Fault Classification of Wind Turbine Gearbox Bearings Based on Convolutional Neural Networks

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Gearbox bearings are critical elements of wind power generation systems. Their stable operation supports the power generation, thus reducing the downtime and improving the economic efficiency of wind farms. With the wide availability of sensors, data-driven methods have started to be utilized instead of physical-based methods for condition monitoring of wind energy infrastructures. Deep learning provides significant advantages to achieving this end due to its ability to extract and select representative features without expert knowledge. The present study proposed an intelligent method based on one-dimensional convolutional neural networks (1D-CNN) to extract useful features from the vibration signals and classify different bearing faults. The performance of the proposed 1D-CNN model was evaluated employing the Case Western Reserve University dataset. As a result, the proposed method achieved an average prediction accuracy of 99.56%. The findings confirmed that the method has good stability and potentially be used to reduce operation and maintenance costs.

Keywords: Wind power, rolling bearing, fault diagnosis, deep learning.

1 Introduction

Energy is among the main pillars of human evolution. Due to global warming (i.e., climate change), the minimization of pollution besides operation and maintenance (O&M) costs during energy production is a matter of concern worldwide [1]. In this regard, energy collected from renewable sources and existing over a broad geographical region offers a great option to achieve this end. Due to its sustainable and clean characteristics, the wind energy sector has attracted continuous attention and has significantly grown during the past two decades [2]. For example, Global Wind Energy Council reported that the global wind energy sector had shown year-to-year growth of 19% in 2019 [3]. The wind turbine (WT) is utilized in order to transfer the wind energy first to mechanical and then the electrical energy [4, 5]. With the exponentially increased wind power capacity, the high O&M costs have become an issue that needs to be addressed extensively. WTs are subjected to harsh environmental conditions such as volatile (i.e., complex alternating) loads, extreme temperature differences, and frequent impact, and therefore, are prone to failure [6]. According to statistics, the annual O&M cost of a WT may reach approximately 3% of its original cost [3]. Currently, how to minimize the wind farm O&M costs with the early and accurate prediction of WT faults stands as an urgent problem to be solved for the wind energy community.

Reliability and safety are among the key terms of industrial operations [7]. Damage to critical components such as gearbox, blades, and generator may lead to considerably high O&M costs of WTs. For example, WT gearboxes are located at high altitudes, so their maintenance is challenging in case of failure. Evidence in the literature indicates that approximately 70% of WT gearbox failures are accounted for due to bearing failures [6]. Any faults in the bearings that support the weight of the WT besides rotating loads affect the efficiency, precision, and stability of the entire unit [8]. Failure to diagnose an incipient bearing fault then may threaten the reliability of WT; consequently, financial loss (i.e., high O&M costs) caused by downtime or even severe health risks (i.e., casualties) are inevitable. Condition monitoring (CM) aims to identify a deviation from the normal operation condition (i.e., fault indication) by monitoring a signal collected from a mechanical system. Many sensors are installed on WT equipment in order to collect WT data and perform CM tasks [9]. Deteriorating performance of a WT gearbox bearing manifests itself with abnormal variations of the temperature, vibration, motor current, and torque responses [10]. Among them, the vibration data are usually utilized to achieve bearing diagnostics and prognostics tasks owing to its advantages, for example, low cost and convenient implementation [8, 11]. An in-depth research work regarding the early fault diagnosis of WT bearings is significant for minimizing the O&M costs, increasing annual power generation, and maximizing the economic benefits [12]. Many scholars have proposed different techniques to diagnose bearing faults based on the traditional (signal processing + feature extraction + machine learning) methods.

