International Core Journal of Engineering Volume 7 Issue 3, 2021
ISSN: 2414-1895 DOI: 10.6919/ICJE.202103_7(3).0033

Prediction of Icing Fault of Wind Turbine Blades Based on DCGAN-CNN

Dengfeng Li, Xixia Huang and Enjie Wu

Marine Technology & Control Engineering Key Laboratory, Shanghai Maritime University, Shanghai, 201306, China.

Abstract

Wind power is widely used as a new type of energy. In view of the impact of the imbalance of normal sample and fault sample data on the accuracy of the model in the operation of the wind turbine, from the perspective of the fault sample, the deep convolution generation adversarial network (DCGAN) is used to expand the fault sample data to form a new balanced data set. Data feature construction obtains new variables, enriches feature dimension information, and uses convolutional neural network to achieve adaptive extraction of fault features. The extracted features are classified by the top-level softmax classifier to obtain the prediction results, thereby establishing a DCGAN-CNN-based Prediction model to complete the icing prediction of the wind turbine. Use the wind turbine data collected by the SCADA system to train and test the model. The experimental results show that the test accuracy of the model reaches 97.5%, which is better than the model trained on the sample set without data enhancement. At the same time, compared with other balanced data methods, the time of the balanced data set obtained by DCGAN and the accuracy of the trained model are both have a significant improvement.

Keywords

Ice Forecast; Deep Convolution Generates Adversarial Network; Random Forest; Convolutional Neural Network.

1. Introduction

Wind power generation is clean, environmentally friendly, and a renewable energy technology with the greatest potential for modern commercialization [1]. The distribution of wind resources in our country presents a typical geographical feature of "more in the north and less in the south". In order to make full use of wind resources, the wind turbines in the north are often built in areas with high altitudes. It is more troublesome to maintain [2].Therefore, it is particularly important to predict the failure of the fan. At present, the methods of establishing fault prediction models based on data mining modeling methods are widely used, but most of the time during the operation of the wind turbine is in a normal state, which causes the problem of imbalance between normal data and fault data.Aiming at the problem of data imbalance, literature [3-4] also uses resampling to reduce normal data, making the ratio of icing data to normal data close to 1:1. Literature [5] et al. proposed an improved comprehensive minority sampling technique SMOTE, the combination of oversampling the minority class and undersampling the majority class can achieve better data balance. Literature [6] proposed a new hybrid preprocessing method to edit unbalanced data. The algorithm first proposes a method of re-sampling training data (SMOTE) using a synthetic minority oversampling technique, and then implements an editing technique to balance the training set based on fuzzy rough set theory. Literature [7] uses a denoising autoencoder (DAE) for automatic enhancement The input data of the method

ISSN: 2414-1895 DOI: 10.6919/ICJE.202103_7(3).0033

first undergoes segmentation and normalization steps. The DAE with a single hidden layer feed forward network is used to encode new data.

However, the data enhancement method using over-sampling technology is only a simple repetition of a small number of samples, so it will overemphasize the existing few samples, which causes a small number of samples to overfit; under-sampling technology discards most of the majority of samples, thereby weakening the influence of some of the samples may cause model deviation; the SMOTE-based method is not simply repeating the positive example, but generating a new few samples through K-nearest neighbors in a local area, but for data with large amounts of data, computational complexity The increase will increase some "noise" at the same time, which will affect the accuracy of the model; using the data enhancement technology of the encoder based on deep learning, it is difficult to guarantee the authenticity of the generated samples when the hidden layer vector distribution is unknown during the encoding and decoding process. The generative adversarial network was proposed by Goodfellow [8] in 2014, allowing the creation of new data sets based on a small amount of available data. Through the adversarial learning of generators and discriminators, the generated data is closer to the original data, and it has been used in many ways. Literature [9-10] applies GAN to the field of image generation, and has achieved good results in both multispectral images and medical images; Literature [11-12] applies GAN to the classification of aquatic products and pearls, and increases by generating pictures The sample set, the trained model has a significant improvement in classification accuracy.

Aiming at the problem of the imbalance between normal wind data and icing data, this paper introduces the generation of confrontation network into industrial data, uses deep convolution to generate confrontation network from the perspective of fault samples, performs data enhancement, obtains a balanced data set, and establish a predictive model of convolutional neural network to realize adaptive extraction of fault features and completes the prediction of icing of the wind turbine blades.

