Probabilistic Gear Fault Diagnosis Using Bayesian Convolutional Neural Network

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Abstract: Vibration measurement-based gear fault diagnoses have shown the promise aspects, where the deep learning methods have been harnessed. However, the traditional deep learning methods are deterministic in nature, and will be prone to false prediction when uncertainties are involved, such as time varying condition and measurement noise. To address these challenges, the fault pattern recognition needs to be performed in a probabilistic manner. Considering the features in vibration time-series usually are massive, in this research we develop a Bayesian convolutional neural network (BCNN) to conduct the gear fault diagnosis under uncertainties. The predictive distribution yielded facilitates the decision making with confidence level, leading to the robustness enhancement of the fault diagnosis. Comprehensive case studies are carried out to validate the proposed methodology.

Keywords: gear fault diagnosis, time varying condition, measurement noise, deep learning, Bayesian convolutional neural network (BCNN).

1. INTRODUCTION

Gear failure will lead to the abnormal function of rotating machinery. Therefore, the reliable health monitoring of the gear plays a vital role. Currently, vibration measurement has been commonly utilized to support the gear fault diagnosis (Saravanan et al, 2009; Shen et al, 2014; Zhang and Hu, 2019). Through analyzing the measurement, different faults can be discriminated. Signal processing analysis is a well-known approach to extract the important features in the measurement, and subsequently to facilitate the fault pattern recognition/discrimination. Recently there are various signal processing methods including the time-domain (Hong and Dupia, 2014), frequency-domain (Sharma and Parey, 2017) and time and frequency-domain methods (Cheng et al, 2010; Jena et al, 2014; Zhang and Tang, 2018; Qin et al, 2019) that have been developed and employed in gear fault diagnosis. Nevertheless, in the scenario when the correlation between the features and faults is complex, these signal processing techniques are not adequate to enable the reliable fault diagnosis task.

Deep learning-based fault diagnosis techniques have attracted the growing interest because of their capability in automatically and powerfully extract the fault-related features, and then build the mapping between the features and faults. Convolutional neural network (CNN), as one most representative class of deep learning methods has been adopted in a broad range of research. Cao et al (2018) used CNN-based transfer learning to conduct gear fault diagnosis using small dataset. Kim and Chi (2019) developed a CNN model which is implemented upon the signal segmentation to fulfill the accurate gear fault diagnosis regardless the measurement location. Li et al (2020) developed a new CNN with residual connection to classify gear pitting faults with mixed operating conditions. In addition to deep learning methods, other data-driven approaches, such as fuzzy inference system, support vector machine and so on have also been attempted to pursue the success of fault diagnosis (Bansal et al, 2013; Zhou and Tang, 2021).

Despite the success of aforementioned methods, the challenges of the practical fault diagnosis remain unsolved. One well-known challenge of conventional deep learning methods is the lack of ability to estimate the uncertainty effect in decision making. The deterministic nature of those methods is prone to false fault prediction if uncertainties inevitably involve. Multiple uncertainty sources in practical implementation exist, including but not limited to the time-varying condition and measurement noise. To minimize the negative effect of uncertainties and accordingly improve the fault diagnosis performance, the diagnosis technique with probabilistic prediction capacity is required. While some probabilistic machine learning methods, such as Gaussian process can fulfill the probabilistic fault diagnosis, they are subject to the limitation of simultaneous feature extraction on a massive number of real-time data (Liang and Zhou, 2021). In this research, we propose to use the Bayesian convolutional neural network (BCNN) which takes full advantage of both CNN and Bayesian optimization. This allows one to comprehensively investigate the uncertainty impact when performing the gear fault diagnosis.

The rest of the paper is organized as follows. Section 2 outlines the gear fault diagnosis framework built upon the BCNN. Section 3 illustrates the feasibility of the framework by implementing the fault diagnosis on a lab-scale gearbox system with different formulated scenarios. Section 4 gives concluding remarks.