To eliminate uncorrelated content, Mishra et al. [13] utilized the instantaneous angular position instead of time for signal processing and benefited from enveloping and order tracking. The researchers tested their four-stage sequential signal processing approach through the data collected from a bearing test setup. The pre-fabricated fault-defined bearings (e.g., rolling element fault) were mounted to the experimental test rig, and the vibration data were then collected under variable shaft speeds. Glowacz et al. [14] proposed an approach to perform a bearing fault diagnosis task. To this end, a feature vector was created employing a method, namely, "Method of Selection of Amplitudes of Frequency." Three traditional methods were utilized to classify bearing faults: 1) Gaussian Mixture Models, 2) Nearest Neighbor, and 3) Nearest Mean classifiers. Later, Zhao et al. [15] processed the vibration data utilizing stochastic subspace identification to extract fault features. The constructed feature vectors were inputted to the multi-kernel support vector machine (SVM) to classify WT-bearing faults. The study concluded that the proposed multi-kernel SVM technique outperformed the traditional pattern recognition methods evaluated within the scope of the research work.

Manual feature selection is a blind, labor-oriented, and subjective process that mainly depends on advanced expertise knowledge. In addition, the traditional fault diagnosis methods consist of shallow structures that are not suitable for learning complicated nonlinear relationships [16]. So, the conventional methods cannot meet the wind farms' actual implementation needs. To overcome these shortcomings, deep learning (DL), which can capture sensitive fault information without expert knowledge, has started to be utilized to diagnose rotary machinery faults over the last decade. As an emerging research field, DL could be a powerful tool to extract the representative features from sensor data and automatically learn discriminative features to classify WT-bearing faults.

In order to perform WT bearing fault diagnosis, Zhang et al. [6] combined the SVM classifier and a one-dimensional convolutional neural network (1D-CNN). The features extracted with the 1D-CNN were then inputted into an optimized SVM classifier. Their study evaluated ten bearing statuses through the vibration signals collected from the Case Western Reserve University (CWRU) dataset. Consequently, it was observed that the proposed method could classify different WT-bearing faults with a recognition accuracy of 98.2%. Hao et al. [16] proposed a new network structure based on a deep belief network (ResNet) to reduce losses and diagnose bearing faults. The researchers replaced the fully connected layer part of the ResNet with the general average pooling technology. The study benefited from the CWRU dataset to interpret the efficacy of the proposed network structure. As a result, it was indicated that the proposed model performed an average accuracy of 99.83% and shortened the training time. Karpat et al. [17] proposed a 1D-CNN model to classify healthy state, inner raceway (IR), and outer raceway (OR) faults under variable operating conditions (i.e., shaft speeds and load torques). The study employed the Paderborn University dataset, another prominent benchmark dataset, to validate their 1D-CNN model. A total of nine classes were identified within the scope of research work; consequently, an average classification accuracy of 93.97% was achieved. He et al. [18] endeavored to diagnose different bearing faults (i.e., healthy state, IR, OR, and rolling element faults) and developed a new intelligent approach by adopting a novel weight strategy to improve robustness. By utilizing the CWRU dataset, a multi-class classification problem that contains ten classes was solved. The proposed method reached a testing accuracy of 99.71%. To solve the problem that small datasets cannot be trained on deep networks, Chen et al. [19] designed an improved model utilizing a deep transfer CNN. The researchers benefited from two experimental datasets (i.e., CWRU and centrifugal pump datasets) to evaluate their model's performance. The study concluded that the proposed deep transfer CNN architecture could reach a prediction accuracy of near 100%. Karpat et al. [20] performed an early fault diagnosis task utilizing simulated vibration data. To this end, the study developed a six-degrees-of-freedom dynamic model of a single-stage gearbox mechanism. In addition, a signal-to-noise ratio of 10 was considered to make the classification task more complicated. As a result, an average accuracy of 93.07% was achieved. Even if the above-discussed methods could accurately diagnose bearing faults in many cases, there is still room for further improvements in this research field.

The present study proposed a 1D-CNN model to extract useful features from original vibration signals and classify different WT-bearing faults. To this end, a multi-class classification problem was solved in the presence of IR, OR, and rolling element faults. The experimental data of the CWRU (i.e., a prominent benchmark dataset) was employed to evaluate the performance of the proposed 1D-CNN model. In order to interpret the stability of the proposed DL-based method, the experiments were repeated five times (number of trials), and the standard deviation value was calculated. As a result, the average prediction accuracy of 99.56% was achieved. The findings showed that the developed method was suitable (in terms of robustness and stability) for detecting outliers and diagnosing different WT gearbox bearing faults. It can potentially reduce O&M costs and improve the predictive maintenance strategies by early WT gearbox bearing fault diagnosis.

