Gear Transmission Fault Classification using Deep Neural Networks and Classifier Level Sensor Fusion

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Abstract: Gear transmissions are widely used in industrial drive systems. Fault diagnosis of gear transmissions is important for maintaining the system performance, reducing the maintenance cost, and providing a safe working environment. This paper presents a novel fault diagnosis approach for gear transmissions based on convolutional neural networks (CNNs) and decision-level sensor fusion. In the proposed approach, a CNN is first utilized to classify the faults of a gear transmission based on the acquired signals from each of the sensors. Raw sensory data is sent directly into the CNN models without manual feature extraction. Then, classifier level sensor fusion is carried out to achieve improved classification accuracy by fusing the classification results from the CNN models. Experimental study is conducted, which shows the superior performance of the developed method in the classification of different gear transmission conditions in an automated industrial machine. The presented approach also achieves end-to-end learning that can be applied to the fault classification of a gear transmission under various operating conditions and with signals from different types of sensors.

Key words: Fault Classification; Fault Diagnosis; Convolutional Neural Networks; Gear Transmission; Decision Fusion.

1 Introduction

Gear transmissions are crucial components in drive systems of various industries such as automobile, railway, aerospace, wind turbine, and manufacturing (Lei *et al.*, 2014). The malfunction of a gear transmission can cause unwanted system downtime, expensive maintenance cost, and even catastrophic accidents. The fault diagnosis of gear transmissions has attracted increasing attention in recent years with the growing demand for high reliability and safety of operation. The accurate diagnosis of the faults can provide valuable information to achieve condition-based maintenance whereby the system reliability and efficiency would be improved. Different fault diagnosis approaches have been developed in recent decades that can be classified into two main categories: model-based approaches and data-driven approaches (Wen *et al.*, 2018). With the advances in the sensor technology and the communication technology, data-driven approaches have gained more attention over model-based approaches due to the difficulties in deriving the model of a complex system.

Vibration and acoustic emission (AE) signals have been widely used to detect the faults ofgear transmissions as these signals can provide accurate health indicators of the monitored gear transmissions (Elasha *et al.*, 2017). Also, accelerometers can be utilized to collect vibration data without interrupting normal operation. In traditional data-driven approaches, feature extraction and selection are first conducted to obtain representative features of the vibration or AE signals. Features in different domains such as the time domain, frequency domain, and the time-frequency domain are extracted. Then, various classification methods are used to diagnose the faults using manually extracted features. Typical classification methods include artificial neural network, decision tree, support vector machine, and random forest. Li and He (Li and He, 2012) developed an approach for health monitoring, and fault diagnosis of gear transmissions based on AE features, through empirical mode decomposition (EMD) that integrates a threshold-based denoising technology. It showed an improved diagnostic performance of gear faults than other EMD-based AE features. Cabrera et al. (Cabrera *et al.*, 2015) developed a fault diagnosis approach for spur gears based on random forest (RF) and wavelet packet decomposition (WPD). The condition parameters of the vibration signal were first extracted by applying WPD with multiple mother wavelets. Then, the energy content of the coefficients for terminal nodes was used as the input feature for the classification using RF. They also studied how to find the optimal number of trees and the number of random features. Li et al. (Li *et al.*, 2015) proposed a multimodal deep support vector classification approach for gear transmission fault diagnosis with multimodal homologous features of the gear transmission vibration measurements in time, frequency and wavelet modalities. Yang et al. (Yang *et al.*, 2015) proposed an improved approach for SVM-based fault diagnosis by optimizing the model parameters of SVM using artificial bee colony algorithm. Their method achieved higher classification accuracy and less computational cost than other optimization algorithms. Lu et al. (Lu, Yan and de Silva, 2015) developed an enhanced feature selection method by integrating genetic algorithm, empirical mode decomposition, and receiver operating characteristic. Li et al. (Li *et al.*, 2016) developed a gear transmission fault diagnosis approach based on wavelet packet transform (WPT) and deep random forest. The statistical parameters of the WPT were first calculated from the collected signals. Two deep Boltzmann machines were then developed for deep representations of the WPT statistical parameters. Finally, a random forest was used to generate the diagnosis results.

