Fault Diagnosis for Wind Turbine Flange Bolts Based on One-Dimensional Depthwise Separable Convolutions

Yongchao Liu, Shuqing Dong, Qingfeng Wang, Wenhe Cai, Ruizhuo Song, and Qinglai Wei

***Abstract*—In this paper, a new bolt fault diagnosis method is developed to solve the fault diagnosis problem of wind turbine flange bolts using one-dimensional depthwise separable convolutions. The main idea is to use a one-dimensional convolutional neural network model to classify and identify the acoustic vibration signals of bolts, which represent different bolt damage states. Through the methods of knock test and modal simulation, it is concluded that the damage state of wind turbine flange bolt is related to the natural frequency distribution of acoustic vibration signal. It is found that the bolt damage state affects the modal shape of the structure, and then affects the natural frequency distribution of the bolt vibration signal. Therefore, the damage state can be obtained by identifying the natural frequency distribution of the bolt acoustic vibration signal. In the present one-dimensional depth-detachable convolutional neural network model, the one-dimensional vector is first convolved into multiple channels, and then each channel is separately learned by depth-detachable convolution, which can effectively improve the feature quality and the effect of data classification. From the perspective of the realization mechanism of convolution operation, the depthwise separable convolution operation has fewer parameters and faster computing speed, making it easier to build lightweight models and deploy them to mobile devices.**

***Index Terms*—Wind turbine flange bolts, one-dimensional convolutional neural network (1DCNN) model, depthwise separable convolutions, damage identification**

I. INTRODUCTION

In the past few years, clean energy technology is developing rapidly. Clean energy plays an important role in protecting the environment, which is widely accepted by countries around the world. As a typical kind of clean energy, wind power is a new force in the development of new energy [1, 2]. With the increase of wind turbine installation, metal supervision and detection technology of key components of wind turbine cannot be ignored. The operating environment of wind turbine has variable wind load and large temperature difference between day and night [3, 4]. The flange bolts of wind turbine are prone to fatigue crack [5]. Once the wind turbine flange bolts reach a certain degree of damage, it is easy to cause the risk of wind turbine tower collapse, which may lead to significant economic loss and social impact. Therefore, timely detection of wind turbine flange bolt damage state is of great significance to ensure the safe operation of the unit. Because of the characteristics of wind turbines, it is inconvenient to use complex testing equipment, and thus it is quite necessary to perform rapid, accurate, and reliable detection on the bolt of wind turbine flange.

Deep learning model is widely used in the field of fault diagnosis, but there are few studies on the identification of damage state of wind turbine flange bolts. In particular, the deep learning classification based on bolt tapping sound signal is less common. Using knock signal is mainly to consider the rapidity of bolt damage state detection. The echo signal is generated by hammering the bolt at the maintenance site of wind turbine. The acoustical signal contains the characteristics of bolt damage state. Then the damage state is classified and identified by deep learning method. A damage identification method for wind turbine flange bolts based on deep learning is proposed. Our contributions in this paper include:

(1) The echo signal characteristics of wind turbine flange bolt percussion are analyzed, and the relationship between the signal characteristics and bolt damage state is analyzed by the empirical mode decomposition (EMD) method.

(2) In order to improve the efficiency of the deep learning algorithm, one-dimensional convolutional neural network (1DCNN) [6–9] adaptively learns the characteristic information of the damage state from the one-dimensional spectrum signal, and then performs classification and recognition.

(3) On the basis of 1DCNN, the depth separable convolution is adopted to further reduce the number of model parameters and the amount of computation, so as to build a more portable classification model, which provides a basis for

Manuscript received: 9 November 2023; revised: 29 January 2024; accepted: 15 February 2024. *(Corresponding authors: Yongchao Liu and Qinglai Wei.)*

Citation: Y. Liu, S. Dong, Q. Wang, W. Cai, R. Song, and Q. Wei, Fault diagnosis for wind turbine flange bolts based on one-dimensional depthwise separable convolutions, *IJICS*, 2024, 29(1), 42–47.