2. METHODOLOGY OVERVIEW

In this section, the gear fault diagnosis framework built upon BCNN model is mathematically outlined. BCNN model fundamentally exploits the architecture of CNN model. The unique difference of BCNN as compared with the CNN is that the training is built upon the Bayesian optimization, yielding the probabilistic weights and biases in the form of distribution in the network. Let $\boldsymbol{\theta}$ be the network unknowns, i.e., $[\mathbf{w}, \mathbf{b}]$. Built upon the training input-output relations denoted as $\mathbf{D}$, the posterior distribution of $\boldsymbol{\theta}$ can be obtained using the Bayes' rule (Zhou and Tang, 2016),

$$p(\boldsymbol{\theta} \mid \mathbf{D}) = \frac{p(\mathbf{D} \mid \boldsymbol{\theta}) p(\boldsymbol{\theta})}{\int p(\mathbf{D} \mid \boldsymbol{\theta}) p(\boldsymbol{\theta}) d\boldsymbol{\theta}} \tag{1}$$

In this research, $\mathbf{D}$ is represented as $\mathbf{D} = [\mathbf{X}, \mathbf{y}]$, where $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, ...]$ denotes the time-series signals and $\mathbf{y} = [y_1, y_2, ...]$ is the associated fault labels. Assume that the input-output relation of single sample can be implicitly expressed as $y = f(\mathbf{x}, \mathbf{w}, \mathbf{b})$. Equation (1) then can be rewritten as

$$\begin{aligned} p(\mathbf{w}, \mathbf{b} \mid \mathbf{X}, \mathbf{y}) &= \frac{p(\mathbf{y} \mid \mathbf{w}, \mathbf{b}, \mathbf{X}) p(\mathbf{w}, \mathbf{b})}{\int p(\mathbf{y} \mid \mathbf{w}, \mathbf{b}, \mathbf{X}) p(\mathbf{w}, \mathbf{b})} \\ &= \frac{p(\mathbf{y} \mid \mathbf{w}, \mathbf{b}, \mathbf{X}) p(\mathbf{w}, \mathbf{b})}{p(\mathbf{y} \mid \mathbf{X})} \end{aligned} \tag{2}$$

It is worth mentioning that there is no analytical form for the posterior distribution shown above. To approximate the posterior distribution, the variational distribution $q(\mathbf{w}, \mathbf{b} \mid \boldsymbol{\varphi})$ that is represented in an analytical form oftentimes is adopted. if $q(\mathbf{w}, \mathbf{b} \mid \boldsymbol{\varphi})$ is a normal distribution, $\boldsymbol{\varphi}$ thus represents the mean and variance of unknowns $\boldsymbol{\theta}$. The variational distribution-based posterior approximation can be achieved by minimizing the Kullback-Leibler (KL) divergence between $p(\mathbf{w}, \mathbf{b} \mid \mathbf{X}, \mathbf{y})$ and $q(\mathbf{w}, \mathbf{b} \mid \boldsymbol{\varphi})$ (Kullback, 1997; Blei et al, 2017).

Once the probabilistic weights and biases of BCNN model are optimized through training, The posterior predictive distribution of $\mathbf{y}^*$ over a set of unobserved time-series $\mathbf{X}^*$ can be formulated as

$$p(\mathbf{y}^* \mid \mathbf{w}, \mathbf{b}, \mathbf{X}, \mathbf{y}, \mathbf{X}^*) = \iint p(\mathbf{w}, \mathbf{b} \mid \mathbf{X}, \mathbf{y}) p(\mathbf{y}^* \mid \mathbf{w}, \mathbf{b}, \mathbf{X}^*) d\mathbf{w} d\mathbf{b} \tag{3}$$

In BCNN-based prediction, for each deterministic input $\mathbf{x}_i^*$, its resulting output $\mathbf{y}^*$ is probabilistic because the weights and biases $[\mathbf{w}, \mathbf{b}]$ are randomly sampled from the optimized variation distribution $q(\mathbf{w}, \mathbf{b} \mid \boldsymbol{\varphi}^*)$. Because of the probabilistic weights and biases, the outputs of all layers other than the input layer become probabilistic. The Monte Carlo analysis is employed to numerically identify the probability distribution of interested output given the input $\mathbf{x}_i^*$.

3. CASE DEMONSTRATION

In this section, the proposed BCNN-based framework is implemented onto the fault diagnosis of a lab-scale gearbox system using vibration measurement. Two cases are formulated to validate the framework.

