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A Robustness Benchmark for Prognostics and Health Management

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Abstract: With the rise of intelligent manufacturing, prognostics and health management(PHM) has developed rapidly as an important part of intelligent manufacturing.Existing deep learning-based PHM methods are data-dependent. However, sensor data often contains noise and is redundant and high-dimensional, making it difficult for the PHM methods to learn a stable set of model parameters, so the methods are likely to be wrong when disturbed. However, the factory hopes that the PHM methods are robust enough to adapt to various perturbations, so it is necessary to perform robustness evaluation on the existing methods in advance for easy deployment. Although the existing robust theoretical analysis methods for neural networks can obtain tight robust boundaries, they consume a lot of computing resources and are difficult to scale to large neural networks. To slove this problem, We design a benchmark for robustness analysis of large deep learning PHM models, in which we test the model robustness using a variety of perturbations to simulate the actual production environment of the factory. Specifically, Gaussian noise is used to test the robustness of the model to background noise; random mask is used to test the robustness of the model to data loss. We hope that our robustness benchmark can serve as a reference for designing PHM models to improve the robustness of factory PHM models.

Key Words: Prognostics and Health Management, Robustness

1 Introduction

In 2015, the Chinese government put forward the "Made in China 2025" plan, and intelligent manufacturing has gradually emerged. Intelligent manufacturing covers machinery, aviation, ships, automobiles, light industry, textiles, food, electronics and other industries [1][2][3]. Different industries have different specific content for intelligent manufacturing. However, each industry need health management of production equipment. Therefore, PHM is a worthy problem to research, which can improve the production efficiency and product quality and reduce the losses caused by equipment failures. An important task in PHM is to predict the time of equipment failure in time[9] and accurately determine the type of equipment failure [12][13].

Due to the amazing performance of deep learning in vision and NLP, more and more researchers try to use deep learning for PHM and have achieved excellent results[4][10]. Existing deep learning-based PHM methods are data-dependent[6][8][12]. However, sensor data often contains noise and is redundant and high-dimensional, making it difficult for the PHM model to learn a stable set of model parameters and to effectively resist perturbation. In actual factories, there are various perturbations such as background noise, missing data, so the device health management model is likely to be wrong in practical applications. As shown in Figure 1, the original data point A is classified as blue class by the model f. When a perturbation ε is applied, $\|\varepsilon\|_p = \xi$, point A may drift to point B, that is, $x_B = x_A + \varepsilon$. When it is at point B, the original data will be judged as yellow class by the model f, and the classification will be wrong. To sum up, the existing PHM methods may be difficult to adapt to the complex and changeable actual factory environment. However, factories always hope that the PHM method is robust enough, so it is necessary to evaluate the robustness of the PHM method in advance in order to actually deploy the PHM method. While the existing robust theoretical analysis methods can obtain approximate boundaries of neural networks, it is difficult to extend to large neural networks at the cost of computational overhead[14][16][14].

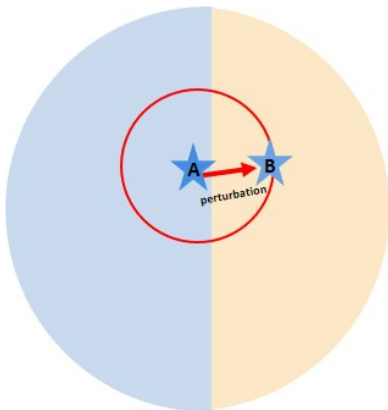

Fig. 1: Neural network misclassifies due to perturbation

To solve this problem, we design a robustness test benchmark for PHM. Considering the complex actual production scenarios of factory, we use a variety of disturbances to simulate the actual production environment of the factory to test the robustness of the model. Specifically, Gaussian noise is used to simulate the background noise generated by factors such as mutual interference of machine vibrations to test the robustness of the PHM method to background noise; random mask is used to simulate the absence of sensor signals to test

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the robustness of the PHM method to data loss.

All in all, the main contributions of the proposed method are summarized as follows:

1) By simulating the complex real scenarios of the factory, we propose a simple and feasible robustness test benchmark for the PHM method to achieve the robustness evaluation.

2)The proposed method is evaluated on CWRU dataset and proven effective.

2 Related Work

Recetly, more and more researchers are paying attention to the application of deep learning in PHM. We will mainly introduce the work related to fault diagnosis.

2.1 Fault diagnosis

Existing deep learning-based methods can be divided into time domain, frequency domain and time-frequency domain according to the information utilization of sensor data.