The remainder of the current paper is organized as follows. The "Methodology" section introduces the fault characteristics of WT-bearings, the CWRU experimental dataset, and the structure of the proposed 1D-CNN model. The "Results and Discussion" section comparatively interprets the experimental findings obtained. The "Conclusion" section summarizes the paper along with the future improvements.

2 Methodology

This section will detail the WT gearbox fault signature, the experimental procedure (i.e., the CWRU dataset), and the layers and main attributes of the proposed 1D-CNN model.

2.1 WT Gearbox Fault Signature

Rotary machinery plays an irreplaceable role and accounts for more than 80% of modern machinery [7]. In a WT gearbox, an unexpected failure inevitably influences the reliability of other linked mechanical equipment. Among all of the rotating machinery, the bearings are one of the key but also vulnerable components. Their health status directly affects the reliability and safety of the entire unit [12]. From this point of view, it is critical to detect and replace faulty WT-bearings in time to prevent catastrophic accidents [8]. The existing literature shows a high failure rate of WT bearings besides yaw-and-pitch systems has been observed [21]. So, an intelligent method that can automatically extract and select useful features to diagnose WT faults is valuable to guide engineering practice. Figure 1 depicts the general structure of a WT.

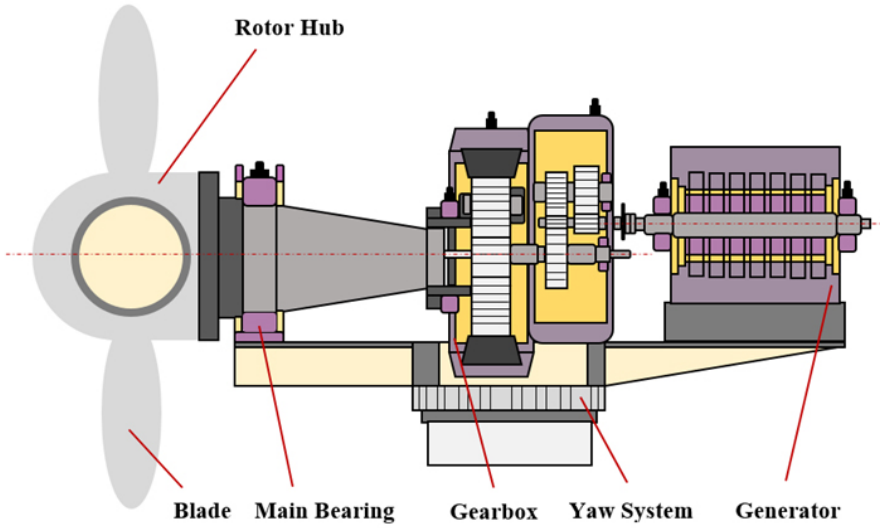

Figure 1: *General structure of a WT.*

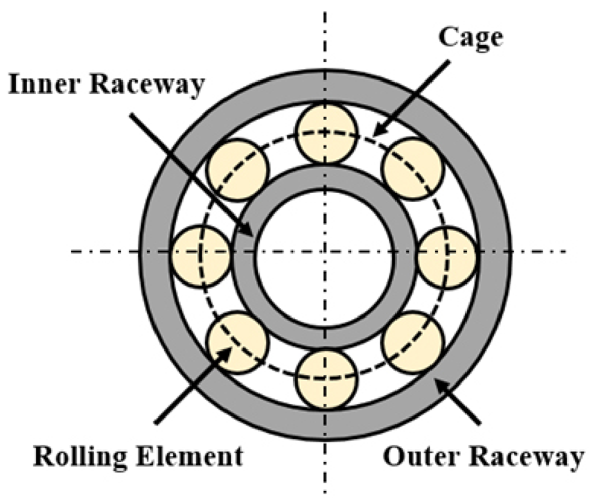

Figure 2: *Configuration of a typical rolling bearing.*

Bearing faults can generally be addressed under two main categories, considering the fault development stages: 1) single-point fault and 2) generalized roughness [22]. Single-point faults include IR, OR, rolling elements, and cage faults. As above-discussed, the deteriorating performance of a WT-bearing manifests itself with abnormal variations of the temperature, vibration, motor current, and torque responses [10]. When a localized WT-bearing fault develops, the collision among the IR, OR, and rolling elements will excite the mechanical system's vibration response. Meanwhile, it should be noted that the vibration response of a WT gearbox (and its components) has the characteristics of continuity and volatility. Figure 2 illustrates the configuration of a typical rolling-element bearing that contains IR, OR, rolling elements, and the cage.

In addition, the bearing rotating frequency and geometry are other merits that influence the single-point fault characteristics [23]. The corresponding problem of WT gearbox bearing fault diagnosis is how to process the collected vibration signals through sensors to obtain useful diagnostic fault features [24]. To achieve this end, the present study proposes a DL-based approach to extract useful features from original vibration signals and classify bearing faults.

