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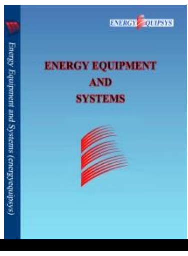

Convolutional neural networks for wind turbine gearbox health monitoring

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ABSTRACT

Between different sources of renewable energy, wind energy, as an economical source of electrical power, has undergone a pronounced thriving. However, wind turbines are exposed to catastrophic failures, which may bring about irrecoverable ramifications. Therefore, they necessarily need condition monitoring and fault detection systems. These systems aim to reduce the number of attempts operators are required to do through the use of smart software algorithms, which are able to understand and decide with no human involvement. The gearboxes are usually responsible for the WT breakdowns. In this paper, convolutional neural networks are employed to develop an intelligent data-based condition-monitoring algorithm to differentiate healthy and damaged conditions that are evaluated with the national renewable energy laboratory (NREL) GRC database on the WT gearbox. Since it is much easier for convolutional neural networks to extract clues from high dimensional data, time-domain signals are embodied as texture images. Results show that the proposed methodology by utilizing a 2-D convolutional neural network for binary classification is capable of classifying the NREL GRC database with 99.76% accuracy.

Keywords: Wind Turbine, Gearbox Condition Monitoring, Convolutional Neural Networks (CNN), Imaging Time-Series.

1. Introduction

The wind power industry is quickly expanding. However, due to the severe working conditions, wind turbines (WTs) are still experiencing a myriad of failures. This will end up increasing the energy price and reducing their reliability [2]. With numerous components in WTs, faults can appear in any of them, which will cause either end of WT operation or damage other elements. Faults in the major drive train components including the main shaft, gearbox, and generator, can cause substantial economic damage. Annualized failure frequency [3] of WT components is shown in Fig. 1.

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As can be seen, the gearbox, with a high downtime per failure, is one of the critical components**.** Gearbox size and its robust connection to other parts make it more difficult to access, repair or replace. Therefore, it is indispensable to enhance the reliability of WT's gearbox, as the second most damage susceptible drive-train component, in order to ensure an efficacious performance of mechanical transmission systems. In this regard, using reliable monitoring and diagnosis systems for gearboxes is of great importance.

Conventional algorithms for evaluating signals and feature extraction including model-based approaches for condition monitoring and fault detection (CMFD) [4] require complex