Yongchao Liu, Shuqing Dong, Qingfeng Wang, and Wenhe Cai are with North China Electric Power Test and Research Institute, China Datang Corporation Science and Technology Research Institute Company Limited, Beijing 100040, China (e-mail: liuyongchao2020@ia.ac.cn; dongshuqing@cdt-kxjs.com; wangqingfeng@cdt-kxjs.com; caiwenhe@cdt-kxjs.com).

Ruizhuo Song is with School of Automation and Electrical Engineering, University of Science and Technology Beijing, Beijing 100083, China (e-mail: ruizhuosong@ustb.edu.cn).

Qinglai Wei is with School of Artificial Intelligence, University of Chinese Academy of Sciences, Beijing 100040, China, with State Key Laboratory of Management and Control for Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing 100190, China, and with Institute of Systems Engineering, Macau University of Science and Technology, Macao 999078, China (e-mail: qinglai.wei@ia.ac.cn).

Digital Object Identifier 10.62678/IJICS202403.10111

the subsequent deployment of classification model on mobile devices.

II. Signal Analysis

In this section, the relationship between bolt damage state and vibration sound signal is explored by bolt knock test and modal simulation test. The bolt knock test is carried out by using real wind power flange bolts, and the simulation test is based on real wind power flange bolts for modeling and modal calculation.

Wind turbine flange bolts and percussion acquisition equipment are shown in Fig. 1. Sound signals are generated by striking bolts with a force hammer and picked up by a directional microphone. The audio length is 0.5–1.0 s and contains one tap echo signal.

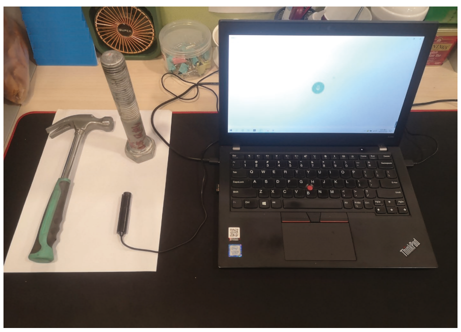


Figure 1 Test equipment.

We prepare seven types of bolts with the same specification as M30 × 200 mm, where the bolts contain grooves with depths of 0.0, 1.0, 1.5, 2.0, 5.0, 10.0, and 15.0 mm, respectively. The width of grooves is the same as 0.5 mm. The bolts with grooves are shown in Fig. 2. According to the fast Fourier transform (FFT) of bolt sound signal, it is found that the frequency spectra of bolt audio signals with different grooves are different.

Figure 2 Seven kinds of test blocks for wind power flange bolts.

III. 1DCNN Classification Method

According to the relationship between bolt knocking signal and bolt damage state, in this section a lightweight 1DCNN model to classify and identify bolt state will be designed. The frequency value of bolt vibration signal is taken as the one-dimensional input of the model, and the damage state of various bolts is taken as the output of the model. In addition, this paper refers to the characteristics of Google lightweight model MobileNet, and changes the standard convolution layer into depth-level separable convolution, which further reduces the computation of the model.

A. Input Data

The original audio signal is transformed by FFT to obtain a one-dimensional frequency array. The index of the array is aligned with the real frequency value through data processing operations. Thus, the index of the one-dimensional vector represents the signal frequency, and the value of the vector represents the amplitude of the signal frequency. The one-dimensional vector contains the characteristic information of the entire spectrum. Compared with two-dimensional matrix, one-dimensional vector input can greatly reduce the number of model parameters and calculation. Then, seven types of bolt samples are knocked to collect echo signals. On average, each type of data sample contains 1000 tapping sounds. A single tap sound signal is input as a model sample. The sample size of model training set and test set is divided as shown in Table 1.

Table 1 1DCNN model dataset.

Depth of slotted bolt (mm)	Total sample size (piece)	Training sample size (piece)	Testing sample size (piece)
0.0	1000	800	200
1.0	1000	800	200
1.5	1000	800	200
2.0	1000	800	200
5.0	1000	800	200
10.0	1000	800	200
15.0	1000	800	200

B. 1DCNN Model

Convolutional neural network (CNN) [10] refers to that at least one layer of the network uses convolutional operations. Convolutional operation is a special linear operation. Each layer of convolutional network usually includes convolutional layer, activation layer, and pooling layer. The input of one-dimensional convolutional neural network is one-dimensional data. The output layer, activation layer, and pooling layer of each convolution also correspond to one-dimensional feature vectors. The convolution kernel also adopts one-dimensional structure. This section will design such a 1DCNN model.