2.2 Experimental Description

The present study utilized the vibration signals collected from the CWRU [25] experimental test rig to evaluate the performance of the proposed DL-based method. The sub-section will address the details of the experimental setup and health conditions (i.e., classes) considered within the scope of research work.

The experimental setup of the CWRU consists of a 2 HP electric motor, a torque transducer/encoder, and a load (i.e., dynamometer). Single-point faults, ranging from approximately 0.18 mm to 1 mm (in diameter), were introduced to the 6205-2RS SKF test bearings with electro-discharge machining. The CWRU dataset includes the vibration signals of the healthy state and three faulty (i.e., IR, OR, and rolling element faults) conditions. Afterward, the bearings (healthy + faulty) supporting the motor shaft were remounted on the test motor, and the data were collected through the accelerometers attached to the housing. The schematic diagram of the CWRU bearing test rig is presented in Figure 3.

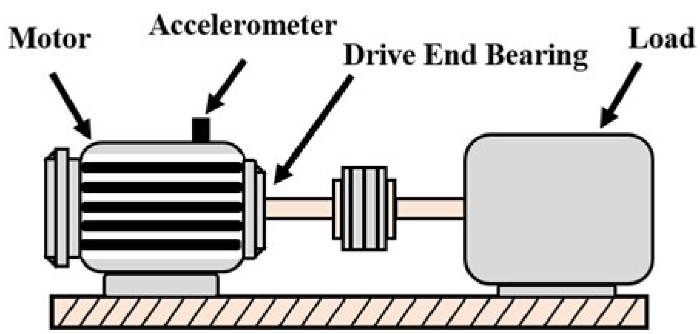

Figure 3: *The schematic diagram of the CWRU test rig.*

This study selected ten classes among the CWRU dataset for testing the proposed 1D-CNN model's performance. In order to interpret the model capabilities under variable conditions, four health statuses (i.e., healthy, IR, OR, and rolling element faults) were considered. In addition, the bearing faults, ranging from 0.18 mm to 0.54 mm (0.007 inches to 0.021 inches), were selected to evaluate the influence of fault diameter on the classification accuracy. The vibration data were collected at 0 HP and 1797 RPM conditions and the samples were collected with 12,000 and 48,000 samples/second sampling rates for drive-end bearing experiments. The description of the dataset considered within the scope of research work is shown in Table 1.

2.3 Model Structure

CNN is a feed-forward multi-stage neural network that mainly contains five layers, namely, (1) convolution layer, (2) activation layer, (3) pooling layer, (4) fully-connected layer, and (5) output layer (see Figure 4). The convolution layer is used to execute convolution operation and then extract local features through the activation layer. CNN structure benefits from the activation layer in order to carry out a nonlinear transformation on the input data (e.g., vibration signal of a WT gearbox bearing). Plus, the Rectified Linear Units (ReLu), Sigmoid, and Hyperbolic Tangent (tanh) are among the most commonly utilized activation functions [6]. On the other side, the pooling layer is mainly utilized to perform a down-sampling operation, prevent overfitting, and reduce the amount of calculation [26].