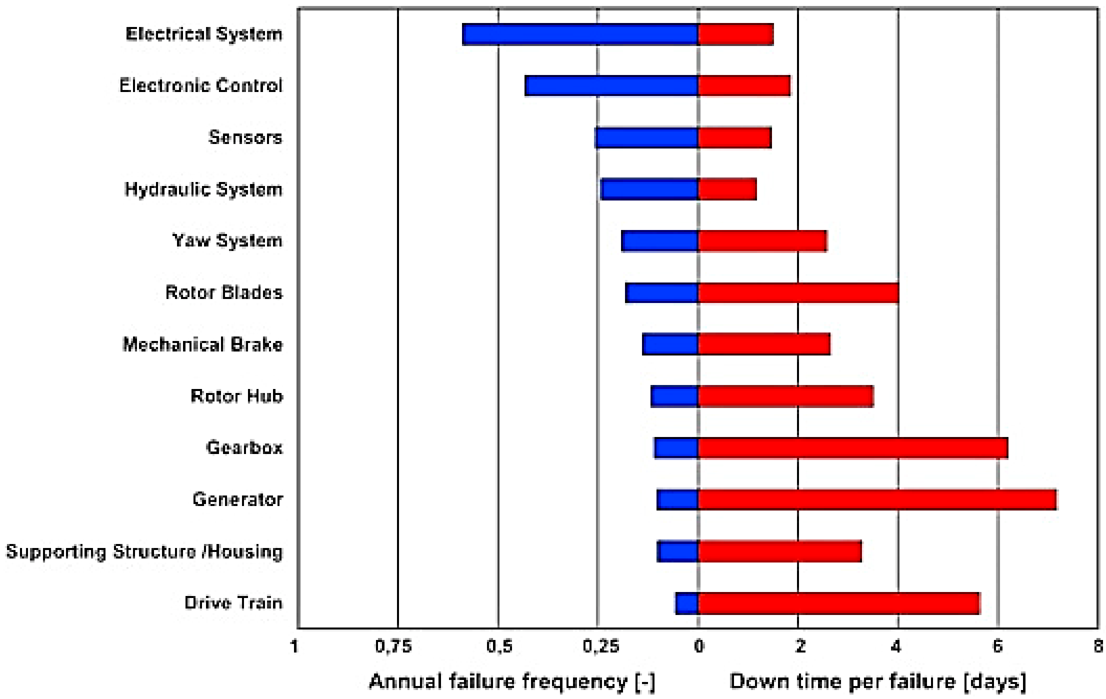


Fig. 1 Annual failure frequency and corresponding downtime for several WT components [3]

engineering knowledge and a thorough understanding of system performance. Further, the established model and rules may vary over the course of time. Consequently, the CMFD systems will experience inaccuracies and biases that bring about poor performance. However, the recently introduced machine-learning algorithm and powerful processors have opened up a new horizon for improving and developing intelligent monitoring systems without human intervention [5]. While data-based approaches have been getting attention for developing reliable automatic health monitoring systems, they require robust algorithms to extract valuable information from available data [6]. Deep learning methods have been widely used in condition monitoring systems [7] due to their ability to build complex nonlinear functions. These algorithms can learn the patterns of various faults from raw [8] or pre-processed signals [9] as well as the extracted features [10]. Different neural network architectures achieved outstanding results for automatic and robust monitoring of WT bearings and gearbox [11-13]. This paper introduces a novel method for WT gearbox health assessment using convolutional neural networks (CNNs), which has made excellent triumphs in computer vision tasks and has also drawn dramatically growing attention in automatic CMFD systems as well. [14] Demonstrated one of the earliest examples of CNN-based models for CMFD by evaluating the health condition of bearings. They obtained vibration signals through two perpendicular accelerometers. To compute the scores for four classes, they used the discrete Fourier transform of normalized signals as input. Sun et al.[15] detected gear faults using a CNN model applied on the multiscale signal features that were extracted using a dual-tree complex wavelet transform. Jing et al. [16] utilized a 1-D CNN for gearbox fault detection based on frequency features of vibration signals and the results are compared with time-frequency data, frequency spectrum, and raw data. In [17], authors proposed a training interference for CNN to detect the bearing faults under various working conditions and noise presence. Bearing faults include: ball fault, inner race fault, and outrace fault. They used a 1-D CNN where drop out is applied on the kernel of the first layer. The experiments are performed on raw Case Western Reserve University (CWRU) Bearing Data. While most studies propose 1-D CNN architectures, recently, digital images are introduced for some engineering applications including health monitoring. Digital grayscale images [18], for instance, are employed for induction motors fault diagnosis based on binary texture analysis. Hoang and Kang [19] and Wei et al. [20] developed a fault detection method for bearings using vibration texture images. Using texture images, [21] offered an approach fault diagnosis of WT actuators and sensors. Statistical, Gabor, wavelet, and granulometric features are extracted and faults are detected using five classification algorithms rather than the CNN algorithm.

In this study, a gearbox health assessment approach has been conducted which is based on vibration signals prepared by the National Renewable Energy Laboratory (NREL). The final intent is to derive a binary classificatory for identifying healthy and damaged conditions. It is an automatic data-based monitoring method that requires no real-time human intervention or prior feature extraction. The utilized vibration acceleration data originated from healthy and damaged gearboxes of a test WT. To propose the algorithm mentioned above, digital images constructed based on the time domain signals are used. Afterward, images are used to train a CNN model. Vibration signals have been dominantly contemplated in condition monitoring of WT gearboxes. Model performance shows the superiority of this methodology. It is capable of classifying the NREL gearbox benchmark with 99.76% accuracy.