2. Related theories

2.1 Deep Convolutional Generative Adversarial Network (DCGAN)

Generative Adversarial Network (GAN) is a deep learning model. The structure diagram is shown in Figure 1. The model learns through the mutual game of G (generative model) and D (discriminatory model) to obtain data similar to real samples. The objective function of generating the confrontation network is:

$$\min_{G}\max_{D} V(D,G) = E_{x\sim P_{data(x)}}[\log D(x)] + E_{z\sim P_{G(z)}}[\log(1-D(G(z)))] \tag{1}$$

Where $x \sim P_{data(x)}$ comes from real data, $z \sim P_{G(z)}$ comes from generated data

Therefore, when optimizing the discriminator, it needs to be maximized $V(D,G)$, and when optimizing the generator, it needs to minimized $V(D,G)$. The formula is as follows:

$$D^* = \arg\max_{D} V(G,D) \tag{2}$$

$$G^* = \arg\min_{G} V(G,D) \tag{3}$$

DCGAN is a generative model obtained by combining CNN and GAN. Its principle is similar to traditional GAN, except that CNN is used in the generator and discriminator part to replace the Multilayer perceptron. Due to the characteristics of convolution, the network can extract better at the same time, because of the existence of convolution, the original real data needs to be converted into an "image" format, which will be introduced later in this article. The improvements of DCGAN are as follows:

1) Use convolutional neural network instead of multilayer perceptron to better extract features.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202103_7(3).0033

2) Use convolutional layer and deconvolution instead of pooling layer, and use convolution instead of fully connected layer.

3) Join the BN (batch normalization) layer to normalize the output of the feature layer together to improve the training speed.

4) Use leakrelu activation function in the discriminator instead of RELU to prevent gradient sparseness. Relu is still used in the generator, but tanh is used in the output layer

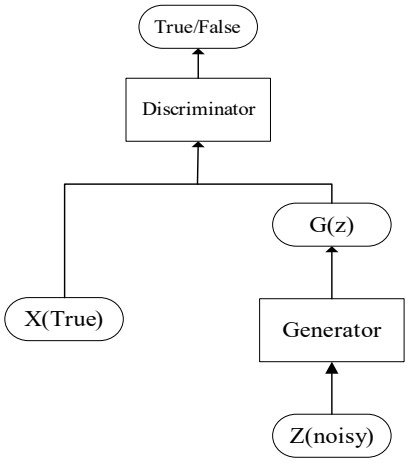

Figure 1. The schematic diagram of GAN

2.2 Convolutional Neural Network

Convolutional neural network is a kind of feedforward neural network that includes convolution calculation and has a deep structure. It is one of the representative algorithms of deep learning and the most widely used model in deep learning. Convolutional neural network includes convolutional layer, pooling layer, fully connected layer, and output layer, as shown in Figure 2. Compared with traditional neural networks, convolutional layers and pooling layers are added to extract abstract features.

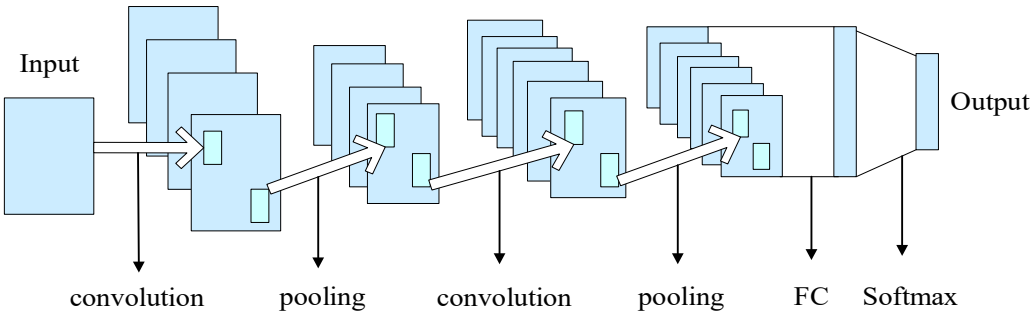

Figure 2. Convolutional neural network diagram

3. Predictive model based on DCGAN-CNN

The parameters collected by the SCADA system include wind speed and power during the operation of the wind turbine. Through data modeling, the hidden relationship between various parameters and wind turbine blade icing is discovered, and a blade icing prediction model based on DCGAN-CNN is established. The model includes three steps: data enhancement, feature construction and model construction. On the basis of the original data, DCGAN is used to enhance the fault samples, and the generated fault samples are added to the original samples to obtain a new balanced sample set. Perform feature construction on the balanced samples to obtain the best feature set as the input of