The time-domain methods use the raw signal of the sensor as the input of the neural network, which has the advantage of being simple and intuitive without excessive preprocessing. Zhuang et al. [11] proposes an MS-DCNN fault diagnosis model, which takes the one-dimensional sensor raw signal as the input of the network, and extracts information at different scales through multi-scale convolutional layers. Guo et al. [7] tries to stack one-dimensional sensor signals into a two-dimensional matrix. Li et al. [5] proposes a fault diagnosis model of MRF-GCN, which uses graph to model sensor time-domain signals, constructs an adjacency matrix based on signal similarity, and adaptively learns the relationship between signals. The above methods achieve good results, but they all ignore the frequency domain information of the original data. Abnormal information usually has a high frequency in the frequency domain compared to normal information. Janssens et al.[12] uses discrete Fourier transform for data processing of raw signals, and fault diagnosis through convolutional neural networks. Although the frequency domain information is considered, the corresponding time domain information is ignored. Therefore, Xu et al. [13] uses continuous wavelet transform to convert the time-domain vibration signal into a two-dimensional grayscale image, considering both time-domain information and frequency-domain information, and used a LeNet-5-based CNN model for fault diagnosis.

However, these methods all rely on the quality of the data, and the data often contains noise, redundancy and high-dimensional feature, making it difficult for the model to learn stable parameters. So when there is perturbation, the model may be wrong.

3 Preliminary

Given training set $\mathcal{X}_{train}$, test set $\mathcal{X}_{test}$, PHM model f, data $x \in X_{test}$, perturbation ε, where $\|\varepsilon\|_p = \xi$

Definition 1: For classification problems, suppose the data $f(x) = y_i$, y_i is the class label of x. If there is perturbation ε such that $x' = x + \varepsilon$, $f(x') = y_j$,$y_j \neq y_i$, then the PHM model f is said to have a perturbation ε with p-norm ξ at data point x is not robust.

Definition 2: Considering that the test set $\mathcal{X}_{test}$ contains multiple data, the robustness of the test set $\mathcal{X}_{test}$ to the perturbation ε with p-norm ξ can be described as: when the perturbation with p-norm ξ is introduced, the PHM model f does not change the classification result of any data in the test set $\mathcal{X}_{test}$.

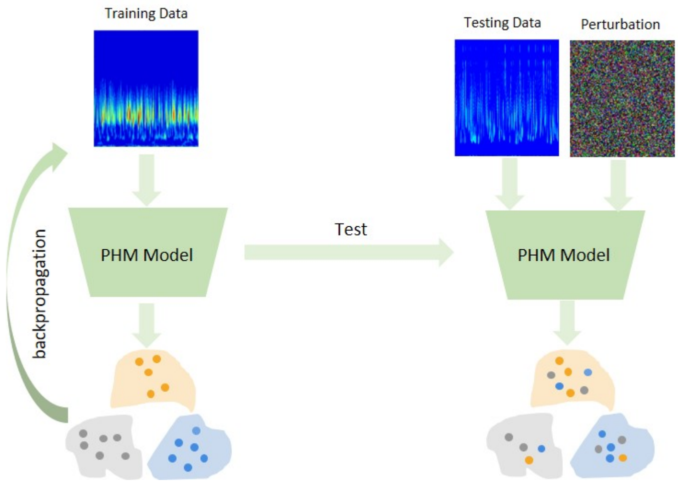

Fig. 2: The overall framework of our approach

Problem: For the model f, the robust perturbation ε with the p-norm of minimum ξ is difficult to solve. Therefore, we hope to obtain the accuracy of the corresponding model for the classification problem under the premise of the p-norm of the given perturbation ε .

4 Method

Figure 2 presents the overall framework of our robustness testing method proposed in this paper. It consists of two processes, the first is to train the model using the original training data to obtain good health management performance, and the next is to inject different perturbations to simulate the actual production environment of the factory when validating the test set to estimate the performance of the model in the real environment. Specifically, Gaussian noise G_N is used to simulate the background noise of the vibration signal to test the robustness of the model to background noise; random mask is used to simulate the absence of vibration signal to test the robustness of the model to data missing.