2.Convolutional Neural Networks

CNNs are the most popular neural architectures in computer-vision applications. They are capable of extracting and learning the best classification features from unprocessed data. Since the feature extraction and decision-making processes are combined, the computational cost is comparatively low in comparison to other techniques. Three major layers comprise a comprehensive CNN structure: a convolutional layer, a pooling layer, and a fully linked layer.

Every single convolution layer has a number of learnable filters that affect receptive fields and extracts local features of the input using the shared weights while sliding across the input. This layer is followed by an activation function that will generate the output. The most common activation function is rectified linear unit (ReLU) that computes the function $f(\mathrm{x}) = \max\{0, \mathrm{x}\}$, and applies elementwise non-linearity to the CNN [23] as well. Convolution layers are usually followed by a pooling layer that aggregates the extracted information. The most frequently used aggregation method is the max-pooling operation that finds the maximum pixel value in receptive fields and results in translation invariance [23]. After extracting useful features through convolution and pooling layers, a fully connected network collects features and computes the class scores. In the output layer, the softmax activation function is used to find the probability of each class. Figure 2 shows the CNN architecture [24].

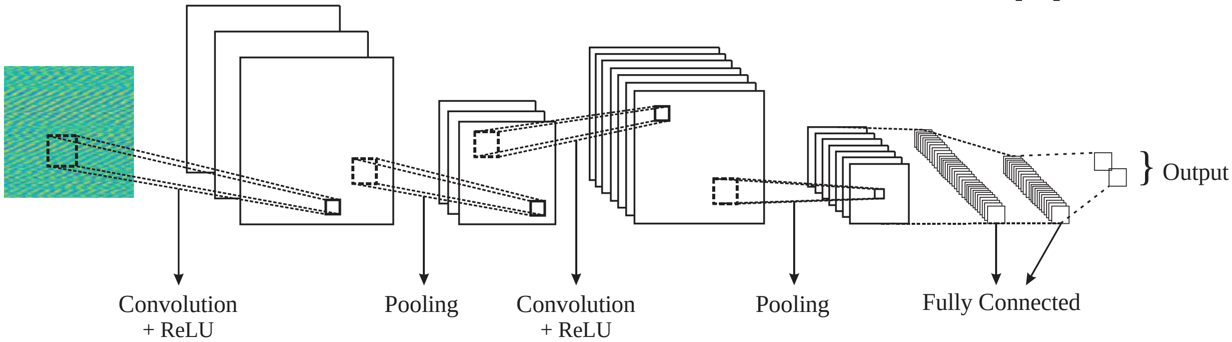


Fig. 2 convolutional neural network architecture

3.Imaging Time-Series

Images are informative data formats that provide the model with intricate structures and correlations within time. Further, converting signals into images can mitigate the noise influence, because it will be represented as light in the image [21]. Also, the development of GPUs resulted in powerful processing units that can provide the required speed for the image-based condition monitoring systems [25]. In this paper, the signal texture imaging method is utilized to represent data as images. The conversion scheme is illustrated in Fig. 3. As can be seen, small patches of signal with the length *N* are used to construct images. More details can be found in [18].

4.Experimental Implementation

4.1.NREL Gearbox Test

NREL has investigated the main causes which result in the premature failure of WT gearboxes [26] intending to extend their lifetime and provide the wind industry some benchmarking datasets benefiting research, development, validation, verification, and advancement of vibration-based wind condition monitoring techniques. This section describes the data collection effort and shared datasets. Under dynamometer tests, the vibration data were collected by accelerometers from a damaged gearbox and a healthy gearbox of the same design. The test turbine is a stall-controlled, three-bladed, upwind turbine with a rated power of 750kW.

4.2.Gearbox Description

Test gearbox has an overall ratio of 1:81.49 and is made up of one low-speed planetary stage (LSS) and two parallel stages, containing one intermediate-speed stage (ISS), and one High-Speed stage (HSS). The LSS and HSS are connected to the rotor and generator respectively, as is shown in Fig. 4. More details about the internal elements of the test gearboxes, gear dimensions, etc. could be found in [27].