However, the traditional data-driven approaches are based on manual feature calculation and selection. The manual process relies heavily on both the knowledge of the failure mechanism and expertise on signal processing of different types of signals. Also, the variance in load and working condition can significantly affect the results. Deep neural networks (DNNs) provide new opportunities for data-driven approaches with the end-to-end learning capability from raw data. DNNs have been successfully implemented in many areas such as speech recognition, computer vision, natural language processing, and robotics. Features can be automatically extracted through training of the deep network structures with massive linear and nonlinear transformations. The superior performance of DNNs has also attracted the strong interest of researchers in the area of machine condition monitoring (Xia *et al.*, 2018). Jia et al. (Jia *et al.*, 2015) developed a DNN-based fault detection method for rotating machines. They used autoencoder to pre-train the DNN model. Then, supervised learning through the back propagation algorithm was conducted to fine-tune the model for fault classification. However, the Fourier transform was still needed to process the original signal. Xia et al. (Xia *et al.*, 2017) proposed a fault diagnosis approach with stacked denoising autoencoder. Their method achieved higher fault diagnosis accuracy and better robustness to noise.

Fully connected DNN structures have a large number of parameters that can cause high computational cost and an increased possibility of overfitting problem. The convolutional neural network (CNN) uses shared weights in the structure, which results in much fewer connections and parameters. It is less likely that the training of the CNN model causes overfitting when compared with fully connected ones. Chen et al. (Chen, Li and Sanchez, 2015) presented a gear transmission fault diagnosis method using vibration signals and CNN. Their approach achieved high classification accuracy. However, the input features to the CNN model were still manually extracted. More recently, Xia et al. (Xia *et al.*, 2018) proposed an improved CNN-based fault diagnosis method for gear transmissions by fusing sensory data from multiple sensors. Raw signals were used directly and provided to the CNN model. With sensor fusion, their method achieved improved diagnosis performance compared with traditional data-driven approaches. However, the sensor fusion in their approach can only apply to the same type of sensors and with the same sampling rate.

This paper develops a novel gear transmission fault diagnosis approach based on the CNN model and decision level sensor fusion. The raw sensory data from multiple sources are directly utilized as the input to the CNN models to classify different types of failures. Then, the classification results from each CNN model are fused at the decision level to produce the final diagnosis result. An experimental study on the gear transmission fault diagnosis of an industrial machine is carried out to evaluate the effectiveness of the developed approach. The rest of the paper is organized as follows. In Section 2 knowledge of CNN and sensor fusion are introduced. Section 3 presents the system framework and the processes of the developed method in detail. Section 4 presents an experimental study of gear transmission fault diagnosis which is to evaluate the effectiveness of the CNN-based fusion approach. Section 5 concludes the paper and proposes possible future work.

2 Background Knowledge

Convolutional neural networks (CNNs) have been successfully implemented in many applications such as object detection in computer vision, sleep disorder diagnosis in humans, and damage assessment in pipelines. A CNN model usually contains numerous multi-stage structures with both linear operations and nonlinear transformations. The intermediate results are named feature maps (LeCun, Kavukcuoglu and Farabet, 2010). The two main operations of a CNN model are convolution and pooling. A CNN model is composed of one or more such 2-layer structures followed by fully connected layers and a final classification layer. The feed-forward operation of CNN can be represented by the following function:

$$g(X) = g_K(\dots g_2(g_1(X,\theta^{(1)}),\theta^{(2)})\dots),\theta^{(K)}) \tag{1}$$

Here X denotes the input data to the CNN model; $\theta^{(1)},\theta^{(2)},\dots,\theta^{(K)}$ are the model parameters including weights and biases; $g_1,g_2,\dots,g_K$ are the operations at each layer. These functions generate intermediate feature maps between layers.

2.1 Convolution Operation

With the convolution operation, the input matrix or vector is convolved with a set of learnable filters togenerate new feature maps (LeCun, Kavukcuoglu and Farabet, 2010). The convolution operation is given by:

$$X_m^{(k)} = f\left(\sum_{m=1}^{M} W_{mm'}^{(k)} * X_m^{(k-1)} + B_{m'}^{(k)}\right) \tag{2}$$