Table 1: Description of the dataset.

Fault Location	Fault Diameter (mm)	Label
None (Healthy)	None	H_0
Inner Raceway	0.18	IR_1
Inner Raceway	0.36	IR_2
Inner Raceway	0.54	IR_3
Rolling Element	0.18	B_4
Rolling Element	0.36	B_5
Rolling Element	0.54	B_6
Outer Raceway (Centered @6:00)	0.18	OR_7
Outer Raceway (Centered @6:00)	0.36	OR_8
Outer Raceway (Centered @6:00)	0.54	OR_9

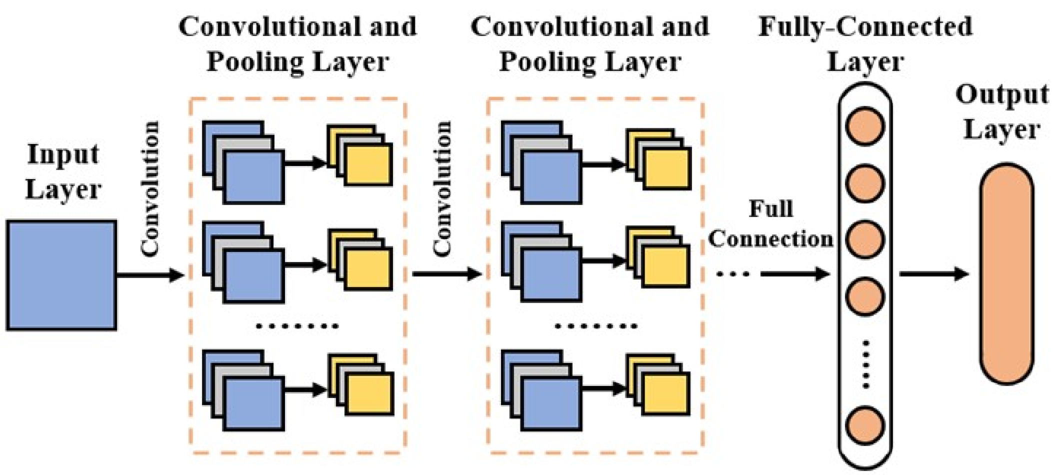

Figure 4: *Classical structure of CNN.*

The present study used 70% of the data for training, 15% for testing, and 15% for validation. The window size was defined as 25000. Dropout is a common method to solve the overfitting problem in DL algorithms [16]. Some neurons are randomly dropped by Dropout to ensure that the neural network only propagates forward during the training iteration. In this regard, the Dropout ratio was set to 0.5 in the present research work. Epoch size was set to 5. The developed 1D-CNN model includes two convolutions and pooling layers (see Table 2).

The present research work used 4 feature maps with kernel size 1 and ReLu function as the activation function in the first layer. The feature map and the kernel size in the second convolution layer were also determined as 4 and 1. The tanh function was utilized as the activation function in the second layer. The Adam (Adaptive Moment Estimation) optimizer was adopted to optimize the network and improve the overfitting problem [16]. The categorical cross-entropy loss function, which has fast convergence speed and strong generalization ability, was used to learn a multi-class classification problem [26].

Table 2: The layers and main attributes of 1D-CNN model.

Layer (Type)	Output Shape	Param #
conv1d (Conv1D)	(None, 25000, 4)	8
max_pooling1d (MaxPooling1D)	(None, 12500, 4)	0
conv1d_1 (Conv1D)	(None, 12500, 4)	20
max_pooling1d_1 (MaxPooling1D)	(None, 6250, 4)	0
dropout (Dropout)	(None, 6250, 4)	0
flatten (Flatten)	(None, 25000)	0
dense (Dense)	(None, 256)	6400256
dense_1 (Dense)	(None, 128)	32896
dense_2 (Dense)	(None, 64)	8256
dense_3 (Dense)	(None, 10)	650

3 Results and Discussion

The present study developed a DL-based approach in order to classify different WT gearbox bearing faults and evaluated its prediction ability, considering multiple fault diameters (from 0.18 mm to 0.54 mm). The CWRU benchmark dataset was employed [25] to achieve this end. In order to evaluate the stability of the proposed DL-based method, the experiments were repeated five times (i.e., number of trials), and the standard deviation value was calculated.