The main function of convolution layer is to extract local features. The corresponding feature map is obtained by convolution operation between convolution kernel and one-dimensional vector. The convolution kernel is like a filter. After the original input is filtered by multi-layer filter, useful features are enhanced and noise interference is reduced. The principle of convolution is shown as

$$x_k^l = \sum_{i=1}^{n} \mathrm{conv}(w_{i,k}^{l-1}, s_i^{l-1}) + b_k^g \tag{1}$$

where x_k^l represents the output of the k-th neuron in layer l and s_i^{l-1} represents the output of the i-th neuron in layer $l-1$. $l = 1,2,\dots$ is the number of the layers of the network. $w_{i,k}^{l-1}$

represents the convolution kernel of the i-th neuron in layer $l-1$ and the k-th neuron in layer l, and n indicates the number of neurons in layer $l-1$. conv$(\cdot)$ represents the convolution operation. b_k^g represents the hyperparameter of the k-th neuron in layer g.

By setting the number of channels in the convolutional layer, the input signal can be raised or lowered to improve the ability of feature representation. The hyperparameters of 1DCNN model are shown in Table 2.

Table 2 1DCNN model hyperparameters.

Number of layer	Structure type	Hyperparameter
1	Convolutional layer 1	Kernel size is 64, filters are 16
2	Activation layer 1	Rectified linear unit
3	Pooling layer 1	Max-pooling
4	Convolutional layer 2	Kernel size is 3, filters are 32
5	BatchNorm layer 1	Batch normalization
6	Activation layer 2	Rectified linear unit
7	Pooling layer 2	Max-pooling
8	Dropout layer 1	Discard rate is 0.5
9	Convolutional layer 3	Kernel size is 7, filters are 32
10	BatchNorm layer 2	Batch normalization
11	Activation layer 3	Rectified linear unit
12	Pooling layer 3	Max-pooling
13	Dropout layer 2	Discard rate is 0.5
14	Convolutional layer 4	Kernel size is 7, filters are 16
15	BatchNorm layer 3	Batch normalization
16	Activation layer 4	Rectified linear unit
17	Pooling layer 4	Max-pooling
18	Dropout layer 3	Discard rate is 0.3
19	Flatten layer 1	—
20	Fully connected layer 1	Number of neurons is 32
21	Activation layer 5	Rectified linear unit
22	Fully connected layer 2	Number of neurons is 7
23	Activation layer 6	Softmax

C. 1DCNN-Depthwise Separable Convolution

In order to reduce the number of parameters and computation, a new CNN structure is developed, where the standard convolution layer is replaced by the depth separable convolution layer. Depthwise separable convolution is a convolution operation proposed in Xception framework [11]. When the number of the available data is small, depthwise separable convolution separately convolves the features of each channel to improve the data utilization efficiency. The design requires fewer computations to be performed and results in smaller models [12]. Except for replacing the convolution layer in the original 1DCNN model, the other layers are not changed. The structure of the improved 1DCNN model is shown in Fig. 3, and the hyperparameters are shown in Table 3.

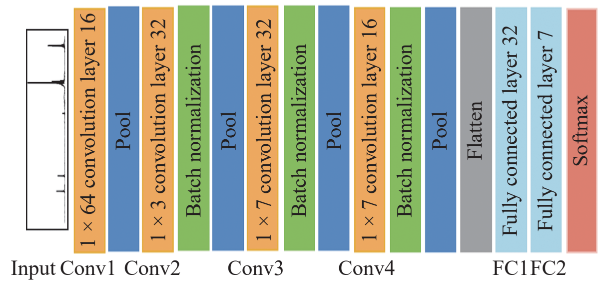


Figure 3 Structure of improved 1DCNN model. The convolution layer is abbreviated as Conv and fully connected layer is abbreviated as FC.

Table 3 1DCNN-depthwise separable convolution model hyperparameters.