Here k is the layer index; $m = 1,2,\dots,M$ denotes the index of feature maps as the input; and $m' = 1,2,\dots,M'$ represents the index feature maps as the output. The $*$ denotes the convolution operation applied to the m'-th filter $W_{mm'}^{(k)}$ with the m-th feature map $X_m^{(k-1)}$. $B_{m'}^{(k)}$ represents the biases. Then, the feature maps are provided to the nonlinear activation function f. In this paper, the rectified linear unit (ReLU) is selected as the activation function. ReLU has been shown to have good performance in many CNN-based models (Xing, Ma and Yang, 2016). The function of ReLU is expressed as:

$$y_{ijk} = \max(0, x_{ijk}) \tag{3}$$

2.2 Feature Pooling Operation

Feature pooling is an operationthat reduces the size of the feature map. A pooling layer fuses nearby values in a feature map to become one value, using a defined operator. Typical pooling operators include average-pooling and max-pooling. In the present work, max-pooling is selected. The formula of max-pooling is:

$$y_{ijk} = \max(y_{i'j'k} : i \le i' < i+u, j \le j' < +v) \tag{4}$$

Here, u denotes the window length of the pooling; and v denotes the window width. Max-pooling generates the largest value within the window as the value of the neighborhood. The stride size can be 1 or larger. Also, the size of the window can be defined based on the training performance.

2.3 Softmax Operation

In the classification of multiple classes, asoftmax layer is usually utilized. Softmax can be seen as the generalized version of logistic regression (D'Ambrosio, Iannello and Soda, 2013). Using a dataset containing n samples $\{x^{(i)}\}_{i=1}^{n}$. $x^{(i)} \in R^m$ has a total number of s classes with the corresponding label set $\{t^{(i)}\}_{i=1}^{n}$ where $t^{(i)} \in \{1,2,\ldots,s\}$. The softmax layer outputs the probabilities of the input data belonging to all s classes. The probabilities generated are given by:

$$P(t^{(i)}=j \mid x^{(i)};\theta^{(L)}) = \left(\sum_{l=1}^{s} e^{(\theta_l^{(L)})^T x^{(i)}}\right)^{-1} \times [e^{(\theta_1^{(L)})^T x^{(i)}} \; e^{(\theta_2^{(L)})^T x^{(i)}} \cdots e^{(\theta_s^{(L)})^T x^{(i)}}]^T \tag{5}$$

where $j = 1, 2, \ldots, s$. $\theta^{(L)} = [\theta_1^{(L)}, \theta_2^{(L)}, \ldots, \theta_s^{(L)}]$ are the softmax model parameters.

2.4 Classifier Level Sensor Fusion

Sensor fusion is the process of integrating data from multiple sensor sources to produce more accurate and reliable information compared with that provided by any individual sensor. Typically, there are three levels of sensor fusion: data level fusion, feature level fusion, and classifier level fusion. Classifier level sensor fusion can be applied to data from different types of sensors. The final decision is obtained by fusing the classification result from each classifier. According to the output types of a classifier, the classifier fusion methods can be divided into three categories: abstract type, rank type, and measurement type, with increased required information (Xia, Kong and Hu, 2011). The measurement type of classifier fusion contains the most information that usually gives the most accurate results. A simple method for the measurement type classifier fusion is to linearly combine the posterior probabilities from each classifier.

3 CNN-based Fault Classification with Classifier Level Sensor Fusion

This paper presents a gear transmission fault diagnosis approach based on CNN models and classifier level sensor fusion. The raw data from different sensors are directly fed into various one-dimensional CNN models. The features are extracted automatically by the training process of the CNN structures. Then, the classification results, generated by the CNN models, are fused at the classifier level to produce more accurate and reliable results. The proposed method can be used with collected signals from different types of sensors and with different sampling rates. The flowchart of the proposed gear transmission fault diagnosis method is shown in Fig.1.

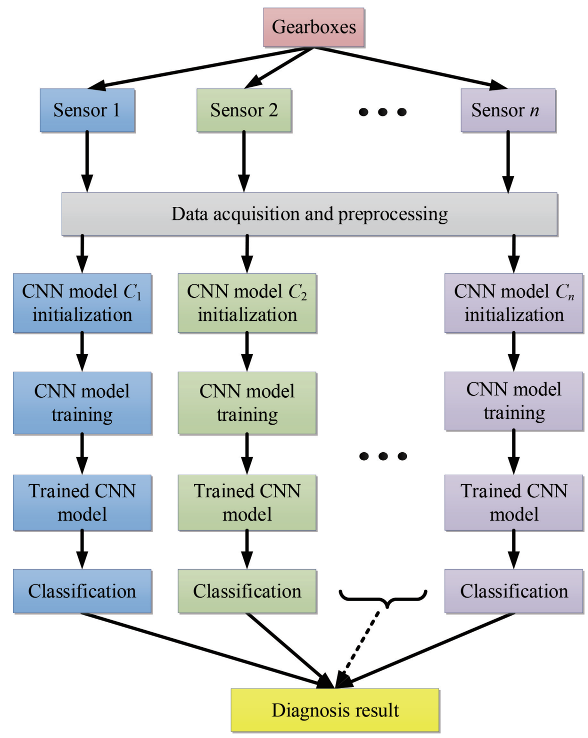

Fig. 1 Flowchart of the gear transmission fault diagnosis approach using CNN and sensor fusion.