4.1 Background Noise

There are various types of sensors in the factory, and the background noise always affects the quality of the data collected by the sensors. Taking the acceleration sensor as an example, it mainly collects vibration signals, and factors such as mutual vibration between machines and tiny vibrations caused by workers moving and transporting vehicles constitute the background noise of the vibration signals.

$$P_G(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}} \tag{1}$$

Where μ and σ^2 are the parameters of the distribution, which are the expectation and variance of the Gaussian distribution, respectively.The equation 1 is abbreviated as $N(\mu, \sigma^2)$.

Here we use Gaussian noise G_N to simulate the factory background noise. Gaussian noise G_N follows a Gaussian distribution $N(\mu, \sigma^2)$ and is formulated as follows:

$$G_N \sim N(\mu, \sigma^2) \tag{2}$$

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For robustness testing, we fuse Gaussian noise with the original test data to reduce the signal-to-noise ratio of the test data, which is formulated as follows:

$$\mathrm{x}' = \mathrm{N_G} + x \tag{3}$$

4.2 Data Missing

Considering that data loss may occur in the actual data collection process, we design a random mask N_M. It is a code of length N, and each bit is 0 or 1 with a certain probability. For the robustness test, we fuse the random mask N_M with the original test data, and randomly change any bit of the test data to 0, the formula is as follows:

$$\mathrm{x}' = \mathrm{N_M} \otimes x \tag{4}$$

5 Experiment

5.1 Dataset

CWRU Bearing Fault Dataset: We use the Case Western Reserve University (CWRU)[20] bearing dataset for fault diagnosis robustness testing. Three different fault sizes are used, namely 7 mils, 14 mils and 21 mils. Each failure size contains three failures, namely inner raceway failure, outer ring failure and ball failure. Including normal types, there are a total of 10 health classes. Each class has four operating conditions: 0 hp/1797 rpm, 1 hp/1772 rpm, 2 hp/1750 rpm and 3 hp/1730 rpm. The sampling frequency of the samples is 12 kHZ. The data is split using the sliding window method with a window length of 1024 and a step size of 256. 70% of the data is used as the training set and 30% of the data is used as the test set.

5.2 Metric

We use four networks for fault diagnosis, namely LeNet[19], AlexNet[18], ResNet18[17] and Resnet50.

For fault diagnosis, the evaluation metric is the accuracy rate, which is defined as the ratio of the number of correct classifications to the total number of classifications.

5.3 Result

Table 1 shows the classification accuracy of the four fault diagnosis models under different disturbances. Here, the Gaussian noise is set to have a mean of 0 and a variance of 0.3. The mask is random 10% of the data bits become 0. It can be seen that when the data is clean, each model can show incredible accuracy. With just a little perturbation, model performance drops significantly, proving our work is very necessary, in factories where such models have the potential to cause major production accidents.

Table 1: Accuracy of fault diagnosis under different perturbations

	LeNet	AlexNet	ResNet18	Resnet50
Clean Data	99.3%	98.2%	98.6%	98.8%
Gaussian Noise	33.9%	37.5%	16.6%	13.0%
Mask Code	94.8%	97.1%	98.2%	87.4%

Comparing Gaussian noise and mask code, we can find that the model is more resistant to the disturbance caused by data missing, because although some data is missing, there are still other data that can provide fault information for the model, and the overall timing structure of data is not corrupted. The Gaussian noise leads to a significant drop in model performance, indicating that background noise will drown out useful information, destroy the correlation between time series data, and make it difficult for the model to extract features that are useful for classification.

From Figure 3, it can be seen that under the Gaussian noise $N(0, 0.5)$, the performance of the model's fault diagnosis is significantly reduced, and the classification is relatively concentrated. This is because the model uses Gaussian noise as the diagnosis object. The fault information is not extracted, that is, Gaussian noise drowns out the original sensor signal.

Figure 5 is accuracy heat maps drawn by superimposing the mean range [0, 0.5] and the variance range [0, 10] Gaussian noise. The yellow area is the area where the model is insensitive to Gaussian noise, and the model can still perform fault diagnosis. Note that the model is much more sensitive to variance than the mean, and only when the variance of the Gaussian noise is small, the model performance drops less. This is because all the time series data are approximately superimposed by a constant, although the numerical changes have a little impact on the model performance, the correlation between the data is still preserved.

As shown in Figure 6, the effect of mask perturbation on model performance is intuitive. As the proportion of missing data increases, the performance of the model gradually declines. This is because the information contained in the time series data is gradually lost, and the time series structure is gradually destroyed, so the model performance gradually declines.

