Establishment of the Defect Detection Model for Gas Turbine Blades

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I. Research Background and Objectives

Gas-fired power generation has been one of the major ways for Taipower to generate electricity, and the maintenance departments need to frequently and extensively perform welding and coating on gas turbine blades to increase the lifespans of the blades. RT testing is one of the most important work items in this process. In the past, the testing performed by experienced technicians was time-consuming, laborious, and costly, and it is no longer sufficient for the mass production of refurbished blades and future automation needs. With the rapid development of artificial intelligence, pattern recognition technology has made great progress in recent years. Among them, the convolutional neural network is one of the current highly developed pattern-processing methods. Many studies have proved that the accuracy and effectiveness of this technique is competitive. Therefore, this study established the M501G blade defect detection model through VGG-19 network transfer learning, and constructed relevant indicators to evaluate the effectiveness and usability of the model, which is beneficial to the realization of the goal of real-time, online and automatic gas turbine blade defect detection.

II. The structure of the M501G blade defect detection model

Deep learning is an integral part of artificial intelligence. It learns various "knowledge" by simulating the structure of the human brain to solve complex classification problems effectively. Among them, transfer learning is to apply the trained network model to a new data set in a similar field, which can not only save the model construction and training work from scratch but also accelerate the learning and optimization of the model, reduce feature extraction time and avoid overfitting caused by too little training data. It has been widely adopted by the academic community recently and achieved good results. The structure of the M501G blade defect detection model established through VGG-19 network transfer learning in this study is shown in Fig. 1. The model consists of data preprocessing, feature extraction, and classification. (1) Data preprocessing: Normalize the image data to limit the range to 0~1 so as to speed up the convergence of the model. (2) Feature extraction: All convolution layers and max-pooling layers of the original VGG-19 network architecture are retained as the feature extraction of the model. (3) Classification: Remove the 3 fully connected layers of the original VGG-19 network architecture but add a flatten layer and Softmax classifier. Among them, the flatten layer is used as an intermediary conversion between the convolution layer and the fully connected layer/classifier, and the Softmax classifier provides the prediction information of category, which maps the output of the neurons in the previous layer to a probability distribution of 0~1, and then predicts the category according to its probability.