Sensory datafrom the monitored gear transmissions are acquired from different sensors. The data contains the signals under normal condition and fault conditions. After proper preprocessing to reduce the effect of noise, the collected data from each sensor is divided into the training subset and the testing subset. For data from each sensor source, a CNN model is constructed. Then, the training subsets are utilized for training the CNN models. Next, the testing subsets are used to evaluate the diagnostic performance and generalization capability of the trained CNN models. The generated probabilities of each class are then fused at the classifier level to obtain the final diagnosis result.

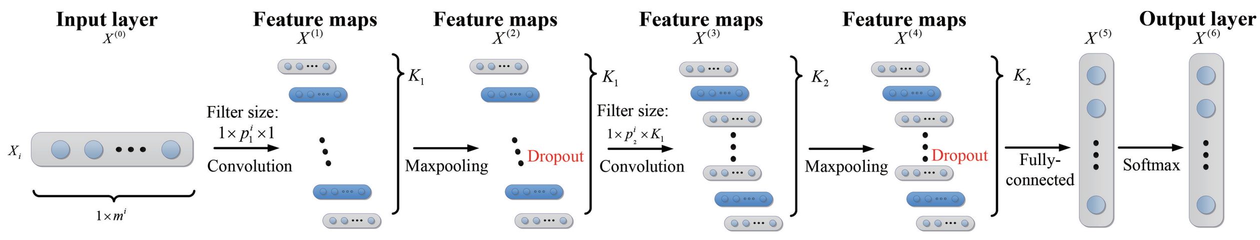

Fig. 2 The CNN model structure of the proposed method.

The detailed structure of the one-dimensional CNN model is shown in Fig. 2. Monitoring data of thegear transmissions from the n sensors X_i, ($i = 1$, $2 \ldots n$) are sent to the n CNN models. Each input X_i has a dimension of $1 \times m^i$. The convolution operation is applied on X_i by K_1^i filters each having a size of $1 \times p_1^i \times 1$. The convoluted result is then activated by the ReLU function. It produces K_1^i feature maps, each with a dimension of $1 \times (m^i - p_1 + 1)$. Followed by the max-pooling layer, the feature maps are subsampled using Equation (4). Another combination of convolution and pooling layers is stacked to the CNN model. With the multiple combinations of convolution and pooling layers, the model can capture representative features from the training process. The feature maps after the last pooling operation are fully connected to produce a one-dimensional vector. Finally, a softmax layer is used to generate the probabilities of the classification of input to each class. Overfitting can be a problem in the training process of deep learning. In this paper, the dropout strategy is utilized to decrease the effect of overfitting (Srivastava *et al.*, 2014).

4 Experimental Study

An experimental study is carried out to check the effectiveness of the proposedgear transmission fault classification approach using CNN and classifier level sensor fusion. Gear transmissions in normal condition and several faulty conditions in the conveyor system of an industrial machine are tested. Magnetically mounted accelerometers are used to collect the vibration signals of the gear transmissions under four conditions. The proposed method is then evaluated by checking the diagnosis performance and by comparison with other cutting-edge fault diagnosis approaches.

4.1 Experimental Setup

In the experiment, the gear transmission condition dataset is acquired from the conveyor subsystem of an automatic fish processing device. Fig. 3 shows the experimental setup. It consists of a motor and a gearbox. Two accelerometers are magnetically mounted both horizontally and vertically on the surface of the gear transmission. Vibration signals are collected for four different gear transmissions with four conditions, as indicated in Fig. 4. A National Instruments PXIe data acquisition system is used to collect the sensory data. The sampling frequency is set to be 5 kHz.