ISSN: 2414-1895 DOI: 10.6919/ICJE.202103_7(3).0033

CNN, train the model, realize the adaptive extraction of fault features and state classification, and finally use the test set to test the performance of the model. The model structure is shown in Figure 3. The specific operation steps are:

1) Data enhancement: Perform data preprocessing on the data collected by SCADA, and use DCGAN to perform data enhancement on fault samples to obtain balanced samples.

2) Feature construction: Visualize the distribution of related data, construct new feature variables, and get a new feature variable set together with the original features, and divide the training set and the test set according to a 7:3 ratio.

3) Model construction: build a DCGAN-CNN prediction model, calculate the loss cost function according to the real label, and combine the Adam optimization algorithm to optimize the CNN model.

4) Icing prediction: Use the training set data to build a model for training. After the model converges, use the test set to test the model to get the prediction result.

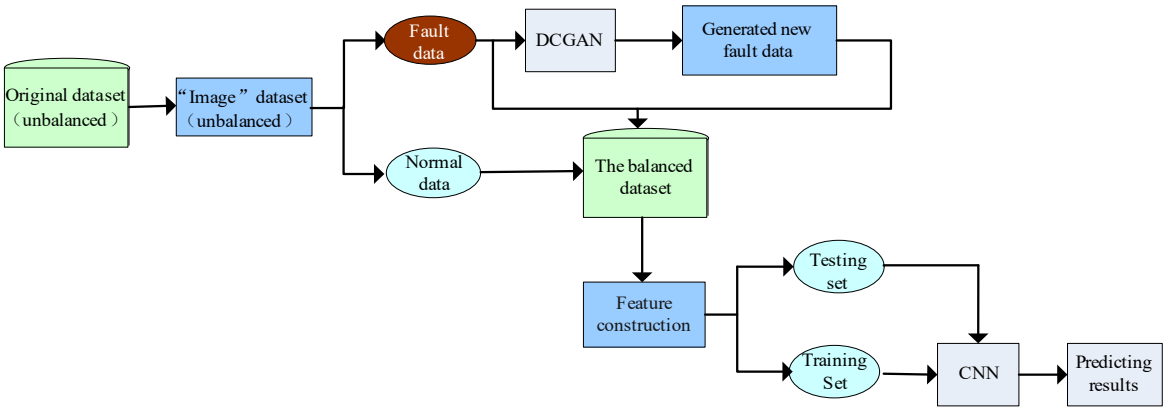

Figure 3. Model structure

4. SCADA data case analysis

4.1 Data analysis

The data in this article comes from the real-time operation data of the No. 15 wind turbine in a wind farm for two months in winter. The real-time data of the SCADA system usually has hundreds of variables. The time stamp and 26 continuous numerical characteristic variables including wind speed, power, yaw angle, and blade speed of the wind turbine are retained through the mechanism model of the wind turbine and manual experience. The data are described in Table 1 below.

The fan is in a normal state for more time during operation, so the ratio of normal data and icing data collected is close to 14:1, which is a data imbalance state and requires data enhancement operations.

Table 1. Main parameter description of SCADA fan data

Title	Title	Title
wind_speed	pitch_speed	pitch_angle
generator_speed	pitch_moto_tmp	yaw_speed
Power	environment_tmp	acc_x
wind_direction	int_tmp	acc_y
wind_direction_mean	pitch_ng5_tmp	
yaw_position	pitch_ng5_DC	

4.2 Data enhancement

Transform structural data into 1-channel one-dimensional time series data (676, 1) by feature splicing, and reconstruct a three-dimensional feature map (26, 26, 1), that is, a "picture" with a width and height

ISSN: 2414-1895 DOI: 10.6919/ICJE.202103_7(3).0033

of 26, and the number of channels is set to 1. As shown in Figure 4. The "picture" obtained is used as the input of the discriminator, and a Gaussian vector with a length of 100 is selected as the input of the generator. The number of training is 20, the batch_size is 16, the learning rate is 0.002, and the momentum optimization function Adam is used. The learning rate is 0.001.