The healthy gearbox was only tested at the Dynamometer Test Facility (DTF) at NREL. The damaged gearbox was sent to a wind farm for field testing in which it experienced two oil-loss events that damaged its internal bearings and gears. The gearbox was later disassembled for analyzing the detail of the actual damage that occurred to the test gearbox. Scuffing, overheating, fretting corrosion, and polishing wear are some of the observed damages in the test gearbox [28]. After installing the condition monitoring equipment, it was tested at DFT with controlled loads which would not lead to any cataclysmic failure of the gearbox. In addition, the damages are detectable through vibration analysis.

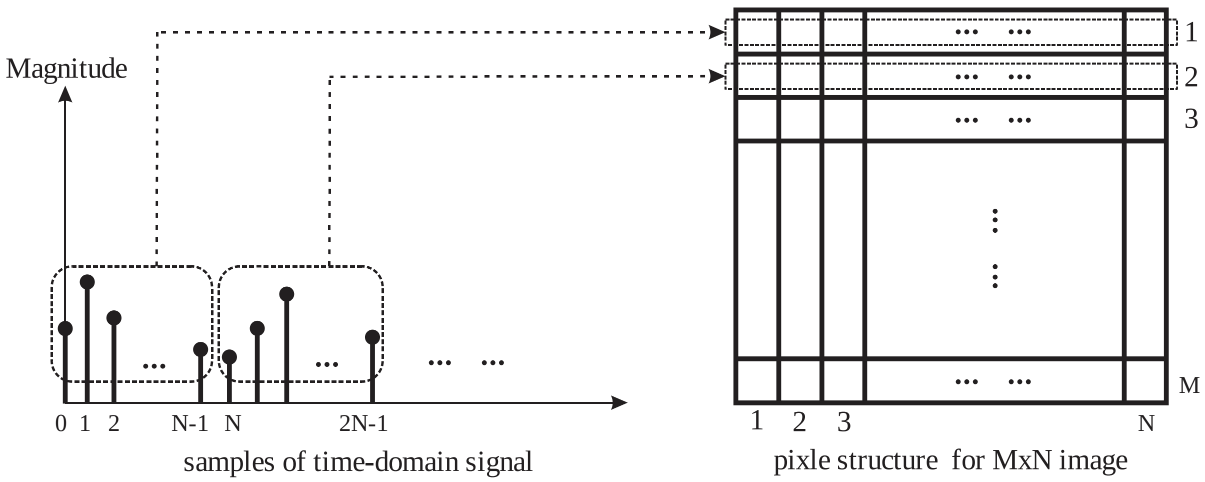


Fig. 3. constructing the texture images

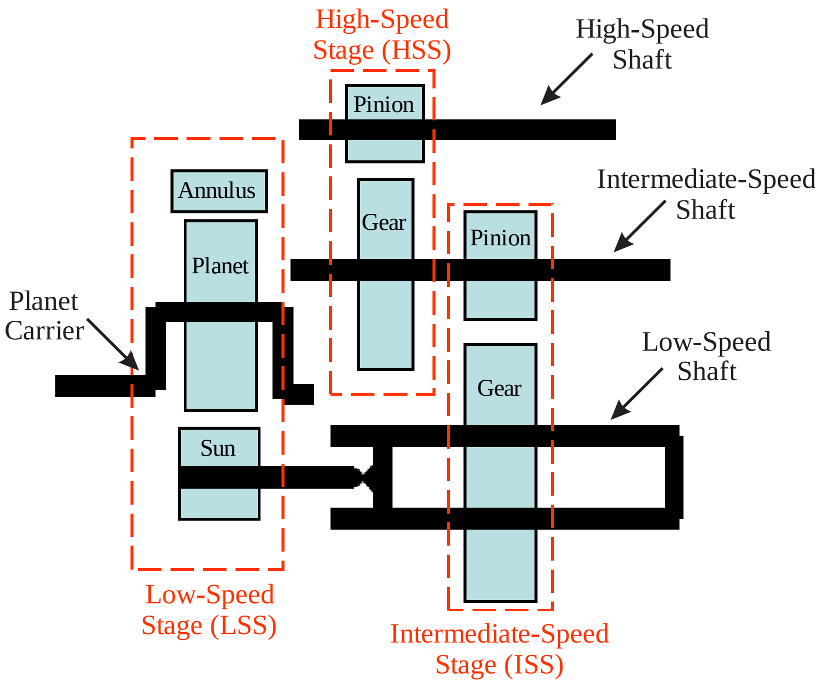


Fig. 4 Test gearbox interior layout [27]

4.3.Vibration Data

Accelerators were installed on the gearbox housing and vibration data was collected at 40 kHz per channel. The accelerometers were located as listed in Table 1[27]. Furthermore, data is provided in engineering units and does not have to be adjusted, scaled or modified.
In DTF at NREL, The test WT's full nacelle and drive train were placed in such a way that the nacelle was secured to the floor without a hub, rotor, or yaw bearing [27]. Also, an authentic field control system was enlisted for providing start-up and system safety. In this dynamometer test, run-in was performed at 50% of rated torque and the generator was activated as it approached the 1800 rpm synchronous speed with the 22.09 rpm main shaft speed. More details about the DTF could be found in [27]. The data files are provided in ten 1-minute data sets for the aforementioned test condition for each gearbox. Acquired healthy and damaged signals are both similar to noise signals and they have nearly the same amplitudes. Hence, there is not any cognizable difference in the signals plot [9].

4.4.Imaging the signals

Each vibration signal is split into 20 non-overlapping sections with the same length so as to acquire enough train/test data. Texture images are obtained using the method explained, and each element is considered as one pixel when converting the matrix to an image. Hence, the values of each element define the color of each pixel. An individual segment of signals is used to construct images of the size $M = N = 224$. Correspondingly, the vibration data of each sensor is converted to 20 images, which means every 1-minute dataset contains 160 images. Hence, $160 \times 10 = 1600$ images, with a size of 224×224 pixels, are available for each class (2 classes). All of the images (AN1 to AN8) are simultaneously fed to the proposed CNN in the training/testing process. Fig. 6 gives an example of images for healthy and damaged gearboxes. As shown in the figure, distinguishing the images of two classes is not readily possible.

