ISSN: 1813-4890

Fault Diagnosis of Analog Circuit based on 1D-CNN-LSTM

Chengda Zhang[1, a], You Yang[2, b], Hao Zhai[1, c]

[1] School of Computer and Information Science, Chongqing Normal University, Chongqing 401331, China

[2] National Center for Applied Mathematics in Chongqing, Chongqing 401331, China

[a]1466381080@qq.com, [b]565357950@qq.com, [c]760113768 @qq.com

Abstract

Analog circuit fault diagnosis is of great significance to the stable operation of electronic equipment, but the current fault diagnosis methods have the problem of relying on manual feature extraction and low robustness. Therefore, this article proposes an end-to-end analog circuit fault diagnosis method based on the combination of one-dimensional convolutional neural network (1D-CNN) and long-term short-term memory network (LSTM). The 1D-CNN-LSTM model is used to perform fault diagnosis experiments on the Sallen-Key low-pass filter circuit, and compared with other mainstream models, the accuracy of the test set is 99.33%. The experimental results show that the model has great advantages in diagnosis accuracy and training time, and it has the feasibility of practical application.

Keywords

Analog circuit, fault diagnosis, deep learning, CNN, LSTM.

1. Introduction

With the rapid development of electronic technology, electronic equipment is widely used in various industries, and the continuous improvement of its integration scale has high requirements for the reliability of the equipment. A statistical report shows that in various electronic equipment, analog circuit boards account for about 20%, but 80% of the failures of the entire equipment are caused by the analog circuit [1-2], so the reliability of the analog circuit plays a decisive role. Due to the effects of continuous input and output, component tolerances, fewer measurable nodes, more nonlinear problems and environmental noise in analog circuits, the fault diagnosis of analog circuits is far more difficult than digital circuits, theories and methods are not yet fully mature. In summary, it is of great significance to realize high-efficiency and low-cost analog circuit fault diagnosis and ensure the stable operation of electronic equipment.

With the in-depth research and application of artificial intelligence, ideas and tools are provided for solving analog circuit fault diagnosis. Therefore, modern fault diagnosis methods based on machine learning have become the current research hotspot of analog circuit fault diagnosis and have been widely used. H.Z. Hu et al. used wavelet packet transform to extract fault features, support vector machine to classify faults, and hybrid weed algorithm to optimize hyperparameters [3]. C.L. Zhang et al. used wavelet transform to extract fault features, generalized multi-core support vector machine to classify faults, and particle swarm optimization to optimize hyperparameters [4]. J. Zhu et al. used wavelet transform to extract fault features, principal component analysis to reduce the dimensionality of features, support vector machine to classify faults, and sine cosine algorithm to optimize hyperparameters [5]. J. Ma et al. used multi-resolution analysis to extract fault features, principal component analysis to reduce the dimensionality of features, back propagation algorithm to classify faults, and particle swarm algorithm to optimize neural network weights [6]. T. Zhong et al. used ensemble empirical mode decomposition to extract fault features, and deep belief network to classify faults [7]. J. Sun et al. used random projection algorithm to reduce the dimensionality of features, and Naive Bayes to classify faults [8]. W. He et al. used cross wavelet transform to extract fault features, local optimal guidance and integrated feature selection to obtain high-dimensional and low-dimensional features, and naive bayes to classify faults [9]. The analog circuit fault diagnosis methods based on machine learning can be divided into three steps: feature extraction, feature selection and classifier classification. Different methods are essentially looking for an optimal combination to make the final recognition rate the highest. These methods artificially cut the fault signal and the diagnosis result into many sub-modules, and each sub-module is learned separately, which leads to two major problems: one is that each module needs to be optimized separately, and the optimization goal and the overall goal cannot be guaranteed to be consistent; The second is error propagation. Errors in the previous step will have a great impact on subsequent modules.