Number of layer	Structure type	Hyperparameter
1	Convolutional layer 1	Kernel size is 64, filters are 16
2	Activation layer 1	Rectified linear unit
3	Pooling layer 1	Max-pooling
4	Depthwise convolutional layer 1	Kernel size is 3, filters are 16
5	BatchNorm layer 1	Batch normalization
6	Activation layer 2	Rectified linear unit
7	Pooling layer 2	Max-pooling
8	Dropout layer 1	Discard rate is 0.5
9	Pointwise convolutional layer 1	Kernel size is 1, filters are 32
10	BatchNorm layer 2	Batch normalization
11	Activation layer 3	Rectified linear unit
12	Pooling layer 3	Max-pooling
13	Dropout layer 2	Discard rate is 0.5
14	Convolutional layer 2	Kernel size is 7, filters are 16
15	BatchNorm layer 3	Batch normalization
16	Activation layer 4	Rectified linear unit
17	Pooling layer 4	Max-pooling
18	Dropout layer 3	Discard rate is 0.3
19	Flatten layer 1	—
20	Fully connected layer 1	Number of neurons is 32
21	Activation layer 5	Rectified linear unit
22	Fully connected layer 2	Number of neurons is 7
23	Activation layer 6	Softmax

IV. Case Study

The 1DCNN model and the improved 1DCNN model are built according to the real bolt acoustic signal dataset, and the numbers of parameters of the two models are compared. In addition, the evaluation indices of the two models are also defined.

A. Data Illustration

The percussive sound signal of each type of bolt sample is processed by FFT. The converted one-dimensional frequency vector is used as the model input. There are seven types of bolt samples with groove depths of 0.0, 1.0, 1.5, 2.0, 5.0, 10.0, and 15.0 mm, respectively. Each class contains 1000 input samples, including 800 as training sets and 200 as verification sets. In addition, additional percussion audio signals of defect bolt samples are added to verify the predictive ability of the model. The additional audio samples are obtained from three categories of bolts with defects of 3, 5, and 10 mm, respectively. Each category contains 100 sound samples.

Since the frequency related to the bolt damage state is mainly concentrated in the low frequency part, the data of the one-dimensional frequency vector from 0 to 9000 Hz are intercepted. In addition, each input vector is normalized to avoid the influence of large value data. The normalization processing is shown as

$$y = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{2}$$

where y is the result of normalization processing, X is the input signal, and $X_{\max}$ and $X_{\min}$ are the maximum and minimum values of the input signal, respectively.

B. 1DCNN Model Parameter Setting

The structure of 1DCNN model for bolt damage classification and recognition proposed in this paper is shown in Table 3. The model first raises the dimension of one-dimensional frequency vector by convolution operation. Then feature extraction is completed through three-layer convolution, activation, and pooling. Finally, the classification is completed by a two-layer fully connected neural network. The original input of the neural network is normalized as one-dimensional frequency vector, which is expressed as (7000, 9000), where 7000 is the total number of sound samples of seven types of bolt samples and 9000 is the length of the one-dimensional frequency vector. The output of the model has seven types of one-hot encoding, representing seven types of bolt samples respectively. The total parameter quantity of the 1DCNN model is 302,247, among which the number of trainable parameters is 302,087.

C. Improved Model Parameter Setting

In the improved model, the total parameter quantity is 294,151, among which the number of trainable parameters is 294,087. Compared with the previous model, the number of parameters is reduced by 8096. In addition, since the convolution operation is generally implemented through image to column (IM2COL), memory reorganization is required [13]. When the convolution kernel is 1×1, there is no need for this operation, and the calculation can be achieved faster. Thus, the pointwise convolution layer can improve the computational speed.

D. Loss Function

Loss function is used to estimate the degree of inconsistency between the predicted value $F(x)$ and the real value Y of the model. It is a non-negative real value function and is usually represented by $L(Y, F(x))$. The smaller the loss function is, the better the robustness of model will be. The cross entropy loss function is used in this paper. It is a loss function often used in classification problems. The calculation principle of cross entropy loss function L is shown as

$$L = -\sum_{m=1}^{K} y_m \log_2(p_m) \tag{3}$$

where K is the number of species and y_m is the label, $y_m = 1$ if the category is 1, while $y_m = 0$ for other cases. Let p_m be the output of the neural network, which is the probability of category m. This output value is calculated using softmax mentioned.