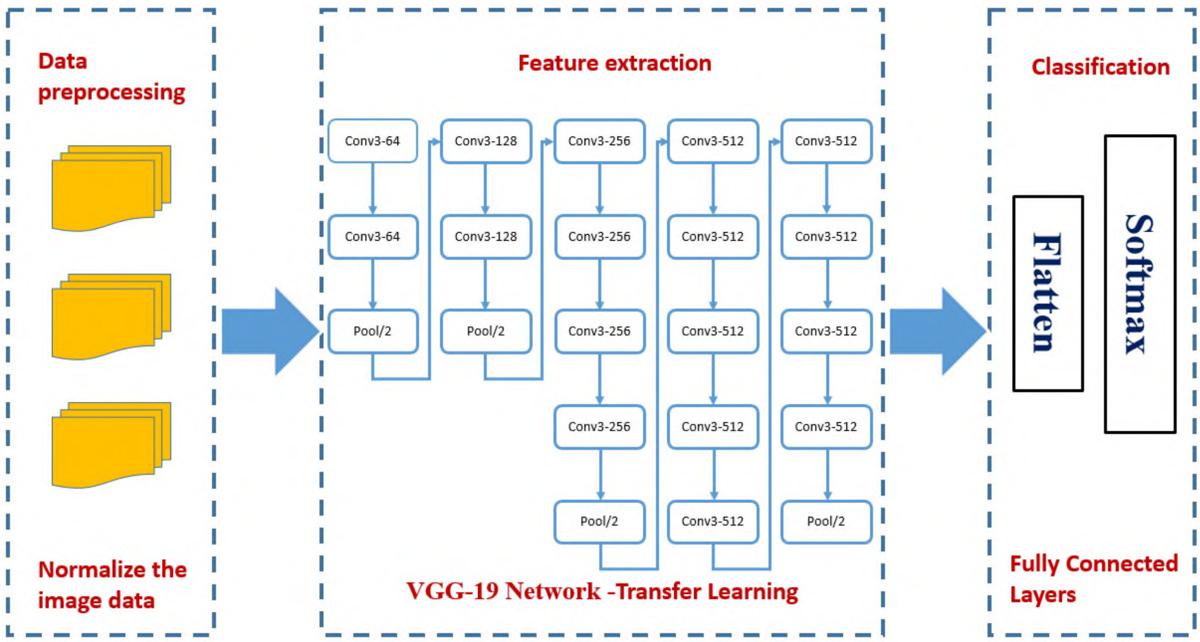

Fig. 1 the structure of the M501G blade defect detection model

Source: this study

III. Conclusions and Suggestions

In this study, the loss and accuracy functions were used to verify the performance of the model, as shown in Fig. 2; a confusion matrix was also constructed to evaluate the classification performance of the model, as shown in Table 1; finally, cross-validation was performed on an independent data set to test the generalization ability of the model. The key findings of this study are listed as follows:

1. The behavior of the loss curve in this study is reasonable, but there is a gap between the training set and the validation set, indicating that the model of this study is somewhat overfitting. The accuracy of equalization images is about 96%, which is better than 90%~95% of X-ray ones.
2. The confusion matrix of this research shows that the classification accuracy, precision, recall rate, specificity, and F-Measure are mostly above 90%, indicating that the capacity of the research model is effective and superior in pattern classification.
3. The mean and standard deviation of the accuracy of X-ray and equalization images obtained through cross-validation in this study are 93.28% (+/-1.12%) and 95.35% (+/-0.72%), respectively. This implies that the generalization of the research model is stable and excellent.

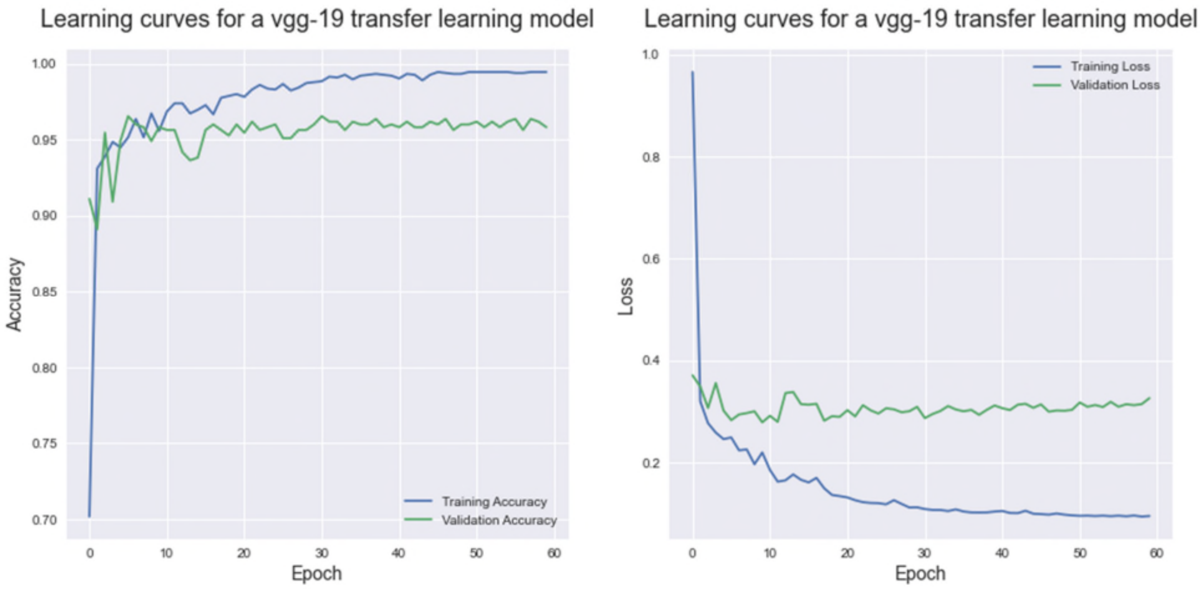

Fig. 2 accuracy and loss curves of equalization images

Source: this study

Table 1 confusion matrix of equalization images

	Accuracy:0.946			
	Precision	Recall	Specificity	F-Measure
A0	0.907	0.84	0.985	0.872
A1	0.857	0.964	0.982	0.908
B0	1.000	0.978	1.000	0.989
B1	0.000	0.000	0.995	0.000
C0	0.937	0.902	0.989	0.919
C1	0.949	0.982	0.994	0.966
D0	1.000	0.978	1.000	0.989
D1	0.000	0.000	0.995	0.000
Categories: A, B, C, D/0: normal, 1: defect				

Source: this study