In recent years, the emergence of deep learning has provided new ideas for analog circuit fault diagnosis. Deep learning is to obtain a feature representation through multi-step feature conversion from the original data features, and further input to the prediction function to obtain the final result. End-to-end learning refers to directly optimizing the overall goal of the task without sub-module training during the learning process. Most deep learning using neural network models is an end-to-end learning. H.H. Yang et al. used a one-dimensional convolutional neural network for analog circuit fault diagnosis [10]. A. Moezi et al. used Fourier transform to convert the fault signal into a spectrogram, and trained a convolutional neural network for fault diagnosis [11]. Y.X. Zhuang et al. used long and short-term memory networks to diagnose bearing faults [12]. Z.Z. Cao et al. used a combination of a one-dimensional convolutional neural network and a long- and short-term memory network for bearing fault diagnosis [13]. G.Q. Zhao et al. used deep confidence networks to diagnose faults in analog circuits [14]. Analog circuit fault diagnosis based on deep learning realizes end-to-end fault diagnosis and solves the problem of multiple modules based on machine learning methods. However, the use of convolutional neural networks alone ignores the time characteristics of the fault signal, and the use of long and short-term memory networks alone increases the training time of the model.

In summary, this article combines the advantages of convolutional neural networks with long-term short-term memory networks, and proposes an analog circuit fault diagnosis that first uses one-dimensional convolutional neural networks to extract fault features, and then uses long-term short-term memory networks to process timing features. The method is compared with mainstream analog circuit fault diagnosis methods to verify the superiority and effectiveness of the model.

2. Diagnostic Model of 1D-CNN-LSTM

2.1. CNN Model

Convolutional neural network (CNN) is a kind of deep feedforward neural network, which has the characteristics of local connection and weight sharing. These characteristics make it have a certain degree of translation, scaling and rotation invariance. Compared to feedforward neural networks, CNN has fewer parameters. It is widely used in image processing, video analysis, natural language processing and other fields [15].

Convolutional neural networks are generally composed of convolutional layers, pooling layers and fully connected layers. The function of the convolutional layer is to extract the features of a local area, and different convolution kernels are equivalent to different feature extractors. In order to calculate the output feature map, the convolution kernel is used to convolve the input feature map separately, and then the convolution results are added together, and a scalar bias is added to obtain the net input of the convolutional layer. The output feature map is obtained after the linear activation function.

$$Z^p = W^p \otimes X + b^p = \sum_{d=1}^{D} W^{p,d} \otimes X^d + b^p \tag{1}$$

$$Y^p = f(Z^p) \tag{2}$$

Where $W^p \in \mathbb{R}^{U \times V \times D}$ is a three-dimensional convolution kernel, and $f(\cdot)$ is a non-linear activation function. Generally, the ReLU function is used.

The role of the pooling layer is to perform feature selection and reduce the number of features, thereby reducing the number of parameters. Pooling refers to down-sampling each area to obtain a value as an overview of this area. There are two commonly used pooling functions. One is maximum pooling. For a region, the maximum activity value of all neurons in this region is selected as the representation of this region.

$$y_{m,n}^d = \max_{i \in R_{m,n}^d} x_i \tag{3}$$

Where x_i is the activity value of each neuron in area R_k^d . The other is average pooling, which generally takes the average value of all neuron activity values in the area.

$$y_{m,n}^d = \frac{1}{\left|R_{m,n}^d\right|} \sum_{i \in R_{m,n}^d} x_i \tag{4}$$

The fully connected layer is a traditional multi-layer perceptron that uses a softmax activation function in the output layer. The main function is to combine the previously extracted features to perform non-linear activation to output the probability distribution of each classification, and then perform classification.

$$p\left(y_j\right) = \frac{\exp\left(y_j\right)}{\sum_{k=1}^{m} \exp\left(y_k\right)} \tag{5}$$

Where $p(y_i)$ is the probability output of the neuron through the softmax function, $\exp(y)$ is the output value of the j neuron in the output layer, and m is the number of target classifications.

2.2. LSTM Model

Long short-term memory network (LSTM) is a variant of cyclic neural network, which can effectively solve the problem of gradient explosion or disappearance of simple cyclic neural network. LSTM network is very suitable for classification, processing and prediction based on time series data.The LSTM network has mainly improved two aspects: one is to introduce a new internal state, and the other is to introduce a gating mechanism, which are forget gate, input gate and output gate. The forget gate controls how much information needs to be forgotten in the internal state at the previous moment; the input gate controls how much information in the candidate state at the current moment needs to be saved; the output gate controls how much information in the internal state at the current moment needs to be output to the external state [15].