E. Evaluation Standard

Common evaluation indices of convolutional neural networks include precision (*P*), recall (*R*), accuracy (Acc), and F1 score (F1). The overall performance of the model is measured by accuracy and F1. The higher the indices are, the better the classification and recognition abilities of the model are [14]. Precision is the proportion of samples that the system determines to be "true" that are actually true. Recall refers to the proportion of truly true samples deemed to be "true". The calculation equations of the four evaluation indicators are shown as

$$P = \frac{T_{\mathrm{P}}}{T_{\mathrm{P}} + F_{\mathrm{P}}} \tag{4}$$

$$R = \frac{T_{\mathrm{P}}}{T_{\mathrm{P}} + F_{\mathrm{N}}} \tag{5}$$

$$\mathrm{Acc} = \frac{T_{\mathrm{P}} + T_{\mathrm{N}}}{T_{\mathrm{P}} + F_{\mathrm{P}} + F_{\mathrm{N}} + T_{\mathrm{N}}} \tag{6}$$

$$\mathrm{F1} = \frac{1}{\frac{1}{P} + \frac{1}{R}} = \frac{2 \times P \times R}{P + R} \tag{7}$$

where T_{P} is the number of positive samples predicted to be positive by the model, and T_{N} is the negative sample number predicted by the model to be negative. Let F_{P} be the number of negative samples predicted to be positive by the model, and F_{N} is the number of positive samples predicted to be negative by the model. According to the maintenance characteristics of wind turbine flange bolts, the detection and identification should avoid missing bolts with defects. This paper pays more attention to recall evaluation index.

V. Result and Analysis

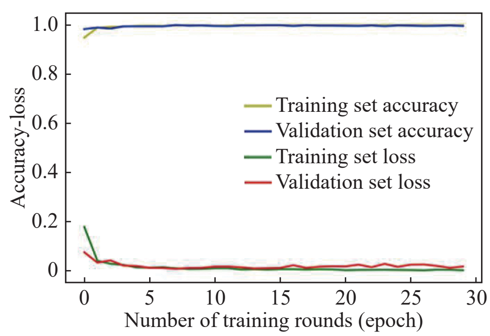
In this section, the two models are tested with different optimizers on the real bolt acoustic signal dataset, and the identification effects of each model on bolt damage state are compared.

After the model structure is determined, the optimization algorithm plays an important role in parameter updating. The goal of deep learning is to constantly change network parameters so that the parameters can perform various nonlinear transformations on the input to fit the output, which is essentially a function to find the optimal solution. The function of the optimizer is to update the parameters with the optimization algorithm so that the function can find the optimal solution. At present, the commonly used optimizers are stochastic gradient descent (SGD), Adam, Adagrad, Adadelta, RMSprop, and so on. This study will compare different optimizers to find the best one. Different optimizers are used to train the model, and the test results are shown in Table 4.

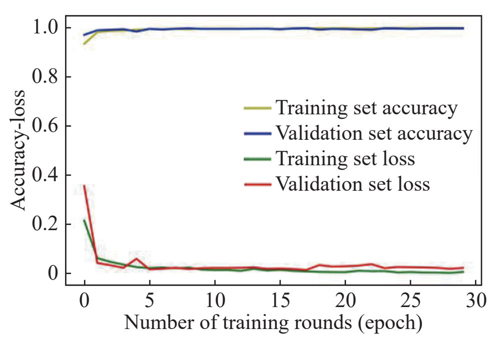
In Table 4, Acc, P, R, and F1 represent accuracy, precision, recall, and F1 score of the test set, respectively. In Table 4, the model trained by SGD or RMSprop has the highest recall rate, while that trained by Adadelta has the lowest recall rate. Here, the RMSprop optimizer is used to train the proposed classification model of flange bolt damage state of wind turbine, and the results are more accurate and effective. The accuracy-loss curves of the two models trained by RMSprop optimizer are shown in Fig. 4.