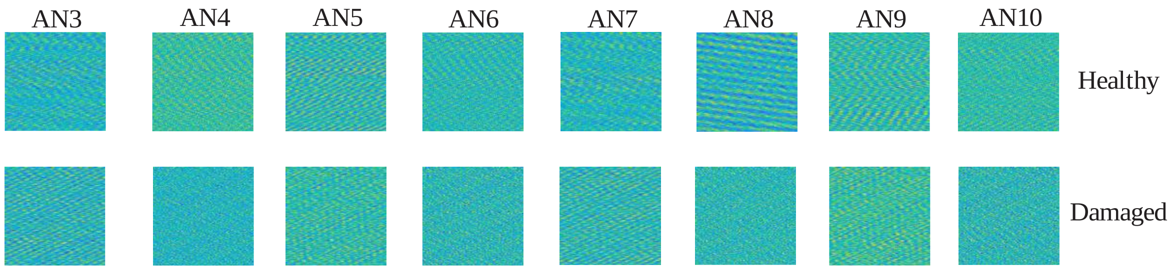


Fig. 5 Example vibration images

4.5.CNN Hyper-parameters

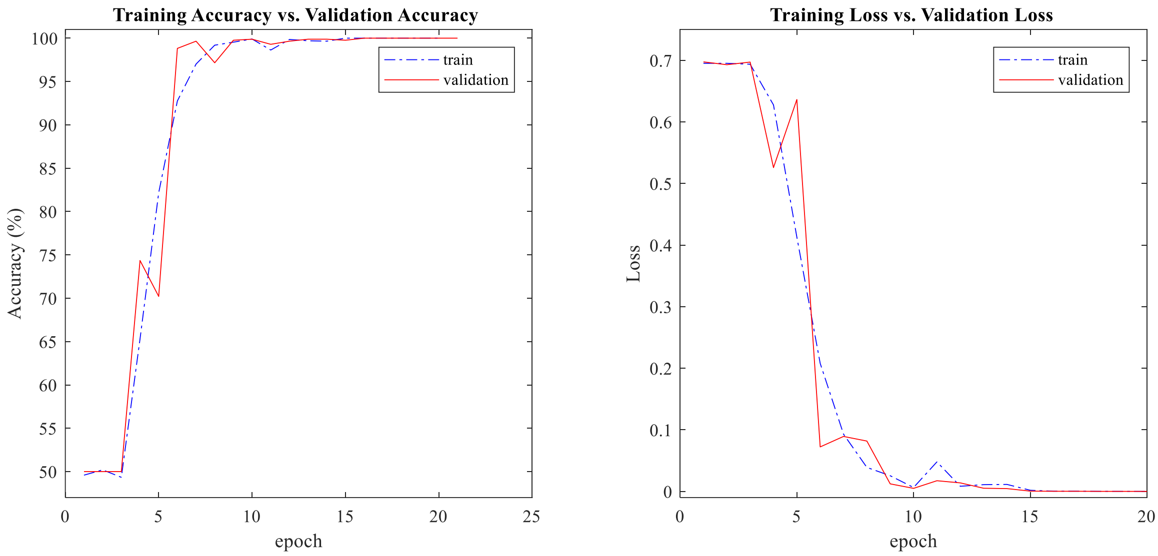
While model parameters vastly affect the model performance, there is no established method to tune the hyper-parameters. In this experiment, the model complexity is increased after each training and inference to get a convincing accuracy. Finally, the proposed model has four convolutional and max-pooling layers followed by two fully connected layers. Table 2 summarizes the selected parameters for the convolutional and pooling layers. The experiments were implemented on an NVIDIA GEFORCE GT 630 M-based GPU system.

5.Results and Discussion

In this work, an approach for condition monitoring of wind turbine gearbox is proposed using convolutional neural network. To train the model, the gearbox vibration dataset provided by NREL is used. Vibration texture images are utilized in the experiments. In addition, the cross-entropy loss function is chosen to train the CNN model. The metrics to measure the model performance are classification accuracy, loss function, confusion matrix, and receptive operating characteristic (ROC) curve. Figure 6 shows the classification accuracy and loss function. Accuracy measures the percentage of correctly classified images. The proposed method can diagnose the damaged gearbox with an astounding final accuracy of 99.76%. As it can be seen in Fig. 6, accuracy and loss function values become constant at last epochs, and proposed CNN could reach a convergence point.

Table 1 . Proposed CNN model structure

No.	Layer Name	Filter Size/Stride	Output Size	Padding
1	Convolution1	5 × 5 × 60/1 × 1	120 × 120 × 60	Yes
2	Max-pooling1	2 × 2	60 × 60 × 60	No
3	Convolution2	3 × 3 × 50/1 × 1	60 × 60 × 50	Yes
4	Max-pooling2	2 × 2	30 × 30 × 50	No
5	Convolution3	3 × 3 × 40/1 × 1	30 × 30 × 40	Yes
6	Max-pooling3	2 × 2	15 × 15 × 40	No
7	Convolution4	3 × 3 × 20/1 × 1	15 × 15 × 20	Yes
8	Max-pooling4	2 × 2	7 × 7 × 20	No
9	Fully Connected1	400	1 × 400	No
10	Fully Connected2	200	1 × 200	No
11	Softmax	2	1 × 2	No



(a) (b)

Fig. 6 (a) accuracy, (b) loss function of the proposed CNN

The confusion matrix can provide a better analysis of the model performance. It demonstrates the correctly classified and misclassified cases. From 420 images associated with the damaged gearbox, 99.76% (419 images) are correctly classified and 0.24% (1 image) are classified as a healthy gearbox.