The cyclic unit structure of the LSTM network first uses the external state at the previous moment and the input at the current moment to calculate three gates and candidate states; then combines the forget gate and the input gate to update the memory unit; finally combines the input gate to change the internal The state information is passed to the external state.

$$\begin{bmatrix} \tilde{c}_t \\ o_t \\ i_t \\ f_t \end{bmatrix} = \begin{bmatrix} \tanh \\ \sigma \\ \sigma \\ \sigma \end{bmatrix} (W \begin{bmatrix} x_t \\ h_{t-1} \end{bmatrix} + b) \tag{6}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{7}$$

$$h_t = o_t \odot \tanh(c_t) \tag{8}$$

Where x_t is the input at the current moment, h_{t-1} is the external state at the previous moment, W and b are the weights and biases, o_t is the output gate, i_t is the input gate, f_t is the forget gate, $\tilde{c}_t$ is the candidate state, c_t is the memory unit, h_t is the external state.

3. Analog Circuit Fault Diagnosis Experiment

In order to verify the effectiveness of fault diagnosis of analog circuits based on 1D-CNN-LSTM, the experimental process shown in Fig. 1 is designed, which mainly includes three steps of fault signal acquisition, model building and performance comparison.

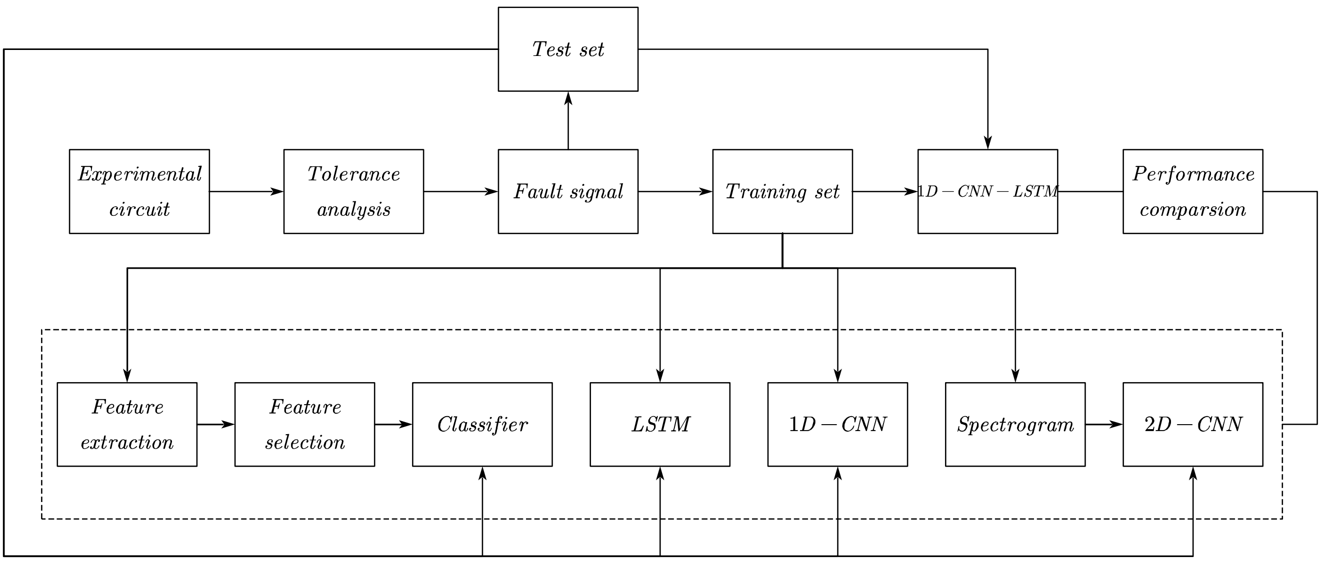

Fig. 1 Experimental process of analog circuit fault diagnosis

3.1. Collection of Fault Signals

The experiment uses a Sallen-Key low-pass filter circuit, and the circuit diagram is shown in Fig. 2. The resistance tolerance is ±5%, and the capacitance tolerance is ±10%. When the nominal value of the component deviates from the original value by 50%, the circuit has a soft fault, ↑ means a large component fault, and ↓ means a small component fault. Divide the circuit into normal state and 8 fault states. The specific settings are shown in Table 1.