During the training process, observe the loss curves of the generator and the discriminator. When the two play close to equilibrium, the discriminator judges the data generated by the generator to be true. Figure 5 shows the spectrogram of the samples generated by DCGAN. For a more intuitive comparison, the spectra of real samples are displayed together. It can be seen that the generated data is similar to the real data and can be used for data enhancement.

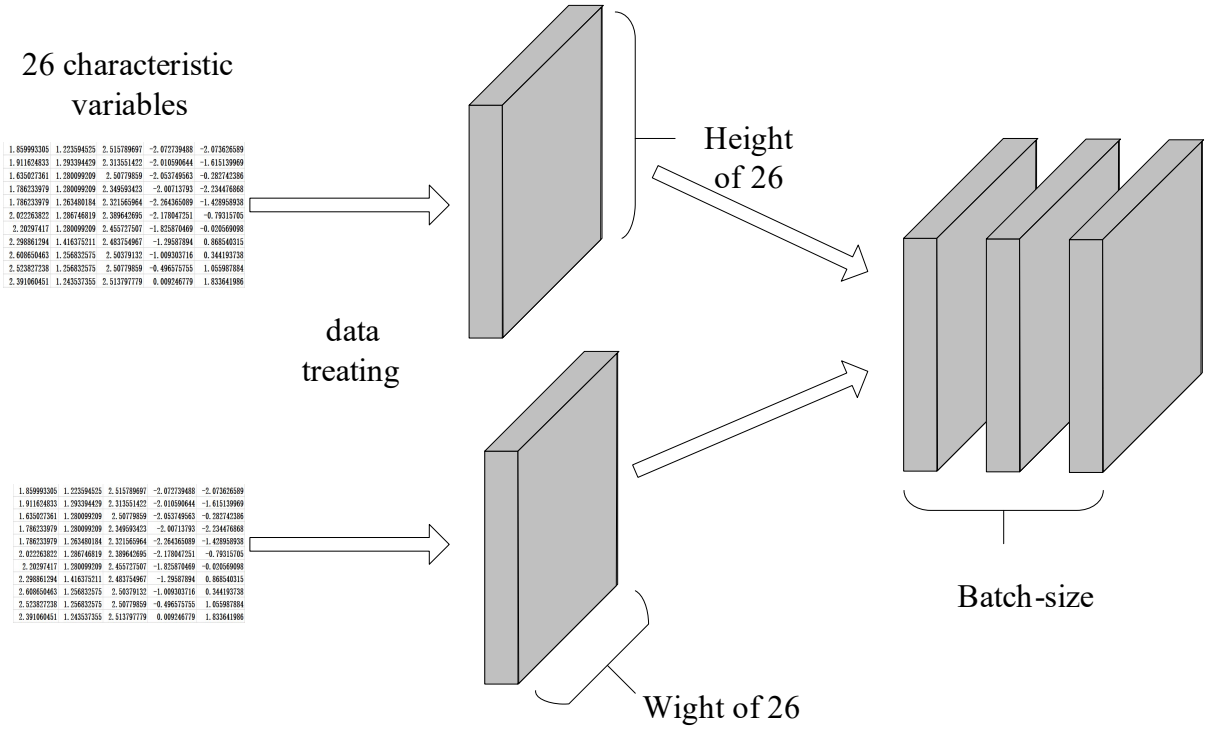

Figure 4. Data preprocessing -Feature splicing

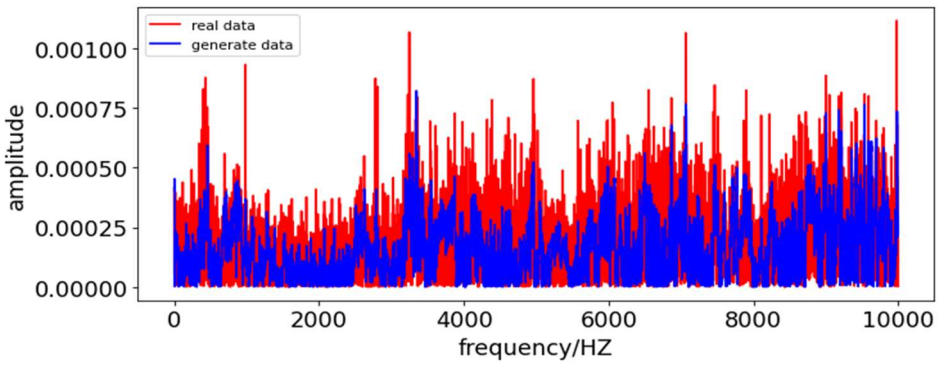

Figure 5. Spectrum comparison chart of real samples and generated samples

4.3 Feature construction

The most important reason for wind turbine blade icing is the low temperature environment, so temperature is a very important parameter. The icing of the blades will cause the motor or transmission system to operate at an overload, and the increase in heat will cause the temperature in the cabin to rise, and the temperature difference between the inside and outside of the cabin will

ISSN: 2414-1895 DOI: 10.6919/ICJE.202103_7(3).0033

increase. Choose to use the difference between the ambient temperature (et) and the cabin temperature (it) to construct a new variable.

$$T = it - et \tag{4}$$

Where: T is the new feature of the structure, it is the cabin temperature, et is the environment temperature