The vibrations signals collected for the different bearing health conditions (see Table 1) through the CWRU experimental setup are demonstrated in Figure 5. Figures 5(a) to (c) represent the signals collected for the bearings with IR fault (labels IR_1, IR_2, and IR_3). Figures 5(d) to (f) stand for rolling element fault data (B_4, B_5, and B_6). Figures 5(g) to (i) depict the signals obtained for bearings with OR fault (labels OR_7, OR_8, and OR_9).

The present study plotted a confusion matrix to interpret further the results obtained. In this regard, the confusion matrix of the first trial is presented in Figure 6. The experimental results showed that the proposed 1D-CNN model classified the healthy state (H_0), rolling element (B_4, B_5, and B_6), and OR faults (OR_7, OR_8, and OR_9) perfectly. With this in mind, Figure 6 also indicates that the model performed relatively poorly in classifying IR faults.

As above-mentioned, the experiments were repeated five times (i.e., number of trials) to evaluate the model stability. The classification accuracies (confusion among the classes) differed slightly between the five tests. Considering all five tests executed, it is worth mentioning that the method has also slightly confused classifying IR_1 and IR_3 and IR_3 and OR_1 classes among themselves. In all tests, the proposed 1D-CNN model showed a prediction accuracy of more than 99%. In this regard, the prediction accuracies obtained were 99.56%, 99.82% (maximum), 99.72%, 99.54%, and 99.16% (minimum), respectively. The standard deviation value was calculated as 0.25. As a result, the average classification accuracy was 99.56% after testing the model with the CWRU dataset.

After five epochs, the loss and accuracy curves obtained for the first trial are depicted in Figure 7. The model has started to converge after only two epochs, indicating a strong converge ability (see Figure 7). The results reported point out that the proposed 1D-CNN model showed good robustness and stability characteristics.

The CWRU dataset is considered a standard reference for model validation and is widely employed for bearing fault diagnostics tasks. For example, Sun et al. [7] proposed a novel diagnosis approach based on an interpretable anti-noise efficient multi-scale CNN. Their study benefited from the CWRU