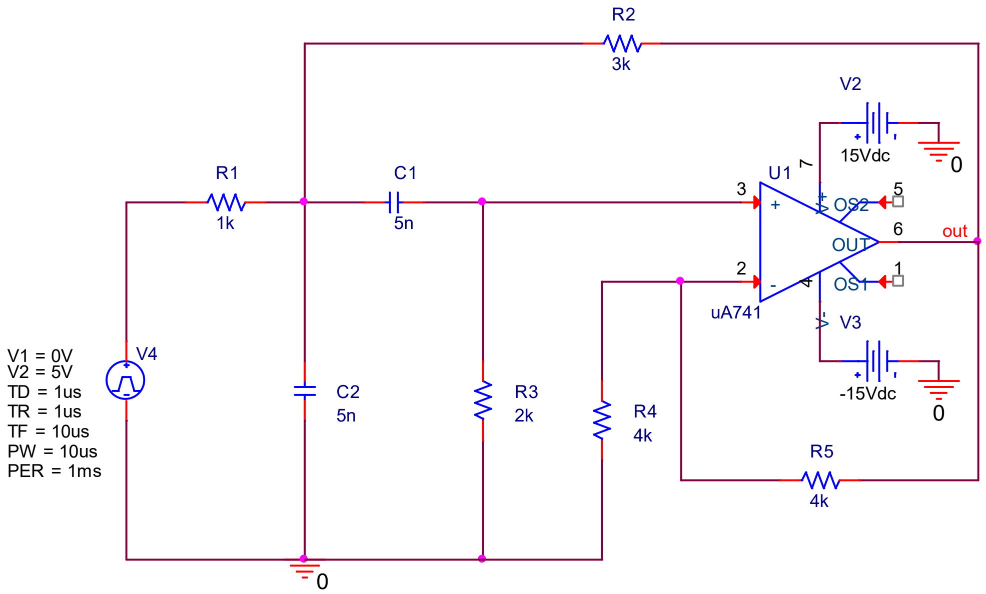

Fig. 2 Sallen-Key low-pass filter circuit

On the OrCAD 17.4 circuit simulation software, build an experimental circuit, input a pulse voltage, perform 100 Monte Carlo analysis on the faults set in Table 1, collect the output waveform within 120μs, and save it as a .csv fault signal file. There are a total of 900 samples in 9 failure states, 630 samples are randomly selected as the training set, and the remaining 270 samples are used as the test set.

Table 1. The fault setting table of the experimental circuit

Fault label	Fault type	Nominal value	Fault value
0	Normal	-	-
1	C_1 ↑	$5nF$	$7.5nF$
2	C_1 ↓	$5nF$	$2.5nF$
3	C_2 ↑	$5nF$	$7.5nF$
4	C_2 ↓	$5nF$	$2.5nF$
5	R_2 ↑	$3k\Omega$	$4.5k\Omega$
6	R_2 ↓	$3k\Omega$	$1.5k\Omega$
7	R_3 ↑	$2k\Omega$	$3k\Omega$
8	R_3 ↓	$2k\Omega$	$1k\Omega$

3.2. Model Building

The model structure of analog circuit fault diagnosis based on CNN-LSTM is shown in Fig. 3. The input layer is used to read the fault signal. In order to meet the input size requirements of the model, it is necessary to reshape the two-dimensional fault signal and convert it into a three-dimensional tensor. In addition, the classification label is mapped into a binary vector through one-hot encoding. The Conv1D layer extracts fault features through a series of one-dimensional convolution kernels, the filter in the convolution is 32, the length of the convolution window is 5, and the activation function selects the ReLU function. The MaxPooling1D layer is used to reduce the dimensionality of features, speed up the signal processing of the next layer, and also retain the timing characteristics of the data to ensure the accuracy of the model. The maximum pooling window size is 3. The LSTM layer extracts the timing features ignored by 1D-CNN through a series of operations of forget gate, input gate and output gate, and improves the accuracy of the model. The Flatten layer flattens the input and does not affect the batch size. The Dense layer is a fully connected layer, which outputs 9 types of fault classification results, and the activation function selects the Softmax function. Finally, the configuration of the training model is completed. Because of the multi-classification problem, the loss function selects the cross-entropy loss function, the gradient descent selects the Adam optimizer, and the learning rate is set to 0.001.

