stability Results for Hilfer-fractional Implicit Differential Equations with Nonlocal Conditions. *Mediterr. J. Math.* **2018**, *15*, 15. [[CrossRef](#)]
22. Yu, Y.; Samali, B.; Rashidi, M.; Mohammadi, M.; Nguyen, T.N.; Zhang, G. Vision-based concrete crack detection using a hybrid framework considering noise effect. *J. Build. Eng.* **2022**, *61*, 105246. [[CrossRef](#)]
23. Zhang, M.; Gao, L.; Chen, W. Research on Fault Prediction algorithm of Charging Pile Based on FASSA-SVM. *Electron. Meas. Technol.* **2022**, *45*, 1–8. [[CrossRef](#)]
24. Wang, Z.; Liu, J. *Power Electronics Technology*; Publishing House of Electronics Industry: Beijing, China, 2009.
25. Zhao, Y.; He, Y. Open circuit fault diagnosis method of DAB converter based on information fusion and deep residual shrinkage network. *Electr. Power Autom. Equip.* **2022**, 1–11. [[CrossRef](#)]
26. Zhou, Y.; Wu, R.; Yu, X. Research and Implementation of CNN-SVM Algorithm for FPGA Deployment. *J. Electron. Meas. Instrum.* **2021**, *35*, 90–98. [[CrossRef](#)]

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