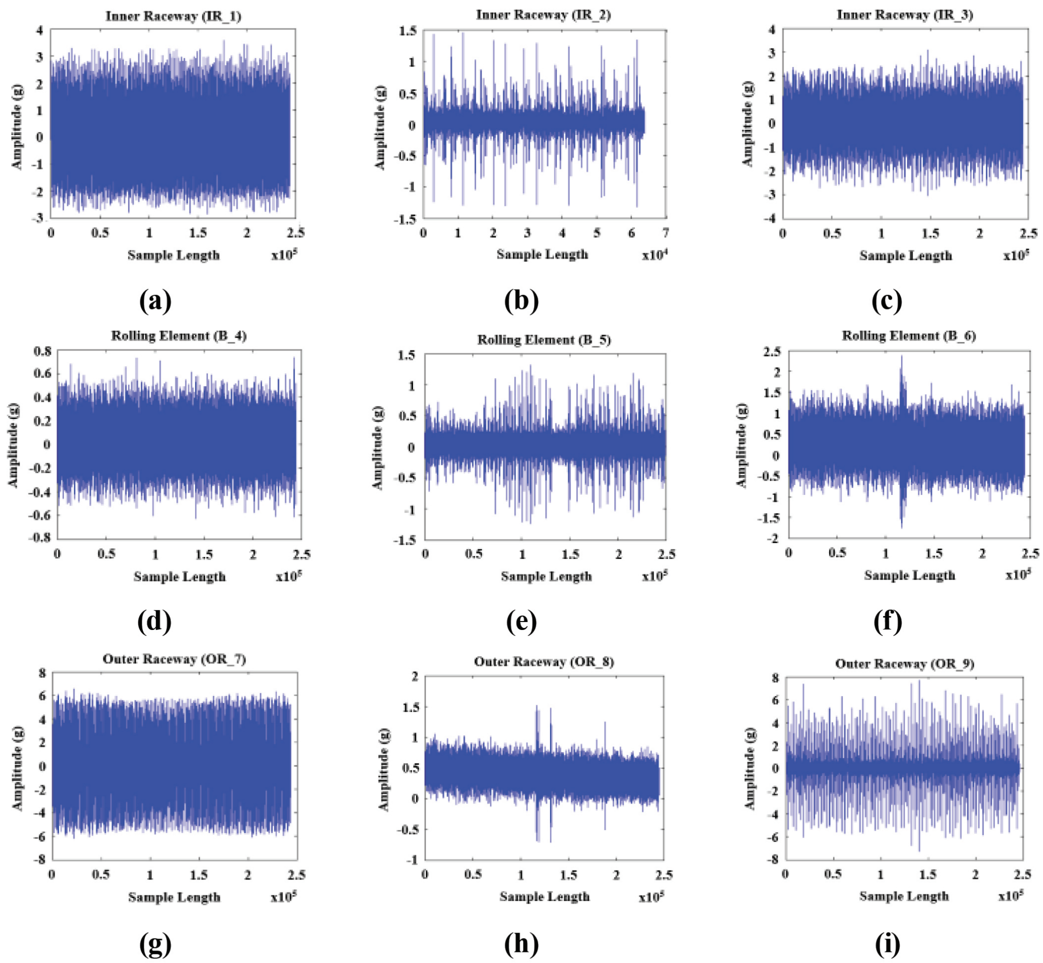

Figure 5: *Vibration signals of fault class IR_1 to OR_9, respectively.*

dataset and identified fifteen classes (i.e., healthy state, IR, OR, and rolling element faults) among the benchmark dataset. The proposed approach achieved an average accuracy of near 100% and outperformed the other methods considered within the scope of research work. Yang et al. [21] combined the 2D-CNN and the random forest (RF) classifier in order to diagnose different WT-bearing faults, considering noisy environments. After training the 2D-CNN, the feature vectors were inputted to the RF classifier to improve its generalization ability. The study concluded that the proposed 2D-CNN-RF model could reach an average prediction accuracy of 99.548% after testing its performance with the CWRU dataset. In order to diagnose bearing faults accurately and automatically, Shao et al. [26] proposed a novel technique, namely, ensemble deep auto-encoders. The study employed the vibration signals collected from the CWRU test rig and further identified twelve (i.e., healthy state, IR, OR, and rolling element faults) health classes. The findings indicated that the proposed technique performed superior to the other intelligent methods evaluated within the scope of research work.

Even if the above-discussed methods could accurately diagnose bearing faults in many cases, there is still room for further improvements in this research field. The present study proposed a 1D-CNN model to extract useful features from original vibration signals and classify different WT-bearing faults. WTs are subjected to harsh environmental conditions such as complex alternating loads and extreme temperature differences and are prone to failure [6]. A lack of prompt and accurate diagnosis of bearing faults may lead