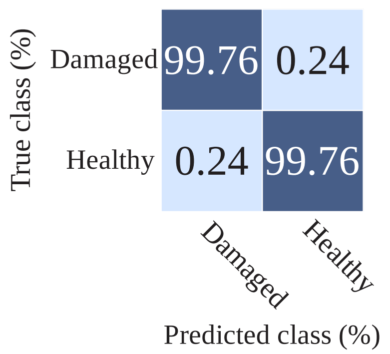


Fig. 7 Confusion matrix

ROC curve is another measurement for evaluating the model performance which can indicate the diagnostic capability of a binary classifier. The area under the ROC (AUC), calculated based on the confusion matrix, shows the predictive performance of the classifier and can vary between 0.5 (random classifier) and 1 (ideal classifier). ROC curve for the proposed algorithm is shown in Fig. 8 and the exact value of AUC is 0.9976. Each image relating to the healthy gearbox that is classified truly is considered as true positive (TP). On the other hand, healthy images which are classified wrongly, are considered as false negative (FN). If an image relating to the damaged gearbox is classified correctly, it will be considered as a true negative (TN), and if not, it will be counted as a false positive (FP). Therefore, true positive rate (the proportion of healthy images which are correctly classified) and false positive rate (the proportion of images that are wrongly identified as such) could be calculated as

$$True\ Positive\ Rate = \frac{TP}{TP + FN} \tag{1}$$

$$False\ Positive\ Rate = \frac{FP}{FP + TN} \tag{2}$$

Clearly, in many scenarios, it will be very difficult to achieve a rich dataset for training. Therefore, in another similar simulation, the proposed CNN has been trained using fewer training images (about 900 images) in order to evaluate its capability, and in the end, it produced similar results. These findings demonstrate that CNN performs admirably when dealing with images of vibration signals. The promising results show that CNNs can help in automating the CMFD systems and increase the reliability of their decisions.

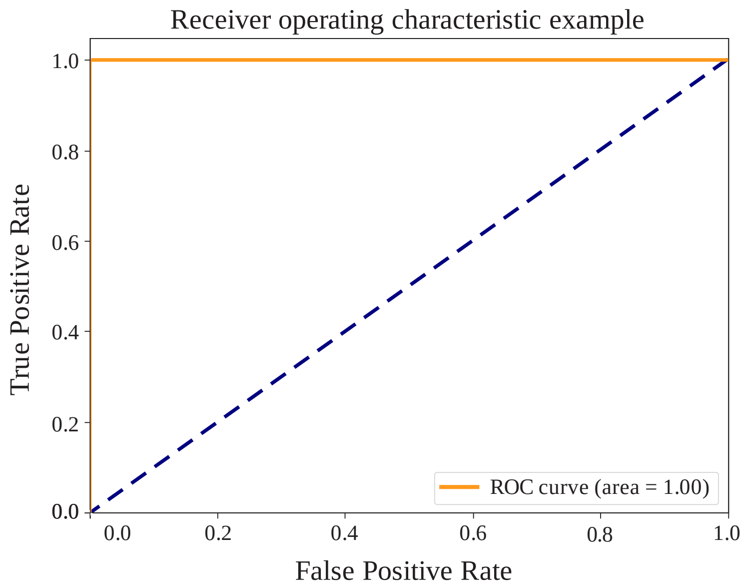


Fig. 8 ROC curve

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6.Conclusion

The intent of this paper was to draw attention to the development of a feature learning algorithm to autonomously classify different conditions with no more required manual feature extraction. A convolutional architecture with vibration texture images as input is utilized to monitor the health condition of a WT gearbox. Signal texture images, that are built based on the magnitude of a signal, are employed to represent time series as images. Referring to the results of the experiments, CNN, as a dominant feature extractor and classifier, achieved 99.76% accuracy and has high robustness. It catches the periodic features of the vibration signals effectively. This shows the capability of this algorithm in solving automatic health monitoring issues based on unprocessed signals.

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