Table 4 Comparison result of different optimizers.

Model	Optimizer	Acc (%)	P (%)	R (%)	F1 (%)	Arithmetic speed (ms/sample)
1DCNN	SGD	99.50	99.50	99.50	99.50	20
	Adam	99.64	99.72	99.64	99.68	20
	RMSprop	99.72	99.72	99.72	99.72	20
	Adadelta	96.14	96.14	96.14	99.50	21
	Adagrad	99.93	99.93	99.93	99.93	20
Improved 1DCNN	SGD	99.71	99.72	99.72	99.72	12
	Adam	99.64	99.64	99.57	99.61	12
	RMSprop	99.71	99.72	99.72	99.72	12
	Adadelta	92.43	99.40	49.22	64.87	12
	Adagrad	99.29	99.36	99.08	99.21	14



(a) 1DCNN model



(b) Improved 1DCNN model

Figure 4 Accuracy-loss curve by RMSprop.

The abscissa of the Fig. 4 represents the number of training rounds, and the ordinate represents the values of accuracy and loss.

VI. Conclusion

Studies have found that bolt damage state is related to the natural frequency of vibration sound. Therefore, a one-dimensional convolutional neural network model is proposed based on the relationship between bolt audio signal and damage state, whose input is a one-dimensional frequency vector. The designed model has four convolution layers and the output is seven kinds of bolt damage states. It is found that the highest recall rate of 1DCNN model on the test set reaches 99.93%, which meets the demand of industrial testing. In addition, the 1DCNN model is improved by replacing the standard convolution layer with the depthwise separable convolution layer. The recall rates of the two models are similar, but the training speed of the improved model is twice that of the original model. The 1DCNN model of depthwise sparable convolution is more likely to be deployed later on to mobile devices.

Acknowledgment

This work was supported in part by the National Key R&D Program of China (Nos. 2021YFE0206100 and 2018YFB1702300), the National Natural Science Foundation of China (No. 62073321), the National Defense Basic Scientific Research Program (No. JCKY2019203C029), and the Science and Technology Development Fund, Macao SAR (No. 0015/2020/AMJ).

References

[1] W. J. Li, Y. G. Liu, H. J. Liang, and Y. J. Shen, A new distributed energy management strategy for smart grid with stochastic wind power, *IEEE Trans. Ind. Electron*., 2021, 68(2), 1311–1321.

[2] Q. Zhang, The current state, problems and development strategies of the wind power industry in the three northeast provinces of China, in *Proc. 2010 World Non-Grid-Connected Wind Power and Energy Conference*, Nanjing, China, 2010, 1–5.

[3] X. Lyu and T. Liu, Intelligent learning based active power regulation of wind turbines considering fatigue reduction, *IEEE Trans. Ind. Inf*., 2022, 18(1), 405–414.

[4] S. Cascianelli, D. Astolfi, F. Castellani, R. Cucchiara, and M. L. Fravolini, Wind turbine power curve monitoring based on environmental and operational data, *IEEE Trans. Ind. Inf*., 2022, 18(8), 5209−5218.

[5] Z. L. Yu, P. W. Sun, and D. Wang, Fatigue life prediction for flange connecting bolts of wind turbine tower, *J. Shanghai Jiaotong Univ. (Sci.)*, 2020, 25(4), 526–530.

[6] H. Wang, Z. L. Liu, D. D. Peng, and Y. Qin, Understanding and learning discriminant features based on multiattention 1DCNN for wheelset bearing fault diagnosis, *IEEE Trans. Ind. Inf*., 2020, 16(9), 5735–5745.

[7] G. Q. Jiang, H. B. He, J. Yan, and P. Xie, Multiscale convolutional neural networks for fault diagnosis of wind turbine gearbox, *IEEE Trans. Ind. Electron*., 2019, 66(4), 3196–3207.

[8] L. Wen, X. Y. Li, L. Gao, and Y. Y. Zhang, A new convolutional neural network-based data-driven fault diagnosis method, *IEEE Trans. Ind. Electron*., 2018, 65(7), 5990–5998.