4.2 Data Description

In this experiment, 1500 samples from the gear transmission of each condition are collected from each sensor. The sampling time is 0.2 seconds for each sample. Therefore, each sample contains 1000 data points. There are 6000 samples in total. The vibration signals of the four different conditions are plotted in Fig. 5. To compose the training and testing datasets, 70% of the samples are included in the

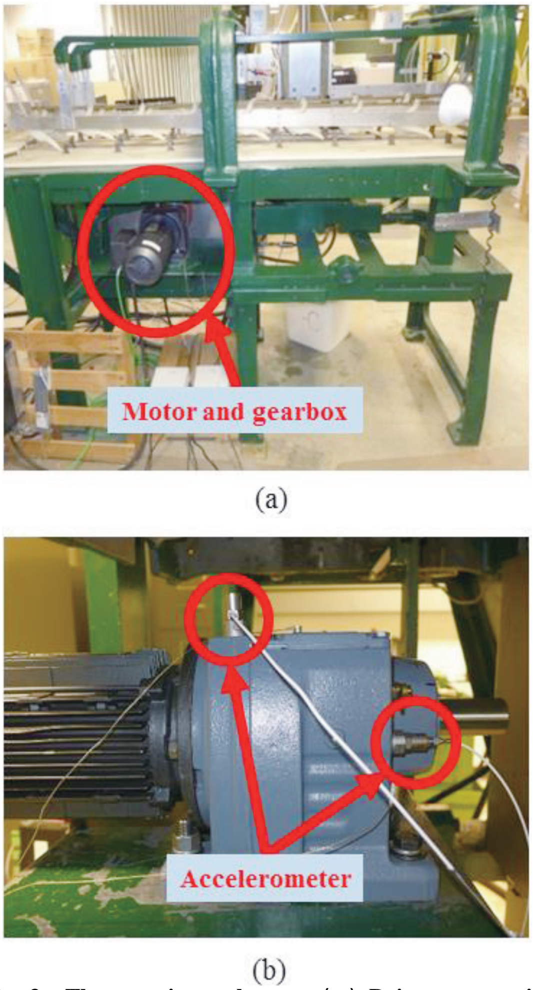

Fig. 3 The experimental setup. (a) Drive system with a motor and gearbox; (b) Vibration signal acquisition using two accelerometers.

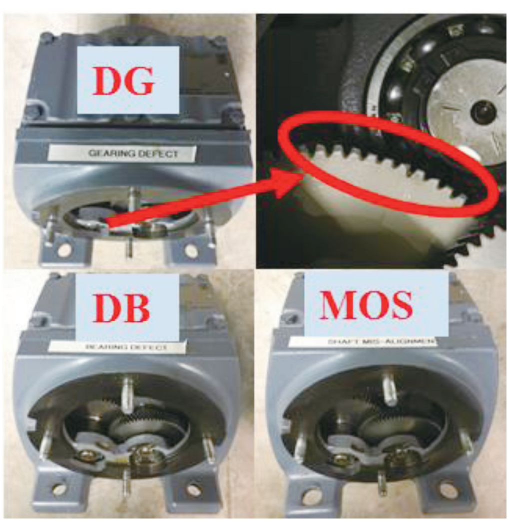

Fig. 4 Faulty gear transmissions including those with gear defect, bearing defect, and misaligned output shaft.

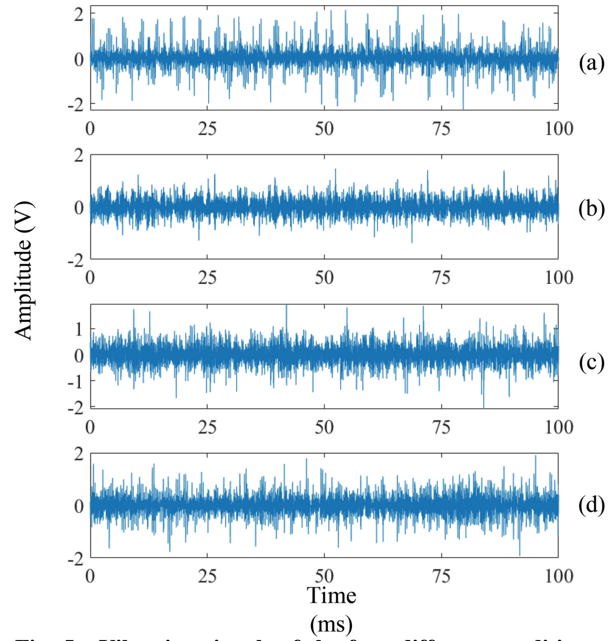

Fig. 5 Vibration signals of the four different conditions.

training dataset. The remaining samples are divided equally to form the validation dataset and the testing dataset. First, the CNN model is trained on the training data to adjust the parameters. The model is then validated using the validation dataset to see if overfitting occurs. The training process will be stopped when the loss starts decreasing slowly, or when it begins to increase. In this experiment, the training process of the CNN model is continued for another period even when the loss begins to increase. Given the loss curve, an appropriate epoch is selected with the corresponding CNN model parameters. The test dataset is used to evaluate the performance of each CNN model. Finally, the classification results from the CNN models are fused to produce the final diagnosis results.