Traditional wind turbines obtain wind energy resources through the rotation of three blades, and visualize the angle data of the three blades. As shown in Figure 6, it can be seen that the distribution is relatively consistent and related to each other, so the average of the three can be used as a new variable, the same as, you can select the average value of the three blade speeds and the temperature of the pitch motor as the new variable.

$$P = avg(p1, p2, p3) \tag{5}$$

$$S = avg(s1, s2, s3) \tag{6}$$

$$M = avg(m1, m2, m3) \tag{7}$$

Where: P, S, M is the feature of the structure, and p, s, m are the blade angle data, blade angular velocity, and pitch motor temperature

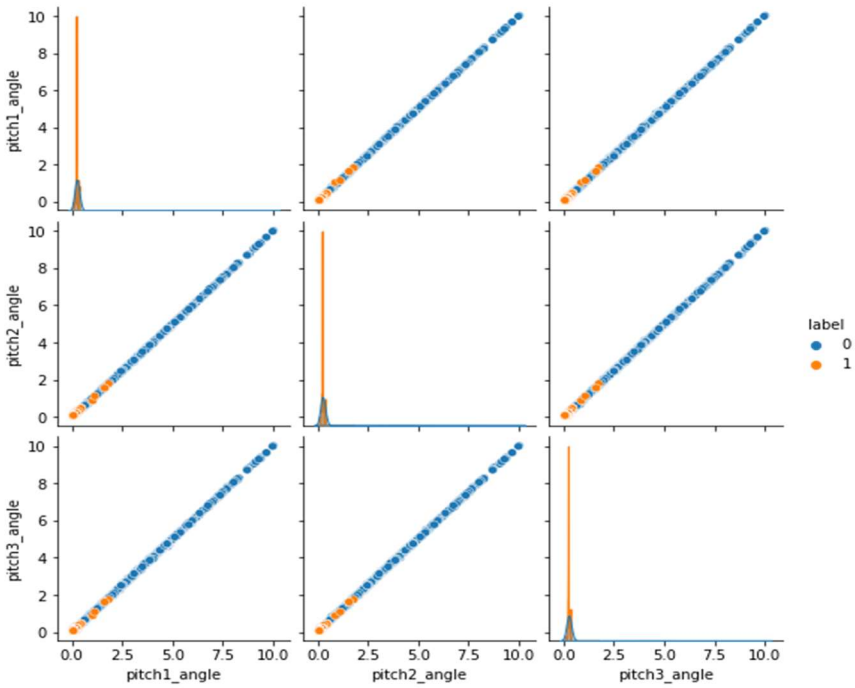

Figure 6. Blade Angle data distribution

4.4 CNN model parameter setting

The CNN structure built in this article is shown in Figure 2. It is composed of convolution-pooling-convolution-pooling-fully connected layers, the size of the convolution kernel is 5×5, the number of convolution kernels is 16 and 32, and the activation function is used Relu function, the pooling layer uses maximum pooling, and the size of the pooling core is 2×2. At the same time, to prevent overfitting, add a Dropout layer with a ratio of 0.25, and choose the Cross -Entropy Loss function as the loss function, and optimize the parameter setting of the Adam function to set the learning rate 0.001, η=0.1, β_1=0.9, β_2=0.999.