[9] T. Ince, S. Kiranyaz, L. Eren, M. Askar, and M. Gabbouj, Real-time motor fault detection by 1-D convolutional neural networks, *IEEE Trans. Ind. Electron*., 2016, 63(11), 7067–7075.

[10] H. D. Shao, H. K. Jiang, H. Z. Zhang, and T. C. Liang, Electric locomotive bearing fault diagnosis using a novel convolutional deep belief network, *IEEE Trans. Ind. Electron*., 2018, 65(3), 2727–2736.

[11] F. Chollet, Xception: Deep learning with depthwise separable convolutions, in *Proc. 2017 IEEE Conference on Computer Vision and Pattern Recognition* (*CVPR*), Honolulu, HI, USA, 2017, 1800–1807.

[12] N I. N. Junejo and N. Ahmed, Depthwise separable convolutional neural networks for pedestrian attribute recognition, *SN Comput. Sci*., 2021, 2(2), 100.

[13] K. Chellapilla, S. Puri, and P. Simard, High performance convolutional neural networks for document processing, in *Proc. 10th International Workshop on Frontiers in Handwriting Recognition*, La Baule, France, 2006.

[14] X. L. Zhang, P. Han, L. Xu, F. Zhang, Y. P. Wang, and L. Gao, Research on bearing fault diagnosis of wind turbine gearbox based on 1DCNN-PSO-SVM, *IEEE Access*, 2020, 8, 192248–192258.

Yongchao Liu received the MS degree from University of Chinese Academy of Sciences, China, in 2023. He is currently an engineer at North China Electric Power Test and Research Institute, China Datang Corporation Science and Technology Research Institute Company Limited, Beijing, China. His research interests include the inspection of metal supervisory parts of electric power industry and intelligent research of nondestructive testing methods.

Shuqing Dong received the MS degree from Southeast University, China, in 2011. He is currently the chief engineer, senior engineer, and master at North China Electric Power Test and Research Institute, China Datang Corporation Science and Technology Research Institute Company Limited, Beijing, China. His research interests include material performance evaluation, accident investigation and analysis, and new process and new method research.

Qingfeng Wang received the PhD degree from Beijing University of Technology, China, in 2014. He is currently the chief engineer, senior engineer, and master at North China Electric Power Test and Research Institute, China Datang Corporation Science and Technology Research Institute Company Limited, Beijing, China. His research interests include material performance evaluation, accident investigation and analysis, and new process and new method research.

Wenhe Cai received the MS degree from Tsinghua University, China, in 1989. He is currently the chief expert, vice president, senior engineer, and master at North China Electric Power Test and Research Institute, China Datang Corporation Science and Technology Research Institute Company Limited, Beijing, China. His research interests include power industry metal supervision parts inspection, accident failure analysis, supervision, safety performance inspection, material identification, technical supervision, equipment life research and evaluation, technical training, new technology promotion, and other works.

Ruizhuo Song received the PhD degree in control theory and control engineering from Northeastern University, Shenyang, China, in 2012. She was a postdoctoral fellow at University of Science and Technology Beijing, Beijing, China, in 2014. She was a visiting scholar at Department of Electrical Engineering, University of Texas at Arlington, Arlington, TX, USA, from 2013 to 2014, and at Department of Electrical, Computer, and Biomedical Engineering, University of Rhode Island, Kingston, RI, USA, in 2018. She is currently an associate professor at School of Automation and Electrical Engineering, University of Science and Technology Beijing, Beijing, China. She has published over 40 journal and conference papers, and coauthored two monographs. Her research interests include optimal control, multiplayer games, neural networks based control, nonlinear control, wireless sensor networks, and adaptive dynamic programming and their industrial applications.

Qinglai Wei received the BS degree in automation and the PhD degree in control theory and control engineering from Northeastern University, Shenyang, China, in 2002 and 2009, respectively. From 2009 to 2011, he was a postdoctoral fellow at State Key Laboratory of Management and Control for Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing, China. He is currently a professor and the associate director at State Key Laboratory of Management and Control for Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing, China. He has authored four books, and published over 80 international journal papers. His research interests include adaptive dynamic programming, neural networks based control, optimal control, and nonlinear systems and their industrial applications.