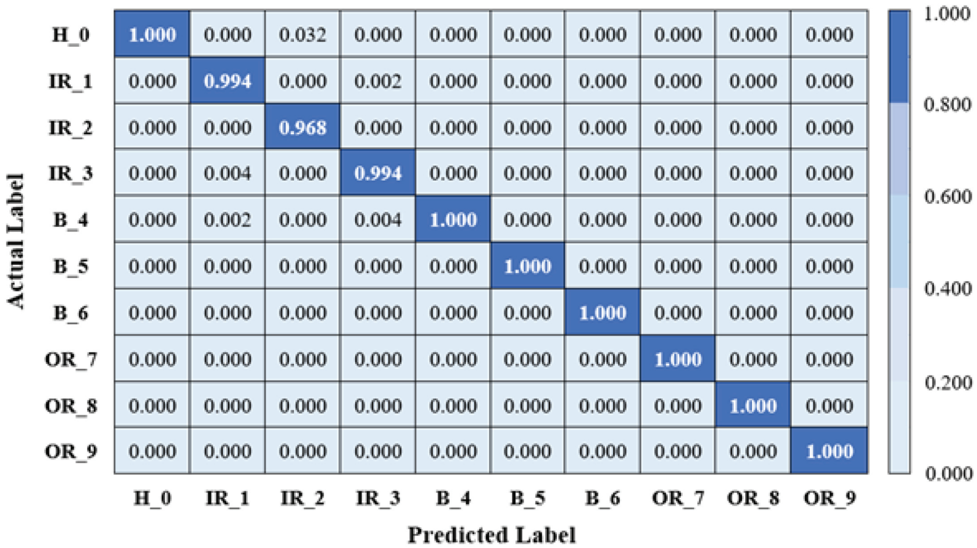

Figure 6: *Confusion matrix for the first trial.*

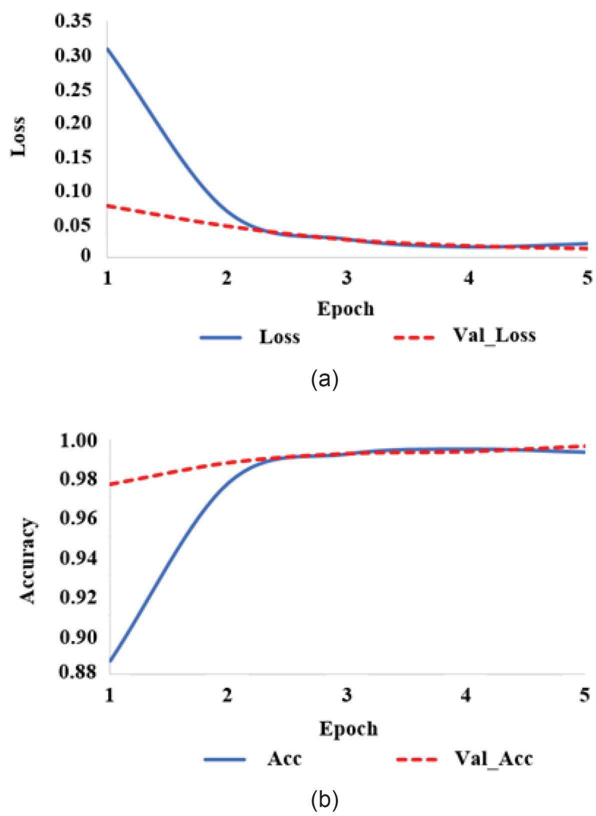

Figure 7: *The performance evaluation for the first trial: (a) loss and (b) accuracy curves.*

to financial loss and severe health risks [27, 28]. To manage the potential failure of WT gearboxes, the automatic and timely monitoring of rolling-element bearing faults is essential. The proposed DL-based approach could reduce O&M costs and improve the predictive maintenance strategies by early WT gearbox bearing fault diagnosis.

4 Conclusions

Wind energy is one of the fastest-growing and promising ways to generate renewable energy. With the wide availability of sensor technologies and ever-increasing computation power, CM has attracted continuous attention for reducing downtime and, thus, O&M costs of WTs. The data-driven intelligent methods could be utilized to establish a relationship between the system's inputs and outputs and achieve CM tasks.

The present study proposed an intelligent WT-bearing fault diagnosis method based on 1D-CNN. The proposed architecture was utilized to extract useful features from original vibration signals and solve a multi-class classification problem. The procedure was applied to the experimental vibration signals, and its performance was comparatively interpreted, considering multiple fault locations and diameters.

The experiments were repeated five times in order to evaluate the model's robustness and stability. As a result, the average classification accuracy of 99.56% was achieved. In addition, the standard deviation value was calculated as 0.25, indicating the stability of the proposed method. The results confirm that the proposed 1D-CNN method was suitable for identifying WT gearbox bearing faults and can optimize maintenance costs by early fault detection. Our method can be easily extended to other large industrial fields. The authors will continue to test their model under variable operating conditions to expand the scope of implementation.

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