ISSN: 2414-1895 DOI: 10.6919/ICJE.202103_7(3).0033

4.5 Analysis of results

Draw the training process trend graph to observe the convergence process and training accuracy during the training process. When the model is trained with unbalanced samples, the model accuracy and loss curve are shown in Figure 7. From the figure, it can be seen that the model training process cannot converge quickly, and the test accuracy can reaches 95% ,but fluctuates greatly. When training the model using the balanced sample set obtained by adding the generated samples, the accuracy and loss curve of the model is shown in Figure 8. It can be seen that the model has begun to converge after 30 iterations, and the test accuracy has reached 97.5%, with high accuracy and less fluctuation.

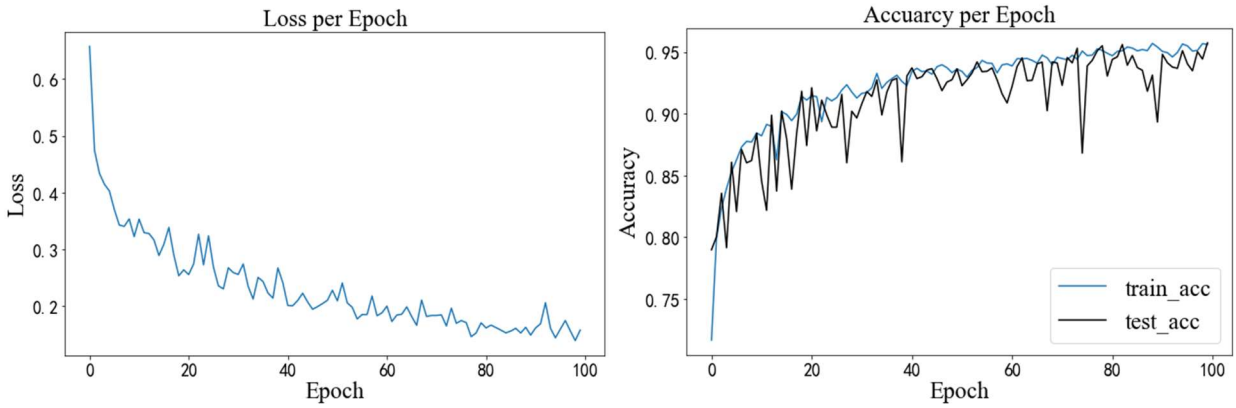

Figure 7. Training loss curve and accuracy curve when unbalanced samples

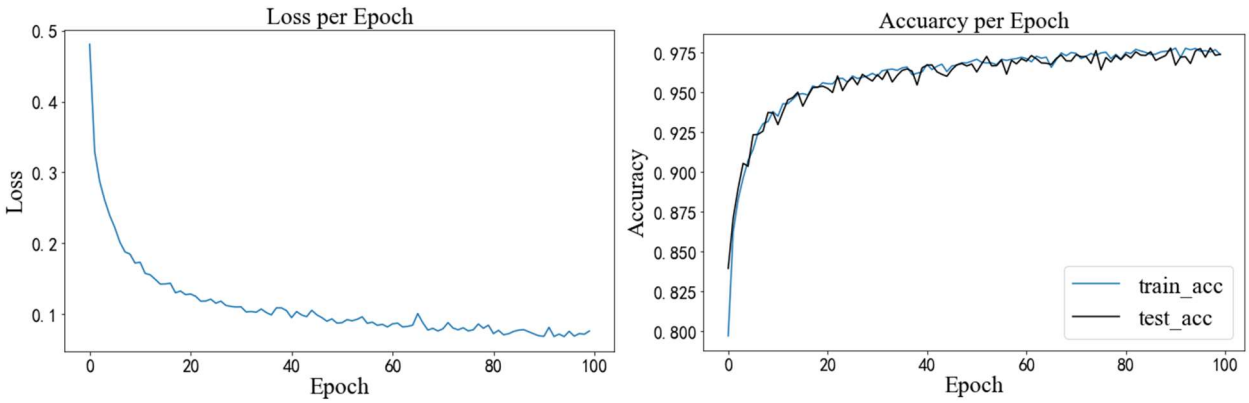

Figure 8. Training loss curve and accuracy curve when balancing samples

In order to further verify the effectiveness of the data generated by DCGAN, SMOTE (synthetic minority oversampling) and undersampling methods are used to obtain a balanced data set, training models and testing accuracy. The experimental results are shown in the table 2. It can be seen that the balanced data training model obtained using DCGAN and SMOTE has higher accuracy, but the DCGAN method takes shorter time than SMOTE.