And ResNet50 appears upturned at the end of the curve in Figure 6, this is because the model has collapsed and the classification is concentrated. As shown in Figure 4, when the data loss is serious, the fault diagnosis ability of the model is close to collapse, and the test samples are mostly divided into a class. When the data is missing 90%, it happens to divide a certain number of test samples into the normal class. The normal class accounts for the highest proportion of the samples, but good results are obtained.

6 Conclusion

In this paper, we propose a robustness test benchmark for PHM, simulate the production environment to test the performance of the model under various conditions, and achieve the evaluation of model robustness. Experiments show that our method is effective and it is necessary to test the robustness of the model.

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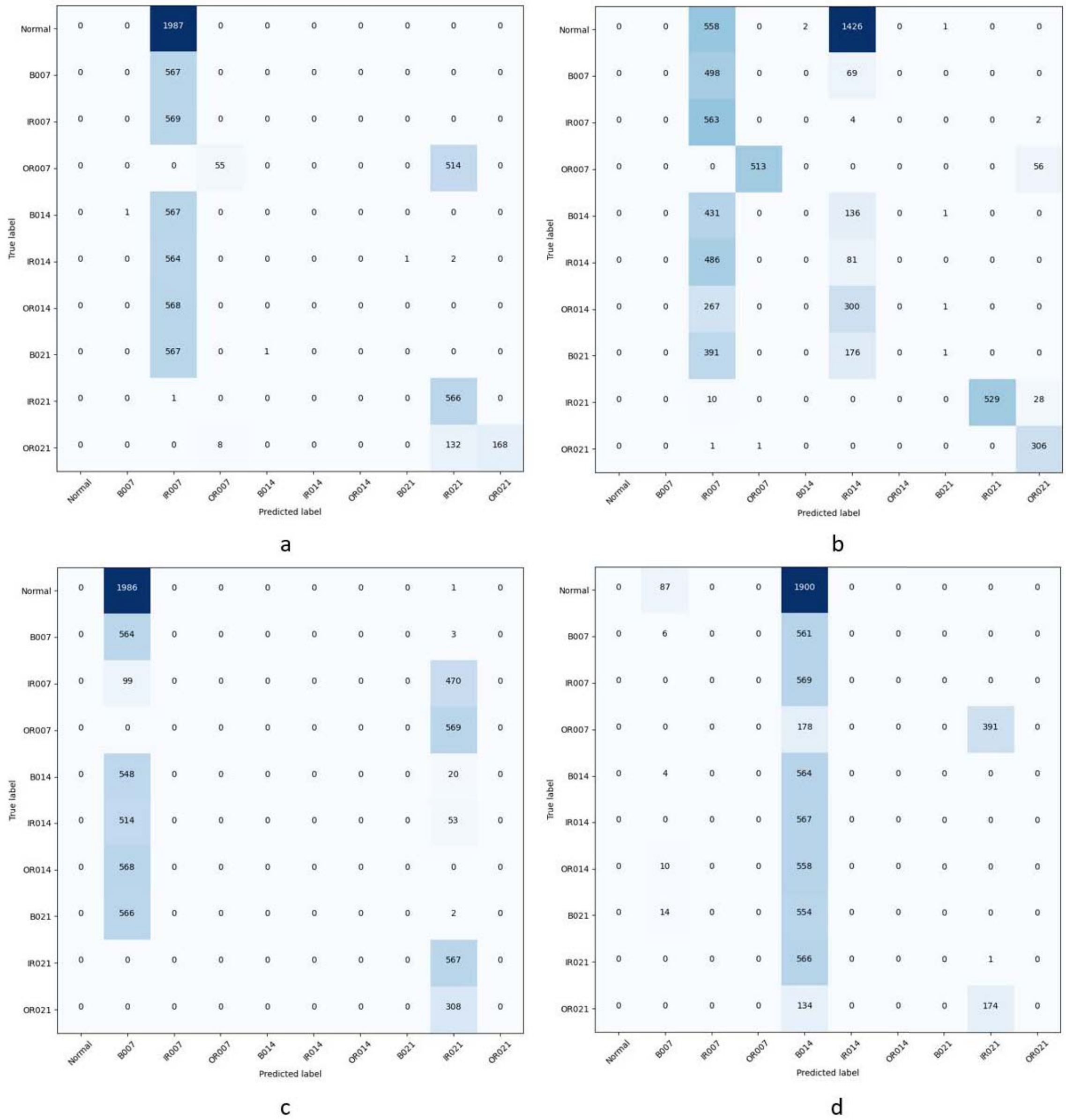

Fig. 3: a: Confusion matrix of AlexNet's fault diagnosis under $N(0, 0.5)$ perturbations. b: Confusion matrix of LeNet's fault diagnosis under $N(0, 0.5)$ perturbations. c: Confusion matrix of ResNet18's fault diagnosis under $N(0, 0.5)$ perturbations. d: Confusion matrix of ResNet50's fault diagnosis under $N(0, 0.5)$ perturbations.