3.1 Data acquisition and BCNN architecture

The gearbox testbed is shown in Figure 1. 9 different fault conditions are manufactured and introduced into the testbed (Figure 2), upon which the corresponding measurements are collected. The same number of data samples are produced through the time-series vibration signals for all fault conditions. Each sample essentially is a time series with 3,600 data points. The overview of the data is given in Table 1.

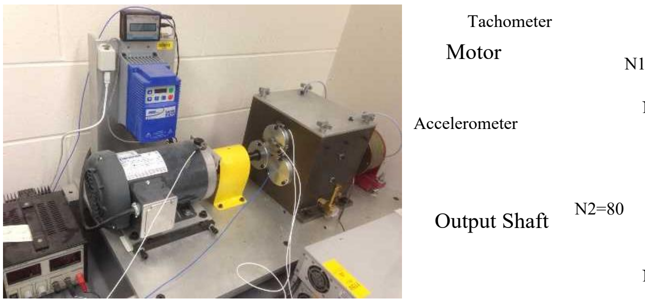


Figure 1. Experimental testbed.

Figure 2. Fault conditions.

Table 1. Gear fault data

Type/Fault class	Fault condition	Data size
1	Healthy	104
2	Missing tooth	104
3	Crack	104
4	Spalling	104
5	Chipping_tip_5 (least severe)	104
6	Chipping_tip_4	104
7	Chipping_tip_3	104
8	Chipping_tip_2	104
9	Chipping_tip_1 (most severe)	104

There are 932 data samples in total to be used in the subsequent analysis. Two different cases are formulated, including: (1) Normal fault classification using the dataset provided; (2) Normal fault classification using the dataset with measurement noise introduced. Since the samples are relatively small-sized, we design a small-scale architecture for BCNN based on the empirical experience. The layer configuration of configured BCNN is shown in Table 2. As can be seen in Table 2, no fully connected layers are built between the convolutional layers and the softmax layer, which significantly reduces the number of learnable parameters.

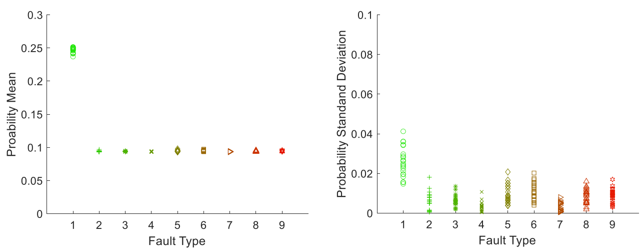
Table 2. BCNN model architecture

Layer	Output shape	Parameter number
Input	$256\times256\times1$	0
Convolutional (filter: $3\times3\times32$) (ReLU)	$128\times128\times32$	608
Convolutional (filter: $3\times3\times64$) (ReLU)	$64\times64\times64$	36,928
Convolutional (filter: $3\times3\times128$) (ReLU)	$32\times32\times128$	147,584
Flatten	131,072	0
Dense (Softmax)	9	2,097,160