4.3 Discussion

First, two CNN models are established to classify thegear transmission fault using vibration signals from each of the two accelerometers. Mini-batch stochastic gradient descent is utilized to update the parameters of the models. The size of the batch is set at 100. The fault diagnosis result on the test dataset is shown by the confusion matrix in Fig. 6. The confusion matrix of the classification results indicates the overall accuracy of the classification, which is 99.81%. It is seen that only two samples were classified incorrectly.

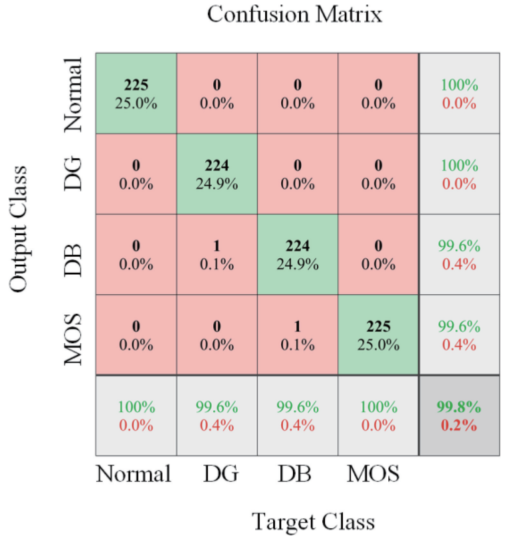

Fig. 6 Confusion matrix of the classification results.

To demonstrate the performance of the developed method, a comparison is conducted between the CNN-based approach and other data-driven approaches with manual feature extraction. Features in both time and frequency domains are calculated. Features selected ina recent paper (M. Xia *et al.*, 2018) are used in this exercise. Then, SVM with a linear kernel, SVM with a quadratic kernel, K-nearest neighbor (KNN), and Weighted KNN are used to classify the faults. The comparison of the results is shown in Fig. 7. All the approaches perform well in detecting the normal condition. The method proposed in the present paper achieves higher diagnosis results than all the other approaches for all the faulty conditions. The CNN-based method with classifier level sensor fusion has the best overall performance.

Next, the effectiveness of the sensor fusion in the proposed method is evaluated by comparing with the diagnosis resultsfor data from one sensor, by the same CNN model. Each test is repeated ten times. The comparison of the averaged training and testing accuracies of the two methods is provided in Table I. The testing accuracy of the proposed method is 99.78%. The result using signals from one sensor is 97.58%. It is seen that the proposed method achieves better diagnosis performance at higher accuracy and lower standard deviation.

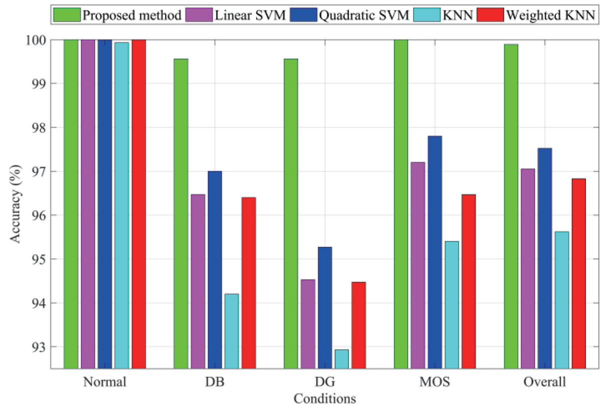

Fig. 7 Results of comparison with other approaches.

Table 1 Classification Results by Sensor Fusion or Single Sensor.

		Average	Standard deviation
Training Accuracy (%)	Multiple sensors	99.96	0.08
	One sensor	98.18	0.69
Testing accuracy (%)	Multiple sensors	99.78	0.33
	One sensor	97.58	1.40

5 Conclusion

This paper presented agear transmission fault diagnosis approach using deep learning and sensor fusion. CNN-based models were used to classify the condition using sensory data from each sensor. Then, classifier level sensor fusion integrated the results from each CNN model to produce the final classification results. The proposed method obtained satisfactory fault classification results. By comparing the developed method and the traditional data-driven approaches with manual feature extraction, the proposed fusion method showed superior performance. The end-to-end learning property enables the general application of the method to gear transmission fault diagnosis with different faults and working conditions. Also, the classifier level sensor fusion can be applied with different sensors and with different sampling rates.

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