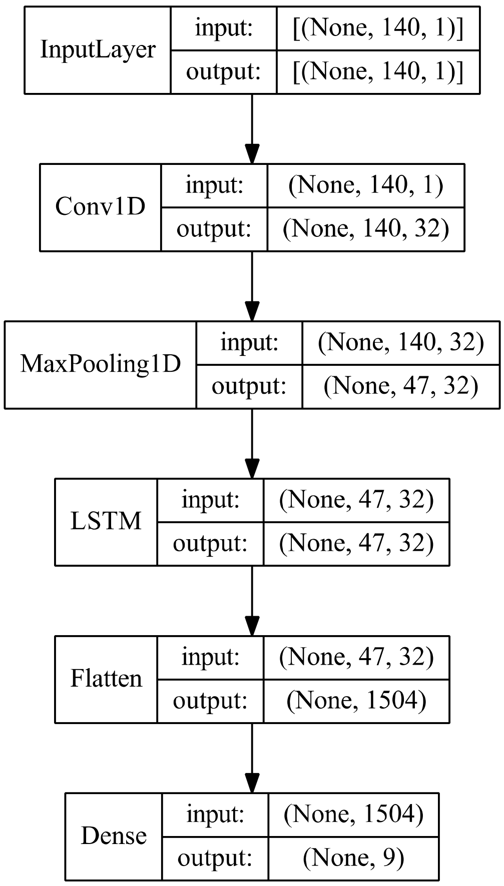

Fig. 3 Model structure diagram

3.3. Performance Comparison

The training loss and accuracy rate curve of the model is shown in Fig. 4. As the number of training iterations increases, the loss rate decreases, and the accuracy rate gradually rises and tends to stabilize. The model performs well.

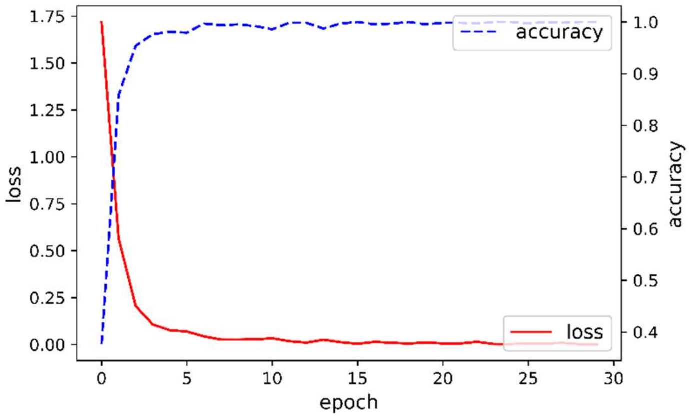

Fig. 4 Training loss and training accuracy

In order to verify the advantages of this model in analog circuit fault diagnosis, another five sets of comparative experiments were carried out using the same data set and different models. The results are shown in Table 2. Experiment 1 uses the 1D-CNN-LSTM model; Experiment 2 uses the LSTM model alone. It is found by comparison that the 1D-CNN-LSTM model has better performance in accuracy and training speed, which solves the problem of the long training time of the LSTM model; Experiment 3 uses the 1D-CNN model alone, and the comparison found that the accuracy of the combination of 1D-CNN and LSTM was improved; Experiment 4 converted the fault signal into a spectrogram, using the 2D-CNN model, but it took a lot of time to convert the fault signal into a spectrogram , And some features will be lost during the conversion process; Experiments 5 and 6 adopt mainstream models based on machine learning, feature extraction of fault signals through wavelet packet transform, principal component analysis for feature selection, SVM/BP for fault classification, and comparisons find the 1D-CNN-LSTM model solves two problems based on machine learning models: individual optimization and error delivery.

Table 2. Performance comparison results

Number	Diagnostic model	Training accuracy	Training time	Test accuracy
1	1D-CNN-LSTM	97.75%	22.29s	99.33%
2	LSTM	96.94%	95.02s	98.56%
3	1D-CNN	96.84%	20.11s	98.17%
4	2D-CNN	97.67%	30.56s	99.12%
5	SVM	96.69%	50.78s	98.34%
6	BP	95.96%	43.74s	97.93%

In summary, the 1D-CNN-LSTM combined model not only uses convolutional neural networks to extract and simplify fault features, but also uses long- and short-term memory networks to extract timing features, which improves the accuracy of fault diagnosis and shows the effectiveness and superiority of the model.