Table 2. Comparison of three data balancing methods

Numble	Model	Accuracy (%)	Time (s)
1	DCGAN-CNN	97.53 ± 0.13	25.15
2	SMOTE-CNN	96.28 ± 0.03	57.10
3	Undersampling-CNN	93.30 ± 0.01	23.03

ISSN: 2414-1895 DOI: 10.6919/ICJE.202103_7(3).0033

5. Conclusion

Aiming at the problem of the imbalance between normal data and fault data samples during the actual operation of the wind turbine, the generative adversarial network is used to expand the data of the fault samples from the perspective of the fault samples to obtain samples similar to the fault samples to achieve the purpose of data enhancement .Meanwhile, the introduction of the deep learning prediction model realizes the process of adaptive extraction of fault features and avoids the uncertainty of artificial feature selection. Through comparative experiments, the test accuracy of the model trained with balanced data is higher than the model trained with unbalanced data. At the same time, the method of generating balanced data proposed in this paper has obvious advantages in terms of training time and the accuracy of the model trained with generated data. Finally, the prediction model established in this paper has verified the feasibility on the No. 15 wind turbine. For different wind turbine operating conditions in actual operation, the migration of the model needs to be considered in the application.

Acknowledgments

National Natural Science Foundation of China (No.61304186).

References

[1] M.Ma, B.He, Y.Guan, et al. Assessment of global wind energy resource utilization potential [J]. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2017

[2] Li Mengyou. Discussion on the repair and maintenance of wind turbines[J]. Science & Technology Information, 2016, 14(26): 33-34China National Standardization Management Committee. Specifications of Crane Design (China Standardization Press, China 2008), p. 16-19.

[3] Meng Hang, Huang Xixia, Liu Juan, Han Zhiliang. Prediction of fan blade icing based on random forest and SVM[J]. Electrical Measurement and Instrumentation, 2020,57(17):66-71.Q. D. Zeng, Q. E. Li: Progress in Civil Engineering, Vol. 32 (2012) No. 9, p. 3077-3080.

[4] Liu Juan, Huang Xixia, Liu Xiaoli. Prediction of fan blade icing based on stack self-encoding network[J]. Computer Applications, 2019, 39(05):1547-1550

[5] V.Chawla, W.K.Bowyer, O.L.Hall, et al. Smote: Synthetic minority over-sampling technique[J]. Journal of Artificial Intelligence Research, 2002, 16(1):321-357

[6] E.Ramentol, N.Verbiest, R.Bello. SMOTE-FRST: A new resampling method using fuzzy roughset theory[J]. Uncertainty Modeling in Knowledge Engineering & Decision Making, 2015, 19(5):800-805

[7] S. Ahmed, W. H. El-Behaidy and A. A. A. Youssif, "Automatic Enhancement of Two-Dimensional Gel electrophoresis images using Denoising Autoencoder," 2019 14th International Conference on Computer Engineering and Systems (ICCES), Cairo, Egypt, 2019:357-361

[8] I.J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio, Generative Adversarial Networks, 2014

[9] J. Feng, H. Yu, L. Wang, X. Cao, Classifification of hyperspectral images based on multiclass spatial – spectral generative adversarial networks, IEEE, Transactions on Geoscience and Remote Sensing 57 (8) (2019) 5329–5343

[10] K. Kim, S. Member, H. Myung, S. Member, Autoencoder-combined generative adversarial networks for synthetic image data generation and detection of jellyfifish swarm, IEEE Access 6 (2018) 54207–54214.

[11] Q. Xuan, Z. Chen, Y. Liu, H. Huang, G. Bao, D. Zhang, Multiview generative adversarial network and its application in pearl classifification, IEEE Transactions on Industrial Electronics 66 (10) (2019) 8244–8252

[12] X. Yi, E. Walia, P. Babyn, Generative adversarial network in medical imaging: a review, Medical Image Analysis 58.2019.