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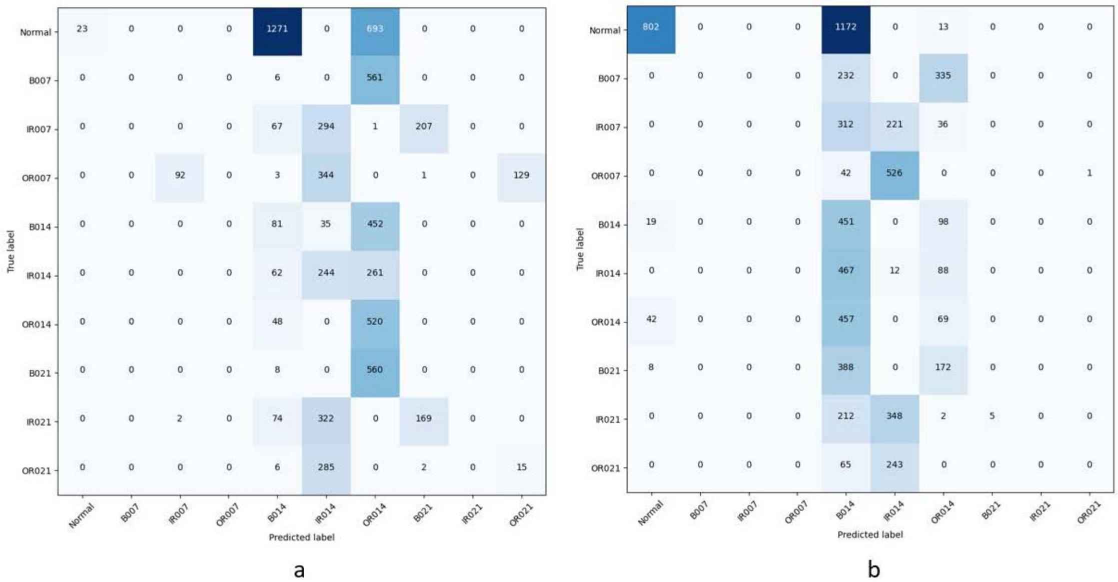

Fig. 4: a: Confusion matrix of ResNet50's fault diagnosis under 80% Mask Code. b: Confusion matrix of ResNet50's fault diagnosis under 90% Mask Code.

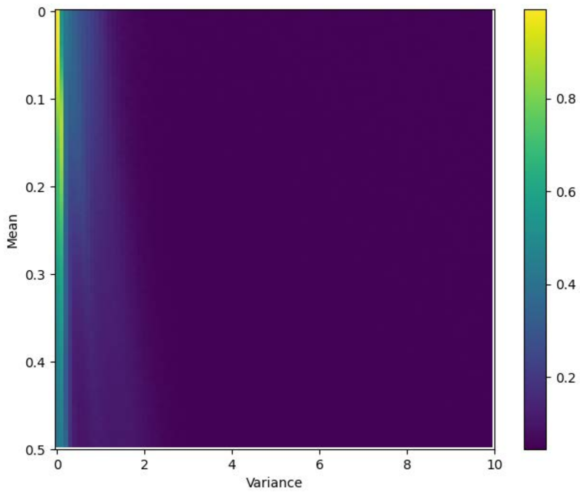

Fig. 5: Accuracy heatmap of LeNet for fault diagnosis under Gauss Noise perturbations

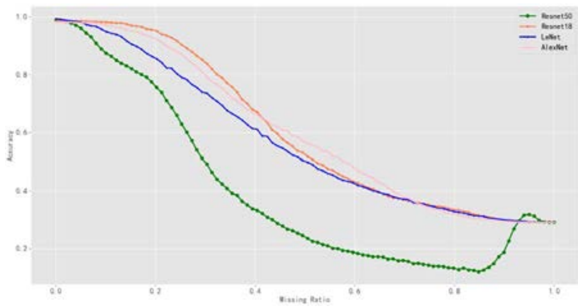

Fig. 6: Accuracy of fault diagnosis under different data missing ratios

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