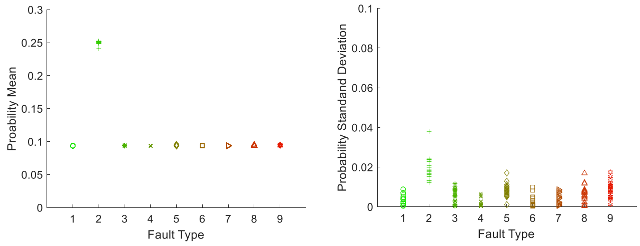
3.2 Case investigations

3.2.1 Fault classification using collected dataset

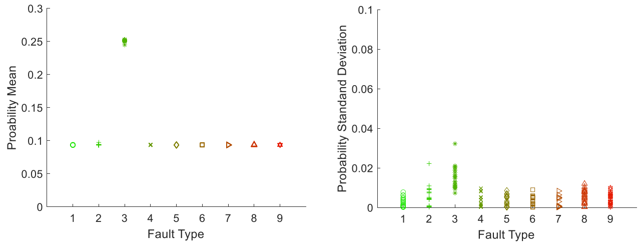
In this case, we split the dataset shown in Table 1 into 80% training and 20% testing data. The stratified splitting is specifically used to ensure the balanced classes. 5% training data are hold out for validation during the model training. By observing the training and validation accuracy tendencies with respect to epoch, it is ensured that there are no model overfitting and underfitting issues. Once the BCNN model is well-trained, we can use it to predict the faults over testing inputs and compared them with the actual faults. As shown in Section 2, the BCNN can yield so called predictive distribution, which generally can be represented by distribution of probability mean and standard deviation. Gathering the probabilistic information of all testing samples yield the result in Figure 3. As can be observed, the probability mean of testing samples for true fault type is much larger than that for other fault types, indicating the accurate classification from a probabilistic perspective. Additionally, the probability standard deviations overall are small. The result indeed illustrates the accurate decision making with high confidence level. The crispy classification is 100% if the classification of the sample is considered as accurate when the actual fault of sample is identified as being the highest probability mean.



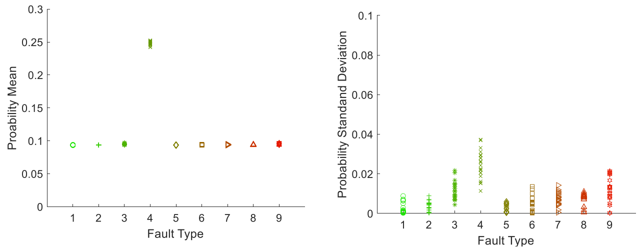
(a)



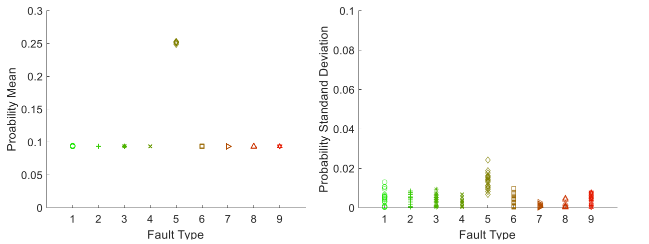
(b)



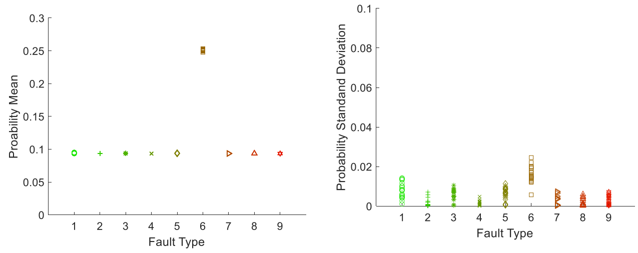
(c)



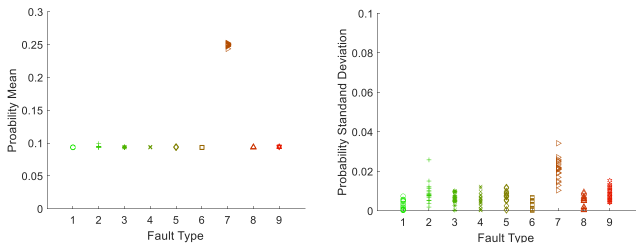
(d)



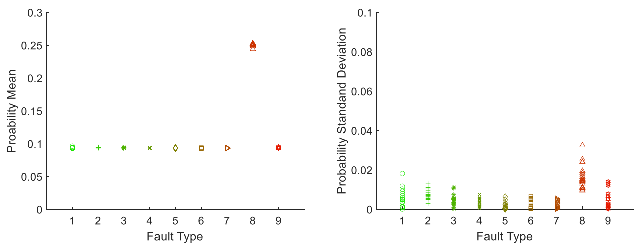
(e)



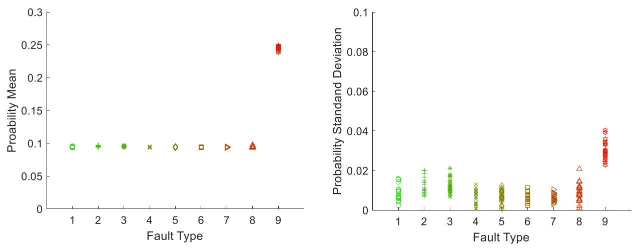
(f)