4. Conclusion

The analog circuit fault diagnosis based on 1D-CNN-LSTM not only solves the two major problems of separate optimization and error transmission of mainstream diagnosis methods based on machine learning, and realizes an end-to-end diagnosis method from fault signals directly to fault classification, but also compared with other end-to-end diagnosis methods, 1D-

CNN is introduced to extract fault features to facilitate the next operation, and LSTM is introduced to extract timing features, which improves the diagnosis accuracy of the model. Through the performance comparison experiments of different models, the effectiveness and superiority of this method for fault diagnosis are verified. However, compared with the single-fault diagnosis, the multi-fault diagnosis method has not been practiced, and how to realize the fault diagnosis without circuit diagram in the actual situation is also the direction of the next research.

Acknowledgments

The authors are grateful to the anonymous reviewers for their valuable comments and suggestions. This work was supported by Chongqing Normal University Fund Program [Program approval No. 21XLB032].

References

[1] G.S. Li, B. Ou, et al: Summary of the development of modern analog circuit fault diagnosis technology, Computer Measurement and Control, Vol. 27 (2019) No. 5, p. 5-8.

[2] D. Binu and B.S. Kariyappa: A survey on fault diagnosis of analog circuits: taxonomy and state of the art, International Journal of Electronics and Communications, Vol. 73 (2017), p. 68-83.

[3] H.Z. Hu, S.L. Tian, et al: The application of HIWO-SVM in analog circuit fault diagnosis, International Journal of Pattern Recognition and Artificial Intelligence, Vol. 29 (2015) No. 8, p. 1550019.1-1550019.27.

[4] C.L. Zhang, Y.G. He, et al: A novel approach for diagnosis of analog circuit fault by using GMKL-SVM and PSO, Journal of Electronic Testing, Vol. 32 (2016) No. 5, p. 531-540.

[5] J. Zhu, Y.Z. He, et al: Fault diagnosis of SVM analog circuit based on sine-cosine algorithm, Navigation and Control, Vol. 17 (2018) No. 4, p. 33-40.

[6] J. Ma, F.L. Zhao, et al: Research on fault diagnosis of analog circuits of MRA-PCA-PSO combination optimization BP neural network, Journal of Electronic Measurement and Instrument, Vol. 32 (2018) No. 3, p. 73-79.

[7] T. Zhong, J.F. Qu, et al: The intermittent fault diagnosis of analog circuits based on EEMD-DBN, Neurocomputing, Vol. 436 (2021), p. 74-91.

[8] J. Sun, G.B. Hu, et al: Fault diagnosis of analog circuit based on random projection and NB network, Journal of Instrumentation, Vol. 40 (2019) No.2, p. 105-112.

[9] W. He, Y.G. He, et al: Analog circuit fault diagnosis via joint cross-wavelet singular entropy and parametric t-SNE, Entropy, Vol. 20 (2018) No.8.

[10] H.H. Yang, C. Meng, et al: Data-driven feature extraction for analog circuit fault diagnosis using 1-D convolutional neural network, IEEE Access, Vol. 8 (2020), p. 18305-18315.

[11] A. Moezi and S.M. Kargar: Simultaneous fault localization and detection of analog circuits using deep learning approach, Computers and Electrical Engineering, Vol. 92 (2021)

[12] Y.X. Zhuang, Q. Li, et al: End-to-end method of bearing fault diagnosis based on LSTM, Noise and Vibration Control, Vol. 39 (2019) No. 6, p. 187-193.

[13] Z.Z. Cao and C.M. Ye: Application of improved CNN-LSTM model in fault diagnosis of rolling bearings, Computer System Application, Vol. 30 (2021) No. 3, p. 126-133.

[14] G.Q. Zhao, X.Y. Liu, et al: A novel approach for analog circuit fault diagnosis based on deep belief network, Measurement, Vol. 121 (2018), p. 170-178.

[15] X.P. Qiu: Neural Network and Deep Learning (China Machine Press, China 2020).