(g)



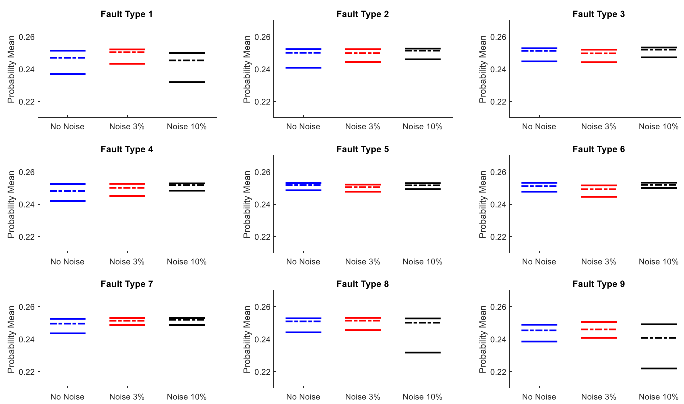
(h)



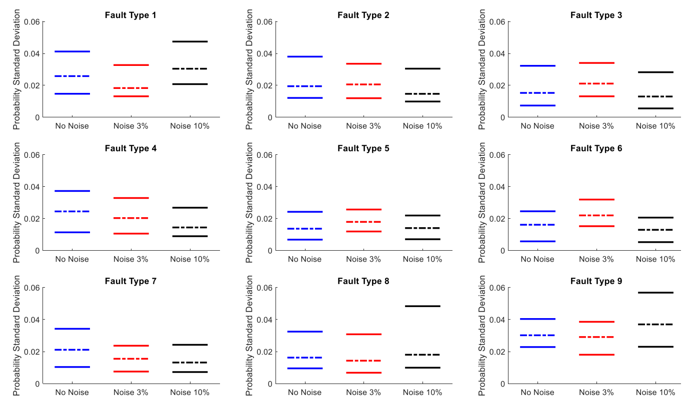
(I)

Figure 3. Classification probability outputs of testing samples with different faults (a) fault type 1; (b) fault type 2; (C) fault type 3; (D) fault type 4; (E) fault type 5; (F) fault type 6; (G) fault type 7; (H) fault type 8; (I) fault type 9.

3.2.2 Fault classification using dataset with additional measurement noise



(a)



(b)

Figure 4. Classification probability outputs of testing samples with different faults with respect to noise level (a) Probability mean; (b) Probability standard deviation.

It is well-known that the measurement inevitably is subject to noise. To examine the feasibility of proposed method in coping with the measurement with degraded quality, we introduce additionally 3% and 10% white noises into the measurement and implement the same analysis procedures mentioned above to analyze the distribution of probability mean values and standard deviations of all testing samples. For the sake of comparison, we put the results of three scenarios, i.e., no noise, 3% noise, and 10% noises together shown in Figure 4.

For conciseness, only the upper and low bounds, and mean of distribution/probability of samples for actual fault are given (solid line denotes the low or upper bound, and dash line denotes the mean). Clearly, the predictions under different noise levels exhibit very small discrepancies. It seems that the worst case (10% noise level) will significantly increase the bands of both probability mean and standard deviation for certain fault conditions, i.e., fault type 1, 8 and 9. That is reasonable since the noise naturally will interfere the decision making. The consequence is, even the decision making is very accurate, i.e., 100% crispy classification accuracy, its confidence level may reduce.

4. CONCLUSIONS

In this research, a Bayesian convolutional neural network (BCNN) is developed to conduct the gear fault diagnosis by taking into the uncertainty effect into account. This deep learning method can yield the probabilistic prediction result, allowing one to further incorporate the empirical knowledge to assist the wise decision making. This unique advantage can enable this method to be tailored for the practical implementations. The case studies that implement the fault diagnosis on a lab-scale gearbox system are carried out to validate the methodology. The results clearly show that the BCNN performs satisfactorily in terms of accuracy using the vibration measurement both with and without noise.

5. ACKNOWLEDGMENTS

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